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Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs

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ABSTRACT

This study aims to investigate the effects of relative advantage, complexity, upper management support, cost, market dynamics, competitive pressure and regulatory support on blockchain adoption for operations and supply chain management among Small-Medium Enterprises (SMEs) in Malaysia. Unlike existing studies that employed linear models with Technology Acceptance Model or United Theory of Acceptance and Use of Technology that ignores the organisational and environmental factors, we adopted the Technology, Organisation and Environment Framework that covers the technological dimensions of relative advantage and complexity, organisational dimensions of upper management support and cost and environmental dimensions of market dynamics, competitive pressure and regulatory support. Empirical data from 194 SMEs were investigated and ranked using a nonlinear non-compensatory PLS-ANN approach. Competitive pressure, complexity, cost and relative have significant effects on behavioural intention. Market dynamics, regulatory support and upper management support were insignificant predictors. SMEs often lack resources for technological investments but faces same requirements for streamlining business processes to optimise returns and blockchain presents a viable option for SMEs' sustainability due to its features of immutability, transparency and security that have the potential to revolutionise businesses. This study contributes new knowledge to the literature on factors that affect blockchain adoption and justifications were discussed accordingly.

1. Introduction

The recent advancement of digital industrial-technological novelty and the creations of diversified gadgets in Industry 4.0 have affected industries in information creation, consumption and exchange; enabling faster, more flexible and efficient processes. This resulted in digital business environments of value co-creation through the use of information and communication technologies (ICT) (Graça & Camarinha-Matos, 2017; Nachira, Dini, & Nicolai, 2007) which, unlike traditional business environments, is an innovative approach for collaborative organisations across different industries to leverage on technological and services resources to effectively respond to customer needs (Senyo, Liu, & Effah, 2019). This environment in which everything an organisation is connected creates a digital imperative for companies to make possible transformations through technology that in turn become enablers for new forms of innovations (Fitzgerald & Kruschwitz, 2014). According to Bär, Herbert-Hansen, and Khalid (2018), limited research focused on how the company can determine the likely gains of Industry 4.0 technologies and their influences on the supply chain and there exists a research gap in implementation strategies. From an information processing viewpoint, digital technologies play a crucial role in managing and processing the exchange of signals for operations and supply chain management. Conventional supply chains are geographically scattered and required link maintenance; and coordination activities between suppliers and customers are no longer self-sufficient (Büyüközkan & Göçer, 2018). Recognizing this, recent literature highlighted the importance of digital technologies in operations and supply chain management including cloud computing (Gonul Kochan, Nowicki, Sauser, & Randall, 2018; Gupta, Seetharaman, & Raj, 2013; Novais, Maqueira, & Ortiz-Bas, 2019), big data analytics (Govindan, Cheng, Mishra, & Shukla, 2018), artificial intelligence (Baryannis, Validi, Dani, & Antoniou, 2018), and blockchain (Kshetri,

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2018; Queiroz & Wamba, 2019). Companies that invest in innovative technologies have recognised their potential to reduce production costs and stay competitive (Bär et al., 2018). Hence, companies need to shift from running uncoordinated silos to integrated operational-improvement around internal end-to-end processes and external customer interactions. Additionally, the use of technologies and operational capabilities would need to be applied in combination and in the correct sequence to achieve a holistic and compound impact (Bollard, Larrea, Singla, & Sood, 2017).

Small-Medium Enterprises (SMEs) however, often lack the resources to invest in recent technologies yet, they share the same need to be efficient and effective in allocating and managing their resources (Sihn, Erol, Ott, Hold, & Jäger, 2016). In Malaysia's dynamic business landscape, SMEs assume a portion of the country's economy and they account for a 37.1% of Malaysia's GDP and is targeted to reach 41% by 2020 (Jaafar, 2018). A recent SME CEO Forum on how digital economy will disrupt businesses in Malaysia acknowledged that although there are many concerns in digitising businesses, SMEs can no longer rely on traditional processes in a digitally transformed world (Low, 2018). According to the report (Business Today, 2018), SMEs in Malaysia would need to view technology as an investment rather than a cost for sustainable growth. Leveraging on technology will allow SMEs to improve "time-to-market" and be more responsive to customer requirements in addition to improving goods and services quality. Despite that, a survey commissioned by Huawei Technologies and SME Corp Malaysia among 2033 SMEs representing all sectors and regions revealed that SMEs despite achieving high computerisation, have found it difficult to address the digitalisation gap for productivity and business gains (Huawei, 2018). The study explored the usage of ICT beyond basic computing further showed low levels of process improvements (less than 20%, supply chain at 12%) thus revealing a hurdle in moving beyond computerisation. SMEs in Malaysia, therefore, are dependent on their ability to adopt technology in order to tap into business opportunities made available via seamless and global platforms and the supporting infrastructures and logistics and to realise greater benefits from digitisation.

The identification and realisation of technological benefits on a digitised supply chain are still untapped due to lack of or delayed organisational transformation (Büyüközkan & Göçer, 2018). Supply chains that are supported for real-time data gathering provide end-to-end visibility that allows managers to access to a large amount of data for better decision making (Wamba, Gunasekaran, Dubey, & Ngai, 2018; Wamba, Kamdjoug, Robert, Bawack, & Keogh, 2018). Under the realm of supply chain management, one such prominent technological benefit is the blockchain technology (Y. Chen, 2018; Kshetri, 2018; Viriyasitavat, Da Xu, Bi, & Sapsomboon, 2018). This study considers blockchain as the technological advance that has the potential to achieve many of the objectives of supply chain management such as cost, quality, speed, dependability and risk reduction (Kshetri, 2018). Most transactions that were conducted with blockchain are deemed to be safer, more transparent and traceable (Queiroz & Wamba, 2019). Blockchains' traceability mechanisms have the potential of preventing fraud across supply chains (R.Y. Chen, 2018; Loop, 2017) and offer improved security, authenticity and legitimacy features which are crucial to supply chains (Wang, Singgih, Wang, & Rit, 2019). Since 2016, Walmart and IBM explored the use of blockchain technology for product tracking via greater supply chain transparency. On a permission-based network pilot project, to track a package of sliced mangoes from a farm in Mexico to the U.S. used to take 6 days, 18 h and 26 min but with the developed software, this was reduced to a mere 2.2 s but noted that human element is far more resistant to control and less predictable (McKenzie, 2018a). Many others are also on track to experiment with blockchain-based technology. For instance, Worldwide Fund for Nature's tuna tracking blockchain (McKenzie, 2018b), blockchain prototype for mapping of sorted documentation of contracts across the entire supply chain (PR Newswire Association, 2019), and Accenture's blockchain and distributed-ledger technology-based circular supply chain to improve environmental sustainability (Partz, 2019). Despite that, blockchain's penetration is still yet to be fully explored (Wang et al., 2019). According to Cosgrove (2019), a Gartner survey with CIOs across industries revealed 1% with actual implementation; 8% were experimenting, and 77% were not interested. In short, although blockchain can be the potential solution to problems inherent in SME supply chain by addressing visibility and traceability issues, its adoption will be a gradual process that requires collaboration between different internal functional units and external players in order for digital transformation to grow and benefit SMEs. According to Queiroz, Telles, and Bonilla (2019), there is a gap in blockchain-supply chain management applications integration literature, but the disruptive effects are already visible despite the technology still in its early stage.

Hence, the primary aim of this study is to address the question of whether the identified technological, organisational and environment (TOE) factors could impact the adoption of blockchain technology in operations and supply chain management among Malaysian SMEs. The TOE framework is based on the innovation adoption theory and presents a holistic and size and industry-friendly insights into adoption factors and challenges (Awa, Ukoha, & Emecheta, 2016). The study is to extend the framework to understand how Malaysian SMEs can navigate the changing technological scene in Malaysia to ride on the waves of digital transformation for managing operations and supply chain. It is further expected that the findings from this study would serve as an indication to other emerging economies in assessing organisational and technological challenges facing SMEs amidst globalisation, integration of industries and markets. Through this enquiry, this study attempts to shed light on the following research questions:

RQ1: What are the factors that drive the intention of Malaysian SMEs to adopt blockchain in operations and supply chain management (BOSCM)?

RQ2: Among the factor(s), which has a greater association with the adoption intention?

The remainder of this paper is organised as follow: Section 2 reviews extant literature and presents the hypothesis for this study. Section 3 outlines the research methods adopted for the study. Section 4 presents the results and Section 5 discusses the findings and their implications. Finally, Section 6 presents a conclusion with the limitations and future directions.

2. Literature review and hypothesis development

Blockchain applications have frequently been discussed in the context of supply chain management and logistics (Hughes et al., 2019) with many reported benefits of blockchain technology according to different features such as extended visibility and transparency (Kshetri, 2018; Wang, Han, & Beynon-Davies, 2018), traceability (R.Y. Chen, 2018), provenance (Gupta, 2017), risks, privacy and security (Kshetri, 2017; Min, 2019). According to Wang et al. (2018), blockchain in the supply chain is an emerging topic where its potential has been recognised and discussed; nevertheless, the current state of blockchain research remains largely exploratory and there is limited empirical evidence on how to use blockchain (Ying, Jia, & Du, 2018).

2.1. Blockchain technology

Blockchain was first introduced in the Bitcoin protocol (Nakamoto, 2008) as a protocol of open, transparent and secure distributed ledger technology (DLT) that eliminates the need for a trusted third party. The unique features of this application layer technology are that it runs on top of the Internet protocol and records transactions in an immutable and trusted manner through the use of cryptographic techniques and distributed consensus algorithms between a group of distributed users

(Tapscott & Tapscott, 2016). Every user on the network must first be connected via a point-to-point network and each receives 2 keys: a public key for used by others when encrypting information and a private key that allows for the reading of a message i.e. signing blockchain transactions. In practice, when a transaction is carried out, it is signed using a private key and broadcasted to its neighbour. This enables authentication and should there be an error during transmission, it will not be decrypted. Other users connected to the network that received the signed transaction are able to verify its validity before transmitting to peers. The transactions are ordered by timestamped blocks by miner nodes through a consensus algorithm. Subsequently, the blocks are broadcast into the network and can be verified to contain valid transactions and that it references a previous block of chain based on the hash. A successful verification subsequently results in the block added into the chain of blocks. Thus, a blockchain is a chain of time-stamped blocks cryptographically linked by hashes (Fernández-Caramés & Fraga-Lamas, 2018). Once they are connected within a chain, they are immutable and are verified using automation and governance protocols (Swan, 2015); the verification process coupled with encryption techniques effectively secures the data against unauthorised access (Wang et al., 2019) and in this manner, "trust" is programmed into the blockchain (Gaehtgens & Allan, 2017) eliminating third-party authentication. Depending on the type of access mechanism, blockchains can be broadly categorised as:

1 Permission-less Blockchains: Every transaction in this blockchain is public and no permission is required before users can read, submit transactions, and participate in the consensus process. Users remain anonymous and are encouraged to participate via an incentive mechanism.
2 Permissioned Blockchains: Access to the blockchain and thus, participation must be preceded by an invitation which is monitored by a consortium or a private single organisation. Many private blockchains are permissioned when there is a need to control which users can transact; or execute smart contracts (codes within blockchains that are automatically executed when conditions are met); or a private blockchain may be deployed on a permission-less blockchain (Fernández-Caramés & Fraga-Lamas, 2018).

