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Strategic foresight and big data analytics as antecedents of SMEs' sustainable competitive advantage: Role of AI utilization

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Abstract
Purpose: This study investigates the association of Strategic foresight and Big data analytical capabilities with SMEs' sustainable competitive advantage through the mediation if AI utilization
Methodology: This study has followed the positivism philosophy and deductive approach. Further, quantitative survey was distributed through cross-sectional survey to the 260 owners and managers of SMEs in Malaysia
Findings: This study found the significant association of SF and BDAC with SMEs' sustainable competitive advantage. Further, AI utilization significantly mediates the relationship of SF and BDAC with SMEs' sustainable competitive advantage.
Limitations: In this study, only quantitative study design was used and data were collected from SMEs of limited cities.
Implications: This study will be helpful for the SMEs' managers and owners to consider the future and also the updated technology to make better decision while meeting the changing customer requirements to sustain their competitiveness. Further, policy makers can also facilitate the SMEs to build their capabilities to foresee the changes in future and adopt the modern technologies i.e. big data and AI which are necessary for survival in dynamic business market.
Originality: To the best of our knowledge none of the previous study has considered how the strategic foresight and big data analytical capabilities can be used along with AI to achieve the sustainable competitiveness among the SMEs of the developing economies.

Key Words: Strategic Foresight, Big data Analytics, SMEs' Sustainable Competitiveness, AI Utilization.

Introduction

In the recent decade, rapid changes in the business environment and introduction of the modern technologies have created the pressure on the manufacturing companies to switch from their cheap labor costs and low-value addition business operating methods to advance technology and business practices (Cao et al., 2020; Li et al., 2020). Previously, the industrial sector was labor-intensive, and their strategic focus was on lowering production costs since their competitors' cost-effective techniques threatened (Cao et al., 2022). Traditional management practices, however, have proven ineffective in dealing with an unpredictable and chaotic environment (Haarhaus & Liening, 2020). Despite a number of major technical advancements, industry 4.0 in particular has altered how organizations design and manufacture products and services regardless of industrial sector (Bibby & Dehe, 2018). Thus, industry 4.0 revolution is haunting the traditional manufacturing firms, particularly manufacturing SMEs, making it increasingly difficult to adopt scalable and lucrative solutions (Rosin et al., 2020). It is already known that more than 90% of businesses in several countries are SME-based (Knight et al., 2020) and responsible for one-third of international merchandise trade (OECD., 2018) which makes it a key element of the economies all over the world. However, SMEs lack the resources and advanced skills making it more difficult for them to meet the industry 4.0 challenges. Consequently, traditional manufacturing firms all over the world are facing challenges of smart transformation which is necessary to sustain their competitive advantage (Li et al., 2021; Warner & Wäger, 2019). Amid industrial revolution 4.0, academic researchers and professionals are also concerned to achieve sustainable competitive advantage.

Previously, researchers have investigated sustainable competitive advantage while considering the smart transformation i.e., Artificial intelligence (Lee et al., 2018), automation (Cao et al., 2020), and manufacturing locations (local/offshore manufacturing units)(Stentoft & Rajkumar, 2020). However, manufacturing firms tend to be risk-averse while acquiring external capabilities and relying on internal resources and capabilities (Cao et al., 2022). On the contrary, developing internal skills and staying current with the external environment is critical for achieving long-term competitive advantage (Raj et al., 2020). Business marketplaces are continually changing, making it challenging to maintain a competitive edge in the long run (Azeem et al., 2021). Competitive advantage helps firms to improve their productivity and efficiency as compared to other competitors (Azeem et al., 2021). More specifically, manufacturing enterprises competing in global marketplaces are more concerned with distinction than other rivals, as this will jeopardize their competitive edge (Azeem et al., 2021).

