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# Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses

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ABSTRACT

The purpose of the study is to examine the relationship between Competitive Pressure (CP), Top Management Commitment (TMC), Employee Adaptability (EA), External Support (ES), Organization Readiness (OR) and Artificial Intelligence Adoption (AIA) among SMES operating in Sabah, Malaysia. By employing judgemental sampling a total of 196 respondents were involved (i.e., owners or managers) in varied SME sectors such as services, manufacturing, construction, agriculture, and mining & quarrying. A survey questionnaire was used for data collection and analysed using Smart PLS 4. The results revealed that top management commitment and organization readiness have a significant relationship with AI adoption. However, competitive pressure, employee adaptability, and external support have an insignificant impact on AI adoption. This suggests that SME organizations may benefit from focusing on and enhancing TMC and OR practices to improve Al outcomes. Overall, these findings can guide decision-making and resource allocation, emphasizing the importance of OR and TMC in driving desired outcomes related to Al and highlighting areas where efforts may not yield significant effects. Based on present technological demands, practical implications and future research directions are also highlighted.

## Background

Prioritizing the development of AI skills among SMEs is a strategic decision by the Malaysian government, considering they make up 98.5 % of businesses in Malaysia and play a significant role by contributing 36.6 % to the nation's GDP (SME Corp and Wei, 2018). Forecasts indicate that the upcoming advancements in big data, machine learning, and automation will have remarkable effects on nations, businesses, and communities. By 2021, the integration of AI is expected to double the pace of innovation and boost productivity enhancements by 60 % in Malaysia (GetITAdmin, 2022). Specifically, the connection between AI and SMEs in Sabah, Malaysia, are characterized by the potential for innovation, efficiency, and growth. However, SME players embracing AI encounter three primary obstacles: lack of thought leadership and leadership commitment to AI investment, scarcity of skills and resources coupled with ongoing learning initiatives, and inadequate advanced analytics, infrastructure, and tools essential for generating actionable insights (Chitturu et al., 2017). Hence, up to the present time, discussions continue to revolve around the topic. Numerous stakeholders engage in conversations regarding AI and SMEs, offering diverse viewpoints.

The swift ascent of digital technology has catalyzed progress in various domains including products, services, and processes as highlighted by Iansiti and Lakhani (2020), as well as innovative business models as noted by Sjödin et al., (2020). Amidst this transformative landscape, Artificial Intelligence (AI) assumes a central and pioneering role, driving the exploration of new frontiers and possibilities (Lu et al., 2022). From a marketing perspective, with the advancements in machine learning and big data analytics, AI has become a powerful tool for marketers to gain insights into consumer behavior, optimize marketing campaigns, and improve overall business performance (Davenport et al., 2020; Huang & Rust, 2022; Verma et al., 2021), enabling marketers to make informed decisions and deliver personalized experiences to customers (Kumar et al., 2021). By leveraging the power of machine

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learning and data analytics, SME marketers can gain new insights into customer behavior and preferences, and use this information to deliver more personalized, effective, and efficient marketing campaigns (Ma and Sun, 2020; Sarath Kumar Boddu et al., 2022; Volkmar et al., 2022). Regardless of the type of SME business, industry size, product & service offered, all this information is extremely important for decision-making. An essential query that remains incompletely addressed pertains to the identification of key determining factors that influence the adoption and acceptance of Artificial Intelligence (AI) within local Small and Medium Enterprises (SMEs).

### *Research gaps and motivation*

Today's increasingly competitive business environment necessitates that every industry participant be equipped with the latest technology, including artificial intelligence. Therefore, the implementation of AI has indeed transformed the way organizations including small and medium enterprises (SMEs) conduct business. AI can be a powerful tool for strategic marketing decision-making (Davenport et al., 2020), and offers numerous advantages and opportunities that can help SMEs enhance their operations, improve strategic decision processes, and optimize overall business performance. However, it's important to note that implementing AI requires careful planning, investment, and expertize (OECD, 2021). SMEs need to assess their specific needs, consider the scalability of AI solutions, and ensure proper training and integration with existing systems. Nonetheless, the potential benefits make AI a powerful tool for SMEs to drive growth, innovation, and competitiveness in today's digital era (Campbell et al., 2020; Kumar et al., 2021). However, it is important to ensure that the data used to train AI models is accurate and unbiased to avoid unintended consequences. Obviously, research in the field of AI and SMEs is still evolving, and several gaps exist that require further investigation (Hansen and Bøgh, 2021; Perifanis and Kitsios, 2023). Although SMEs contribute to the country's (Sabah's) local economic structure, they fall far behind in terms of new technology and AI adoption (Ambad et al., 2020; Jaganathan et al., 2018). The primary causes for the absence of AI integration in local SMEs are a lack of fundamental understanding of AI capabilities and inadequate resources for AI adaptation (Rosa et al., 2021). Furthermore, the number of studies of AI and SME-related research in Sabah Malaysia is also limited. According to the Economic Census 2016–2021, there are 55,702 SME participants in Sabah. In 2021, SME players will contribute a total of $518,075,000 to the gross domestic product (GDP), making the study of SME players highly pertinent (SME Corporation Malaysia, 2017).