There are many existing works of literature on the use of blockchain technology and how it can add value to supply chains. However, the adoption of blockchain is still in its nascent stage. Academic research as listed in the earlier section have reviewed and discussed on a conceptual level how blockchain can meet supply chain objectives, but few have focused specifically on SMEs or on a practitioner's perspective.

Blockchain enabled transactions offers a level of transparency that is important for enhancing traceability of supply chains. Abeyratne and Monfared (2016) contend that transparency enables decision-makers to understand the effect and consequences of decisions, but it can be a difficult task in ensuring information collected is accurate and establishing a secure data flow between parties. Relying on a single third party puts the organisation at a single point failure risk in addition to other concerns such as vulnerability to hacking and technical capabilities. Participants in the supply chain can gain access and share the same information within the system. This transparency is also important to gain consumer trust in products (Loop, 2017) through the assurance of product origin, authenticity and integrity (Montecchi, Plangger, & Etter, 2019).

Information stored on blockchains is immutable resulting from the technology's distributed consensus mechanism. This offers an added protection on supply chains against tampering, fraud via authentication and reliable transactions. Blockchain technology is an option for certification of authenticity in a transparent way whereby all involved parties may collectively agree on protocols (Montecchi et al., 2019; Tucker & Catalini, 2018) to verify or certify a transaction and thus assuring its authenticity. Every transaction is recorded in real-time and smart contracts allow for immediate execution of software when conditions are met creates a more efficient response system that is trusted by all signatories (Casey & Wong, 2017). Together, blockchain technology assures the integrity of products where only one true copy of information exists (Wang et al., 2019).

In the context of supply chains, blockchain offers provenance of knowledge that can reduce perceived risks and also simplify supply chains via intermediaries cost reductions while protecting valuable information (Montecchi et al., 2019) and increased operational efficiency and ultimately reduce waste and cost (Wang et al., 2019). Mackey and Nayyar (2017) state that blockchain enables tracking of raw materials and finished goods by its participants, who could verify data authenticity and hence it is useful for detecting fakes. Researchers like Foerstl, Schleper, and Henke (2017) and Tian (2017) support the use of blockchain in tracing the origin of goods and production process and food safety as well as ownership (Toyoda, Takis Mathiopoulos, Sasase, & Ohtsuki, 2017) and security (Shanley, 2017).

2.2. Adoption model

Many researchers have researched and written work on adoption of blockchain technologies in the supply chain. Some of the common models that were employed include Technology Acceptance Model (TAM) (Kamble, Gunasekaran, & Arha, 2018) and the Unified Theory of Acceptance Model (UTAUT) (Francisco & Swanson, 2018; Queiroz & Wamba, 2019). In order to complement these past studies, this study employed the Technology-Organisation-Environment (TOE) Framework established by Tornatzky, Fleischer, and Chakrabarti (1990) in preference of its focus on technological, environmental and organisational factors that influence the decision to adopt technological innovations. As the decision to adopt technology in an organisation content depends on the technological, environmental and organisational factors, TOE offers a more comprehensive view of the adoption of technology (Mohtaramzadeh, Ramayah, & Cheah, 2018). Specifically, as the TOE framework has united both human and non-human factors into a single framework, this renders better strength over other traditional models such as TAM, Diffusion of Innovation, and UTAUT (Awa, Uko, & Ukoha, 2017). TOE has been widely used in various IT adoption studies (Lin, 2014; Yeh & Chen, 2018) and in the Malaysian context (Ooi, Lee, Tan, Hew, & Hew, 2018). Moreover, Clohessy, Acton, and Rogers (2018) also opined that the TOE framework could be applied to understand the adoption of blockchain by organisations. According to Baker (2012), TOE framework could be adopted in broad conditions depending on the select choice of organisational, technological and environmental factors because different innovations have different adoption factors and so too will different culture and contexts.

2.3. Hypotheses development

2.3.1. The technological dimensions

Relative advantage is defined as the positive difference between organisational benefits and the efforts required to adopt blockchain technology that mainly centres on non-tangible benefits as improved reputation, heightened customer satisfaction and enhanced response speed (Wu, Kao, & Lin, 2013). Relative advantage has been an essential factor in the adoption of new technological applications (Kapoor, Dwivedi, & Williams, 2014), for instance, interbank mobile payments (Kapoor, Dwivedi, & Williams, 2015), supply chain (Bhattacharya & Wamba, 2015), and business intelligence system (Puklavec, Oliveira, & Popovič, 2018). When effectively incorporated, SMEs that adopt blockchain for OCSM are able to enjoy many advantages due to greater transparency and enhanced security for improved supply chain traceability. Additionally, SMEs will enjoy greater efficiency and speed in operations through streamlined business processes.

In considering technological implementations, the infrastructure of the technology is vital and influences the eventual usage and when combined with existing resources can enhance competitiveness (Yeh & Chen, 2018). The functionalities and thus amount of assistance that can be obtained through use of technology would vary depending on the applications, generations of technology, and devices as well as vendors (Dwivedi, Rana, Janssen et al., 2017). Likewise, technological integration is important yet complicated in blockchain implementation especially for the supply chain as it involves multi-party collaboration (Saberi, Kouhizadeh, Sarkis, & Shen, 2018). Complexity refers to the complexity of technology implementation and the technology itself (Bhattacharya & Wamba, 2015). Generally, a high degree of complexity confuses users and causes them to have difficulty in understanding and using a technology, which in turn adversely impacts its adoption decision (Slade, Dwivedi, Piercy, & Williams, 2015; Slade, Williams, Dwivedi, & Piercy, 2015; Slade, Williams, & Dwivedi, 2014). Past studies have also shown strong correlations between aspects of functional utilities to adoption intention, meaning the extent of simplicity or difficulty of using a particular technology affects the adoption of technology (Alalwan, Dwivedi, & Rana, 2017; Dwivedi, Rana, Janssen et al., 2017). Furthermore, an individual's attitude towards technology is largely shaped by the perception to which the technology is complicated (Dwivedi, Rana, Janssen et al., 2017; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Rana, Dwivedi, Lal, Williams, & Clement, 2017). The technical complexity of blockchain is challenging for individuals to understand and have confidence in participation unless blockchain technology can be readily integrated into existing systems there will be little utility value. Blockchain's transaction mechanisms as described in earlier sections have a major speed concern. Also, its implementation would partly be hindered by its immaturity security challenges (Saberi et al., 2018). Eventually, users would feel anxious when they have a little control over the outcome from the system (Rana, Dwivedi, Williams, & Weerakkody, 2016), while firms will be less likely to adopt this new technology if it is complex and incompatible with existing processes (Shi & Yan, 2016; Wu et al., 2013).

A conducive environment is also important in nascent stages of system implementation in order to garner use (Dwivedi, Kapoor, Williams, & Williams, 2013). Given the recent hype and development of blockchain, Malaysia has spearheaded several initiatives to not only create awareness of the technology via academia (Sani, 2018) but also encouraged its adoption and use (Go, 2019; Idris, 2018). Malaysia's environment is favourable for embracing the new technology and organisations are willing listeners and the time is ripe to board the "blockchain train" (Ng, 2018). If blockchain is to be perceived as an advantageous but complicated tool to use or implement, the upper management shall also provide a higher level of support to the employees in helping them to learn it. The reason being is that the upper management would not want to lost relative advantages offered by blockchain over its costs of implementation. This assertion is similar to Mousavizadeh, Harden, Ryan, and Windsor (2015), who discovered that the various benefits of implementing a knowledge management system would motivate the upper management to provide their support during the implementation. Identically, Bueno and Gallego (2017) asserted if the new system (such as ERP) implementation is complex, upper management shall provide a greater level of support. Finally, in the words of Al-Alak and Alnawas (2011), the support rendered by upper management is a critical factor that contributes to the success of complicated system implementation.

This study is also expecting that the relative advantage and complexity of blockchain are positively associated with the cost of blockchain implementation. An advantageous technology like blockchain is usually perceived as a costly system to implement (Tashkandi & Al-Jabri, 2015). According to Slade, Williams et al. (2015), many new products are considered risky. Despite the advantages, blockchain implementation is considered risky due to its complexity, uncertainty, privacy and security concerns as well as lack of knowledge. Hence, higher cost is usually involved during the implementation of a complicated technology, for example, a lot of training may need to be provided to the end-users before they can get themselves familiarise with the new and yet complicated technology like blockchain (Gallardo, Hernantes, & Serrano, 2018; Museli & Jafari Navimipour, 2018). With these arguments, the following hypotheses are formulated accordingly:

Hypothesis 1. Relative advantage is positively related to the intention to adopt BOSCM.

Hypothesis 2. Relative advantage is positively related to upper management support.

Hypothesis 3. Relative advantage is positively related to cost.

Hypothesis 4. Complexity is negatively related to the intention to adopt BOSCM.

Hypothesis 5. Complexity is positively related to upper management support.

Hypothesis 6. Complexity is positively related to cost.

2.3.2. The organisation dimensions

Organisational factors refer to the conditions such as readiness to provide support or barrier from the viewpoint of managers (Yeh & Chen, 2018) and are used to indicate whether or not firms have the technical and financial resources for technical investments (Sealy, 2012). Upper management support refers "to the degree to which upper management understands the importance of and is involved" in blockchain adoption (Ooi, Lee et al., 2018, p.379). Managerial obstacles have huge impacts over the adoption decisions and are often tied to the strategic goals of firms especially during technological implementation (Yeh & Chen, 2018). Conversely, upper management commitment can encourage the diffusion of technology but must remain actively engaged to achieve desired results (Dubey et al., 2018). Blockchain technology is considered an investment that requires new hardware and software, which is costly for both organisations and partners (Mougayar, 2016). Here, cost refers to the fee chargeable for obtaining and implementing blockchain technology (Hanif, Hafeez, & Riaz, 2010). The perception of value for money paid is significant in determining the intention to adopt (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016) and a higher amount of cost is normally a hindrance to the adoption of new technology and systems among companies (Kuan & Chau, 2001; Shi & Yan, 2016). As such, we propose that:

Hypothesis 7. Upper management support is positively related to the intention to adopt BOSCM.