Previously, research investigations have considered several factors to achieve a competitive advantage, however, knowledge sharing and innovation have been found as the key contributing factors (Azeem et al., 2021). Another study has mentioned that today's organizations are operating in the dynamic and higher uncertain business environment and changes in business practices are emerging due to several contributing factors i.e., competition at the global level, diversification, and modern technology (Flaih & Chalab, 2022). To overcome the higher uncertainty, it is noted that strategic agility can facilitate the organizations while improving the internal operations of manufacturing firms speedily (Flaih & Chalab, 2022). However, under such uncertain business markets, there is a dire need for continuous observation of the environment to exploit business opportunities and overcome future challenges. Due to the rapid pace of change and volatility in the external environment, modern corporate organizations confront several obstacles. As a result, they must employ cutting-edge strategies and tactics to stay up to date with these developments. To the extent that it still isn't enough, strategic planning is a methodical technique that foresees companies' future possibilities and equips them to face them. Instead, it calls for honing your strategic foresight talents and future map and scenario preparation skills (Flaih & Chalab, 2022). Another study emphasizes that there is a dire need of utilizing a systematic approach to look beyond the current situation and consider the possible future events and challenging situations (Flaih & Chalab, 2022). This constant search in the business environment will be helpful to achieve organizational goals and also keep ahead from competitors (Flaih & Chalab, 2022). Thus, continuous observation of the business environment can be fulfilled through strategic foresight. Strategic foresight is a long-term focus that considers potential future events that might influence current actions and improve a firm's performance (Baškarada et al., 2016). Strategic foresight improves the recognition, monitoring, and analysis of changes in the business environment and prospective possibilities by identifying potential outcomes and countermeasures (Baškarada et al., 2016; Sardar, 2010).

Manufacturing enterprises' capacity to adapt and remain resilient in a quickly changing and uncertain environment is a key factor in predicting their performance in this chaotic world where markets and whole sectors are continually developing, colliding, dividing, changing, and declining (Teece, 2007). Similarly, the need for consideration of strategic decisions is also higher under uncertain business environment i.e., innovation strategies, budgeting and other structural-level policies (Vecchiato, 2015). Environmental scanning looks for the diverse upcoming events and their causes (Shoemaker, 2006). Strategic foresight focuses on the activities which are helpful for the firm’s future growth and success (Porter, 2010). In particular, the skills of integration, strategic decision, and environmental assessment are all key elements of strategic foresight (Paliokaité, 2010). Furthermore, it is mentioned that strategic foresight includes the methods, procedures, and activities needed to predict future occurrences and modifications in the outside world in addition to analyzing the consequences and their progression and coming up with remedies (Vecchiato, 2015). However, the future cannot be fully predicted but its preparation accordingly can be helpful to sustain and maintain a better position as compared to other players in the market (Vecchiato, 2015).

In addition, businesses ought to act wisely in order to choose a strategy and provide an appropriate reaction to the dynamic character of the business environment in the present day (Ahmed et al., 2021). Currently, customers’ demands and business practices are rapidly changing and organizational reliance on sustainable competitive advantage has increased for the achievement of their goals. The adoption of sustainable development requires an innovative environment, modern technology and infrastructure (Ahmed et al., 2021). Additionally, there is a dire need for the utilization of strategic intelligence to convert useful information from data that may create differentiation from other competitors (Ali et al., 2019). But in the contemporary artificial intelligence (AI) environment, massive amounts of data are being created by both public and private sector organizations, making the current era known as the big data age. Because of this, significant advancements in data analysis, visualization, and storage technologies and techniques have been recorded and happen owing to the rapid growth in data volume, variety, velocity, and veracity (Mikalef et al., 2019).To obtain useful information from the data, a firm’s Big data analytical capabilities are crucial as it utilizes the organization-wide data, technology and its talent (Akter et al., 2016; Kiron et al., 2014) and transforms the organizational approach to doing the business (Akter et al., 2016).

