External knowledge sourcing, organizational ambidexterity and manufacturing performance: a new insight for dynamic operation management

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Abstract

Purpose – This study intends to examine the relationships between external knowledge sourcing (EKS), organizational ambidexterity (OA), and manufacturing performance (MP) in the context of large manufacturing firms within a dynamic environment setting. The research framework and derived hypotheses are grounded in the knowledge-based view (KBV) and dynamic capability (DC) theories.

Design/methodology/approach – A self-administered online survey was used in this study to gather data. Respondents were the operation leaders representing large manufacturing firms. The collected data were screened for invalid responses, and hypotheses were tested using structural equation modeling.

Findings – The study reveals that OA and EKS play key roles in achieving a better MP. Likewise, OA also mediates the relationship between EKS and MP.

Research limitations/implications – Cross-sectional data were collected from large manufacturing firms within five focus sectors in Malaysia. A similar study can be conducted with more sectors of different contexts to confirm the findings.

Practical implications – Knowledge is critical for the firm to react to environmental dynamism, and the ability to manage it ambidextrously will enable the firm to enhance its performance.

Originality/value – This study offers empirical insights from the perspective of the large manufacturing firms in Malaysia, which are undergoing an Industrial Revolution 4.0 (IR4.0) transformation. This study bridges the knowledge gap by revealing the value that EKS can facilitate MP, exploring OA as the prevalent factor and demonstrating how KBV and DC can be applied in this study.

Keywords External knowledge sourcing, Organizational ambidexterity, Manufacturing performance, Large manufacturing firm, Industry 4.0

Paper type Research paper

1. Introduction

The manufacturing industry contributes significantly to Malaysia's annual gross domestic product (GDP). However, its growth rate has lately decreased (MITI, 2018). The key indicator of its growth is productivity which has registered negative growth for the past four years (MPC, 2021). At the same time, the advent of Industrial Revolution 4.0 (IR4.0) has altered the global and local manufacturing landscape (Cheah and Tan, 2020). Due to competition from neighboring countries with cheaper labor costs, it must increase productivity and adopt IR4.0 advanced manufacturing technologies (MITI, 2018). After recognizing the need to hasten the adoption and dissemination of this new knowledge, the Malaysian government announced two IR4.0 blueprints to accelerate the implementation of these cutting-edge technologies. Recent studies show that nations participating in the hi-tech value chain, including Malaysia,

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have a poor technology adoption rate due to a lack of knowledge, skilled workers, leadership, and skepticism about its benefits (Cirera *et al.*, 2021). March (1991) indicates such challenges as a mismatch between exploration and exploitation learning. A state in which a company is reliant on perfecting its existing methods and prevents it from seeking new approaches. In essence, firms that focus on exploration may end up with many undeveloped ideas, and firms that focus on exploitation may lose out on new market possibilities or have goods that do not fit the preferences of customers (March, 1991).

OA refers to a company's capacity to manage its resources ambidextrously. It involves exploring new markets or technologies while improving its market share via product and process innovation (Raisch and Birkinshaw, 2008). Given that many manufacturers have limited resources to implement IR4.0, the ability of the company to manage its resources wisely and balance its learning approach will set it apart. The results of the interaction between external knowledge sourcing (EKS) and organizational ambidexterity (OA) will enable managers to choose the optimal degree of learning approach to be adopted according to market circumstances. At the same time, the current Covid-19 pandemic has introduced new challenges due to new business strategies and production patterns (EPU, 2021). Hence, it is also an opportunity for the study to verify the contribution of EKS and OA within an extremely dynamic market condition instead of in an economic equilibrium situation, as highlighted by the majority of literature. Likewise, it is equally important for industry players to gauge their operation performance within a dynamic yet competitive environment (Tan and Wong, 2015). Raising productivity involves improving cost, quality, flexibility and delivery, which are non-financial performance indicators that manufacturing firms track. As a result, MP was chosen as the dependent variable (DV) for this study. As such, understanding the interaction of EKS, OA and manufacturing performance (MP) within a consistent model also serves as one of a kind study on the whole, especially within a volatile market condition.

Furthermore, the post-Covid outlook predicts a significant global economic comeback beyond 2021. Adopting new technologies and digitalization is critical for the manufacturing sector to profit from the rebound (Cirera *et al.*, 2021). Yet IR4.0 and pandemics have created a dynamic environment that renders existing knowledge obsolete. Many firms lack the knowledge to adapt to this ever-changing globalized knowledge-based economy (Narkhede, 2017). Moreover, extant literature demonstrates a segmented approach to addressing these challenges. It lacks a comprehensive approach to combining related concepts into a single theoretical understanding. Existing literature primarily focuses on the direct link between a broad idea of knowledge management (KM) and OA (e.g. Rialti *et al.*, 2020). Still, there is a lack of clarity about which KM activities affect OA and what kinds of OA-related activities affect MP. Even though there are recent efforts to study KM activities separately (e.g. AlShawabkeh *et al.*, 2020) or the importance of knowledge assets for OA (e.g. Ali *et al.*, 2022), how to obtain the knowledge is generally left out. Besides, research on specific KM activities and MP is limited (Tan and Wong, 2015), and studies between OA and MP are even rarer. Some studies even suggest expanding its model to include other antecedents for OA (e.g. Kafetzopoulos, 2020) or indicating the potential of having a different mediator between KM and performance (e.g. Migdadi, 2020). Table 1 summarizes some findings and limitations of recent empirical studies on KM, OA and performance. As a result, to address these gaps, this study investigates the links between EKS, OA and MP. How OA mediates, the relationship between EKS and MP is analyzed too. Since KM is an umbrella terminology that covers all sorts of KM processes according to context (Andreeva and Kianto, 2011), having EKS within this study is important. IR4.0 technologies are advanced technologies mostly available overseas, especially from competitors' ends (Prange and Bruyaka, 2016). Understanding how EKS behaves in such a dynamic environment will provide practical contributions to sourcing these technologies.

No.	Study	The relevant findings	Limitations
1	Ali *et al.* (2022)	Knowledge assets (human capital, organizational capital, social capital) are central to pursuing organizational ambidexterity	The findings lack how the knowledge assets can increase their knowledge stock which is critical for achieving organizational ambidexterity
2	AlShawabkeh *et al.* (2020)	Knowledge management is an integral part of project success only through the induction of organizational ambidexterity	The knowledge management aspect only covers knowledge sharing, application, storage and integration but lacks how knowledge can be acquired in the first place
3	Kafetzopoulos (2020)	Organizational ambidexterity will lead to superior business performance in environmental uncertainty conditions with the support of two antecedents, namely proactiveness and quality orientation	The author pointed out that one key limitation is to further expand the model using different factors of antecedents
4	Migdadi (2020)	Knowledge management processes (KMPs) only impact organizational performance through a mediator (innovation capability)	The KMPs have a significant direct relationship with organizational performance despite a full mediation relationship. Hence the model can be further expanded using other mediators
5	Rialti *et al.* (2020)	Big data analytics and knowledge management capabilities will positively impact organizational ambidexterity and strategic flexibility	The knowledge management capabilities have been considered as one single aggregate construct. Hence, the authors suggested that future studies can unpack the construct and test the specific knowledge management practices for better clarity on to what extent the different practices influence ambidexterity

Source(s): Authors' own work

Table 1. Findings and limitations of recent empirical studies on knowledge management, organizational ambidexterity and performance

KBV and DC provide the grounding theories for the research framework. KBV is considered a subset of the Resource-based View (RBV) theory based on Grant's (1996) seminal work. It stresses that knowledge resources are often implicit and unique to each organization (Alavi and Leidner, 2001). The ability of the organization to transmit and collect knowledge resources is vital for the business's long-term competitive advantage (Ong and Tan, 2022). DC is selected as it highlights the capability of the firm to manage and use its knowledge resources at the right time to create a favorable outcome for the firm (Sánchez *et al.*, 2019). Since OA is a capability of the firm to balance its exploration and exploitation efforts (March, 1991), it is therefore often regarded as the core DC for an organization (Raisch and Birkinshaw, 2008).

In conclusion, this study provides a richer theoretical understanding and knowledge expansion in KM and OA. Likewise, it gives a much-needed practical answer for firms that need to adopt new technologies but lack expertise and resources within a dynamic environment. This empirical study revealed a fresh perspective with practical implications. Managers and policymakers can consider such a holistic approach in designing strategic policies to improve the IR4.0 technologies adoption rate. So far as one can tell, no such study has been able to examine the influence on MP from EKS and OA simultaneously. Therefore, we intend to contribute to the extant literature by (1) having a detailed discussion of EKS, OA and MP; (2) sharing the existing key relationship between them; (3) positing a research model that indicates their interrelationship; (4) providing hypotheses and empirically verified them; and (5) discussing its practical and theoretical implications.

2. Literature review

2.1 Manufacturing performance

Scholars believe organizational performance is difficult to comprehend and quantify (Snow and Hrebiniak, 1980). MP, an expression of a manufacturing firm's performance, can be measured in various methods (Adebanjo *et al.*, 2017). Its measurement can take several forms depending on the scope of the study, the period examined and the criteria applied. For example, product and process innovation studies will consider cost, quality and delivery as part of the measures. Studies on quality and business excellence consider superiority, creativity and product development indicators (Ng and Jee, 2012). According to Cheah and Tan (2020), its terminology also varies depending on the study's nature. Usually includes firm performance, organizational performance, operational performance and manufacturing strength. Even though MP varies depending on the circumstances, a firm's ultimate goal is to achieve good performance (Snow and Hrebiniak, 1980). Hence, evaluating its impact is a crucial indicator of the sector's health (Narkhede, 2017). Therefore, manufacturing firms must assess their operational and production performance (Tan and Wong, 2015).