An extensive study on the influence of AI adaptability has previously been conducted (i.e., Dondapati et al., 2022; Keegan et al., 2022; Kopalle et al., 2022; Manis and Madhavaram, 2023; Mikalef et al., 2021, 2023; Olstad et al., 2022; Saura et al., 2021). Nevertheless, as SMEs function in their own unique ecosystems broad conclusions cannot be generalized to them. Hence, the study seeks to examine the relationship between Competitive Pressure (CP), Top Management Commitment (TMC), Employee Adaptability (EA), External Support (ES), and Organization Readiness (OR) on AI adoption from the perspective of SME management (i.e., owner or manager) in Sabah. Besides, in Sabah Malaysia particularly, the factors influencing success or failure in the adoption of AI systems in SMEs remain unknown. Because Sabah SMEs have five different sectors (i.e., services, manufacturing, construction, agriculture, and quarrying & mining), addressing these research gaps will contribute to a better understanding of the determining factors associated with AI adoption among SMEs, leading to the development of effective strategies, frameworks, and tools to support SMEs in harnessing the benefits of AI technologies (Drydakis, 2022; Ragazou et al., 2023).

To provide greater clarity, the subsequent statement delineates certain gaps in research concerning the application of AI within Small and Medium Enterprises (SMEs) in Sabah, Malaysia. The research gaps can be summarized as follows:

*Limited understanding and resources in AI adoption for local SMEs*

There is a lack of fundamental understanding among local SMEs in Sabah regarding the capabilities and potential benefits of AI. SMEs often face challenges due to inadequate resources for adapting and integrating AI technologies into their operations.

*Lack of AI adoption studies in Sabah, Malaysia*

Despite the significant contribution of SMEs to the local economy, there is a scarcity of comprehensive studies focused on AI adoption within this region. The unique business ecosystem of Sabah's SMEs demands research specific to this context, as broad conclusions drawn from other studies may not apply directly. Although Sabah's SMEs significantly contribute to the GDP, there is a lack of comprehensive research focused specifically on their AI adoption patterns and challenges.

*Sectorial variation and determinants of AI success*

SMEs in Sabah are spread across diverse sectors, each with its own dynamics and challenges. Factors that determine the success or failure of AI adoption in different sectors of Sabah's SME landscape remain unexplored. The specific factors that influence the adoption of AI systems in SMEs within the Sabah region are yet to be identified. Understanding these factors is crucial for developing tailored strategies and frameworks that address the unique challenges faced by Sabah SMEs.

*Limited perspective on SME management*

Previous studies have examined AI adoption from various perspectives but might lack insights from the perspective of SME management (i.e. owners or managers). Investigating AI adoption through the lens of SME management could provide valuable insights into decision-making processes and challenges faced by decision-makers. There is a need to develop effective strategies, frameworks, and tools that can assist Sabah SMEs in harnessing the benefits of AI technologies.

*Need for effective strategies and tools*

There is a need to develop effective strategies, frameworks, and tools that can assist Sabah SMEs in harnessing the benefits of AI technologies. Addressing this gap would support SMEs in making informed decisions and navigating the complexities of AI adoption. Addressing these research gaps through a focused study can provide valuable insights into the unique challenges and opportunities that AI adoption presents for SMEs in Sabah, contributing to more informed decision-making and strategies in the context of AI integration.

## Literature review

### *Artificial intelligence (AI)*

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)*

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)*

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)*

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)*

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)*

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

The research methodology involved the identification of six significant variables, categorized as INTERNAL (Top Management Commitment, Organizational Readiness, Employee Adaptation) and EXTERNAL (Competitive Pressure, External Support) factors, to comprehensively explore AI adoption among SMEs in Sabah, Malaysia. Hypotheses were formulated based on existing theoretical models and previous research studies (Daoud et al., 2021; Rosa et al., 2021), establishing testable relationships between the variables. The resulting conceptual model, depicted in Figure 1, visually represents these relationships and draws on established theoretical foundations to provide a comprehensive understanding of the factors influencing AI adoption within the local SME context.