Hypothesis 8. Cost is negatively related to the intention to adopt BOSCM.

2.3.3. The environment dimensions

Environmental factors considered in this study include market dynamics, competitive pressure and regulatory support. According to Schuetz and Venkatesh (2019), environmental factors provide insight into how blockchain technology initiatives can overcome some of the challenges such as high monetary and time costs. Market dynamics refer to the continuous changing state of an environment that is highly competitive and complex (Wu et al., 2013). Wang et al. (2018) use a blockchain maturity model for blockchain adoption considered market dynamics based on 5-stage taxonomy model cautioned that businesses should conduct extensive feasibility studies prior to implementation. Competitive pressure refers to the internal pressure and the desire to gain a competitive advantage that drives companies to adopt innovative technologies while facing pressure from upstream and downstream players in the supply chain as well as pressures from new developments in business models and industry standards (Shi & Yan, 2016). Guo and Liang (2016) pointed out that problems related to regulation and actual implementations of decentralised systems remain unsolved and called

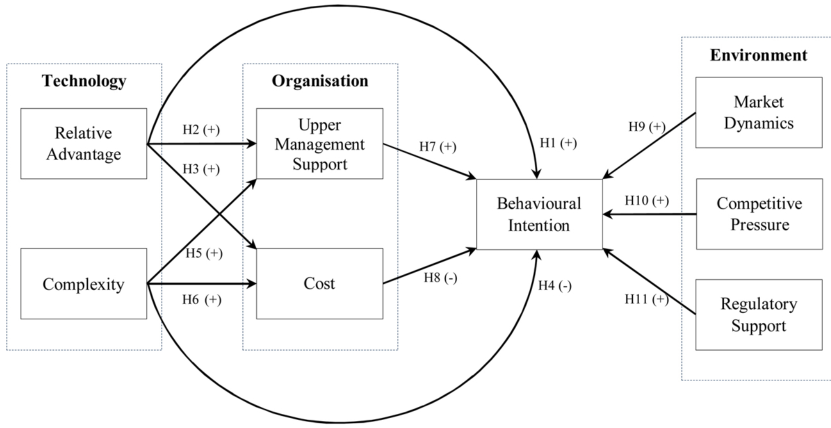

Fig. 1. Research Model.

for the urgent development of industry standards. The regulatory environment was among significant indicator in studies pertaining to blockchain adoption (Lindman, Tuunainen, & Rossi, 2017; Swan, 2015). In a study on the sustainability of supply chains, pressure and/or incentive by governmental bodies and regulatory bodies are important for supply chain sustainability especially to deal with issues of infrastructure, coordination, assist in risk management, and etc. (Mangla et al., 2018). In this study, regulatory support refers to policies and laws that play an important role in promoting adoption of blockchain technologies and when support is ample adoption tend to be quick (Shi & Yan, 2016). Hence, the following hypotheses are posited:

Hypothesis 9. Market dynamics are positively related to the intention to adopt BOSCM.

Hypothesis 10. Competitive pressure is positively related to the intention to adopt BOSCM.

Hypothesis 11. Regulatory support is positively related to the intention to adopt BOSCM.

These hypotheses and their relationships to BOSCM adoption intention are illustrated in Fig. 1 below which forms the underlying research model of this study.

3. Research methodology

3.1. Sampling and data collection

The questionnaires were disseminated via a professional data collector and the respondents were from SMEs based in Klang Valley, Malaysia. Baumann, Hoadley, Hamin, and Nugraha (2017) found the use of professional data collection service to be reliable with access to high-quality data. The SMEs were identified from the Companies Commission of Malaysia (also known as Suruhanjaya Syarikat Malaysia). Random sampling was employed to preserve the anonymity of respondents as also used by Ooi, Lee et al. (2018). Companies Commission of Malaysia was chosen as our source for the sampling frame as it is a statutory body that oversees the registration of businesses and companies in Malaysia. Klang Valley was selected as our sampling location because of its high contribution to the country's GDP (i.e., 40% in 2018) and among the top four states in Malaysia in terms of economic growth (Department of Statistics Malaysia, 2018).

From the 203 survey questionnaires collected, only 194 were used during the data analysis stages as 9 of them were discarded due to incomplete responses. This sample size shall fulfil the minimum sample size requirement for performing the PLS-SEM analysis under the ten times rule (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). According to an article by Dawson Consulting (2018), many of the challenges faced by SMEs are similar to larger enterprises but they can be particularly tricky for smaller businesses to address largely due to lack of investment power along with limited resources and talent. Additionally, smaller companies are often disadvantaged in terms of supplier relationships and do not have the scale to leverage. It is important that SMEs recognise the power structures between buyer and supplier (Vaaland & Heide, 2007). Often times, with a modest budget, it can be a huge challenge for SMEs to achieve the level of visibility and capabilities that are required to match large enterprises (Dawson Consulting, 2018). Issues such as new technology and R&D are usually regarded as low priority items and this is also related to the behavioural side of management (Vaaland & Heide, 2007). Furthermore, SMEs face coordination and responsiveness problems with other members of the supply chain as a result of their poor innovative capabilities (Kumar & Singh, 2017). Blockchain can be considered an affordable solution and SMEs may have greater agility to take the opportunity. In a less complicated eco-system, SMEs have a shorter reaction time.

3.2. Measures

All constructs and measurement items were derived to fit into the context of this study from previous literature to ensure construct validity and reliability. These are shown in Appendix 1. The items for relative advantage, complexity, market dynamics and competitive pressure are derived from Wu et al. (2013). Upper management support, cost and regulatory support are derived from Shi and Yan (2016). Behavioural intention is derived from Yang, Lee, and Zo (2017). A 7-point Likert scale that ranged from "1 – Strongly Disagree" to "7 – Strongly Agree" was used as the measurement scale for all constructs.

4. Data analyses and results

The demographic profile of the respondents is shown in Table 1.

4.1. Preliminary analyses

We conducted a preliminary examination on the prerequisites for the multivariate statistical test that include data normality, the linearity of relationships, homoscedasticity and multicollinearity. From the one-sample Kolmogorov-Smirnov test shown in Table 2, it is clear that the data is not normally distributed because all two-tailed asymptotic significance is less than 0.05.

We continued to examine the linearity of relationships between the constructs and Table 3 indicates that there are linear relationships between the constructs as the *p*-values are below 0.05. However, based on the *p*-values of the deviation from linearity, we also found non-linear components for the relationships between all the constructs except the relationship between market dynamics and behavioural intention which has a *p*-value greater than 0.05.

Table 1
Demographic information.

		Frequency	Percent
Gender	Female	108	55.7
	Male	86	44.3
Age (years)	25 - 34	70	36.1
	35 - 44	74	38.1
	45 - 54	34	17.5
	55 and above	12	6.2
	Prefer not to state	4	2.1
Number of years with the organisation (years)	Less than 1	27	13.9
	1 and less than 6	65	33.5
	6 and less than 10	53	27.3
	10 and above	41	21.1
	Prefer not to state	8	4.1
Your main job position	Junior management (e.g. assistant manager, system analysis engineer)	70	36.1
	Middle management or Head of Department	56	28.9
	Senior management or Director	41	21.1
	Other	27	13.9
Your primary job scope	R & D	32	16.5
	Production	49	25.3
	Marketing	28	14.4
	Administration	25	12.9
	Human Resource	13	6.7
	Information Technology	14	7.2
	Procurement	21	10.8
	Other	12	6.2
Which of the following best describe your present level of understanding on blockchain technology?	Learning the technology	67	34.5
	Testing the technology	22	11.3
	Implementing the technology	30	15.5
	None	75	38.7
Age of firm (years)	5 or less	36	18.6
	more than 5 but less than 10	69	35.6
	At least 10	89	45.9
Category of your organisation's products	Electrical and electronics	56	28.9
	Chemical	33	17.0
	Textile	17	8.8
	Food	18	9.3
	Rubber and Plastic	20	10.3
	Machinery and Hardware	10	5.2
	Other	40	20.6
Number of employees in your organisation	Less than 50	36	18.6
	50 - 100	99	51.0
	More than 100	59	30.4

In terms of multicollinearity problem, Table 4 shows that all VIFs are less than 10 and all tolerances are greater than 0.10, we, therefore, conclude that there is no problem of multicollinearity.

To assess the existence of homoscedasticity, we examined the scatter plots of the regression standardised residual. Homoscedasticity which is also known as homogeneity of variance is assessed based on the dispersion of regression standardised residual and if the residuals are scattered evenly along a straight line then homoscedasticity is achieved because the variance is almost the same. As the residuals are distributed along a straight diagonal line, this indicates the fulfilment of homoscedasticity assumption.

4.2. Common Method Bias (CMB)

Given the data of the exogenous and endogenous constructs were collected from a single source, hence, there is a possibility that common method bias may arise. To tackle this issue, we used both procedural and statistical remedies (Hew & Sharifah, 2017; Leong, Jaafar, & Ainin, 2018). During the data collection, we assured the anonymity of respondents and there is no right or wrong response. Statistically, we conducted Harman's single factor and the result showed that a sole factor explains 47% of the total variance. As this is less than 50%, there is no issue of CMB (Wong, Tan, Tan, & Ooi, 2015). Moreover, the correlation coefficients (Table 7) are less than 0.90 indicating there is no CMB problem (Lai & Hitchcock, 2017). In addition to that, we further confirmed the non-existence of CMB by performing a common method factor analysis based on the substantive and method variance (Tan & Ooi, 2018). All first order constructs were transformed into single-item second-order constructs. In Table 5, it is demonstrated that all the substantive loadings are significant while the method loadings are either negative or very small and mostly insignificant. The ratio of the substantive variance to the method variance is significantly large at 69:1. Therefore, it is confirmed that CMB is inconsequential.

4.3. Measurement model

After the assessment of multivariate assumptions and CMB, we continued to evaluate the quality of the measurement model (Fig. 2). The verification of convergent validity was done based on the value of the average variance extracted (AVE) that is greater than 0.50 (Table 6). On the other hand, construct reliability was validated based on the value of Cronbach's alpha and composite reliability which is greater than 0.70 (Teo, Tan, Ooi, Hew, & Yew, 2015).

In terms of discriminant validity, several approaches were used. First, we deployed the conventional Fornell-Larcker's criterion and found that the square root of AVE is greater than the correlation coefficients (Table 7). Then we also checked the cross-loadings and Table 8 shows that all loadings load strongly to the respective construct and weakly on irrelevant constructs. Finally, we used the recently introduced HTMT criterion and Table 9 shows that all HTMT ratio is less than the threshold of 0.90 (Henseler, Ringle, & Sarstedt, 2014). The SRMR index for the measurement model is 0.061 which is less than the threshold of 0.08 (Bentler & Huang, 2014). Hence, the model has a good fit with the data.