The existing literature distinguishes between two forms of measurement. Objective indicators, such as financial outcomes (Migdadi *et al.*, 2017), are measurable. In contrast, subjective indicators rely on judgmental assessment (e.g. cost, quality, delivery, flexibility). The plant does not influence external sales or costs. Hence, assessing its performance using such financial metrics is not legitimate (Ramayah *et al.*, 2004). Besides, financial metrics like return on investment (ROI) usually need a longer duration to produce accurate indicators (Partanen *et al.*, 2020). At the same time, Dess and Robinson (1984) also pointed out that reliable, objective data are difficult to get and usually confidential, especially financial data, which is vulnerable to variation due to varying accounting practices across respondents' organizations. Traditionally scholars used accounting metrics to assess MP, but recently, they have shifted their focus towards more realistic operating goals (Ahmad *et al.*, 2019). Some researchers believe financial metrics are inadequate to assess actual performance. Since they do not account for intangible resources such as firm-based knowledge and people-based skill sets (Grant, 1991). Thus, it may not be appropriate to depict the true performance nature of the production environment. Furthermore, Dess and Robinson (1984) and Dawes (1999) empirical studies have also confirmed a strong correlation between objective and subjective measurements.

The literature has taken a distinct approach so far for firm performance measurements. Although the approaches differ, MP indicators are crucial for a firm, particularly in a dynamic environment (e.g. Patel *et al.*, 2012; Tamayo-Torres *et al.*, 2017). Besides, Scholars have a consensus that MP indicators consist of cost, quality, delivery and flexibility (e.g. Aboelmaged, 2014; Ahmad *et al.*, 2019; Al-Sa'di *et al.*, 2017; Rosenzweig and Easton, 2010; Schroeder, 2015; Tan and Wong, 2015). Thus, MP with those subjective measurement indicators is selected for this study.

2.2 External knowledge sourcing

From an organizational standpoint, a company acquires external knowledge and then applies it to enhance its operations (Mohamad *et al.*, 2017). According to Eisenhardt and Santos (2002), knowledge sourcing is an important KM technique to gain relevant knowledge. Likewise, Davenport and Prusak (1998) also claimed that knowledge acquisition is one of the methods for organizations to generate new knowledge; failing to do so might lead to its destruction. Some scholars regard the customer's voice as the most reliable external knowledge source. The firm's ability to understand its customers' demands is a vital source of external knowledge (Nguyen and Harrison, 2019). However, according to Dahiyat (2015), the capability to source external knowledge lies beyond a firm's boundaries. It entails maintaining active communication and close contact with different network sources. Brunswicker and Vanhaverbeke (2015) regard the six important external sources as direct customers, indirect customers, suppliers, universities or research organizations, experts on intellectual property rights and network partners.

Brunswicker and Vanhaverbeke (2015) also put forth two strategies involved in EKS. The first approach is a full-scope sourcing strategy, where a company actively seeks out innovative ideas from several sources throughout the ecosystem and across all knowledge disciplines. The second strategy is called the application-oriented sourcing strategy. For this strategy, the firm tends to focus more on its areas of interest and solicit ideas directly from end-users or suppliers. From the KBV perspective, all this knowledge is specific market knowledge crucial for the company to implement the best business plans and establish a sustainable competitive advantage (Barney, 1991). The firm that fails to venture outside its boundary may pursue knowledge identical to what it already possesses (Hughes *et al.*, 2020). Thus, EKS plays a key role for firms to capture the latest knowledge and insights to inspire new ideas and innovation. It is, therefore, a foundation for firms to gain a competitive advantage (Narkhede, 2017; Yang, 2012).

2.3 Organizational ambidexterity

The strategic management literature mentions OA as a strategy to balance exploration and exploitation-related activities (e.g. Asif, 2017; Dolsen and Chinnam, 2017; He and Wong, 2004). O'Reilly and Tushman (2013, p. 234) define it as the ability "to compete in mature technologies and markets where efficiency, control and incremental improvement are prized and also compete in new technologies and markets where flexibility, autonomy and experimentation are needed." Both activities use different approaches to learning and compete for limited resources. Because of these factors, businesses prioritize one activity over the other. However, a competency trap might result from it (too much exploitation and neglect of environmental improvement). Or a failure trap (too much exploration without meeting the existing market's demands) (Hughes *et al.*, 2020). Because both activities require the use of limited resources, the total result will be a zero-sum game in the case of a tradeoff (Wei *et al.*, 2014). Firms that manage tradeoffs can have positive synergistic impacts (He and Wong, 2004).

Yang (2012) elaborates that exploration capabilities involve learning and adopting new processes, products and services. In contrast, exploitation capabilities relate to improving its existing resources and processes. Knowledge derived from exploration and exploitation learnings will increase the knowledge stock. Such knowledge enables the organization to adjust its strategy in response to the environment (Paiva *et al.*, 2008). As a result, a dynamic environment such as IR4.0 entails searching for new technologies to establish new possibilities (Zhou *et al.*, 2016). Scholars began to combine the ideas of KM and OA. For example, Han (2019) found that ambidextrous knowledge exchange between firms will lead to innovation success.

Even though the OA idea is gaining steam, the research is still scant and contradictory, particularly on empirical proof of OA's influence on MP. O'Reilly and Tushman (2013) reviewed the development of current research on OA and claimed that ambidexterity and business performance have a beneficial relationship. In recent research, such associations refer to as complementing exploration and exploitation. Their simultaneous implementation will yield better results than separate (Liao and Li, 2019). Moreover, such linkages thrive in uncertain environments with sufficient resources, especially large businesses. Raisch and Birkinshaw (2008) request further investigation of alternative strategies and OA based on these premises. Having EKS as the predictor for OA and MP as the criterion will provide greater insight into how OA behaves in a highly dynamic environment.

2.4 Research hypotheses

2.4.1 External knowledge sourcing and manufacturing performance. The customer's needs constantly evolve in a globalized market, and the manufacturing firm's knowledge stock needs to align to support those needs (Nguyen and Harrison, 2019). Furthermore, the competitive market also resulted in high variability of products manufactured in low volume. According to Zhou and Liu (2012), the manufacturing firm's flexibility is essential to remain competitive, and EKS plays a vital role in enabling it. Likewise, an earlier study by Tan and Wong (2015) on the local front found that external knowledge sources, especially from customers and suppliers, positively impacted MP.

Besides, Kocoglu *et al.* (2012) also claim that EKS is a form of technological capability for a highly technology-driven firm to enhance its MP. Apart from that, EKS can also increase its competency by enhancing its performance in cost, quality, flexibility and delivery (Ahmad *et al.*, 2019). Likewise, Nguyen and Harrison (2019) claimed that customer knowledge would give the manufacturing firm direct access to the market's requirements. Such knowledge will allow the firm to work on innovative solutions to respond to market fluctuation quickly and with greater precision, minimizing production costs in return (Nguyen and Harrison, 2019). Furthermore, a recent study also suggested that knowledge acquisition can positively impact large manufacturing firms' operational performance and financial performance through some mediating factors (Migdadi, 2020).

Therefore, existing knowledge will render obsolete in a dynamic market if no constant new knowledge stream supports decision-making (Macau *et al.*, 2016). Narkhede (2017) confirmed this notion by pointing out that external knowledge allows India's manufacturing sector to gain its competitive edge in terms of better quality, greater flexibility and efficiency. Hence all these findings can sum up to indicate a positive link between EKS and MP, and we hypothesize as follow:

H1. EKS has a positive effect on MP.

2.4.2 Organizational ambidexterity and manufacturing performance. Although OA studies cover various fields, their methodological setups and empirical outcomes are inconclusive (Junni *et al.*, 2013). So far, there have been several research studies on its influence on business performance (e.g. Gibson and Birkinshaw, 2004; Kafetzopoulos, 2020) and firm performance (e.g. Dezi *et al.*, 2019; He and Wong, 2004). However, there is still uncertainty concerning OA's interaction with MP. A meta-analysis study by Junni *et al.* (2013) indicates specific gaps in OA's impact on manufacturing companies. The study revealed a positive association between exploration and exploitation in isolation with performance. Yet, the influence of OA on performance suggests otherwise. They believe static or dynamic working environments have a role in defining the relationship. In response to these findings, Tamayo-Torres *et al.* (2017) empirically investigated OA's link to MP with environmental dynamism as a determining factor. They utilized a sand-cone model to study the relationship in a static and dynamic setting. Their finding indicates that manufacturing firms with OA capacity will respond to market requirements in a dynamic environment by improving quality, lowering costs and expanding production flexibility. Likewise, Scott (2016) also claimed that an ambidextrous supply chain would be able to respond to environmental dynamics and gain improvement in cost, quality, delivery and flexibility.

While a firm may use OA's idea for learning, it can also support execution, as Hernández-Espallardo *et al.* (2011) discovered in their study. Thus, some research combined OA with other operational management tactics, such as absorptive capacity, to gauge their impact on MP (e.g. Patel *et al.*, 2012). The more internal and external information a company can integrate, the greater its ambidexterity and beneficial impact on its performance (Dezi *et al.*, 2019). Patel *et al.* (2012) showed that operational ambidexterity increases manufacturing flexibility, which leads to improved performance. They asserted that operational ambidexterity allows for a balanced learning strategy. It ensures long-term work practices while incorporating new procedures in a fast-paced setting. However, they recommend that future research look at other manufacturing capacities such as cost, quality and inventory turn (delivery).