It is also noted that the ability to handle big data makes the firms more successful as compared to others (Dubey et al., 2019). BDA capability provides competency and insight while acquiring and evaluating the data (Wamba et al., 2017). Similarly, it is established that big data analytical capabilities make it possible for firms to achieve sustainable performance including economic, social and environmental elements (Jeble et al., 2018). Big data significantly produces innovation capabilities which is helpful to achieve competitiveness (Tan et al., 2015) and sustainability (Mavi & Mavi, 2019). However, the study findings regarding the association of BDA and sustainable outcomes are fragmented (Song et al., 2017). Further, BDA capabilities are also helpful to reduce the business environment uncertainty (Chong et al., 2016).
Previously, the empirical investigations regarding the way to transform Big Data Analytical capabilities into competitive outcomes are scarce and limited firms around the globe have clear understanding of big data analytical capabilities (Chong et al., 2016). Big data and predictive analytics assist organizations in lowering costs (Dubey et al., 2019), producing products faster (Giannakis & Louis, 2016), and developing new products or services to satisfy changing client requirements. In the similar vein, the rapid advancements in technology and business markets require the structured and unstructured data available in the organizations to generate meaningful insights regarding the customer's behavior, interests and services usage to achieve a competitive advantage (Ghasemaghaei & Calic, 2020; Mikalef et al., 2019). Further, empirical investigations regarding the role of BDA capabilities towards business value are also at the earlier stage of development (Ciampi et al., 2021; Lin et al., 2020). The literature lacks theoretical insights regarding the business value produced by big data which needs further empirical evidence for better understanding (Ghasemaghaei & Calic, 2020; Ghasemaghaei, 2021; Mikalef et al., 2019).
More specifically, globalization and rapid advancements all over the world make the products and services obsolete in a shorter time that need to focus on the future proofing. This situation is more critical for small and medium-sized industries because they encompass the major portion of businesses all over the world and significantly contribute to the income of economies. Further, SMEs lack the resources as compared to large-scale firms which need the establishment of proper mechanisms and technological advancement to overcome emerging challenges. Previously, studies have highlighted the importance of strategic foresight to achieve sustainable outcomes, however, their findings are fragmented and limited studies have considered the scenario of small and medium-sized companies (Baškarada et al., 2016; Jadhav, 2021; Vecchiato, 2015). Additionally, technological innovation i.e., big data analytical capabilities has determined the essential element to achieve competitive outcomes (Ciampi et al., 2021), however, AI as a tool to transform the information gathered from data into a competitive advantage is still evolving. Therefore, this study will analyze the relationship of strategic foresight and big data analytics capabilities with SMEs' competitive advantage through the mediation of AI utilization

Literature Review

Strategic Foresight

Rapid changes in the political, economic, social, technical, business practices, and consumer requirements in the current period necessitate that businesses adapt in an innovative, quick, and sustainable manner (Asmai et al., 2022). Further, the world has entered in the age of information and advanced technology that means the changes and challenges will emerge with higher intensity stresses the need to develop the organizational ability to predict future knowledge and information more creatively (Paliokaitė et al., 2014). Strategic foresight enables business management to make decisions that are both justifiable now and considering the long-, medium-, and short-term futures (Murphy et al., 2021). Decision-makers may impact the future of the company by using strategic foresight to assist them to come up with acceptable and pertinent strategies (Haarhaus & Liening, 2020). Thus, strategic foresight has gained attention as the logical and significant element to survive the business in fast-paced environment along with the interest from the academic researcher.

Big Data Analytics Capabilities

Business analytics utilization can be seen as the organizational dynamic capability (Chen et al., 2016; Wang et al., 2022). Though it looks at data analysis and knowledge management practices, the Knowledge-Based View (KBV) does not expand on the variety of approaches to problem resolution that big data makes feasible. The restricted perspective of big data analytical capabilities provided by the RBV, which sees data as a rich information resource but does not focus on the procedures needed to release its potential, may be overcome through the application of the DCV (Ferraris et al., 2018). The dynamic capability perspective, in particular, makes it possible to look at the ways that big data assets and processes need to be continually reconfigured in order for the knowledge that is extracted to be effectively used for the many operational and strategic purposes inside the organization. In particular, the dynamic capability perspective makes it possible to look at the ways that big data assets and processes need to be regularly rearranged so that the knowledge that is collected may be efficiently used for a variety of operational and strategic objectives inside the company. It accomplishes this by examining big data's potential for many uses in addition to viewing it as a resource that adds value. The need for big data systems to continuously reapply and learn routines to make companies capable of examining new multifaceted data and remaining competitive over time is satisfied by the development of organizational-wide big data analytical capabilities, which can be defined as the firm's unique and inimitable abilities to successfully utilize big data to obtain strategic insights (Mikalef et al., 2019). The study also mentioned that tangible resources, intangible resources, and human skills are the three main components that contribute to big data analytics capabilities (Gupta & George, 2016). However, in this study, big data is explained as the firm's competence to provide deep business insights which have been gathered and analyzed from big data (Kozanoglu et al., 2022). Furthermore, big data analytics is made up of three main competencies: talent, technology, and management (Yasmin et al., 2020). Where big data infrastructure defines organizational capacity, technical competence displays the actual technological infrastructure and its strength, and Knowledge capital is referred to as big data talent capabilities (Wamba et al., 2017).