### *Research instruments*

Six significant variables, categorized as INTERNAL factors (Top Management Commitment (TMC), Organizational Readiness (OR), and Employee Adaptation (EA)) and EXTERNAL factors (Competition Pressure (CP) and External Support (ES)), formed the conceptual foundation of the proposed model. Fig. 1 depicts our proposed research model, which is based on the examined theoretical models and the main factors described above.

The study utilizes a seven-point Likert scale with options ranging from 1 (strongly disagree) to 7 (strongly agree). All six variables of the model are measured this way and adopted from Daoud et al. (2021) and Rosa et al. (2021). The draft version of the measurement scale has been validated (i.e. face validity) by two experts (i.e., academicians) and two SME owners. Based on their input, the questionnaire was revised for usage in a pilot study to check understandability and reliability. The unit of analysis was the individual. Smart PLS 4 was used to analyse the data, and the Path model was utilized to test the hypothesis using regression coefficients. Smart PLS 4 was chosen because it is appropriate for the analysis of small data samples and the study is focused on validating a theoretical framework from a prediction standpoint (Hair et al., 2019).

### *Sampling and data collection*

The respondents involved owners or managers of SMEs in varied sectors such as services, manufacturing, construction, agriculture, and mining & quarrying which are located and operated in Sabah Malaysia. The owner or management of the company is chosen as the response since they are the decision makers for the adoption of new technologies such as AI. It is presumed that ownership has comprehensive information about AI customization. The sampling frame consisted of Sabah's SME industries (a total of 55,702) listed and registered in SME Corporation Malaysia. Before the business owner or manager responded to the survey questions sent via email, Google forms, and phone calls, the researcher requested permission from the management. The data collection were made between January and April 2023. The minimum sample size was determined using G*Power, a software tool developed by Faul et al. (2009). Given that the model consists of five predictors, the effect size is established at 0.15, and the desired power is set at 0.95. In business and social science studies, it is commonly recommended that a minimum power of 0.8 be utilized as the minimum acceptable power (Hair et al., 2013; Gefen et al., 2010). The minimum sample size required was determined to be 138 by computations. A total of 300 questionnaires were distributed, retrieving 196 valid responses, establishing a response rate of 65.3 %, which is deemed satisfactory and exceeding the minimum amount required. This study utilizes a judgemental sampling technique, spanning various industries and business sizes. It selectively chooses respondents who hold executive or managerial roles and are actively involved in deploying artificial intelligence inside their respective companies. To rule out Common Method Bias (CMB) of the measurement items in the developed model, this study adopted Harman's single-factor test. The first component accounted for 36.8% of the total variation. Because a single component does not explain the majority of the variance, CMB is determined to be insignificant in this circumstance (Podsakoff et al., 2003).

## Results

### *Respondents profile*

The data represents the distribution of Small and Medium-sized Enterprises (SMEs) across different sectors. Table 1 shows the number of SMEs and the corresponding percentage for each sector. In total, there

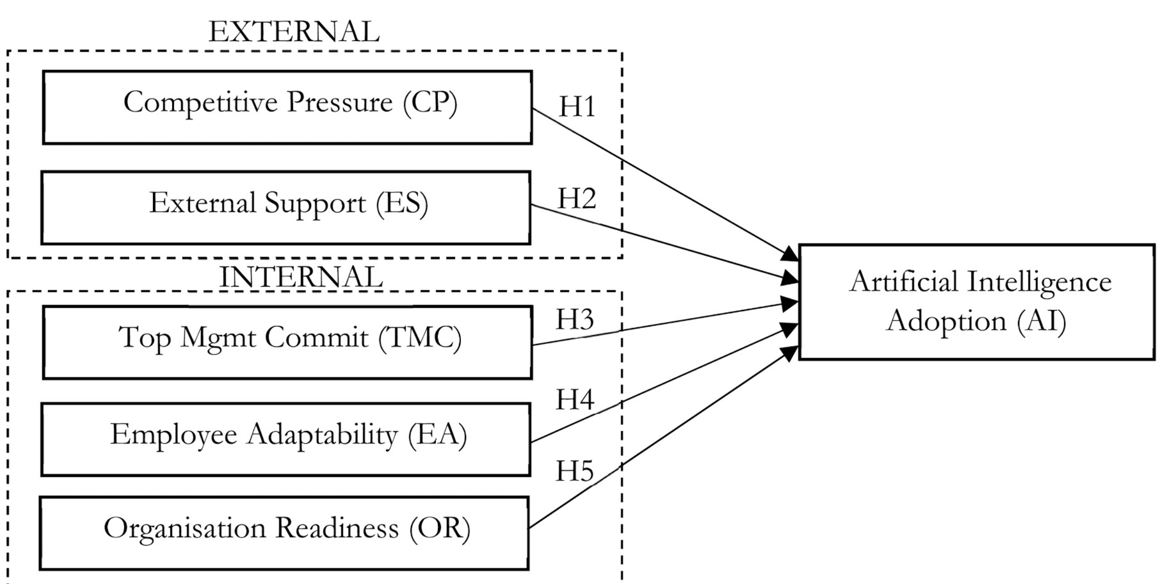


**Fig. 1.** Conceptual framework of the study.
Source: Adopted and modified from (Daoud et al., 2021; Rosa et al., 2021).