The measurement model explains 79.1% of the variance in behavioural intention, 75.1% variance in cost and 15.8% variance in upper management support (Table 10). Since these percentages are greater than 10%, therefore, the measurement model has substantive and satisfactory predictive power (Eom, Wen, & Ashill, 2006). In terms of predictive relevance, based on Stone-Geisser's Q^2 (Table 11) which are positive and substantially large, hence, the exogenous constructs are highly relevant to the endogenous constructs.

In accordance with Wassertheil and Cohen (2006), an f^2 greater than 0.02, 0.15 and 0.35 is considered as having small, medium and large effect size. Table 12 shows that complexity has a large effect size on cost while competitive pressure has a medium effect size on behavioural intention. Similarly, the relative advantage also has a medium effect size on cost and upper management support. The rest of the exogenous constructs have small effect sizes.

4.4. Structural model

The structural model (Fig. 3) shows that out of the 11 paths, 7 paths are significant yielding a significant path percentage of 63.6%. Table 13 shows that competitive pressure ($\beta = 0.483$, $p < 0.001$), complexity ($\beta = -0.231$, $p < 0.001$), cost ($\beta = 0.172$, $p < 0.001$) and relative advantage ($\beta = 0.404$, $p < 0.001$) have significant effects on behavioural intention. However, market dynamics ($\beta = -0.014$, $p = 0.845$), regulatory support ($\beta = 0.127$, $p = 0.06$) and upper management support ($\beta = 0.024$, $p = 0.737$) do not have significant effects on behaviour intention. Upper management support is influenced by relative advantage ($\beta = 0.438$, $p < 0.001$) but not complexity ($\beta = -0.088$, $p = 0.269$). However, cost is affected by complexity

Table 2
One-sample Kolmogorov-Smirnov test for normality of distribution.

	N	Normal Parameters[a,b]		Most Extreme Differences			Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
		Mean	Std. Deviation	Absolute	Positive	Negative		
RA1	194	4.90	1.270	0.165	0.165	−0.154	2.300	0.000
RA2	194	4.88	1.241	0.193	0.193	−0.152	2.688	0.000
RA3	194	4.56	1.361	0.196	0.196	−0.160	2.732	0.000
RA4	194	4.91	1.243	0.174	0.174	−0.140	2.430	0.000
RA5	194	4.92	1.252	0.164	0.164	−0.155	2.291	0.000
CPX1	194	5.14	1.187	0.177	0.137	−0.177	2.463	0.000
CPX2	194	5.12	1.185	0.165	0.160	−0.165	2.293	0.000
CPX3	194	5.18	1.152	0.187	0.169	−0.187	2.604	0.000
CPX4	194	5.08	1.206	0.179	0.161	−0.179	2.489	0.000
CPX5	194	5.08	1.197	0.170	0.168	−0.170	2.368	0.000
UMS1	194	4.49	1.210	0.204	0.178	−0.204	2.836	0.000
UMS2	194	4.39	1.204	0.225	0.224	−0.225	3.129	0.000
UMS3	194	4.38	1.151	0.231	0.223	−0.231	3.218	0.000
UMS4	194	4.27	1.244	0.202	0.169	−0.202	2.810	0.000
UMS5	194	4.40	1.171	0.211	0.186	−0.211	2.939	0.000
CST1	194	4.92	1.119	0.194	0.194	−0.167	2.704	0.000
CST2	194	4.79	1.147	0.199	0.199	−0.162	2.771	0.000
CST3	194	4.84	1.129	0.186	0.186	−0.154	2.591	0.000
CST4	194	4.88	1.122	0.188	0.188	−0.150	2.619	0.000
CST5	194	4.79	1.133	0.196	0.196	−0.170	2.735	0.000
MDY1	194	4.86	1.238	0.178	0.178	−0.147	2.478	0.000
MDY2	194	4.72	1.277	0.219	0.219	−0.162	3.051	0.000
MDY3	194	4.68	1.415	0.152	0.152	−0.135	2.123	0.000
CPR1	194	4.15	1.380	0.184	0.184	−0.151	2.560	0.000
CPR2	194	4.54	1.288	0.234	0.234	−0.158	3.253	0.000
CPR3	194	4.48	1.166	0.244	0.244	−0.174	3.393	0.000
CPR4	194	4.42	1.203	0.266	0.266	−0.198	3.708	0.000
CPR5	194	4.44	1.165	0.267	0.267	−0.223	3.716	0.000
RGS1	194	3.90	1.300	0.233	0.175	−0.233	3.240	0.000
RGS2	194	3.89	1.210	0.283	0.238	−0.283	3.942	0.000
RGS3	194	4.05	1.225	0.272	0.223	−0.272	3.787	0.000
RGS4	194	4.07	1.215	0.260	0.209	−0.260	3.619	0.000
BI1	194	4.42	1.326	0.196	0.176	−0.196	2.730	0.000
BI2	194	4.45	1.343	0.203	0.203	−0.199	2.827	0.000
BI3	194	4.42	1.270	0.206	0.206	−0.186	2.872	0.000

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

[a] Test distribution is Normal.

[b] Calculated from data.

Table 3
ANOVA test for linearity.

			Sum of Squares	df	Mean Square	F	Sig.
RA * BI	Between Groups	(Combined)	196.587	15	13.106	27.877	0.000
		Linearity	183.368	1	183.368	390.044	0.000
		Deviation from Linearity	13.219	14	0.944	2.008	0.019
	Within Groups		83.682	178	0.470		
CPX * BI	Between Groups	(Combined)	112.574	15	7.505	9.603	0.000
		Linearity	32.659	1	32.659	41.788	0.000
		Deviation from Linearity	79.915	14	5.708	7.304	0.000
	Within Groups		139.115	178	0.782		
UMS * BI	Between Groups	(Combined)	99.363	15	6.624	8.023	0.000
		Linearity	26.309	1	26.309	31.866	0.000
		Deviation from Linearity	73.054	14	5.218	6.320	0.000
	Within Groups		146.962	178	0.826		
CST * BI	Between Groups	(Combined)	122.652	15	8.177	14.854	0.000
		Linearity	74.808	1	74.808	135.892	0.000
		Deviation from Linearity	47.845	14	3.417	6.208	0.000
	Within Groups		97.988	178	0.550		
MDY * BI	Between Groups	(Combined)	167.799	15	11.187	14.084	0.000
		Linearity	149.741	1	149.741	188.525	0.000
		Deviation from Linearity	18.058	14	1.290	1.624	0.076
	Within Groups		141.381	178	0.794		
CPR * BI	Between Groups	(Combined)	192.133	15	12.809	38.504	0.000
		Linearity	176.608	1	176.608	530.896	0.000
		Deviation from Linearity	15.525	14	1.109	3.333	0.000
	Within Groups		59.214	178	0.333		
RGS * BI	Between Groups	(Combined)	98.020	15	6.535	7.046	0.000
		Linearity	28.943	1	28.943	31.209	0.000
		Deviation from Linearity	69.078	14	4.934	5.321	0.000
	Within Groups		165.074	178	0.927		

(continued on next page)

Table 3 (*continued*)

			Sum of Squares	df	Mean Square	F	Sig.
RA * UMS	Between Groups	(Combined)	148.545	20	7.427	9.755	0.000
		Linearity	41.582	1	41.582	54.611	0.000
		Deviation from Linearity	106.963	19	5.630	7.394	0.000
	Within Groups		131.724	173	0.761		
CPX * UMS	Between Groups	(Combined)	67.174	20	3.359	3.149	0.000
		Linearity	5.605	1	5.605	5.255	0.023
		Deviation from Linearity	61.570	19	3.241	3.038	0.000
	Within Groups		184.515	173	1.067		
RA * CST	Between Groups	(Combined)	168.624	19	8.875	13.832	0.000
		Linearity	125.659	1	125.659	195.841	0.000
		Deviation from Linearity	42.965	18	2.387	3.720	0.000
	Within Groups		111.645	174	0.642		
CPX * CST	Between Groups	(Combined)	186.122	19	9.796	25.996	0.000
		Linearity	170.944	1	170.944	453.649	0.000
		Deviation from Linearity	15.178	18	0.843	2.238	0.004
	Within Groups		65.567	174	0.377		

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

Table 4
Test for multicollinearity.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	−0.252	0.264		−0.957	0.340		
	RA	0.436	0.085	0.416	5.135	0.000	0.172	5.821
	CPX	−0.253	0.068	−0.229	−3.749	0.000	0.302	3.317
	UMS	0.025	0.045	0.023	0.571	0.569	0.708	1.413
	CST	0.203	0.087	0.172	2.326	0.021	0.206	4.847
	MDY	−0.010	0.067	−0.010	−0.148	0.883	0.249	4.018
	CPR	0.519	0.068	0.470	7.667	0.000	0.301	3.324
	RGS	0.135	0.040	0.125	3.399	0.001	0.836	1.196

a. Endogenous construct: BI

Coefficients[b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.856	0.374		7.641	0.000		
	RA	0.402	0.074	0.429	5.432	0.000	0.710	1.408
	CPX	−0.081	0.078	−0.082	−1.036	0.302	0.710	1.408

b. Endogenous construct: UMS

Coefficients[c]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0.350	0.192		1.827	0.069		
	RA	0.282	0.038	0.318	7.426	0.000	0.710	1.408
	CPX	0.611	0.040	0.653	15.240	0.000	0.710	1.408

c. Endogenous construct: CST

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

($\beta = 0.653$, $p < 0.001$) and relative advantage ($\beta = 0.317$, $p < 0.001$). In terms of mediation effect, Table 14 shows that cost has partial competitive mediation effects on the relationships between complexity-behavioural intention and relative advantage-behavioural intention.

4.5. Importance Performance Map Analysis (IPMA)

IPMA is also known as priority analysis, importance-performance matrix or impact-performance map which extends the results of path coefficient (importance) by integrating the average values of latent

Table 5
Common method factor analysis.