AI Utilization

In recent years, advancements in technology especially AI have revolutionized all sectors of life (Wamba-Taguimdje et al., 2020). In particular, AI has demonstrated its use in management, manufacturing, marketing, and customer service (Jelonek et al., 2020). However, AI applications usage can be segregated in two broad perspectives i.e., AI automation and AI augmentation (Gupta & George, 2016). Where AI automation can be explained as the replacement of human work through machines and technology, however, AI augmentations increase the intelligence of humans while presenting insights that support in decision-making process. Further, both features of AI including automation and augmentation are helpful in the firm's processes and influence the customer while improving products and services.

Automation

Automation is the term used to describe scenarios in which machines take the role of humans, as in the case of assembly line robots. This assertion holds true for the automation that artificial intelligence (AI) facilitates, but it leaves out the important modifications that AI brings about (Gupta & George, 2016). Recent developments in AI have made it possible for computers to learn, develop, and adapt, leading to a long-term increase in performance (Coombs et al., 2020). Thus, even more complex cognitive activities like learning and problem-solving may be automated by AI technology. In terms of real-world application, artificial intelligence (AI) is used in the manufacturing and construction industries to automate planning, budgeting, inventory control, and replenishment (Wamba-Taguimdje et al., 2020). In order to improve the customer experience, AI may provide customers digital services and robots in the service environment (Prentice & Nguyen, 2020). An example of this is provided by chatbots, which are conversational software systems that simulate human interactions (Nuruzzaman & Hussain, 2018). Chatbots can help users using text or speech interfaces (Castillo et al., 2021). Thus, a role that was formerly occupied by a human employee is being filled by chatbots.

AI may produce new or improved goods and services as well as automate processes for consumers in addition to automating work within an enterprise. Conversational intelligent agents, like Apple's Siri and Amazon's Alexa, are a good illustration of this (Castillo et al., 2021; Prentice & Nguyen, 2020).

These agents are capable of automating tasks such as placing calls, sending texts, and initiating voice requests to start a playlist. In order to provide voice-activated smart home automation, these agents may also be linked to devices like Arduino and Raspberry Pi (Matei & Iftene, 2019). The advancement of facial recognition technology in smartphones, which expedites the user authentication process, serves as another example. These examples show how artificial intelligence (AI) may be used to a wide range of tasks and how many different types of professions can be automated.

Augmentation

The recent development in technology especially AI applications are performing complex tasks better than humans in respect of speed and cognitive ability (Jarrahi, 2018). Thus, AI can be used as an alternative of the human mind and overcome the limitation of humans (Iftikhar et al., 2020). In this era, firms have to make decisions from enormous data and information and required intelligence and cognitive capability. As a result, AI can be helpful in making logical judgments and producing insights from such massive amounts of data (Borges et al., 2021). Data analytics may use data to make exact decisions and predictions at the transactional level (Makarius et al., 2020). In order to have a thorough understanding of how their consumers see their offers, businesses are finding it more important to apply AI in the study of views, attitudes, and emotions associated with a certain good or service (Bytniewski et al., 2020; Jelonek et al., 2020). Further, AI maximizes the customer's intelligence by providing features in products and services. Conclusionary, AI has several implications for healthcare in detecting diseases and surgeries (Jarrahi, 2018), public relations (Galloway & Swiatek, 2018), marketing (Pani et al., 2020) and the fashion industry (Wamba-Taguimdje et al., 2020).

Sustainable Competitive Advantage

According to Porter (1996), a firm's competitive edge is its capacity to provide greater value, either by providing the same advantages at a lower cost or by outperforming its rivals on one or more fronts in a way that more than makes up for a higher price. Further successful businesses outperform and remain competitive with their main competitors. In addition to significant performance differences, brands, especially well-known market leaders, can have levels of perceptual advantage that are difficult to replicate due to their strong brand equity (Banmairuroy et al., 2022; Keller & Price, 2011) and brand salience (Ehrenberg et al., 1997) that frequently displace alternatives. However, the achievement of a sustainable competitive advantage necessitates that an organization persistently pursue administrative, technological, perceptual, and/or product innovations to gain a lasting competitive edge (Lengnick-Hall, 1992). Since these factors make it more difficult for rivals to reach parity, competitive advantage is most durable when such resources are precious, uncommon, and difficult to imitate (Adama et al., 2024; King, 2007).