**Table 1**
Respondents' profile based on sector.

| SMEs 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 and above | 42 | 21.42 |
| **Gender** | | |
| Male | 124 | 63.26 |
| Female | 72 | 36.73 |

are 196 SMEs participated in this study, with each sector contributing to the overall percentage. The services sector has the highest number of SMEs, with 65 enterprises, accounting for 33.16 % of the total. Manufacturing comes next with 32 enterprises, representing 16.32 % of the total. The construction sector has 21 SMEs, accounting for 10.71 % of the total. Agriculture has the largest number of SMEs, with 76 enterprises, representing 38.77 % of the total. Lastly, the quarrying and mining sector has the lowest number of SMEs, with only 2 enterprises, making up 1.02 % of the total. In terms of age, the largest group falls within the 34–41-year-old category, with 66 respondents. This is followed by the 42–49-year-old category with 53 respondents. The smallest age group is the 18–25 years old category, with only 6 participants. In terms of gender, the majority of respondents are male, with 124 participants, while the female respondents are represented by 72 participants. The sector profile of samples is consistent and representative of the SMEs in Sabah (DOSM, 2021).

*Validity of measurement model*

The validity of a measurement model refers to the degree to which the model accurately measures the construct or concept it is intended to measure. It is an essential aspect of research and ensures that the measurements used in a study are reliable and meaningful. According to Hoyle (2011) and Kline (2010), a measurement model assesses latent variables or composite variables. Meanwhile, measurement model validity is measured by using three criteria which are construct validity, convergent validity and discriminant validity (Ahmad et al., 2016; Hair et al., 2019).

*Convergent validity*

To assess the convergence of constructs, factor loadings, composite reliability (CR) and average variance explained (AVE), and reliability (Cronbach's Alpha) were calculated (Fornell & Larcker, 1981). When all three of the following requirements are met, there is evidence for convergent validity: (a) CR values are 0.7 or higher, (b) all standardized factor loadings are 0.5 or greater, and (c) AVE values are 0.5 or greater (Cheung et al., 2023; Henseler et al., 2015). Based on the result in Table 2, it appears that the measurement model meets the requirements for construct reliability (CR), standardized loading, average variance extracted (AE), and reliability of the construct (Cronbach's Alpha). The CR values range from 0.995 to 0.877, indicating the measurement model's high internal consistency and dependability. A higher CR value indicates that the observed indicators measure their respective latent constructs with greater reliability. The range of standard loading values is between 0.696 and 0.992. These values represent the intensity of the relationship between the observed indicators and their respective latent constructs. Greater standardized loadings indicate that the indicators are significantly related to the underlying constructs. The AE values vary

**Table 2**
Construct validity and reliability.

| Construct | Code/ Items | Loadings | AVE | CR | Cronbach's Alpha |
|---|---|---|---|---|---|
| Artificial Intelligence 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 | | | |
| Employee 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 |
| | ES3 | 0.849 | | | |
| | ES4 | 0.760 | | | |
| Organization Readiness (OR) | OR1 | 0.996 | 0.959 | 0.989 | 0.986 |
| | OR2 | 0.964 | | | |
| | OR3 | 0.973 | | | |
| | OR4 | 0.982 | | | |
| Top Management Commitment (TMC) | TMC1 | 0.875 | 0.961 | 0.990 | 0.986 |
| | TMC3 | 0.871 | | | |
| | TMC4 | 0.876 | | | |
| | TMC5 | 0.850 | | | |

between 0.64 and 0.990. These values represent the quantity of observed indicator variance that is explained by their respective latent constructs. Higher AE values indicate that the constructs explain a greater proportion of the indicator variance. Cronbach's Alpha values range from 0.800 to 0.993. Similar to CR, Cronbach's Alpha is a measure of internal consistency reliability. Cronbach's Alpha values that are greater indicate greater reliability and consistency among the measurement model's elements.