Path	Substantive loading	Substantive variance	*T*-Statistics	*p*-values	Path	Method loading	Method variance	*T*-Statistics	*p*-values
BI → BI1	1.011	1.023	38.372	0.000	Method → BI1	−0.046	0.002	1.465	0.144
BI → BI2	0.924	0.854	27.289	0.000	Method → BI2	0.020	0.000	0.640	0.522
BI → BI3	0.946	0.895	39.140	0.000	Method → BI3	0.027	0.001	1.038	0.300
CPR → CPR1	1.282	1.642	25.264	0.000	Method → CPR1	−0.424	0.180	6.724	0.000
CPR → CPR2	0.713	0.508	10.028	0.000	Method → CPR2	0.179	0.032	3.052	0.002
CPR → CPR3	0.595	0.354	10.326	0.000	Method → CPR3	0.366	0.134	6.309	0.000
CPR → CPR4	0.997	0.995	28.244	0.000	Method → CPR4	−0.044	0.002	1.062	0.289
CPR → CPR5	1.012	1.024	26.309	0.000	Method → CPR5	−0.069	0.005	1.519	0.129
CPX → CPX1	0.979	0.959	67.665	0.000	Method → CPX1	−0.014	0.000	0.724	0.469
CPX → CPX2	0.920	0.845	44.042	0.000	Method → CPX2	0.050	0.003	2.114	0.035
CPX → CPX3	0.915	0.837	52.404	0.000	Method → CPX3	0.055	0.003	2.481	0.013
CPX → CPX4	0.992	0.983	58.206	0.000	Method → CPX4	−0.035	0.001	1.543	0.123
CPX → CPX5	1.010	1.020	72.506	0.000	Method → CPX5	−0.055	0.003	2.956	0.003
CST → CST1	0.962	0.925	36.682	0.000	Method → CST1	0.002	0.000	0.049	0.961
CST → CST2	1.000	1.000	46.219	0.000	Method → CST2	−0.028	0.001	1.064	0.288
CST → CST3	0.883	0.779	27.698	0.000	Method → CST3	0.084	0.007	2.487	0.013
CST → CST4	0.970	0.941	36.404	0.000	Method → CST4	−0.013	0.000	0.433	0.665
CST → CST5	0.922	0.851	23.914	0.000	Method → CST5	−0.017	0.000	0.387	0.699
MDY → MDY1	0.865	0.749	21.948	0.000	Method → MDY1	0.121	0.015	2.920	0.004
MDY → MDY2	0.975	0.950	36.369	0.000	Method → MDY2	−0.008	0.000	0.280	0.780
MDY → MDY3	1.059	1.121	26.004	0.000	Method → MDY3	−0.114	0.013	2.496	0.013
RA → RA1	1.052	1.106	20.115	0.000	Method → RA1	−0.094	0.009	1.739	0.083
RA → RA2	1.024	1.049	26.168	0.000	Method → RA2	−0.062	0.004	1.483	0.139
RA → RA3	0.708	0.502	5.987	0.000	Method → RA3	0.186	0.035	1.637	0.102
RA → RA4	0.927	0.860	18.783	0.000	Method → RA4	0.034	0.001	0.641	0.522
RA → RA5	1.012	1.025	25.299	0.000	Method → RA5	−0.050	0.002	1.120	0.263
UMS → UMS1	0.940	0.883	60.940	0.000	Method → UMS1	0.015	0.000	0.955	0.340
UMS → UMS2	0.934	0.872	62.878	0.000	Method → UMS2	0.028	0.001	1.953	0.051
UMS → UMS3	0.964	0.929	88.003	0.000	Method → UMS3	−0.046	0.002	2.532	0.012
UMS → UMS4	0.925	0.855	60.403	0.000	Method → UMS4	0.007	0.000	0.351	0.726
UMS → UMS5	0.962	0.925	108.683	0.000	Method → UMS5	−0.005	0.000	0.387	0.699
RGS → RGS1	0.927	0.859	59.852	0.000	Method → RGS1	0.047	0.002	2.374	0.018
RGS → RGS2	0.943	0.889	81.804	0.000	Method → RGS2	−0.005	0.000	0.305	0.761
RGS → RGS3	0.954	0.910	84.551	0.000	Method → RGS3	−0.022	0.000	1.282	0.200
RGS → RGS4	0.951	0.904	85.426	0.000	Method → RGS4	−0.019	0.000	1.116	0.265
	Mean	0.909				Mean	0.013		

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

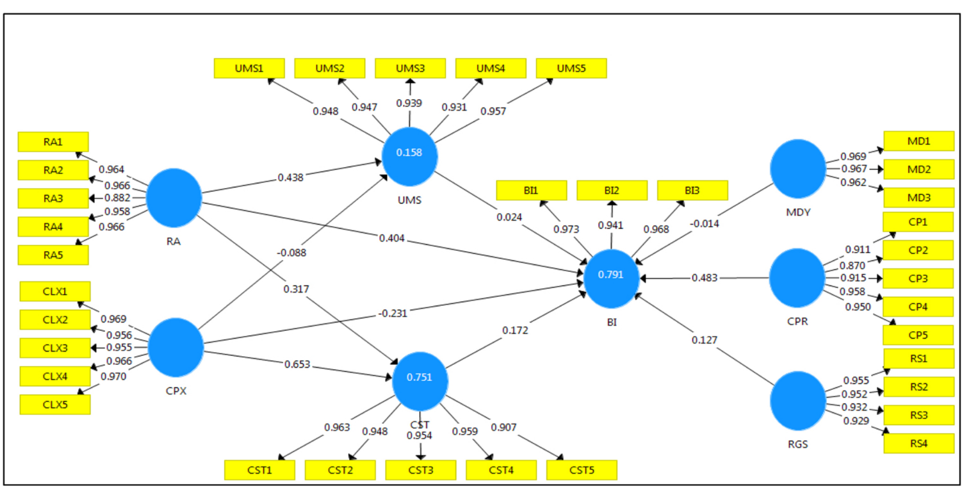

Fig. 2. Measurement model.
Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioral intention.

construct scores (performance). More specifically, it contrasts the unstandardised total effects (importance) in the structural model and the average values of the latent construct scores on a scale ranging from 0 to 100% of performance. IPMA analysis is only performed on endogenous constructs in order to assess and compare the importance and performance of all the relevant exogenous constructs (Ringle & Sarstedt, 2016). The IPMA map is divided into four quadrants based on the mean values of importance and performance. In general, constructs in the lower right quadrant should be prioritised for improvement followed by the upper right, lower left and upper left quadrant (Ooi, Hew, & Lee, 2018). Fig. 4 shows that the mean values of importance and performance are 0.163 and 60.305% respectively for behavioural intention. Fig. 5 shows that the mean values of importance and performance are 0.485 and 66.338% respectively for cost. Similarly, Fig. 6

Table 6
Convergent validity.

Constructs	AVE	Composite Reliability	Cronbach's Alpha
BI	0.923	0.973	0.958
CPR	0.849	0.966	0.955
CPX	0.928	0.985	0.981
CST	0.896	0.977	0.971
MDY	0.933	0.977	0.964
RA	0.899	0.978	0.971
RGS	0.888	0.969	0.959
UMS	0.892	0.976	0.970

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

Table 7
Fornell-Lacker's criterion for discriminant validity.

	BI	CPR	CPX	CST	MDY	RA	RGS	UMS
BI	**0.961**							
CPR	0.840	**0.921**						
CPX	0.361	0.480	**0.963**					
CST	0.584	0.678	0.824	**0.946**				
MDY	0.695	0.684	0.499	0.615	**0.966**			
RA	0.806	0.799	0.540	0.669	0.858	**0.948**		
RGS	0.343	0.246	0.023	0.066	0.236	0.213	**0.942**	
UMS	0.329	0.246	0.149	0.133	0.432	0.391	0.355	**0.945**

Note: Diagonal element is the square root of AVE; RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

indicates that the mean value of importance and performance are 0.175 and 66.338% respectively for upper management support.

In terms of priority for improvement in behavioural intention, competitive pressure should be given the utmost priority followed by cost, relative advantage, upper management support, regulatory support, complexity and market dynamics. For improvement in cost, the priority should be given first to upper management support followed by relative advantage. To improvise upper management support, relative advantage should be prioritised over complexity.

4.6. *Artificial neural network analysis*

Standard linear models such as multiple regression analysis (MRA) and structural equation modelling (SEM) are inadequate in explaining the complex nature of human decision-making processes as these analysis methods could only detect linear relationships (Liébana-Cabanillas, Marinkovic, Ramos de Luna, & Kalinic, 2018). Furthermore, MRA and SEM are compensatory models with the assumption that a decrease in one component can be compensated with an increase in other components based on a linear equation that link the exogenous constructs with the endogenous constructs. However, in this study, the exogenous constructs are non-compensable. That is to say, a decrease in upper management support cannot be compensated with an increase in regulatory support as both constructs are distinctive in terms of definitions and conceptualisation, hence they are not interchangeable. To address this problem, artificial neural network (ANN) is performed on top of the PLS-SEM analysis in view of its ability in capturing both linear and nonlinear relationships within a non-compensatory model (Hew & Kadir, 2016). Compared to linear models, ANN models are robust against noises, non-normality of distribution, homoscedasticity, nonlinearity and multicollinearity problems (Hew, Leong, Tan, Lee, & Ooi, 2018). Actually, ANN models have outperformed the conventional statistical techniques (e.g. MRA, SEM, logistics) due to its high degree of prediction accuracy (Leong, Hew, Lee, & Ooi, 2015). In addition, ANN models have the capacity to learn, it is therefore regarded as powerful statistical models (Ooi, Hew, & Lin, 2018). Nevertheless, the "black-box" nature of ANN is inappropriate in ascertaining the significance

Table 8
Cross-loadings.

	BI	CPR	CPX	CST	MDY	RA	RGS	UMS
BI1	**0.973**	0.826	0.345	0.576	0.633	0.752	0.366	0.281
BI2	**0.941**	0.772	0.291	0.488	0.733	0.821	0.289	0.390
BI3	**0.968**	0.823	0.406	0.619	0.638	0.751	0.335	0.277
CPR1	0.726	**0.911**	0.286	0.513	0.517	0.623	0.238	0.149
CPR2	0.756	**0.870**	0.358	0.513	0.733	0.820	0.193	0.382
CPR3	0.797	**0.915**	0.587	0.746	0.695	0.807	0.219	0.224
CPR4	0.809	**0.958**	0.481	0.676	0.608	0.711	0.249	0.198
CPR5	0.777	**0.950**	0.484	0.660	0.595	0.715	0.234	0.182
CPX1	0.350	0.474	**0.969**	0.817	0.457	0.499	0.050	0.103
CPX2	0.351	0.460	**0.956**	0.778	0.532	0.567	0.003	0.200
CPX3	0.364	0.468	**0.955**	0.786	0.522	0.554	0.021	0.202
CPX4	0.340	0.460	**0.966**	0.799	0.453	0.489	0.023	0.108
CPX5	0.336	0.451	**0.970**	0.790	0.439	0.489	0.012	0.102
CST1	0.558	0.632	0.804	**0.963**	0.605	0.648	0.078	0.127
CST2	0.529	0.586	0.794	**0.948**	0.583	0.636	0.011	0.110
CST3	0.592	0.665	0.789	**0.954**	0.622	0.662	0.093	0.150
CST4	0.559	0.642	0.778	**0.959**	0.583	0.644	0.061	0.135
CST5	0.523	0.686	0.734	**0.907**	0.511	0.575	0.071	0.104
MDY1	0.684	0.694	0.543	0.624	**0.969**	0.852	0.242	0.435
MDY2	0.661	0.646	0.503	0.597	**0.967**	0.830	0.203	0.413
MDY3	0.670	0.643	0.399	0.561	**0.962**	0.805	0.238	0.403
RA1	0.761	0.766	0.493	0.599	0.830	**0.964**	0.219	0.402
RA2	0.747	0.742	0.530	0.638	0.840	**0.966**	0.168	0.396
RA3	0.805	0.791	0.458	0.645	0.737	**0.882**	0.236	0.238
RA4	0.738	0.735	0.560	0.660	0.832	**0.958**	0.183	0.405
RA5	0.767	0.752	0.514	0.630	0.826	**0.966**	0.205	0.411
RGS1	0.400	0.298	−0.049	0.049	0.307	0.266	**0.955**	0.372
RGS2	0.340	0.218	−0.026	0.049	0.245	0.207	**0.952**	0.321
RGS3	0.263	0.193	0.095	0.073	0.141	0.154	**0.932**	0.318
RGS4	0.244	0.187	0.123	0.094	0.142	0.137	**0.929**	0.315
UMS1	0.306	0.179	0.183	0.142	0.448	0.395	0.326	**0.948**
UMS2	0.317	0.206	0.191	0.165	0.429	0.400	0.303	**0.947**
UMS3	0.263	0.242	0.123	0.112	0.330	0.288	0.340	**0.939**
UMS4	0.368	0.318	0.032	0.068	0.416	0.379	0.390	**0.931**
UMS5	0.280	0.209	0.183	0.143	0.399	0.363	0.313	**0.957**