According to marketing theory, the most important resources and competencies are those that produce and sustain great customer value (Narver & Slater, 1990). In the current period, markets have a more dynamic nature as rivals innovate, get the upper hand, and then lose it when others equal or surpass them through their innovation capacity (Behl et al., 2022). Businesses must improve their capacity to predict, understand, and react to changes in the business marketplaces more quickly and effectively than their competitors if they want to maintain their competitive edge (Hossain et al., 2022). Another investigation distinguished between temporary competitive advantage and sustainable competitive advantage (Banmairuroy et al., 2022). Where sustainable competitive advantage is achieved when competitors are unable to duplicate the unique sources of advantage, contrary to earlier goals of increased short-term profits. Similarly, with the lens of RBV, a firm's valuable, uncommon, imitable, and non-alternative resources are the main determinants in the development of sustained competitive advantage (Barney & Clark, 2007). Likewise, sustainable competitive advantage is described as the firm's ability to generate better economic value as compared to rivals (Hansen et al., 2008).

Theoretical Framework

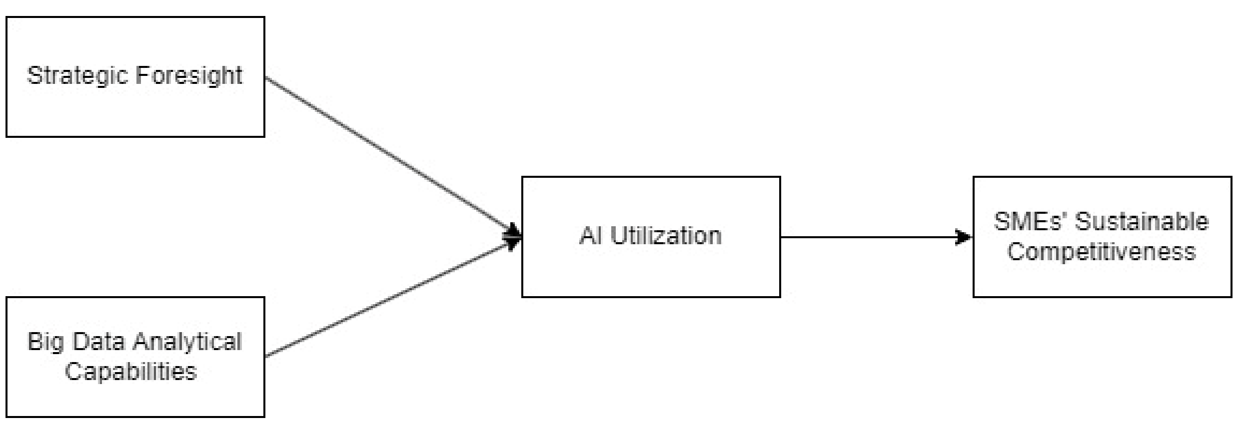

Figure 1: Theoretical Framework

Research Methodology

This study aims to investigate the relationship of strategic foresight and big data analytical capabilities with SMEs' sustainable competitive advantage through the mediating role of AI utilization.

Sample Design and Data Collection

In the current study data was collected from the SMEs of Malaysia. Small and medium-sized enterprises (SMEs) in Malaysia are those with up to 200 workers and RM50 million in yearly sales (SMECorp.Malaysia, 2013). For data collection 400 questionnaires were distributed to the owners and managers of SMEs operating in Malaysia through convenient sampling technique. Finally, 260 questionnaires were useable from the 300 returned ones which is adequate sample (Rasoolimanesh & Ali, 2018).