Although the OA and MP's empirical study is scarce and literature still conceptualizes such a relationship, there are generally indications that OA brings positive performance outcomes. Hence, we propose that:

H2. OA has a positive effect on MP.

2.4.3 External knowledge sourcing and organizational ambidexterity. According to Grant (1996), the basis of a firm's core capability is its knowledge which is also the fundamental argument of KBV. Together with DC, they explain the importance of balancing internal and external knowledge sources as part of the organization's operation strategy. Therefore EKS is considered a key strategy for the firm to increase its knowledge resources (Xie *et al.*, 2019). Krishnan and Jha (2011) confirmed such an argument in their study of how firms in developing countries can compete with multinational firms in the same market. They claim that firms with limited technological capabilities must fill their knowledge gaps through EKS and then infuse them into their core capabilities to strengthen their technical capabilities. Such an ambidextrous practice has been gaining traction recently, with many firms allying with other firms due to complex manufacturing operation needs (Song *et al.*, 2016). Furthermore, according to Matthews *et al.* (2015), EKS stimulates innovation and acts as a feedback mechanism for the firm to optimize its knowledge stock by balancing exploratory and exploitative learning.

Dolsen and Chinnam's (2017) research provides further insight into this perspective. They argue that the exploitation approach can only allow a manufacturing firm to meet its customers' demand up to a certain level. An exploration approach will have to kick in to achieve beyond that. This finding suggests the importance of EKS to supplement its existing know-how and achieve a balanced learning approach. Likewise, Dezi *et al.* (2019) also conclude that much of the unknown knowledge can only be attained through EKS. Manufacturing firms that widen their knowledge scope through EKS can understand their exploitation needs and enhance their knowledge of exploration needs (Xie *et al.*, 2019). In summary, EKS complements exploration and exploitation activities. Hence, we can conclude that:

H3. EKS has a positive effect on OA.

2.4.4 The mediating effect of organizational ambidexterity. According to Cheah and Tan (2020), KM will cause the company to manage its knowledge ambidextrously. The argument is that EKS enable inter-organizational learning where each firm tends to supplement its knowledge stock from another party. However, both sides must ensure they can continue learning new knowledge from each other. This interaction is termed a reciprocity loop and requires that their core knowledge is effectively protected against potential leakages that might jeopardize the relationships (Oorschot *et al.*, 2018). As a result, it will strike a balance in discovering and leveraging its core expertise to impact MP positively. Such a claim was also empirically established in another study, which indicates the ability to use both exploration and exploitation-based innovation mediates the influence of EKS on a company's performance (Hernández-Espallardo *et al.*, 2011). Besides, Yang *et al.* (2014) stated that enterprises sourcing new knowledge through inter-organizational learning would seek a balance in knowledge sharing and protection resulting in ambidextrous learning. Such an approach will allow them to preserve relationships and knowledge exchange. Hence, positively affects new product development (Guo *et al.*, 2020).

Several researchers also claimed that alliance allows new knowledge to be learned and utilized to benefit the participating firms. For example, Lin *et al.* (2013) argue that inter-organizational collaboration and intra-organizational learning enable a company to achieve a high level of exploration and exploitation operations, resulting in increased productivity. Similarly, Tamayo-Torres *et al.* (2017) argued that a firm with the ability to acquire new knowledge and apply on-hand knowledge would drive MP in a dynamic environment. As such, if a firm can balance both learning approaches, it can further increase its knowledge through EKS for optimum gain in its performance. Hence it is, therefore, likely that:

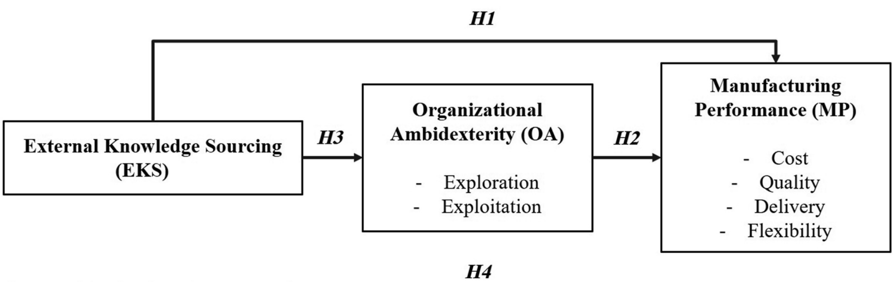
H4. OA mediates the relationship between EKS and MP.

2.5 Research framework

As shown in Figure 1, a research framework is formed through the literature review. The derived hypotheses and the constructs' interrelationships are grounded in the KBV and DC theories.

3. Research methodology

The first national IR4.0 blueprint *(Industry4Fwrd)* specifically highlights five key focus sectors with the potential to adopt these advanced technologies: electrical and electronic, machinery and equipment, chemical, medical devices and aerospace (MITI, 2018). Thus, the study population will cover all the large manufacturing firms from these sectors as listed in the Federation of Malaysian Manufacturers (FMM) 2020 directory. Large firm size was selected due to their tendency to have slack resources (Rosenzweig and Easton, 2010), which is crucial for the firm to pursue ambidexterity (Dezi *et al.*, 2019). A non-probability purposive sampling technique was used to determine the large firms with employees of 200 and above. The self-administered online survey questionnaire was pretested by a panel of ten experts from the industry and academia, and improvements were made based on their feedback to ensure better clarity. It then got emailed to the target operation manager, general manager, COO or CEO. The questionnaire set consists of four main sections and thirty-four questions. The measurement items used in the survey are listed in the Appendix. As recommended by several academics, this study also used personal networks and follow-up phone calls to boost



Source(s): Authors' own work

Figure 1.
Research framework

the participation rate (Hung *et al.*, 2011). Out of the 343 questionnaires, 145 were useable for analysis, representing a usability rate of 42.3%.

We selected a six-point Likert scale for all the measurement items to avoid central tendency errors (Cooper and Schindler, 2014). All the items were either adapted or adopted from previous studies that demonstrated high reliability and validity. A twelve items scale for MP was adopted from Ahmad *et al.* (2019). As for measuring EKS, six items were adopted from Brunswicker and Vanhaverbeke (2015). OA measurement items consist of a ten items scale adopted from Kafetzopoulos (2020). All the collected raw data were subjected to data screening before using it for structural equation modelling.

4. Findings

4.1 Profile of participating companies

Table 2 lists the breakdown of the participating company's profile. The majority of the firms are located in the state of Penang (43%), Selangor (31%) and Johor (23%). As for company ownership breakdown, foreign investors control most of these businesses, which make up 58.62%, compared to domestic businesses, which make up 31.72%. These percentages matched industrial sector statistics, with most participating companies belonging to the electronic and electrical sectors (55.86%). In addition, Malaysia's electrical and electronic industry is predominantly founded by multinational organizations. Thus, this explained the distribution of company ownership and sector.

Demographics	Frequencies	Percentage (%)
Location of Manufacturing Base		
Johor	23	15.86
Kedah	11	7.59
Kelantan	0	0
Wilayah Persekutuan	0	0
Melaka	9	6.21
Negeri Sembilan	4	2.76
Pahang	7	4.83
Penang	43	29.66
Perak	15	10.34
Perlis	0	0
Sabah	0	0
Sarawak	1	0.69
Selangor	31	21.38
Terengganu	1	0.69
Type of Industry Sector		
Electrical and Electronics	81	55.86
Machinery and Equipment	16	11.03
Chemicals/Petrochemical/Plastics/Rubbers	38	26.21
Medical Devices	8	5.52
Aerospace	2	1.38
Company Ownership		
100% Foreign Owned	85	58.62
100% Local Owned	46	31.72
50% Foreign Owned; 50% Local Owned	3	2.07
>50% Foreign Owned; <50% Local Owned	7	4.83
<50% Foreign Owned; >50% Local Owned	3	2.07
Others	1	0.69

Source(s): Authors' own work

Table 2. Participating company's profile

4.2 Data analysis

The data were subjected to a screening process. Since the Likert scales were used to measure, outliers were not a major concern (Narkhede, 2017). Subsequently, Microsoft Excel was used to determine the presence of straight-lining responses by assessing the standard deviation value of the responses. Straight-lining responses will result in a standard deviation of zero, but none were detected. Next, we used SmartPLS version 3.3.3 (Ringle *et al.*, 2015) and IBM SPSS version 26 as the statistical analysis tools. SmartPLS is partial least squares (PLS) modelling software used for hypothesis testing. The main reasons to choose PLS are its ability to handle smaller sample sizes, non-normally distributed data and formative constructs (Hair *et al.*, 2018b).

Common method bias (CMB) may skew the result due to single source data (Podsakoff *et al.*, 2012; Kock, 2015). Kock (2015) proposed full collinearity testing to determine the presence of CMB. This method involves regression of the construct's latent variable score with randomized numbers. A variance inflation factor (VIF) value of below 3.3 indicates the absence of CMB, as shown in Table 3. Besides that, Harman's single factor test was also carried out using un-rotated factor analysis. The result indicates seven distinct factors account for 73.71% of the variances, and the first factor only accounts for 34.45% of the variance. According to Podsakoff *et al.* (2003), CMB is not an issue if no single factor accounts for most of the variances. Hence, CMB is not a major concern for this study.