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

Table 9
Heterotrait-Monotrait Ratio (HTMT).

	BI	CPR	CPX	CST	MDY	RA	RGS	UMS
BI								
CPR	0.878							
CPX	0.373	0.493						
CST	0.605	0.702	0.845					
MDY	0.723	0.712	0.513	0.634				
RA	0.836	0.829	0.553	0.689	0.886			
RGS	0.345	0.248	0.081	0.074	0.230	0.210		
UMS	0.337	0.254	0.155	0.137	0.442	0.398	0.363	

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

Table 10
Predictive power (R^2).

	R Square	*R* Square Adjusted
BI	0.791	0.783
CST	0.751	0.748
UMS	0.158	0.149

Note: CST = Cost, BI = Behavioural intention, UMS = Upper management support.

Table 11
Predictive relevance: Stone-Geisser's Q^2 value (Geisser, 1975; Stone, 1974).

	SSO	SSE	Q^2 (= 1-SSE/SSO)
BI	582.000	163.609	0.719
CPR	970.000	277.346	0.714
CPX	970.000	181.774	0.813
CST	970.000	220.973	0.772
MDY	582.000	154.903	0.734
RA	970.000	217.441	0.776
RGS	776.000	212.925	0.726
UMS	970.000	226.871	0.766

Note: SSO = Sum of square observations, SSE = Sum of square prediction errors; RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

Table 12
Effect size (f^2).

	BI	CPR	CPX	CST	MDY	RA	RGS	UMS
BI								
CPR	0.333							
CPX	0.077			1.216				0.007
CST	0.029							
MDY	0.000							
RA	0.134			0.286				0.162
RGS	0.064							
UMS	0.002							

Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

levels of causal relationships (Hew, Leong, Ooi, & Chong, 2016). Hence, to complement each other, we have combined SEM with ANN by using the significant predictors identified in PLS-SEM analysis as the input neurons for the ANN models (Chong, 2013). The architecture of an ANN model consists of the input, hidden and output layers (Leong, Hew, Tan, & Ooi, 2013). Based on the feed-forward-back-propagation algorithm and with the use of multilayer perceptrons, we computed the root mean square errors (RMSE) and the normalised importance of the input neurons (Hew et al., 2018). To reduce the over-fitting problem, we employed a ten-fold cross-validation approach which uses 10% of the data in testing while the remaining 90% in training of the neural networks (Leong, Hew, Ooi, & Lin, 2019). For both hidden and output layers, the sigmoid was selected as the activation function. Fig. 7 shows

Table 13
Path analysis.

Hypotheses (effects)	Path	β	*T*-statistic	*p*-value	Remark
H1 (+)	RA → BI	0.404	5.684	0.000**	Supported
H2 (+)	RA → UMS	0.438	4.654	0.000**	Supported
H3 (+)	RA → CST	0.317	5.792	0.000**	Supported
H4 (-)	CPX → BI	−0.231	3.579	0.000**	Supported
H5 (+)	CPX → UMS	−0.088	1.106	0.269^{ns}	Not supported
H6 (+)	CPX → CST	0.653	13.302	0.000**	Supported
H7 (+)	UMS → BI	0.024	0.336	0.737^{ns}	Not supported
H8 (-)	CST → BI	0.172	2.417	0.016*	Not Supported
H9 (+)	MDY → BI	−0.014	0.195	0.845^{ns}	Not supported
H10 (+)	CPR → BI	0.483	5.778	0.000**	Supported
H11 (+)	RGS → BI	0.127	1.879	0.060^{ns}	Not supported

Note: *$p < 0.05$, **$p < 0.001$, ^{ns} = not significant; RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioural intention.

the ANN model for behavioural intention while Fig. 8 portraits the ANN model for cost.

In terms of model fitness, Table 15 shows that for the ANN model of behavioural intention, the RMSE mean values for training and testing are relatively small at 0.0707 and 0.0715 respectively. In the same vein, Table 16 shows that for the ANN model of cost, the mean values of RMSE for training and testing are very small at 0.0655 and 0.0650 respectively. These verify that the ANN models fit very well with the dataset. Similar to Leong et al. (2018), we computed the R^2 and found that the ANN models explain 48.07% of the variance in behavioural intention and 30.76% of the variance in cost.

To compare the importance of the predictors, we computed the normalised importance by dividing the relative importance with the highest relative importance and state the value in percentage. Table 17 shows that for behavioural intention, competitive pressure is of highest normalised importance followed by relative advantage, cost and complexity while Table 18 shows that for cost, complexity is the most important predictor followed by relative advantage.

5. Discussion

This study reveals significant blockchain adoption factors within the dimensions of technological, organisational and environment which

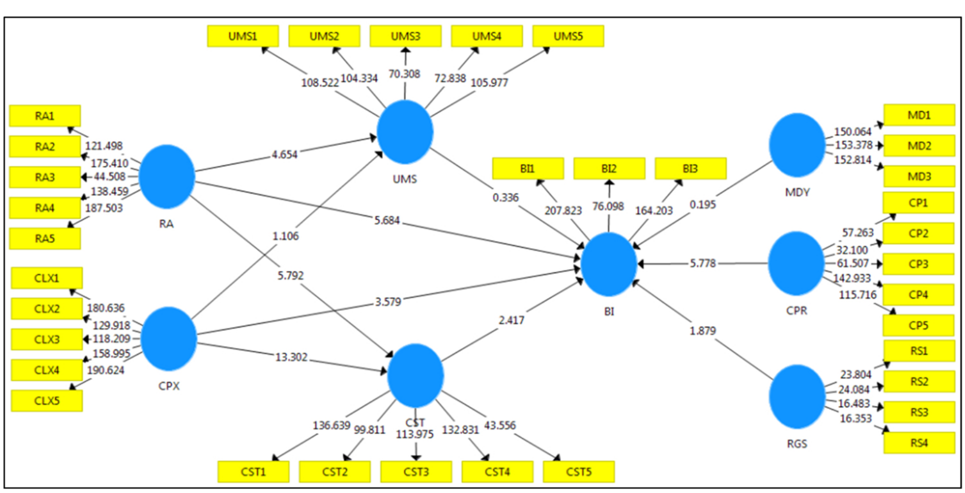

Fig. 3. Structural path diagram.
Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support, BI = Behavioral intention.

Table 14
Specific indirect effect.

	Specific Indirect Effects	T Statistics	*p*-values
CPX → CST → BI	0.113*	2.385	0.017
RA → CST → BI	0.055*	2.123	0.034
CPX → UMS → BI	−0.002^{ns}	0.261	0.794
RA → UMS → BI	0.011^{ns}	0.305	0.760

Note: *$p < 0.05$, ^{ns} = not significant; RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, BI = Behavioural intention.

can be used as a foundation for advancing blockchain adoption by SMEs for operations and supply chain management. The top four significant considerations as shown by the study are competitive pressure, complexity, cost and relative advantage whereas market dynamics, regulatory support and upper management support were found to be insignificant.

The results showed relative advantage as a significant exogenous construct in determining blockchain adoption. This is consistent with prior studies on adoption considerations (Bhattacharya & Wamba, 2015; Ramayah, Ling, Taghizadeh, & Rahman, 2016; Swan, 2015). It has been suggested that blockchain could be the game changer for the supply chain industry (Galvin, 2017; Pilkington, 2016). The potential can be clearly seen in terms of providing a networked ledger of information that is accessible and shared real time by everyone on the network. This promotes transparency and gradually this would lead to the creation of a single version of truth for all parties on the network. Perhaps the most significant benefit would be the elimination of costly third parties that would cause a delay in the network. Blockchain-reliability meant that material transportation can be facilitated more effectively with automated governance requirements. Developed understanding of these advantages over existing legacy systems enhances relationships with various stakeholders and can also be perceived that more opportunities will be present. Adoption would, therefore, depend on the clear proposition of advantages. This is consistent with Wang et al. (2019), who reported perceived benefits to serve as the main reason that blockchain is significant in supply chains.

Complexity was also found to be a significant inhibitor of adoption. In the context of this study, the complexity of blockchain can be expressed in terms of process efficiency, usage and system functionality. From a technical perspective, blockchain is an integration of technologies that creates new ways of data management and scalability; however, despite the many reported benefits, blockchain also brings performance issues (Lu, 2019). Conversely, familiarity with blockchain can be translated as taking lesser time to task completion and the lesser the perceived complexity, the greater the enhancement it has on job performance, and ease of using the system. Accordingly, the anxiety of using blockchain systems will result in lower levels of adoption. This has also been validated by earlier findings of Swan (2015) and Tsai, Lai, and Hsu (2013). It should be noted that familiarity with an innovation reduces the perceived complexity, according to Vasseur and Kemp (2015).