Questionnaire

In the current study, instruments were adopted from the already established studies. Strategic foresight. Four essential components i.e., competitive intelligence, technical intelligence, and political environment foresight were used to gauge strategic foresight. Nine items were used to quantify customer foresight (Hofmann, 2020). Further, 7-itmes instrument of Torres P et al. (2010) was adopted to test competitive intelligence. Additionally, technological intelligence was assessed using five questions that were adopted from Ashton and Stacey (1995). The political environment foresight was also examined using a 3-item measure that was modified from Adegbile et al. (2017). Moreover, big data analytical capabilities were measured through 15 items scale DalleMule and Davenport (2017). Similarly, AI utilization was assessed through 7-item scale adopted from Paschen et al. (2019). However, sustainable competitive advantage was measured through the 5-items scale of Elgarhy and Abou-Shouk (2023).
The data analysis via Smart PLS 4 employed partial least square - structural equation modeling (PLS-SEM) as the goal of the study is to investigate the relationship between the variables rather than to create a new theory. Notably, PLS-SEM offers a flexible approach to model development, making it a useful tool when SEM is utilized to explain the association among variables (Hair Jr et al., 2017; Ringle et al., 2015).

Findings

This research is appropriate for PLS-SEM, since it does not require a large sample size or a normal distribution of data (Ringle et al., 2015). The current factor loadings, path coefficient values, and significant levels were all bootstrapped using PLS 4.0. Both a measurement model and a structural model were evaluated.

Data Normality

Despite the necessity of verifying data normalcy before inferential statistics, PLS-SEM ignores it (Hair et al., 2007). By using the data's skewness, kurtosis, and histogram, this study was able to assess the normality of the data. The skewness and kurtosis values of the research constructs varied from 2 to +2, indicating a normal distribution.

Common Method Bias

A single respondent's data collection may result in common method bias (Kock, 2015). This study used the variance inflation factor (VIF) to measure common method bias using a comprehensive collinearity test. In order to prevent common method bias, the VIF value should not be more than 3.3. In this study, the VIF value of every build was below 3.3, indicating the lack of common method bias.

Demographics

The demographic analysis of the 260 respondents from SMEs is given in the following Table 1. In the following Table 1 shows that 62 respondents (23.8%) were male and 198 respondents (76.2%) were female. A total of 95 (36.5%) respondents were between the ages of 26 and 31 years, 62 (23.8%) respondents were between the ages of 32-37 years, 15 (5.8%) participants were from 44-49 years, 10 (3.8%) respondents were from 50-55 years and just 17 (6.5%) participants were above 56 years. Regarding their educational background, 152 (58.5%) of the respondents have completed diploma followed by the 93 (35.8%) participants with bachelor and only 15 (5.8%) respondents have completed Masters. Furthermore, 78 (30%) respondents have experience of 1-3 years, 59(22.7%) participants have experience of 4-6 years and followed by 106 (40.8%) participants with 7-9 years of experience followed by the 17 (6.5%) participants with over 10 years of experience

Table 1: Demographics

Variables	Category	Frequency	Percentage
Gender	Male	62	23.8
	Female	198	76.2
Age	26 to 31 years	95	36.5
	32-37 years	62	23.8
	38-43 years	61	23.5
	44-49 years	15	5.8
	50-55 years	10	3.8
	56 years and above	17	6.5
Education	Diploma	152	58.5
	Bachelor's degree	93	35.8
	Master's degree	15	5.8
Years of Establishment/ Experience	Up to 1 to 3 year	78	30.0
	4 - 6 years	59	22.7
	7 - 9 years	106	40.8
	10 years and above	17	6.5

Measurement Model Assessment

The average variance extract (AVE), loadings, and composite reliability (CR) were used to evaluate the convergent validity. With the exception of 12 items from 59 total items were eliminated because of lower outer loading. Further, Table 2 shows that the value of factor loadings of all the remaining items were surpassed 0.60. This study's CR scales had a value greater than the suggested threshold of 0.70. All constructions' AVEs also exceeded the suggested threshold of 0.50 (Ringle et al., 2015) [62]. 4.5. The ability to discriminate The Heterotrait-Monotrait Correlation ratio, or HTMT ratio, is a sophisticated way to evaluate discriminant validity. Consequently, in order to test the discriminant validity of the research variables, the HTMT ratio as well was applied (Henseler et al., 2015).