4.2.1 Measurement model. The structural model consists of a single-order construct, EKS and two higher-order constructs (HOC), OA and MP. OA is a reflective-reflective HOC and MP is a reflective-formative HOC. With the presence of HOCs, the assessment of the measurement model will follow a disjoint two-stage reporting approach (Sarstedt *et al.*, 2019). The first-stage report will cover all the indicators measurements for the LOC. The second stage report will include LOCs as the indicators for the HOC.

Since the first stage model consists of all reflective indicators, we assess the reliability and validity of the measurement model following the guidelines proposed by Hair *et al.* (2019). Firstly, the indicators loading should be greater than or equal to 0.708 and the average variance extracted (AVE) should be greater than or equal to 0.5. Secondly, the composite reliability and Cronbach's alpha values should fall between 0.6 and 0.7 to indicate internal consistency reliability. Finally, the heterotrait-monotrait (HTMT) correlation ratio was used for discriminant validity assessment. Henseler *et al.* (2015) proposed a threshold of 0.85 for unique constructs and 0.90 for conceptually similar constructs.

4.2.1.1 First stage measurement model. Table 4 indicates the first-stage measurement result. All the indicator loading, AVE, Cronbach's Alpha, and CR values are within the threshold. However, according to Hair *et al.* (2017), loading between 0.40 and 0.70 should remain unless deleting the item leads to higher compositive reliability and AVE value. We deleted one item from EKS and one item from exploitation.

Table 5 highlights the HTMT ratio between the constructs. None of the constructs' HTMT ratio is above the stricter 0.85. Therefore, we can conclude that respondents perceived them as unique.

4.2.1.2 Second stage measurement model. Upon completing the first stage of measurement model analysis, we saved the latent score generated and used that as the indicator for the second stage of HOC (Sarstedt *et al.*, 2019). Table 6 indicates the reliability and validity value

EKS	OA	MP
1.473	2.540	2.099

Source(s): Authors' own work

Table 3.
Full collinearity testing

Lower order constructs	Items	Loading	AVE	Cronbach's alpha	CR
External Knowledge Sourcing	EKS_1	0.725	0.535	0.785	0.852
	EKS_2	*0.610*	*0.489*	*0.792*	*0.851*
	EKS_3	0.696			
	EKS_4	0.761			
	EKS_5	0.773			
	EKS_6	0.698			
Exploration	Explore_1	0.863	0.731	0.878	0.916
	Explore_2	0.888			
	Explore_3	0.823			
	Explore_4	0.845			
Exploitation	Exploit_1	0.753	0.609	0.839	0.885
	Exploit_2	*0.464*	*0.533*	*0.818*	*0.869*
	Exploit_3	0.850			
	Exploit_4	0.819			
	Exploit_5	0.674			
	Exploit_6	0.792			
MP_Quality	MP_Quality_1	0.871	0.839	0.903	0.940
	MP_Quality_2	0.941			
	MP_Quality_3	0.934			
MP_Cost	MP_Cost_ 1	0.792	0.798	0.873	0.922
	MP_Cost _2	0.938			
	MP_Cost_ 3	0.942			
MP_Delivery	MP_Delivery_1	0.977	0.956	0.954	0.977
	MP_Delivery_2	0.978			
MP_Flexibility	MP_Flexibility_1	0.944	0.822	0.928	0.949
	MP_Flexibility_2	0.903			
	MP_Flexibility_3	0.903			
	MP_Flexibility_4	0.874			

Note(s): Item in Italic indicates deleted item due to low loading value
Source(s): Authors' own work

Table 4. Measurement model results for disjoint first-stage lower order constructs

	EKS	Exploitation	Exploration	MP_ Cost	MP_ Delivery	MP_ Flexibility	MP_ Quality
EKS							
Exploitation	0.430						
Exploration	0.373	0.71					
MP_Cost	0.273	0.442	0.484				
MP_Delivery	0.192	0.378	0.405	0.848			
MP_ Flexibility	0.421	0.607	0.594	0.577	0.492		
MP_Quality	0.466	0.618	0.362	0.624	0.581	0.492	

Source(s): Authors' own work

Table 5. HTMT values (discriminant validity) of disjoint first-stage lower order constructs

for the second-stage reflective constructs, and Table 7 shows their discriminant validity value. All values are within the threshold, affirming that the reflective constructs are valid for the measurement model.

As for the formative construct MP, we assessed its value using the guideline proposed by Hair *et al.* (2019). The first test is to determine the measurement items' convergent validity. According to Jarvis *et al.* (2003), the items are not supposed to covary. We conducted a redundancy test to determine its relationship with a reflective global single item gathered in the survey (Cheah *et al.*, 2019). Hair *et al.* (2019) suggested a minimum value of 0.7 for the path coefficient to establish convergent validity. However, Cheah *et al.* (2019) claimed that 0.7 is a rough guideline. Therefore Sarstedt *et al.* (2019) recommended performing a boostrapping procedure to determine the confidence interval. The bootstrapping result indicates a lower limit of 0.584 and an upper limit of 0.763. Therefore, the path coefficient of 0.662 is within the interval, thus establishing convergent validity. Figure 2 shows the convergent validity of MP.

Since the formative indicators are unique (Hair *et al.*, 2018a; Jarvis *et al.*, 2003), the subsequent test is to detect the presence of multicollinearity between the indicators. According to Hair *et al.* (2017), a VIF value above five signifies a correlation among the indicators. Table 8 shows that all the VIF values are below three. Hence multicollinearity is

Table 6.
Measurement model results for disjoint second-stage reflective constructs

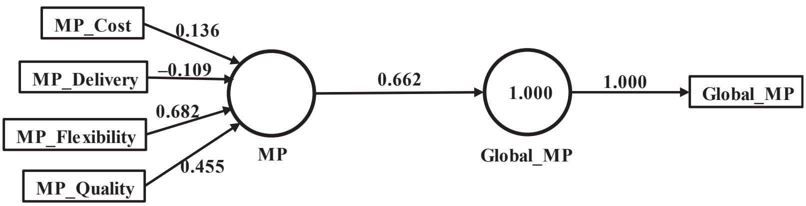
Constructs	Items	Loading	AVE	Cronbach's alpha	CR
EKS	EKS_1	0.720	0.535	0.785	0.852
	EKS_3	0.698			
	EKS_4	0.773			
	EKS_5	0.773			
	EKS_6	0.688			
OA	Exploitation	0.916	0.809	0.765	0.894
	Exploration	0.882			

Source(s): Authors' own work

Table 7.
HTMT values (discriminant validity) of disjoint second-stage constructs

	EKS	OA
EKS		
OA	0.478	

Source(s): Authors' own work



Source(s): Authors' own work

Figure 2.
Convergent validity of formative construct (MP)

Table 8.
Measurement model for formative higher order constructs

Higher order constructs	Items	Weights	p-value	Loading	p-value	VIF
Manufacturing performance	MP_Cost	0.136	0.222	0.657	$p < 0.01$	2.911
	MP_Delivery	−0.109	0.264	0.558	$p < 0.01$	2.694
	MP_Quality	0.455	$p < 0.01$	0.778	$p < 0.01$	1.576
	MP_Flexibility	0.682	$p < 0.01$	0.906	$p < 0.01$	1.452

Source(s): Authors' own work

not an issue. The final assessment determines the indicator's weight and significance (Hair *et al.*, 2017). If the outer weight is not significant, the value of the outer loading is considered. A loading of 0.5 and above indicates that the items should be retained (Hair *et al.*, 2017). In this study, MP_Cost and MP_Delivery weight is insignificant, but their loading is above 0.5, as shown in Table 8. Hence, they are retained and signify the formative construct passed all these assessment criteria.

4.2.2 Structural model. Since the measurement model is validated, we verified the hypotheses through structural path coefficient measurement. However, before doing that, we executed the bootstrapping routine since our data are not multivariate normal (Hair *et al.*, 2017). We calculated Mardia's coefficients using Cain *et al.* (2017) web-based statistical analysis tool, Web Power (URL https://webpower.psychstat.org/models/kurtosis/). The calculation indicates a skewness of $\beta = 30.871, p < 0.01$ and kurtosis of $\beta = 108.640, p < 0.01$, which is above the cutoff value of $\beta = 3.0$ for skewness and $\beta = 20$ for kurtosis (Kline, 2016). We executed the bootstrapping with 5000 subsamples and a 0.05 significance level. Besides reporting the standard t-value and p-value, we also report the 95% confidence interval value (Aguirre-Urreta and Rönkkö, 2018). Hair *et al.* (2017) state that the relationship is valid if there is no zero straddles between the intervals. Besides that, Hair *et al.* (2019) also suggested checking out for any collinearity between the constructs as it may bias the results. A VIF value of above five will indicates collinearity among the constructs. Table 9 provides a summary of the results.

From the table, all three main hypotheses (H1, H2, H3) were supported with EKS ($\beta = 0.228$, $p = 0.009$) and OA ($\beta = 0.566$, $p < 0.01$), positively related to MP and EKS ($\beta = 0.396$, $p < 0.01$), also positively related to OA. Furthermore, both EKS and OA also managed to explain 47.5% of the variance for MP with an R^2 of 0.475. Likewise, EKS managed to explain 15.7% of the variance in OA. In regards to how the exogenous construct affects the endogenous construct, Cohen (1988) suggests an effect size of 0.01, 0.09 and 0.25 as small, medium and large effects. EKS effect MP marginally with a small effect size of 0.083, whereas OA effect MP significantly with an effect size of 0.514. EKS also has a medium effect on OA, with a value of 0.186. Furthermore, all the VIF values are below five; hence there is no collinearity between the constructs.