In this study, the cost is affected by the complexity and relative advantage. This is not surprising that the availability of financial resources is determined by perceived ease of use as well as the value that the technology is perceived to bring about. A possible explanation of this may be that SMEs perceive that a complicated yet advantageous technology like blockchain shall be costly to implement (Gallardo et al., 2018; Museli & Jafari Navimipour, 2018; Tashkandi & Al-Jabri, 2015). Similarly, the relative advantage is also positively associated with upper management support, and this supports the study conducted by Mousavizadeh et al. (2015), which found that the various benefits of implementing a knowledge management system have positive effects on upper management support. In the context of this study, it is posited that the use of BOSCM could offer numerous advantages, which motivate the upper management to provide their support in the implementation. Moreover, the linkage between complexity and upper management support is insignificant. Upper management will not provide their support during the implementation even if blockchain is complicated to use and implement. Although this finding does not support the past studies (Al-Alak & Alnawas, 2011; Bueno & Gallego, 2017), it is believed that this finding could be explained by the fact that blockchain is still in its infancy in Malaysia

Upper management support is insignificant in this study, this could be due to the reason that upper management is not convinced or does not have sufficient knowledge on the benefits of the blockchain. Often, management and investments decisions of SMEs are directed by management support (Maduku, Mpinganjira, & Duh, 2016) and if upper management is more knowledgeable about the technology, they would be more likely to develop a positive adoption intention and support its adoption. This is consistent with the study's findings that upper management support is influenced by relative advantage.

Surprisingly, the cost was not empirically supported as an inhibitor but a motivator that drives the intention to adopt. Nonetheless, this refreshing result does not agree with the past studies (Kuan & Chau, 2001; Shi & Yan, 2016). Perhaps, as discussed earlier, given the relative advantages offered, even if blockchain is perceived as a costly (average mean equals 4.84) tool, SMEs still intend to adopt it (average mean equals 4.43).

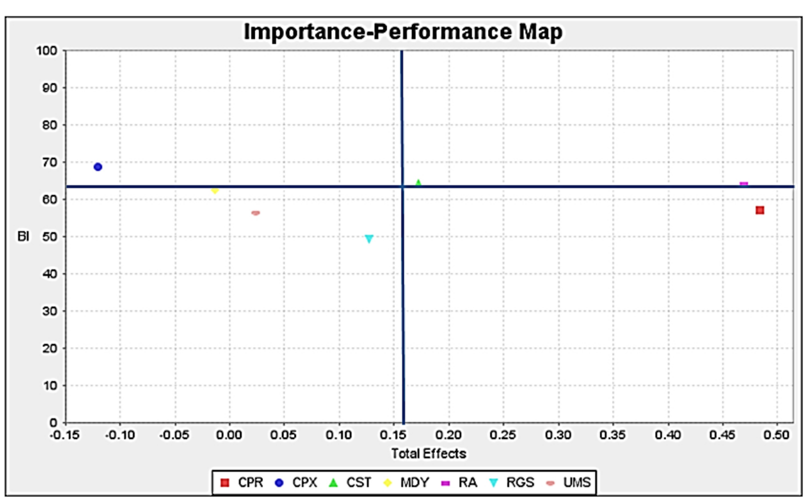

Fig. 4. IPMA for behavioural intention.
Note: RA = Relative advantage, CPX = Complexity, UMS = Upper management support, CST = Cost, MDY = Market dynamics, CPR = Competitive pressure, RGS = Regulatory support.

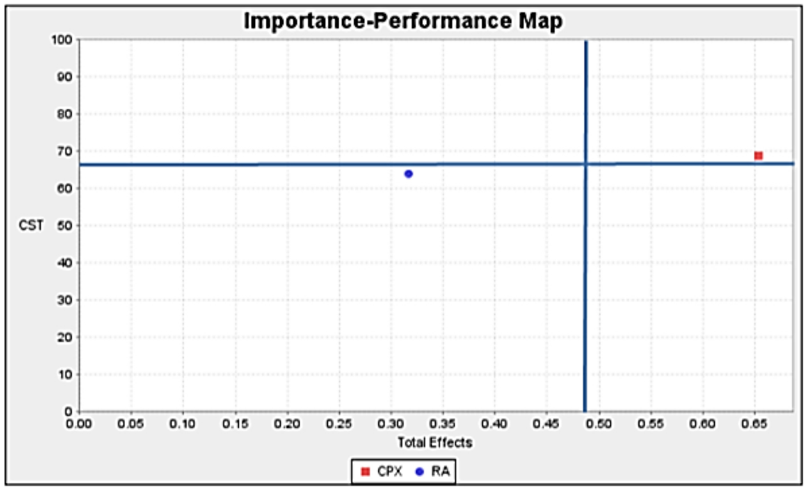

Fig. 5. IPMA for cost.
Note: RA = Relative advantage, CPX = Complexity.

The impact of competitive pressure on SME's blockchain adoption intention is significant. This implies that SMEs are compelled to stay relevant and competitive in their business environment. This reflects the presence of rivalry and decisions are driven by the ability to stay at the forefront of technological innovation. Prior literature on competitive pressure has also established that technological innovation is important for a company to remain competitive (Iansiti & Lakhani, 2017; Pilkington, 2016; Wang et al., 2018).

Blockchain like artificial intelligence is among one of the latest technologies that disrupts and transforms industries. They are distinctly complex and blockchain can be assisted or enhanced via artificial intelligence (Xing & Marwala, 2018). According to a recent study on artificial intelligence by Duan, Edwards, and Dwivedi (2019), legal concerns have become a major challenge and the role of government is critical, particularly on how government can develop sufficient policy, regulations and legal framework to guide and prevent misuse of technology. A comprehensive understanding of emerging technology such as blockchain is needed to establish related regulatory frameworks (Lu, 2019). The same can be inferred for blockchain regulations in Malaysia. In this study, market dynamics and regulatory support are insignificant. The lack of standards and regulations that can support SMEs in Malaysia where blockchain technology is concerned. As alluded in earlier sections, blockchain is still in its infancy in Malaysia and although there exists initiatives to drive blockchain; few have been implemented. Large enterprises in Malaysia have piloted or sandboxed the technology but many remained at the conceptual stage. It is not surprising that SMEs in Malaysia are currently not immersed with technology. Furthermore, the lack of trialability may further compel SMEs to be less ambitious in experimenting with blockchain.

5.1. Theoretical implications

This study has answered to a call made by Ying et al. (2018), who stressed that there is currently an urgent need to enrich the current state of blockchain research, which is largely exploratory in nature, with empirical evidence. Indeed, the literature on blockchain thus far is mostly in the form of literature review (for e.g., Hughes et al., 2019; Lu, 2019; Min, 2019; Queiroz et al., 2019; Wamba, Kamdjoug et al., 2018; Wang et al., 2018) and is rather conceptual in nature (for e.g., Francisco & Swanson, 2018). Even if some researchers have devoted efforts in obtaining empirical evidence, these studies are rather narrow with the focus of a sole entity (Ying et al., 2018), qualitative in nature (Wang et al., 2019), and based upon the TAM (Kamble et al., 2018) or UTAUT theoretical frameworks (Francisco & Swanson, 2018; Queiroz & Wamba, 2019). In this manner, through the theoretical lens of TOE framework and empirical evidence from Malaysian SMEs, this study is expected to contribute to the ever-growing literature on BOSCM and adds diversity to the literature on adoption models for technological innovations using an empirical approach.

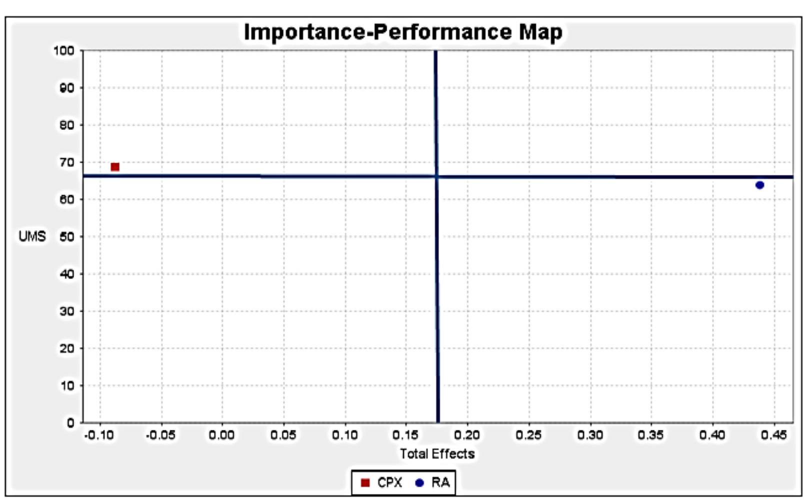

Fig. 6. IPMA for upper management support.
Note: RA = Relative advantage, CPX = Complexity.

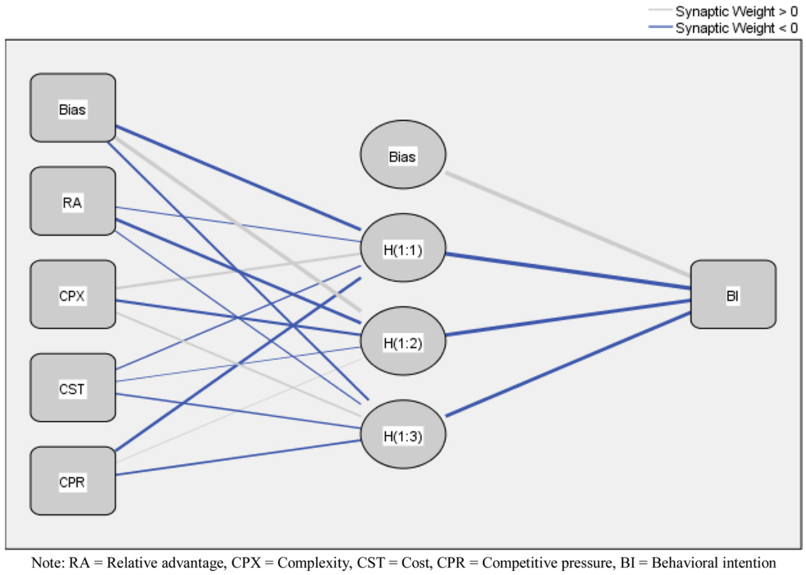

Fig. 7. Neural network model 1.
Note: RA = Relative advantage, CPX = Complexity, CST = Cost, CPR = Competitive pressure, BI = Behavioral intention.

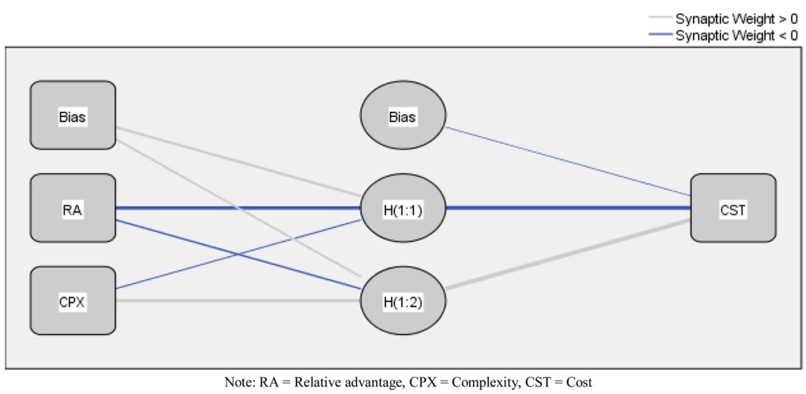

Fig. 8. Neural network model 2.
Note: RA = Relative advantage, CPX = Complexity, CST = Cost.