*Discriminant validity*

The objective of the discriminant validity assessment is to ensure that a reflective construct has the strongest associations with its own indicators in the PLS path model (Hair et al., 2017; Hair et al., 2019). The Fronell-Larcker criterion is one of the most widely used methods for evaluating the discriminant validity of measurement models (Ab Hamid et al., 2017). According to this criterion, the square root of the average variance extracted (AVE) by a construct must be greater than the construct's correlation with all other constructs (Ab Hamid et al., 2017; David Alarcón and Sanchez, 2015). However, we decided to utilize the Heterotrait-Monotrait ratio of the correlation (TMT) approach criterion because it has high sensitivity and specificity in detecting discriminant validity problems (Henseler et al., 2015). Based on the HTMT values in Table 3, it can be concluded that the measurement model demonstrates satisfactory discriminant validity among the constructs under investigation. Specifically, all values are below 0.85, suggesting that there is

**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** | | | | |
| Employee 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** |

adequate discriminant validity among the constructs. Each construct's correlations with indicators of other constructs are lower than their correlations with indicators of the same construct, indicating that the constructs are distinct and not highly overlapping.

### *Assessment of structural model*

In PLS-SEM, the structural model evaluation focuses on determining the significance and relevance of path coefficients, followed by the model's explanatory and predictive power. Specifically, the structural model reflects the paths hypothesized in the research framework. The hypothesized paths from the research framework are reflected in the structural model. The significance of pathways, as well as the $R^2$ and $Q^2$, are used for the evaluation. Based on Fig. 2, shows that the $R^2$ value of a model is 0.441, which means that approximately 44.1 % of the variability in the dependent variable can be explained by the independent variables included in the model. In other words, the independent variables (i.e., CP, ES, EA, OR, and TMC) collectively account for 44.1 % of the variation observed in the dependent variable (i.e., AI).

The quality or goodness of the model is measured by the strength of each structural path, which is determined by the $R^2$ value for the dependent variable, which should be equal to or greater than "0.1" (Falk and Miller, 2014). Table 4 and Fig. 2 show that the $R^2$ value of 0.441 is more than 0.1. As a result, predictive capacity is established. $Q^2$ also confirms the predictive importance of endogenous components. A $Q^2$ greater than "0" indicates that the model is predictively relevant ($Q^2 = 0.339$). In addition, the model fit was evaluated using SRMR. The SRMR score was 0.059, which is less than the necessary value of "0.10", indicating an acceptable model fit (Hair et al., 2016).

The results revealed that Top Management Commitment (TMC) and Organization Readiness (OR) have a significant impact on Artificial Intelligence (AI) adoption (OR – AI: $\beta = 0.444$, $t = 6.324$, $p < 0.001$) and (TMC – AI: $\beta = 0.333$, $t = 4.16$, $p < 0.001$). Hence, H2 and H5 were supported. However, the results also revealed that CP, EA, and ES have an insignificant impact on AI. Hence, H1, H3, and H4 were not supported or rejected. The statistically significant positive relationship indicates that changes or interventions related to TMC and OR can potentially have a meaningful impact on Al. This suggests that SME organizations may benefit from focusing on and enhancing TMC and OR practices to improve Al outcomes. Overall, these findings can guide decision-making and resource allocation, emphasizing the importance of OR and TMC in driving desired outcomes related to Al and highlighting areas where efforts may not yield significant effects. Unfortunately, this outcome differs slightly from the conclusions of earlier research (Rosa et al., 2021), where it was determined that both TMC and OR did not exhibit significance. Simultaneously, it's worth noting a parallel between the findings of the present study and previous research conducted by Daoud et al. in 2021. Their study also examined the CP variable and concluded that it holds significance, thus providing further support for the hypothesis under consideration.

## Discussion

The study showed that Top Management Commitment (TMC) and Organization Readiness (OR) had a substantial effect on AI adoption, confirming hypotheses H2 and H5. The considerable positive relationship between TMC, OR, and AI adoption implies that investments in these areas may have a major influence on AI outcomes for SMEs. These results may help to guide decision-making and resource allocation by emphasizing the relevance of OR and TMC in obtaining desired AI goals and recognizing areas where efforts may be ineffective. For strategic decision-making, the significant relationship between OR and Al implies that organizations should focus on optimizing their organization readiness to improve Al outcomes (Aboelmaged, 2014). This could involve streamlining processes, enhancing efficiency, and investing in technological advancements to leverage the potential benefits of Al. Given the significant relationship between TMC and AI, organizations should prioritize the development and training of employees in relevant technological and managerial competencies. This includes providing opportunities for upskilling and reskilling to ensure that the workforce possesses the necessary skills to effectively utilize AI technologies. However, contradictory results were observed in small and medium-sized enterprises lacking top management commitment (Furuholt and Ørvik, 2006). This study asserts that the lack of support from top management is one of the reasons for the lack of adaptation of AI among SMEs.