As for mediation analysis, a boostrapping indirect effect method was applied, as suggested by Preacher and Hayes (2008). It is an explicit mediation analysis technique, and the bootstrap confidence interval is used to assess the t-value and p-value (Rungtusanatham *et al.*, 2014). From Table 10, EKS → OA → MP ($\beta = 0.224, p < 0.01$) shows an interval without a zero straddle in it. Hence the mediation relationship exists, and H4 is supported. Besides that, we also measure the indirect effect size (v) by squaring the standardized indirect effect (Std Beta) as per the recommendation from Lachowicz *et al.* (2018). They also suggest following the benchmark threshold for R^2. Hence, a v value of 0.05 indicates that OA has a small effect on this mediation relationship.

One of the key objectives of PLS-SEM is to maximize the explanation power of the model. By doing this, it will be possible to extrapolate the findings from the sample data to the population interest (Hair *et al.*, 2020). Hair *et al.* (2019) proposed running the blindfolding technique to determine the predictive relevance Q^2 value. Typically, a number between 0.25 and 0.50 represents the structural model's medium to substantial predictive importance (Hair *et al.*, 2020). The Smart-PLS reports a Q^2 value of 0.337 and 0.380 for MP and OA, respectively. Thus, it is considered to have a medium-level predictive relevance.

However, recent literature claims that R^2 and Q^2 are not the true representation of the model's out-of-sample predictive relevance because they utilize the same data set instead of a holdout sample for calculation (e.g. Hair and Sarstedt, 2021; Shmueli *et al.*, 2019). Instead, Shmueli *et al.* (2019) suggested executing the PLSpredict procedure that determines a Q^2predict value from a randomly selected holdout sample. The procedure will compare the

Table 9.
Structural model assessment results

Hypothesis	Relationship	Std Beta	Std error	t-values	*p*-values	BCI LL	BCI UL	R^2	f^2	Effect size	VIF
H1	EKS → MP	0.228	0.096	2.383	0.009	0.078	0.395	0.475	0.083	Small	1.186
H2	OA → MP	0.566	0.085	6.652	$p < 0.01$	0.397	0.685		0.514	Big	1.186
H3	EKS → OA	0.396	0.063	6.335	$p < 0.01$	0.265	0.477	0.157	0.186	Medium	1.000

Source(s): Authors' own work

predictive accuracy of the PLS model against a naïve benchmark model. The model has predictive relevance if the Q^2predict value is above zero (Hair *et al.*, 2020). Subsequently is to determine the strength of the model's predictive power by comparing the root mean squared error (RMSE) value of the measurement items (Hair *et al.*, 2020; Shmueli *et al.*, 2019). If the PLS model has more items with lower RMSE than the linear model (LM), it has high predictive power. It has medium predictive power if both models have the same number of RMSE. However, if the LM model has more items with lower RMSE, it has low predictive power. From Table 11, the PLS model has a Q^2predict value above zero and half of its RMSE values lower than the LM model and thus is considered to have medium predictive power.

5. Discussion and conclusion

The findings reveal that for a firm to achieve a better MP involves having the ability to explore new external knowledge. At the same time, balancing its internal and external knowledge resources is vital to sustaining its MP within a dynamic market. Even though the findings differ from the study of Migdadi (2020), which claimed that KM has no direct impact on large manufacturing firm performance, it aligns with the claim that a mediator will result in a positive relationship. Likewise, the results of Kafetzopoulos's (2020) research also indicate that OA will have a greater influence on firm performance in a dynamic environment which is consistent with the finding of this study. Besides, the study of Zhou and Liu (2012) and Tan and Wong (2015) also revealed that external knowledge sources play an important role in achieving a better MP. Studies in environmental dynamism also underscore the importance of increasing knowledge stock through external sourcing (Kocoglu *et al.*, 2012; Nguyen and Harrison, 2019). This study provides clear evidence that an ambidextrous firm must focus on enhancing its knowledge, which will enable it to keep up with the market fluctuation and improve its MP.

In conclusion, the manufacturing industry is crucial to the nation's GDP growth. At this juncture, extreme dynamic external factors such as Covid-19 pandemic shocks and the prevalence of IR4.0 are taking a toll on its sustainability. It has to transform itself out of these situations. The research finding comes at the right time to provide the necessary understanding of utilizing the resources optimally to increase new knowledge. Practising such strategies will enable it to swiftly transition into a digitally integrated way of running its

Hypothesis	Relationship	Std Beta	Std error	t-values	*p*-values	BCI LL	BCI UL	*v*
H4	EKS → OA → MP	0.224	0.05	4.453	$p < 0.01$	0.139	0.299	0.05

Source(s): Authors' own work

Table 10. Indirect effect hypothesis testing

Constructs	Q^2Predict	Item	PLS RMSE	LM RMSE	PLS-LM	Q^2Predict
MP	0.168	MP_Cost	0.988	0.970	0.018	0.130
		MP_Delivery	1.002	1.001	0.001	0.098
		MP_Flexibility	0.945	0.964	−0.019	0.243
		MP_Quality	0.938	0.960	−0.022	0.233
OA	0.132	Exploitation	0.944	0.904	0.040	0.130
		Exploration	0.964	0.977	−0.013	0.098

Source(s): Authors' own work

Table 11. PLSpredict result

operation. As a result, manufacturing firms benefit from the IR4.0 advanced technology and remain relevant.

6. Theoretical implications

As discussed earlier, prior research is mainly carried out when the market is stable. Besides, the study on the interaction between multiple management practices, especially within a dynamic market environment, is limited (Walker, 2004). The IR4.0 and Covid-19 pandemics impelled this research towards formulating a theoretical framework to examine how KM and operation management theories interact during such unpredictive market conditions. Therefore, from a theoretical perspective, the findings provide three main contributions towards knowledge expansion in both these fields. Firstly, it validates how the underpinning theories of KBV and DC behave in a truly dynamic market. Such findings allow the researchers to compare how these theories behave in economic equilibrium conditions.

Additionally, our findings confirm that OA and EKS are key capabilities within the DC framework that enable firms to navigate market uncertainties. By expanding the understanding of KBV and DC, our findings have both theoretical and practical implications, providing novel insights into the behavior of these theories in dynamic market contexts. Thirdly, this study also provides empirical evidence for the earlier proposed conceptual framework of Cheah and Tan (2021) and Cheah and Tan (2020). By substantiating the framework with empirical findings, we contribute to validating and refining their conceptual work, thereby strengthening the theoretical foundation of their proposed model. Lastly, the determination of OA as the mediator further compliment the request from Gibson and Birkinshaw (2004) to confirm whether boundary condition plays a role in the effectiveness of OA as a mediator. As such, our findings further expand the knowledge of OA beyond a stable business environment and conclude that OA is an assuring factor for a firm to sustain its performance in a complex organizational environment.

7. Practical implications

The findings of this study have several important practical implications for managers and policymakers. Such findings will enable them to formulate the right approach to improve the productivity and efficiency of the manufacturing sector. In summary, OA and EKS play critical roles in obtaining a higher MP. Therefore, managers who intend to adopt new IR4.0 technologies should balance sourcing new knowledge and improving existing ones. However, they need to focus on external sources such as customers, suppliers and other research institutions instead of internal sources such as firms from the same industry or within the organization. They should also find ways to enrich their knowledge through trade shows, training, seminars or conferences. Likewise, the managers must ensure their staff have similar exposure to this external knowledge. For niche knowledge, a firm can consider a joint venture with other firms to gain mutual knowledge. Once new knowledge is obtained, managers can assimilate it into existing knowledge to generate new ideas and opportunities to improve the firms' MP.

The government can introduce specific training programs highlighting the latest technologies and market trends in the manufacturing sector. It can also help to link up the players from the manufacturing sectors and local research institutions through public-private partnerships (PPP) programs (MITI, 2018). This approach will facilitate knowledge and resource sharing in R&D and training to enhance the IR4.0 technology adoption rate. Besides, the government must consider re-skilling and up-skilling training programs or seminars that cover the latest and conventional knowledge. Focusing on these aspects will ensure sustainable knowledge for the firms to continue exploring and exploiting new possibilities to enhance their MP. As for the policymakers, they can work on policies that support the overall technology adoption process. For example, duty exemption for IR4.0-related equipment and training machines or tax relief option for companies that invest in that equipment. Such policies will indirectly help to encourage more companies to source this new knowledge externally.

As for the researcher, the findings confirm the theoretical framework for this research, which reflects on its unique interactions model and can further set the stage for future theoretical expansion.

8. Limitations and future research

While the results align with all the hypothesized relationships, there are a few limitations despite carefully thought-out approaches to minimize them. The main one is the cross-sectional nature of the data collection, carried out during the Covid-19 pandemic, where many respondents were working from home, and plant production was low. As such, the actual working condition may have influenced the reaction of the respondents. Secondly, the data were collected from large firms in five IR4.0 focus sectors. Therefore, a certain level of caution is needed when interpreting the result from different contexts. A longitudinal approach can allow a better grasp of the relationships in both dynamic and economic equilibrium conditions. A similar study can be carried out with more sectors moving forward to enable the greater generalization of the findings.