Table 15
RMSE for neural network model 1*.

Training N	SSE	RMSE	Testing N	SSE	RMSE	Total
173	0.830	0.0693	21	0.062	0.0543	194
173	0.813	0.0686	21	0.071	0.0581	194
175	0.922	0.0726	19	0.043	0.0476	194
176	0.999	0.0753	18	0.035	0.0441	194
173	0.775	0.0669	21	0.424	0.1421	194
176	0.907	0.0718	18	0.016	0.0298	194
175	0.925	0.0727	19	0.253	0.1154	194
173	0.871	0.0710	21	0.402	0.1384	194
174	0.836	0.0693	20	0.035	0.0418	194
175	0.859	0.0701	19	0.035	0.0429	194
Mean	0.874	0.0707	Mean	0.138	0.0715	
Std. deviation	0.0656	0.0024	Std. deviation	0.1601	0.0430	

Note: *Endogenous constructs = Behavioural intention; N = sample size, SSE = Sum square error, RMSE = Root mean square error.

Table 16
RMSE for neural network model 2*.

Training N	SSE	RMSE	Testing N	SSE	RMSE	Total
173	0.876	0.0712	21	0.068	0.0569	194
173	0.547	0.0562	21	0.057	0.0521	194
173	0.634	0.0605	21	0.044	0.0458	194
175	0.802	0.0677	19	0.083	0.0661	194
176	0.965	0.0740	18	0.338	0.1370	194
172	0.837	0.0698	22	0.061	0.0527	194
171	0.747	0.0661	23	0.062	0.0519	194
173	0.585	0.0582	21	0.105	0.0707	194
176	0.875	0.0705	18	0.072	0.0632	194
177	0.651	0.0606	17	0.049	0.0537	194
Mean	0.752	0.0655	Mean	0.094	0.0650	
Std. deviation	0.1413	0.0062	Std. deviation	0.0875	0.0264	

Note: *Endogenous construct = Cost; N = sample size, SSE = Sum square error, RMSE = Root mean square error.

5.2. Practical implications

This study reveals the inter-relationship between the core constructs as hypothesised. For example, cost and behavioural intention exhibit a strong variance of 75.1% and 79.1% respectively, the cost is also shown to be largely affected by the complexity and competitive pressure exerts a moderate impact on behavioural intention. Likewise, the impact of relative advantage is moderate on cost and upper management support. In addition, the cost is shown to partially mediate the relationships between complexity and behaviour intention as well as relative advantage and behavioural intention.

Table 17
Sensitivity analysis for neural network model 1*.

Relative importance	RA	CPX	CST	CPR
Network 1	0.239	0.155	0.184	0.421
Network 2	0.220	0.143	0.166	0.471
Network 3	0.260	0.158	0.202	0.381
Network 4	0.258	0.162	0.176	0.403
Network 5	0.342	0.131	0.018	0.509
Network 6	0.325	0.139	0.148	0.388
Network 7	0.326	0.093	0.121	0.460
Network 8	0.230	0.081	0.147	0.542
Network 9	0.284	0.152	0.157	0.407
Network 10	0.232	0.150	0.203	0.415
Average importance	0.272	0.136	0.152	0.440
Normalised importance (%)	61.8	31.0	34.6	100.0

Note: * Endogenous construct = Behavioural intention; RA = Relative advantage, CPX = Complexity, CST = Cost, CPR = Competitive pressure.

Table 18
Sensitivity analysis for neural network model 2*.

Relative importance	RA	CPX
Network 1	0.282	0.718
Network 2	0.213	0.787
Network 3	0.159	0.841
Network 4	0.328	0.672
Network 5	0.435	0.565
Network 6	0.320	0.680
Network 7	0.358	0.642
Network 8	0.222	0.778
Network 9	0.259	0.741
Network 10	0.222	0.778
Average importance	0.280	0.720
Normalised importance (%)	38.9	100.0

Note: * Endogenous construct = Cost; RA = Relative advantage, CPX = Complexity.

Furthermore, this research indicates that competitive pressure should be given priority for improvement followed by cost, relative advantage and upper management support. Competitiveness is thus the catalytic force which if improved can fasten adoption by SMEs. This is an important revelation as SMEs have been constrained by low penetration of technological resources and as a result unable to secure a competitive advantage (Rao & Kumar, 2018). Malaysia has begun to explore blockchain adoption in the supply chain (Manning, 2019) and Malaysia is considered to have a positive opportunity to be globally competitive (Pikri, 2019). However, given the increased transparency that is resulted from blockchain adoption, firms are advised that a careful analysis is required in order to understand stakeholders' reaction to a fully transparent supply chain in which close monitoring of customer and other parties including competitors becomes possible (Montecchi et al., 2019).

For improvement in cost, upper management support is crucial which can be supported by relative advantage. The SME sector in Malaysia is an important market for blockchain. Decision makers should be aware and informed of the advantages of adopting the technology in order to be able to make sound judgements in terms of investment as well as talent development. In order to stay competitive, SMEs should take a bold step towards exploring technological innovations – they have the advantage of a smaller eco-system that involves fewer entities and also the ability to react faster.

6. Conclusions

This study has provided an overview of potential factors of consideration from a holistic view via the TOE framework. In response to RQ1, cost, competitive pressure, complexity, and relative advantage exhibit a significant relationship with the intention to adopt BOSCM among Malaysian SMEs. On the other hand, market dynamics, regulatory support, and upper management support were insignificant. Pertaining to RQ2, the ANN analysis shows that competitive pressure matters most in the adoption of BOSCM. While this study may not be comprehensive, it does include some of the common factors such as management support, regulatory support, competitive pressure, costs and the results were surprising. Hence, this study may provide a reference to academics as well as practitioners.

6.1. Limitations and future research directions

There is tremendous scope for further research in this area. Firstly, this study is conducted in Malaysia with SMEs concentrated within Klang Valley. Future studies may consider cross-country or among neighbouring countries that are more technologically advanced. Secondly, this study considers selected elements within the TOE framework, an extension of the TOE may possibly add insights to the findings. Blockchain has been reported to eliminate inter-organisational intermediaries and trust is established via the networked nodes (Ying et al., 2018). Further studies need to be carried out to understand the impact of confidentiality, integrity of data and privacy have on adoption decisions and blockchain's role in protecting sensitive information. In a study of ten blockchain logistics implementations, there was initially no disintermediation for two applications and in seven applications, intermediation took place in the form of new service providers. If participants were not persuaded to use the application, transparency would become difficult and traceability of good flows will not be supported (Tönnissen & Teuteberg, 2019). Hence the impact of blockchain on supply chain disintermediation and its applicability is unclear. There are also availability concerns with the blockchain technology, consequently, companies seeking to adopt this technology may require a more focused and comprehensive evaluation from a quantified perspective. Furthermore, the inherent characteristics of blockchain technology may need to be assessed in terms of its viability for adoption from various perspectives such as interoperability, transaction speed and costs. Additionally, each organisation is different in culture, infrastructure and industry sectors that together, may result in a different decision in adopting blockchain. Existing studies have thus far either reported on blockchain-based designs of business processes models or technology but not the relationship between them. Thus further studies are required to understand the impact of information sharing and resources to better help organisations make adoption decisions (Pan, Pan, Song, Ai, & Ming, 2019). Hence the findings of this study may not be taken as a one-fit-blanket that applies to all. Few studies have extensively reported on the cost associated with blockchain implementations apart from prototype and feasibility studies (Hughes et al., 2019). This scarcity further impedes the study from drawing comparisons with similar works on the same technology and as such, firms thinking to incorporate blockchain into their existing business models would require further consideration on the necessity of such technology (Queiroz et al., 2019). That said, the amount of attention generated by blockchain serves as a reminder that organisations can no longer maintain traditional ways of doing things but would need to embrace change. Technology will radically transform operations and organisations need to be prepared.

Declaration of Competing Interest

None.

Appendix 1 Survey Items

Relative Advantage	
RA1:	BOSCM can quickly complete the firm's operations
RA2:	BOSCM can enhance the efficiency of operations and supply chain management
RA3:	BOSCM can increase firm's profits
RA4:	BOSCM is helpful for operations and supply chain management
RA5:	BOSCM is convenient for me to manage operations and supply chain.
Complexity	
CLX1:	Learning how to operate BOSCM is not simple
CLX2:	Learning how to operate BOSCM requires much effort
CLX3:	I believe that the use of BOSCM requires ample experience
CLX4:	I believe that my firm does not understand how to use BOSCM
CLX5:	I believe that BOSCM tools are not easy to use
Upper Management Support	
UMS1:	Upper managers actively respond and pay attention when a project is initiated
UMS2:	Upper managers support by providing labour resources, finances and materials for BOSCM
UMS3:	Upper managers are willing to accept risks when adopting BOSCM
UMS4:	Upper management inspire employees to apply latest blockchain technologies in daily work.
UMS5:	Upper management encourages innovation
Cost	
CST1:	Adopting BOSCM will increase hardware and facility cost
CST2:	Adopting BOSCM will increase operations and maintenance cost
CST3:	The cost of BOSCM is unclear and not easily understandable
CST4:	The cost of BOSCM is high for my firm
CST5:	The cost of confirming transactions in BOSCM is high
Market Dynamics	
MD1	Customer preferences or requirements are always changing in my industry
MD2	My industry is sensitive to changes in the marketplace
MD3	In my industry, change is difficult to predict
Competitive Pressure	
CP1:	My firm believes that we may lose customers if we do not use BOSCM
CP2:	My firm believes that using BOSCM to gain competitiveness is important when making strategic decisions
CP3:	My firm believes that other firms in our industry have recently begun to explore BOSCM
CP4:	Social features such as customs and cultures force my firm to look into BOSCM
CP5:	Competitive pressures force my firm to look into BOSCM
Regulatory Support	
RS1:	BOSCM development receives financial support from the government or relevant authorities
RS2	Relevant policies are introduced by the government to boost BOSCM development
RS3	There is legal support in the use of BOSCM
RS4	The laws and regulations that exist nowadays are sufficient to protect the use of BOSCM
Behavioural Intention	
BI1	I predict my firm would adopt BOSCM in the future
BI2	I predict I would use BOSCM in the future
BI3	My firm intends to digitally transform operations and supply chain management through BOSCM

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