Table 2: CFA

Constructs		Loading	Alpha	Rho_A	CR	AVE
AI Utilization	AIU1	0.876	0.813	0.839	0.875	0.593
	AIU2	0.73				
	AIU3	0.821				
	AIU4	0.883				
	AIU5	0.462				
Big Data Analytical Capabilities	BDAC12	0.633	0.897	0.908	0.916	0.526
	BDAC14	0.581				
	BDAC2	0.541				
	BDAC3	0.778				
	BDAC4	0.819				
	BDAC5	0.794				
	BDAC6	0.745				
	BDAC7	0.823				
	BDAC8	0.727				
	BDAC9	0.752				
Sustainable Competitive Advantage	SCA1	0.815	0.914	0.919	0.936	0.744
	SCA2	0.903				
	SCA3	0.86				
	SCA4	0.895				
	SCA5	0.836				
Strategic Foresight	SF11	0.784	0.931	0.935	0.939	0.476
	SF12	0.731				
	SF14	0.77				
	SF15	0.736				
	SF16	0.633				
	SF17	0.754				
	SF18	0.747				
	SF20	0.619				
	SF21	0.7				
	SF23	0.714				
	SF24	0.594				
	SF3	0.694				
	SF4	0.651				
	SF5	0.635				
	SF7	0.635				
	SF8	0.68				
	SF9	0.606				

Table 3: HTMT Ratio

	AIU	BDAC	SCA	SF
AIU				
BDAC	0.863			
SCA	0.585	0.635		
SF	0.773	0.795	0.809	

Structural model assessment

The structural model was evaluated subsequent to the measurement model's evaluation. Therefore, path coefficients, standard errors, and t-values were used to assess the model's relevance. The association between the constructs of this study was investigated through bootstrapping at SMARTPLS 4.0. Following the measurement evaluation, an assessment of the structural model was conducted. The evaluation of the research model's relevance was conducted using path coefficients, t-values, and standard errors. In Smart PLS 4, bootstrapping was used to evaluate each and every hypothesis (Richter et al., 2023). The direct assumptions were also empirically tested (see Table 4 and Fig. 1). Critical ratio analysis was used to assess the hypotheses ($P < 0.05$; $t>1.645$). All the hypothesis of this study are supported.

Table 4: Path Coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIU -> SCA	0.5	0.5	0.067	7.441	0
BDAC -> AIU	0.524	0.522	0.063	8.348	0
SF -> AIU	0.305	0.312	0.063	4.863	0
Higher Order Constructs					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
SF -> AIU -> SCA	0.153	0.157	0.044	3.46	0.001
BDAC -> AIU -> SCA	0.262	0.26	0.045	5.843	0

Discussion and Conclusion

The empirical analysis's results are presented in this study, which investigated the influence of big data analytical skills and strategic foresight on the sustained competitive advantage of Malaysian SMEs. Furthermore, it delves into the ways in which the use of AI functions as a mediator, clarifying the processes by which these tactical endeavors foster enduring competitive edge. The results of this study show that SF significantly influences the SMEs’ sustainable competitive advantage which is concurrent with the previous investigation (HALIM et al., 2022; Panjaitan et al., 2022).

In the same manner, this study's results showed a substantial and positive correlation between BDAC and durable competitive advantage, which is consistent with earlier research by Behl et al. (2022). In addition, artificial intelligence plays a major mediating role in the interaction between sustainable competitive advantage and big data analytical capabilities and strategic foresight. These outcomes also align with earlier research findings, which emphasize the substantial contribution AI makes to the long-term competitiveness of the companies (Al-Shami et al., 2022). According to another research of Calic and Ghasemaghaei (2021) using big data in conjunction with AI may assist make better judgments and maintain an organization's competitiveness in the commercial marketplaces over the long term.

Therefore, manufacturing SMEs and policy makers should focus on the measures to enable these small firms through training to foresight the future changes and incorporate the advanced technologies i.e., big data and AI to transform the business innovation and provide the sustainable competitiveness over others.

Implications

The study's conclusions have important ramifications for SMEs looking to strengthen their competitive edge in a market that is changing quickly. It becomes clear that strategic foresight is essential for SMEs to be able to predict market trends, spot new possibilities, and take proactive measures to address obstacles. SME decision-making processes may be strategically positioned to promote resilience and adaptation by including foresight.

Furthermore, the importance of big data analytical skills for SMEs cannot be overstated. SMEs may make data-driven choices, streamline operations, and obtain insightful knowledge about market dynamics and consumer behavior by utilizing and analyzing large datasets. This study emphasizes how crucial it is to spend money on data analytics tools and infrastructure in order to fully utilize big data for long-term competitive advantage.

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