Top Management Commitment (TMC) plays a crucial role in influencing AI technology adoption among SMEs (Daoud et al., 2021). Top management, including executives and senior leaders, have the authority and responsibility to set the vision and strategic direction of the

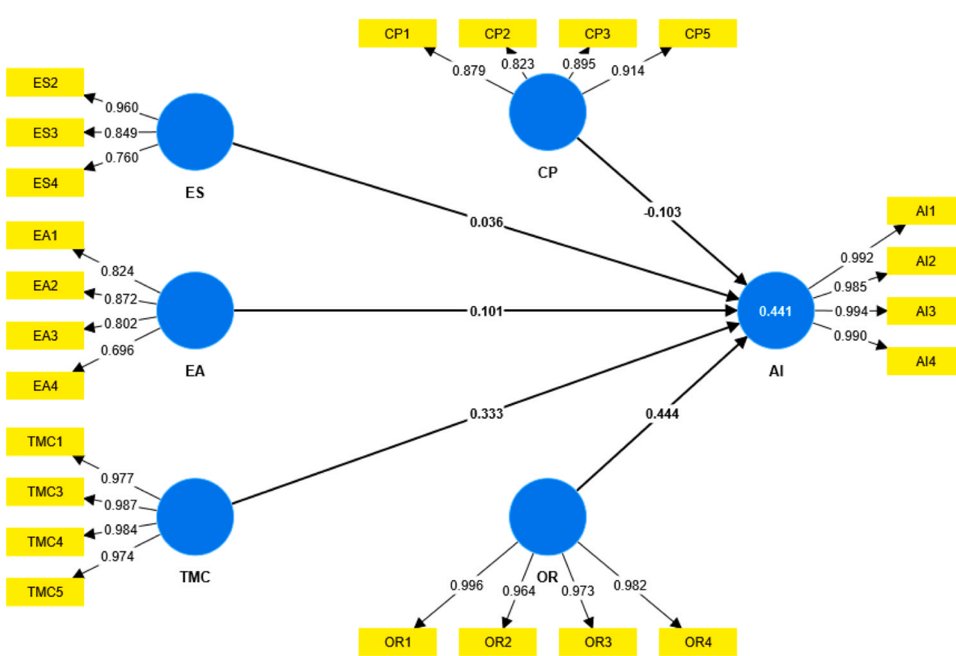


**Fig. 2.** Path coefficient.

**Table 4**
Hypothesis Testing (Path Coefficient).

| Hypothesis | | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (O/STDEV) | P values | Result |
|---|---|---|---|---|---|---|---|
| H1 | CP -> Al | -0.103 | -0.093 | 0.067 | 1.539 | 0.125 | Rejected |
| H2 | TMC -> AI | 0.333 | 0.329 | 0.080 | 4.164 | 0.000 | **Supported** |
| H3 | EA -> Al | 0.101 | 0.104 | 0.069 | 1.458 | 0.146 | Rejected |
| H4 | ES -> Al | 0.036 | 0.048 | 0.075 | 0.474 | 0.636 | Rejected |
| H5 | OR -> Al | 0.444 | 0.445 | 0.070 | 6.324 | 0.000 | **Supported** |
| | | Estimate | Threshold | | | | |
| Goodness | $R^2$ | 0.441 | (More than 0.1) | | | | Acceptable |
| of the | $Q^2$ | 0.339 | (Greater than 0) | | | | Acceptable |
| Model | SRMR | 0.059 | (Less than 0.1) | | | | Acceptable |

organization. When there is a strong commitment from top management to embrace AI technology, it signals to the rest of the organization that AI is a strategic priority (Jayashree et al., 2021; Mikalef et al., 2023). This commitment helps align the efforts and resources of the organization towards AI adoption. Top management commitment is essential for allocating resources, including financial, technological, and human resources, towards AI initiatives (Dubey et al., 2018; Soltani, 2005). Without the support and commitment of top management, it can be challenging to secure the necessary resources to invest in AI technology, infrastructure, and talent acquisition (Deepu and Ravi, 2021; Lemos et al., 2022). TMC ensures that the SME organization allocates adequate resources to support the successful adoption and implementation of AI. Undoubtedly, the cultivation of unwavering commitment from top management is essential in efficiently carrying out any important commitment, such as implementing artificial intelligence (AI) technology. The very first phase involves educating senior executives and providing them with comprehensive and concise information regarding the potential advantages of artificial intelligence (AI) and its pertinence to the firm's strategic objectives. The efficacy of AI in fostering growth, efficiency, and innovation can be substantiated through the utilization of success stories and case studies derived from comparable industries. Furthermore, it is imperative to ensure that adopting artificial intelligence (AI) aligns with the organization's strategic goals. Companies can be convinced or motivated by emphasizing the potential of AI to contribute to competitive advantage, revenue expansion, cost reduction, and improved customer experiences, which are their key focus areas. Ultimately, AI vendors must provide support to organizations in formulating a comprehensive and attainable strategy for integrating AI technology. This encompasses delineating the various stages, timeframes, milestones, and anticipated results of each respective phase. This framework offers an organized approach that senior executives can adopt and monitor.