Furthermore, future studies can also consider extending this study to small and medium enterprises, which form a bulk of the companies in Malaysia. A case studies approach for a few companies can allow a more in-depth understanding and comparison between the practices. Besides that, similar studies can be replicated using different aspects of KM, such as knowledge sharing, knowledge protection or a combination of multiple KM practices. Another possible consideration would be validating the performance measures by comparing results between objective and subjective organizational performance measures for a more nuanced understanding. All these recommendations will allow a more comprehensive understanding of how the manufacturing sector behaves dynamically.

References

Aboelmaged, M.G. (2014), "Linking operations performance to knowledge management capability: the mediating role of innovation performance", *Production Planning and Control*, Vol. 25 No. 1, pp. 44-58, doi: 10.1080/09537287.2012.655802.

Adebanjo, D., Teh, P.L. and Ahmed, P.K. (2017), "The impact of supply chain relationships and integration on innovative capabilities and manufacturing performance: the perspective of rapidly developing countries", *International Journal of Production Research*, Vol. 56 No. 4, pp. 1708-1721, doi: 10.1080/00207543.2017.1366083.

Aguirre-Urreta, M.I. and Rönkkö, M. (2018), "Statistical inference with PLSc using bootstrap confidence intervals", *MIS Quarterly*, Vol. 42 No. 3, pp. 1001-1020, doi: 10.25300/MISQ/2018/13587.

Ali, M., Shujahat, M., Ali, Z., Kianto, A., Wang, M. and Bontis, N. (2022), "The neglected role of knowledge assets interplay in the pursuit of organisational ambidexterity", *Technovation*, Vol. 114 August 2021, 102452, doi: 10.1016/j.technovation.2021.102452.

Al-Sa'di, A.F., Abdallah, A.B. and Dahiyat, S.E. (2017), "The mediating role of product and process innovations on the relationship between knowledge management and operational performance in manufacturing companies in Jordan", *Business Process Management Journal*, Vol. 23 No. 2, pp. 349-376, doi: 10.1108/BPMJ-03-2016-0047.

Ahmad, N., Lazim, H.M., Shamsuddin, A., Wahab, E. and Abu Seman, N.A. (2019), "The relationship between technological capability and manufacturing performance", *International Journal of Supply Chain Management*, Vol. 8 No. 2, pp. 930-938.

Alavi, M. and Leidner, D.E. (2001), "Review : knowledge systems: management knowledge and foundations conceptual", *MIS Quarterly*, Vol. 25 No. 1, pp. 107-136.

AlShawabkeh, R., Rumman, A., Al-Abbadi, L. and Abu Rumman, A. (2020), "The intervening role of ambidexterity in the knowledge management project success connection", *Problems and Perspectives in Management*, Vol. 18 No. 3, pp. 56-66, doi: 10.21511/ppm.18(3).2020.05.

Andreeva, T. and Kianto, A. (2011), "Knowledge processes, knowledge-intensity and innovation: a moderated mediation analysis", *Journal of Knowledge Management*, Vol. 15 No. 6, pp. 1016-1034, doi: 10.1108/13673271111179343.

Asif, M. (2017), "Exploring the antecedents of ambidexterity: a taxonomic approach", *Management Decision*, Vol. 55 No. 7, pp. 1489-1505, doi: 10.1108/MD-12-2016-0895.

Barney, J. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99-120, doi: 10.1177/014920639101700108.

Brunswicker, S. and Vanhaverbeke, W. (2015), "Open innovation in small and medium-sized enterprises (SMEs): external knowledge sourcing strategies and internal organizational facilitators", *Journal of Small Business Management*, Vol. 53 No. 4, pp. 1241-1263, doi: 10.1111/jsbm.12120.

Cain, M.K., Zhang, Z. and Yuan, K.H. (2017), "Univariate and multivariate skewness and kurtosis for measuring nonnormality: prevalence, influence and estimation", *Behavior Research Methods*, Vol. 49 No. 5, pp. 1716-1735, doi: 10.3758/s13428-016-0814-1.

Cheah, S.C. and Tan, C.L. (2020), "Knowledge management, organizational ambidexterity, and manufacturing performance in the era of industry 4.0: a proposed model", *International Journal of Industrial Management*, Vol. 5 No. 1, pp. 10-19, doi: 10.15282/ijim.5.0.2020.5696.

Cheah, S.C. and Tan, C.L. (2021), "Knowledge management, innovation capability, and manufacturing performance in the era of industry 4.0: a proposed model", *Global Business and Management Research: An International Journal*, Vol. 13 No. 1, pp. 38-51.

Cheah, J.H., Ting, H., Ramayah, T., Memon, M.A., Cham, T.H. and Ciavolino, E. (2019), "A comparison of five reflective–formative estimation approaches: reconsideration and recommendations for tourism research", *Quality and Quantity*, Vol. 53 No. 3, pp. 1421-1458, doi: 10.1007/s11135-018-0821-7.

Cirera, X., Mason, A.D., de Nicola, F., Kuriakose, S., Mare, D.S. and Tran, T.T. (2021), *The Innovation Imperative for Developing East Asia*, The World Bank, Washington, DC. doi: 10.1596/978-1-4648-1606-2.

Cohen, J. (1988), *Statistical Power Analysis for the Behavioral Sciences*, 2nd., LAWRENCE ERLBAUM ASSOCIATES, New York, available at: https://www.utstat.toronto.edu/~brunner/oldclass/378f16/readings/CohenPower.pdf.

Cooper, D.R. and Schindler, P.S. (2014), *Business Research Methods*, 12th ed., McGraw-Hill/Irwin, NY.

Dahiyat, S.E. (2015), "An integrated model of knowledge acquisition and innovation: examining the mediation effects of knowledge integration and knowledge application", *International Journal of Learning and Change*, Vol. 8 No. 2, pp. 101-135, doi: 10.1504/IJLC.2015.074064.

Davenport, T. and Prusak, L. (1998), *Working Knowledge : How Organizations Manage what They Know*, Harvard Business School Press, Boston, MA.

Dawes, J. (1999), "The relationship between subjective and objective company performance measures in market orientation research: further empirical evidence", Marketing Bulletin-Department of Marketing Massey University, Vol. 10 No. 1996, pp. 65-75.

Dess, G.G. and Robinson, R.B. (1984), "Measuring organizational performance in the absence of objective measures: the case of the privately-held firm and conglomerate business unit", *Strategic Management Journal*, Vol. 5 No. 3, pp. 265-273, doi: 10.1002/smj.4250050306.

Dezi, L., Ferraris, A., Papa, A. and Vrontis, D. (2019), "The role of external embeddedness and knowledge management as antecedents of ambidexterity and performances in Italian SMEs", *IEEE Transactions on Engineering Management*, Vol. 68 No. 2, pp. 1-10, doi: 10.1109/tem.2019.2916378.

Dolsen, M. and Chinnam, R.B. (2017), "Developing innovation capability in a mass production organization", *Journal of Enterprise Transformation*, Vol. 8289, December, pp. 1-23, doi: 10.1080/19488289.2017.1409297.

Eisenhardt, K.M. and Santos, F.M. (2002), "Handbook of strategy and management", *Handbook of Strategy and Management*, Vol. 1 No. 1, pp. 139-164.

Epu, E.P.U. (2021), *Twelfth Malaysia Plan 2021-2025, A Prosperous, Inclusive, Sustainable Malaysia*, Economic Planning Unit, Putrajaya.

Gibson, C.B. and Birkinshaw, J. (2004), "The antecedents, consequences, and mediating role of organizational ambidexterity", *Academy of Management Journal*, Vol. 47 No. 2, pp. 209-226, doi: 10.5465/20159573.

Grant, R.M. (1991), "The resource-based theory of competitive advantage: implications for strategy formulation", *California Management Review*, Vol. 33 No. 3, pp. 114-135, doi: 10.2307/41166664.

Grant, R.M. (1996), "Toward a knowledge-based theory of the firm", *Strategic Management Journal*, Vol. 17, Special Issue, pp. 109-122, doi: 10.1002/smj.4250171110.

Guo, W., Yang, J., Li, D. and Lyu, C. (2020), "Knowledge sharing and knowledge protection in strategic alliances: the effects of trust and formal contracts", *Technology Analysis and Strategic Management*, Vol. 32 No. 11, pp. 1366-1378, doi: 10.1080/09537325.2020.1769840.

Hair, J.F., Jr (2020), "Next-generation prediction metrics for composite-based PLS-SEM", *Industrial Management & Data Systems*, Vol. 121 No. 1, pp. 5-11, doi: 10.1108/IMDS-08-2020-0505.

Hair, J.F., Astrachan, C.B., Moisescu, O.I., Radomir, L., Sarstedt, M., Vaithilingam, S. and Ringle, C.M. (2020), "Executing and interpreting applications of PLS-SEM: updates for family business researchers", *Journal of Family Business Strategy*, xxxx, 100392, doi: 10.1016/j.jfbs.2020.100392.

Hair, J.J.F., Hult, G.T.M., Ringle, C. and Sarstedt, M. (2017), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed., SAGE Publications, Inc. Printed.

Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019), "When to use and how to report the results of PLS-SEM", *European Business Review*, Vol. 31 No. 1, pp. 2-24, doi: 10.1108/EBR-11-2018-0203.