Organization Readiness (OR) plays a significant role in influencing AI technology adoption among SMEs. AI adoption requires a robust technological infrastructure that can support the implementation and integration of AI systems and applications (Jöhnk et al., 2021). Organization Readiness involves evaluating and improving the technological infrastructure to ensure it can accommodate AI requirements, such as processing power, data storage capacity, and network bandwidth. AI adoption often entails changes in work processes, roles, and responsibilities (Hashim et al., 2021; Hradecky et al., 2022). OR involves effectively managing these changes by providing clear communication, training, and support to employees. It is important to engage employees throughout the AI adoption process, addressing any concerns or resistance they may have. Organization Readiness ensures that employees understand the benefits of AI technology, are equipped with the necessary skills, and are prepared to adapt to new ways of working (Aboelmaged, 2014; Jalagat, 2016). By addressing these aspects of Organization Readiness, SMEs can enhance their readiness to adopt AI technologies, overcome potential barriers, and maximize the benefits of AI adoption. Establishing a level of organizational readiness holds a vital role in the successful adoption of artificial intelligence. Several practical guidelines can be proposed to aid organizations in efficiently managing their readiness to implement artificial intelligence. A thorough evaluation of the organization's existing technological infrastructure, data quality, and IT capabilities would be the base to identify the company's position and capacity in adopting new technology. This inquiry seeks to identify the strengths and shortcomings that may impact the application of artificial intelligence. In addition, it is imperative to ensure that senior staff and top management align with the aims and advantages of the AI effort. The dedication of top management establishes the foundation for the level of preparedness inside a business. To enhance effectiveness, it is advisable to commence by formulating a well-defined artificial intelligence strategy that delineates the goals, objectives, and anticipated consequences of AI adoption. To progress, it is imperative to recognize deficiencies in abilities and allocate resources towards training initiatives to enhance employees' proficiencies in AI-related domains. This encompasses technological proficiencies such as programming, machine learning and data analysis.

The influence of CP, EA, and ES on AI adoption, on the other hand, was shown to be insignificant, with no support or rejection of hypotheses H1, H3, and H4. The lack of statistically significant relationships suggests that changes in these variables (i.e. CP, EA, ES) may not have a significant impact on the variable Al (or its manifestation). Practically, this implies that efforts targeting changes in CP, EA, or ES may not yield substantial or noticeable effects on Al, and other factors should be considered or explored. The findings of this research are extremely reflected in the actual state of SME activities in Sabah (Jaganathan et al., 2018). This absence may disproportionately impact SMEs, whose limited financial, technical, and human resources may impede the establishment of a successful digital technology adoption path (Battistoni et al., 2023; Wu et al., 2023). A possible rationale for the insignificant effect of CP on the Adoption of Artificial Intelligence is the presence of specific industry-specific or organizational attributes that pose challenges to the successful integration of AI. These challenges may arise from the inherent characteristics of their operational procedures or the specific nature of the data they handle. In instances of this nature, the impact of competitive pressure may be diminished as the potential benefits derived from artificial intelligence may not be as significant. Moreover, the implementation of artificial intelligence (AI) frequently necessitates substantial investments in several aspects, such as technological infrastructure, the gathering and administration of data, the recruitment of skilled personnel, and the continuous upkeep of the system. In situations where an organization is confronted with financial or resource limitations, the prioritization of investing in artificial intelligence (AI) may be overshadowed by more pressing and urgent considerations.(Oz and Sosik, 2000; Wei and Pardo, 2022).

The significance of employee adaptation in effectively integrating emerging technologies like artificial intelligence (AI) is widely acknowledged. However, there may be certain situations where EA may not exert a substantial influence, like the finding in this study. When integrating artificial intelligence entails utilizing extensively automated procedures that necessitate limited human involvement, the level of concern over employee adaptability may be insignificant (Oz and Sosik, 2000; Wei and Pardo, 2022). For example, in cases where artificial intelligence (AI) is predominantly employed for data analysis and decision-making tasks, with no requirement for considerable employee interaction, the need for employees to adapt to the technology may be constrained. Furthermore, specific AI applications require the acquisition of specialized technical skills, which may only be viable or practical for some personnel. For example, it may not be feasible for individuals in non-technical positions within an organization to acquire expertize in developing intricate machine-learning algorithms. As for the insignificant effect of ES is possible due to some organizations might already have a strong internal team with the necessary expertize in AI development, implementation, and management when they decided to adopt AI in their process. In such cases, they might not rely heavily on external support because they can leverage their own resources to adopt and integrate AI technologies effectively. Furthermore, companies that are not IT or AI-based and leverage AI to make their process and decisions more efficient would face straightforward AI implementations that involve off-the-shelf solutions or basic applications, organizations might not need extensive external support. Many AI tools and platforms are designed to be user-friendly and require minimal technical expertize to get started (Haleem et al., 2022).