Hair, J.F. and Sarstedt, M. (2021), "Explanation Plus prediction—the logical focus of project management research", *Project Management Journal*, Vol. 52 No. 4, doi: 10.1177/87569728211999945.

Hair, J.F., Sarstedt, M., Ringle, C.M. and Gudergan, S. (2018a), *Advanced Issues in Partial Least Squares Structural Equation Modeling (PLS-SEM)*, Sage, Thousand Oaks.

Hair Jr, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2018b), *Multivariate Data Analysis*, 8th ed., Cengage Learning EMEA, Hampshire.

Han, Y. (2019), "The relationship between ambidextrous knowledge sharing and innovation within industrial clusters: evidence from China", *Interdisciplinary Journal of Information, Knowledge, and Management*, Vol. 14, pp. 145-163, doi: 10.1525/cmr.2016.58.4.5.

He, Z.L. and Wong, P.K. (2004), "Exploration vs. exploitation: an empirical test of the ambidexterity hypothesis", *Organization Science*, Vol. 15 No. 4, pp. 481-495, doi: 10.1287/orsc.1040.0078.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135, doi: 10.1007/s11747-014-0403-8.

Hernández-Espallardo, M., Sánchez-Pérez, M. and Segovia-López, C. (2011), "Exploitation- and exploration-based innovations: the role of knowledge in inter-firm relationships with distributors", *Technovation*, Vol. 31 Nos 5-6, pp. 203-215, doi: 10.1016/j.technovation.2011.01.007.

Hughes, P., Hughes, M., Stokes, P., Lee, H., Rodgers, P. and Degbey, W.Y. (2020), "Micro-foundations of organizational ambidexterity in the context of cross-border mergers and acquisitions", *Technological Forecasting and Social Change*, Vol. 153 July 2019, 119932, doi: 10.1016/j.techfore.2020.119932.

Hung, R.Y.Y., Lien, B.Y.H., Yang, B., Wu, C.M. and Kuo, Y.M. (2011), "Impact of TQM and organizational learning on innovation performance in the high-tech industry", *International Business Review*, Vol. 20 No. 2, pp. 213-225, doi: 10.1016/j.ibusrev.2010.07.001.

Jarvis, C.B., Mackenzie, S.B. and Podsakoff, P.M. (2003), "A critical review of construct indicators and measurement model misspecification in marketing and consumer research", *Journal of Consumer Research*, Vol. 30 No. 2, pp. 199-218, doi: 10.1086/376806.

Junni, P., Sarala, R.M., Taras, V. and Tarba, S.Y. (2013), "Organizational ambidexterity and performance: a meta-analysis", *Academy of Management Perspectives*, Vol. 27 No. 4, pp. 299-312, doi: 10.5465/amp.2012.0015.

Kafetzopoulos, D. (2020), "Organizational ambidexterity: antecedents, performance and environmental uncertainty", *Business Process Management Journal*, Vol. 27 No. 3, doi: 10.1108/BPMJ-06-2020-0300.

Kline, R.B. (2016), *Principles Ans Practise of Structural Equation Modeling*, Forth Edit., The Guilford Press, New York.

Kock, N. (2015), "Common method bias in PLS-SEM: a full collinearity assessment approach", *International Journal of E-Collaboration*, Vol. 11 No. 4, pp. 1-10, doi: 10.4018/ijec.2015100101.

Kocoglu, I., Imamoglu, S.Z., Ince, H. and Keskin, H. (2012), "Learning, R&D and manufacturing capabilities as determinants of technological learning: enhancing innovation and firm performance", *Procedia - Social and Behavioral Sciences*, Vol. 58, pp. 842-852, doi: 10.1016/j.sbspro.2012.09.1062.

Krishnan, R. and Jha, S. (2011), "Innovation strategies in emerging markets: what can we learn from Indian market leaders", *ASCI Journal of Management*, Vol. 41 No. 1, pp. 21-45.

Lachowicz, M.J., Preacher, K.J. and Kelley, K. (2018), "A novel measure of effect size for mediation analysis", *Psychological Methods*, Vol. 23 No. 2, pp. 244-261, doi: 10.1037/met0000165.

Liao, Y. and Li, Y. (2019), "Complementarity effect of supply chain competencies on innovation capability", *Business Process Management Journal*, Vol. 25 No. 6, pp. 1251-1272, doi: 10.1108/BPMJ-04-2018-0115.

Lin, H.E., McDonough, E.F., Lin, S.J. and Lin, C.Y.Y. (2013), "Managing the exploitation/exploration paradox: the role of a learning capability and innovation ambidexterity", *Journal of Product Innovation Management*, Vol. 30 No. 2, pp. 262-278, doi: 10.1111/j.1540-5885.2012.00998.x.

Macau, F., Brito, L.A.L. and Duarte, A.L.C.M. (2016), "Effects of knowledge development and culture of competitiveness on the performance of service-oriented and product-oriented firms", *Knowledge and Process Management*, Vol. 23 No. 3, pp. 219-229, doi: 10.1002/kpm.1510.

March, J.G. (1991), "Exploration and exploitation in organizational learning", *Organization Science*, Vol. 2 No. 1, pp. 71-87, doi: 10.1287/orsc.2.1.71.

Matthews, R.L., Tan, K.H. and Marzec, P.E. (2015), "Organisational ambidexterity within process improvement: an exploratory study of four project-oriented firms", *Journal of Manufacturing Technology Management*, Vol. 26 No. 4, pp. 458-476, doi: 10.1108/JMTM-12-2013-0184.

Migdadi, M.M. (2020), "Knowledge management processes, innovation capability and organizational performance", *International Journal of Productivity and Performance Management*, Vol. 71 No. 1, doi: 10.1108/IJPPM-04-2020-0154.

Migdadi, M.M., Zaid, M.K.A., Yousif, M., Almestarihi, R. and Al-Hyari, K. (2017), "An empirical examination of knowledge management processes and market orientation, innovation capability, and organisational performance: insights from Jordan", *Journal of Information and Knowledge Management*, Vol. 16 No. 1, pp. 1-32, doi: 10.1142/S0219649217500022.

MITI, M. of I. T. & I. (2018), "Industry 4wrd: national policy on industry 4.0. Kuala lumpur", available at: https://www.miti.gov.my/miti/resources/NationalPolicyonIndustry4.0/Industry4WRD_Final.pdf

Mohamad, A.A., Ramayah, T. and Lo, M. (2017), "Knowledge management in msc Malaysia : the role of information technology capability", *International Journal of Business and Society*, Vol. 18 No. S4, pp. 651-660.

MPC M. P. C. (2021), "Malaysia productivity report 2021", p. 92, available at: www.mpc.gov.my

Narkhede, B.E. (2017), "Advance manufacturing strategy and firm performance: an empirical study in a developing environment of small- and medium-sized firms", *Benchmarking: An International Journal*, Vol. 24 No. 1, pp. 62-101, doi: 10.1108/BIJ-05-2015-0053.

Ng, P.K. and Jee, K.S. (2012), "Innovating TQM, CE and KM for productive manufacturing in a Malaysian firm", *Total Quality Management and Business Excellence*, Vol. 23 Nos 9-10, pp. 1089-1105, doi: 10.1080/14783363.2012.704283.

Nguyen, H. and Harrison, N. (2019), "Leveraging customer knowledge to enhance process innovation", *Business Process Management Journal*, Vol. 25 No. 2, pp. 307-322, doi: 10.1108/BPMJ-03-2017-0076.

Ong, E.C. and Tan, C.L. (2022), "Soft TQM, agility, and knowledge management deliver organizational performance: a study of Malaysian manufacturing organizations in the electrical and electronics sector", *Global Business and Organizational Excellence*, Vol. 41 No. 4, pp. 28-47, doi: 10.1002/joe.22155.

Oorschot, K.E.V., Solli-Sæther, H. and Karlsen, J.T. (2018), "The knowledge protection paradox: imitation and innovation through knowledge sharing", *International Journal of Technology Management*, Vol. 78 No. 4, pp. 310-342, doi: 10.1504/ijtm.2018.095760.

O'Reilly, C.A. and Tushman, M.L. (2013), "Organizational ambidexterity: past, present, and future", *Academy of Management Perspectives*, Vol. 27 No. 4, pp. 324-338, doi: 10.5465/amp.2013.0025.

Paiva, E.L., Roth, A.V. and Fensterseifer, J.E. (2008), "Organizational knowledge and the manufacturing strategy process: a resource-based view analysis", *Journal of Operations Management*, Vol. 26 No. 1, pp. 115-132, doi: 10.1016/j.jom.2007.05.003.

Partanen, J., Kohtamäki, M., Patel, P.C. and Parida, V. (2020), "Supply chain ambidexterity and manufacturing SME performance: the moderating roles of network capability and strategic information flow", *International Journal of Production Economics*, Vol. 221 August, 107470, doi: 10.1016/j.ijpe.2019.08.005.

Patel, P.C., Terjesen, S. and Li, D. (2012), "Enhancing effects of manufacturing flexibility through operational absorptive capacity and operational ambidexterity", *Journal of Operations Management*, Vol. 30 No. 3, pp. 201-220, doi: 10.1016/j.jom.2011.10.004.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: 10.1037/0021-9010.88.5.879.

Podsakoff, P.M., MacKenzie, S.B. and Podsakoff, N.P. (2012), "Sources of method bias in social science research and recommendations on how to control it", *Annual Review of Psychology*, Vol. 63, pp. 539-569, doi: 10.1146/annurev-psych-120710-100452.