## Conclusion and future research

In conclusion, this study examined the determining factors associated with artificial intelligence (AI) adoption among SMEs in Sabah. The data was examined using Smart PLS 4 software based on 196 respondents who were gathered using a judgemental sampling technique. All research instruments and survey data acquired from the measurement model and structural model utilizing the "bootstrapping" analysis and the "PLS-SEM" method are legitimate and trustworthy. Based on the overall findings, organizations are advised to prioritize investments in TMC and OR to enhance AI outcomes. While CP, EA, and ES may still be important considerations, their impact on AI adoption may not be as significant. By strategically allocating resources and addressing the specific challenges faced by SMEs, organizations can increase their chances of successful AI adoption and utilization. Addressing these issues will contribute to a better understanding of the opportunities and challenges associated with AI adoption in SMEs, leading to the development of effective strategies, frameworks, and tools to support SMEs in harnessing the benefits of AI technologies. Overall, there is still a need for sustainable development in Sabah, and the adoption of AI technology may aid in this endeavor. Using AI technologies as supporting tools will be difficult if they are not adequately embraced, and these issues must be overcome for AI to obtain universal acceptance.

Because SMEs in Sabah are still in the early stages of adoption, this research solely focuses on the general use of AI technology. As a result, future research should examine the acceptability of AI technology from a more specialized standpoint, such as AI in product development, customer support, sales and advertising. Another limitation of the study is the small sample size (i.e. 196). The findings and conclusions drawn from a small sample may not be representative of the entire population or SMEs in general. A small sample size reduces the generalizability and external validity of the study's findings. Furthermore, the small sample size may limit the variability of the data, potentially impacting the robustness and reliability of the findings. With fewer data points, it becomes more challenging to capture the full range of experiences, perspectives, and contexts related to AI adoption in SMEs. SMEs in different regions may face unique challenges and opportunities related to AI adoption. Factors such as local regulations, market conditions, cultural norms, and available resources can vary across regions, impacting the adoption and outcomes of AI initiatives. Therefore, the findings of this study may not necessarily reflect the experiences or patterns observed in SMEs outside of Sabah. To enhance the external validity of the study, future research should consider expanding the scope to include SMEs from diverse regions, allowing for a more comprehensive understanding of the factors influencing AI adoption and their implications. This would help to provide a broader perspective on the challenges and opportunities faced by SMEs in different contexts and facilitate the development of more robust and applicable strategies for AI adoption. Lastly, given that this study is quantitative in nature and relies on the perspectives of respondents rather than direct observations of AI implementation and adoption within companies, it is recommended that future research endeavors employ a qualitative research design or conduct case studies. This will enable greater comprehension of the determining factors and obstacles that influence companies' decisions to adopt AI in their organizational contexts.

## Ethical Statement/Approval

This research project does not involve the use of animal or human subjects and is therefore exempt from review under the Bioethics Act. The data collected and analyzed in this research were obtained solely from questionnaire sources, with explicit consent obtained from the participants and did not contain sensitive information. Therefore, the execution of this research did not necessitate any specific ethical approval.

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## CRediT authorship contribution statement

**Suddin Lada:** Conceptualization, Methodology, Writing- Original draft preparation, Writing- Reviewing and Editing. **Brahim Chekima:** Conceptualization, Methodology, Writing- Original draft preparation, Writing- Reviewing and Editing. **Mohd. Rahimie Abdul Karim:** Methodology, Software, Validation, Formal analysis. **Noor Fzlinda Fabeil:** Methodology, Software, Validation, Formal analysis. **Mat Salleh Ayub:** Methodology, Software, Validation, Formal analysis. **Sharifah Milda Amirul:** Methodology, Software, Validation. **Rudy Ansar:** Writing- Reviewing and Editing, Methodology, Software, Validation, Formal analysis. **Mohamed Bouteraa:** Writing- Reviewing and Editing, Methodology, Software, Validation, Formal analysis. **Lim Ming Fook:** Writing- Reviewing and Editing, Methodology, Software, Validation, Formal analysis. **Hafizah Omar Zaki:**, Methodology, Software, Validation, Formal analysis.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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