Prange, C. and Bruyaka, O. (2016), "Better at home, abroad, or both? How Chinese firms use ambidextrous internationalization strategies to drive innovation", *Cross Cultural and Strategic Management*, Vol. 23 No. 2, pp. 306-339, doi: 10.1108/CCSM-07-2014-0079.

Preacher, K.J. and Hayes, A.F. (2008), "Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models", *Behavior Research Methods*, Vol. 40 No. 3, pp. 879-891, doi: 10.3758/BRM.40.3.879.

Raisch, S. and Birkinshaw, J. (2008), "Organizational ambidexterity: antecedents, outcomes, and moderators", *Journal of Management*, Vol. 34 No. 3, pp. 375-409, doi: 10.1177/0149206308316058.

Ramayah, T., Sulaiman, M., Jantan, M. and Ching, N.G. (2004), "Manufacturing performance : a glimpse from the Malaysian", *International Journal of Innovation and Incubation*, Vol. 1 No. 1, pp. 63-90.

Rialti, R., Marzi, G., Caputo, A. and Mayah, K.A. (2020), "Achieving strategic flexibility in the era of big data: the importance of knowledge management and ambidexterity", *Management Decision*, Vol. 58 No. 8, pp. 1585-1600, doi: 10.1108/MD-09-2019-1237.

Ringle, C.M., Wende, S. and Becker, J.-M. (2015), "'Smart PLS 3.' boenningstedt: SmartPLS GmbH", available at: http://www.smartpls.com.

Rosenzweig, E.D. and Easton, G.S. (2010), "Tradeoffs in manufacturing? A meta-analysis and critique of the literature", *Production and Operations Management*, Vol. 19 No. 2, pp. 127-141, doi: 10.1111/j.1937-5956.2009.01072.x.

Rungtusanatham, M., Miller, J.W. and Boyer, K.K. (2014), "Theorizing, testing, and concluding for mediation in SCM research: tutorial and procedural recommendations", *Journal of Operations Management*, Vol. 32 No. 3, pp. 99-113, doi: 10.1016/j.jom.2014.01.002.

Sánchez, Á.M., Pérez-Pérez, M. and Vicente-Oliva, S. (2019), "Agile production, innovation and technological cooperation: overlapping priorities of manufacturing firms", *Baltic Journal of Management*, Vol. 14 No. 4, pp. 597-615, doi: 10.1108/BJM-12-2018-0410.

Sarstedt, M., Hair, J.F., Cheah, J.H., Becker, J.M. and Ringle, C.M. (2019), "How to specify, estimate, and validate higher-order constructs in PLS-SEM", *Australasian Marketing Journal*, Vol. 27 No. 3, pp. 197-211, doi: 10.1016/j.ausmj.2019.05.003.

Schroeder, C. (2015), *The Challenges of Industry 4 . 0 for Small and Medium-Sized Enterprises*, Friedrich Ebert Foundation, Bonn.

Scott, N. (2016), "The impact of ambidexterity in supply chain capabilities on manufacturing performance: examples from the global semiconductor industry", *International Journal of Logistics Systems and Management*, Vol. 23 No. 3, pp. 394-417, doi: 10.1504/IJLSM.2016.074718.

Shmueli, G., Sarstedt, M., Hair, J.F., Cheah, J.H., Ting, H., Vaithilingam, S. and Ringle, C.M. (2019), "Predictive model assessment in PLS-SEM: guidelines for using PLSpredict", *European Journal of Marketing*, Vol. 53 No. 11, pp. 2322-2347, doi: 10.1108/EJM-02-2019-0189.

Snow, C.C. and Hrebiniak, L.G. (1980), "Strategy, distinctive competence, and organizational performance", *Administrative Science Quarterly*, Vol. 25 No. 2, p. 317, doi: 10.2307/2392457.

Song, S.H., Kim, M.J. and Kang, J. (2016), "The effects of ambidextrous alliances on product innovation", *Journal of Global Scholars of Marketing Science*, Vol. 26 No. 1, pp. 4-18, doi: 10.1080/21639159.2015.1116780.

Tamayo-Torres, J., Roehrich, J.K. and Lewis, M.A. (2017), "Ambidexterity, performance and environmental dynamism", *International Journal of Operations & Production Management*, Vol. 37 No. 3, pp. 282-299, doi: 10.1108/IJOPM-06-2015-0378.

Tan, L.P. and Wong, K.Y. (2015), "Linkage between knowledge management and manufacturing performance: a structural equation modeling approach", *Journal of Knowledge Management*, Vol. 19 No. 4, pp. 814-835, doi: 10.1108/JKM-11-2014-0487.

Walker, R.M. (2004), "Innovation and organisational performance: evidence and a research agenda", Advanced Institute of Management Research Paper, (002), pp. 1-56, doi: 10.2139/ssrn.1306909.

Wei, Z., Zhao, J. and Zhang, C. (2014), "Organizational ambidexterity, market orientation, and firm performance", *Journal of Engineering and Technology Management - JET-M*, Vol. 33, pp. 134-153, doi: 10.1016/j.jengtecman.2014.06.001.

Xie, X., Gao, Y., Zang, Z. and Meng, X. (2019), "Collaborative ties and ambidextrous innovation: insights from internal and external knowledge acquisition", *Industry and Innovation*, Vol. 27 No. 3, pp. 285-310, doi: 10.1080/13662716.2019.1633909.

Yang, D. (2012), "The effect of intangible resource bundling on ambidextrous capabilities—the moderating effect of EO and MO", *Business Management Dynamics*, Vol. 2 No. 5, pp. 1-4.

Yang, S.M., Fang, S.C., Fang, S.R. and Chou, C.H. (2014), "Knowledge exchange and knowledge protection in interorganizational learning: the ambidexterity perspective", *Industrial Marketing Management*, Vol. 43 No. 2, pp. 346-358, doi: 10.1016/j.indmarman.2013.11.007.

Zhou, J. and Liu, Y. (2012), "A study of knowledge transfer on flexible manufacturing capability and manufacturing performance", *Advanced Materials Research*, Vol. 542 No. 543, pp. 335-338, doi: 10.4028/www.scientific.net/AMR.542-543.335.

Zhou, Y., Lu, L. and Chang, X. (2016), "Averting risk or embracing opportunity? Exploring the impact of ambidextrous capabilities on innovation of Chinese firms in internationalization", *Cross Cultural & Strategic Management*, Vol. 23 No. 4, pp. 569-589, doi: 10.1108/CCSM-07-2014-0085.

Appendix

External knowledge sourcing (Brunswicker and Vanhaverbeke, 2015)
Indicate the intensity of sourcing new knowledge through interaction with (on a scale from 1 to 6, where 1 = not practised, 2 = very rarely practised, 3 = rarely practised 4 = occasionally practised, 5 = highly practised, and 6 = very highly practised)
EKS_1: Direct customer (such as main distributor, reseller, original equipment manufacturer, etc)
EKS_2: Indirect customer (such as end-user)
EKS_3: Supplier (such as equipment/tool supplier, indirect/direct material supplier human resource supplier, training provider, etc)
EKS_4: Universities and research organization
EKS_5: Experts on intellectual property rights (such as Intellectual Property Corporation of Malaysia, patent agent or consultant, etc)
EKS_6: Network partners (such as joint venture partners, competitors, etc)
Organizational Ambidexterity (Kafetzopoulos, 2020)
Please indicate your level of agreement pertaining to below statements about organizational ambidexterity practises (on a scale from 1 to 6, where 1 = strongly disagree, 2 = moderately disagree, 3 = slightly disagree, 4 = slightly agree, 5 = moderately agree, 6 = strongly agree)
Exploration
Explore_1: My company looks for novel (innovative) technological ideas by thinking "outside the box."
Explore_2: My company bases its success on its ability to explore new technologies
Explore_3: My company creates products or services that are innovative to the firm
Explore_4: My company aggressively ventures into new market segments
Exploitation
Exploit_1: My company commits to improving quality
Exploit_2: My company commits to lowering cost
Exploit_3: My company continuously improves the reliability of its products and services
Exploit_4: My company increases the levels of efficiency in its operations
Exploit_5: My company constantly surveys existing customers' satisfaction
Exploit_6: My company fine-tunes what it offers to keep its current customers satisfied
Manufacturing performance (Ahmad *et al.*, 2019)
Our company has performed better than our main competitors in the following areas. On a scale from 1 to 6, where 1 = strongly disagree, 2 = moderately disagree, 3 = slightly disagree 4 = slightly agree, 5 = moderately agree, 6 = strongly agree
Quality
MP_Quality_1: Improve high-performance product features
MP_Quality_2: Offer consistence and reliable product quality
MP_Quality_3: Improve conformance to product specification
Cost
MP_Cost_1: Reduce inventory
MP_Cost_2: Reduce production costs

(*continued*)

Table A1. Constructs' indicators and supporting references

MP_Cost_3: Reduce production lead time
Delivery
MP_Delivery_1: Improve fast delivery
MP_Delivery_2: Improve delivery on time
Flexibility
MP_Flexibility_1: Make rapid volume changes
MP_Flexibility_2: Adjust capacity quickly
MP_Flexibility_3: Adjust product mix quickly
MP_Flexibility_4: Improve rapid equipment changeover
Global_MP
Overall, the manufacturing performance of the company has been doing relatively well

Table A1.

Source(s): Authors' own work

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