Antecedents of IoT adoption in food supply chain quality management: an integrative model

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Abstract

Purpose – The introduction of quality management Internet of things (QM IoT) can help food supply chain members to enhance real-time visibility, quality, safety and efficiency of products and processes. Current literature indicates three main research gaps, including a lack of studies in QM IoT in the food supply chain, the vagueness of integrative adoption of new technology framework and deficient research covering both adoption attitude and intention in the same model. This study aims to propose an analysis model based on the technological–organizational–environmental (TOE) framework and reinforced by the collaborative structure to capture the importance of the supply chain network.

Design/methodology/approach – The partial least square-structural equation modeling (PLS-SEM) was applied to test the impacts of the adoption factors on QM IoT adoption attitude and intention among 197 respondents in food manufacturing in Thailand.

Findings – The results indicated that compatibility, trialability, adaptive capacity, innovative capability, executive support, value chain partner pressure, presence of service provider and information sharing significantly impacted the attitude toward QM IoT adoption, while adaptive capability, innovative capability and information sharing directly influenced the QM IoT adoption intention. Furthermore, the attitude toward QM IoT adoption positively impacted the QM IoT adoption intention.

Practical implications – This study contributed to academicians by proposing a more solid adoption framework for QM IoT area. In addition, the business practitioners could actively prepare themselves for the QM IoT adoption, whereas the service providers could provide better and suitable service.

Originality/value – This research contributes to the building of a more solid framework and indicates significant factors that impact the attitude toward QM IoT adoption and adoption intention.

Keywords Supply chain, Quality management, Internet of things, Adoption intention, Food manufacturing, Attitude toward adoption

Paper type Research paper

1. Introduction

The Internet of things (IoT) has been introduced to various industries since 1999. IoT captures the data from "things" without human intervention, transfers those data to computers on its own via Internet and produces meaningful information. To illustrate, it could track and trace everything, generate a warning on replacing, repairing or recalling and help reduce waste, loss and costs (Kevin, 2009).

Globalization has pushed food to travel a longer distance from producers to consumers, so keeping the quality and safety of food along the supply chain has become a crucial challenge

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(Aung and Chang, 2014). It could be seen that several food quality and safety incidents, such as melamine in milk powder, drug clenbuterol in pig meat, gutter oil in the food, chemical elements in duck eggs, were found globally (Ying and Fengquan, 2013).

Quality management Internet of things (QM IoT) was applied to strengthen the quality and food safety along the processes in the food supply chain. For instance, the electric nose could be used in quality control to accept or refuse incoming raw materials of some food industries, such as coffee, tea, fish and fruit, while some applications could actively determine the origin of olive oil and oranges (Peres *et al.*, 2007). Furthermore, the attached Radio Frequency Identification (RFID) on the cheese package could determine the humidity, temperature, product handling, mold growing, biological contamination, acid corrosion, ammoniacal gases, ripening status and other important data, such as the kind of milk, manufacturer, batch and batch qualification (Pérez-Aloe *et al.*, 2007). In addition, QM IoT could track the quality of wine during transporting, storing and vending with the reach of your finger (Mattoli *et al.*, 2009), while traceability investigation can be done faster than the traditional ways as the supply chain networks get shared the proper and real-time data (Hong *et al.*, 2011).

Currently, there are studies on the adoption of IoT in several industries. For food-related industries, a few numbers of studies explored IoT adoption, including in the food retail supply chain (Kamble *et al.*, 2019b), agro-food small and medium enterprises (SMEs) (Ahmad Tarmizi *et al.*, 2020), fish supply chain network (Verdouw *et al.*, 2016), cheese supply chain (Jedermann *et al.*, 2009), agricultural supply chain and distribution (Jayashankar *et al.*, 2018; Lin *et al.*, 2016; Shi and Yan, 2016), smart farming (Walter *et al.*, 2017) and Greek fresh produce supply chain (Manos and Manikas, 2010). However, the existing literature mainly discussed on the adoption of IoT rather than that of QM IoT. QM IoT crucially plays an important role in the food supply chain as it helps to strengthen the food quality and safety within and among firm's supply chain. To fill this unavailable QM IoT adoption study gap, the authors projected the first research objective which is to examine the factors that impact the QM IoT adoption in the food supply chain.

When discussing the adoption of a new process, technology or invention, some research brought in the technological–organizational–environmental (TOE) framework in analyzing the adoption factors of those in various industries, such as in semiconductor industry (Hwang *et al.*, 2016), SME's e-business (Chong *et al.*, 2009), logistic service provider (Hsu and Yeh, 2017; Rey *et al.*, 2021), healthcare industry (Karahoca *et al.*, 2018), e-learning platform (Huang *et al.*, 2020) and so on. However, TOE framework has its own limit on the generalization and vagueness of the constructed factors (Gangwar *et al.*, 2015; Hwang *et al.*, 2016). The authors filled this research gap by proposing the second research objective which is to create an integrative QM IoT adoption model that covers the supply chain collaborative perspectives.

We reinforced the TOE framework by integrating the traditional adoption theories that are dispersedly used in the current research, including the diffusion of innovation theory (DOI) (Rogers, 1995), technology acceptance model (TAM) (Davis, 1989), unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al.*, 2003), under privacy calculus theory (PVC) (Dinev and Hart, 2006), dynamic capability (TDC) (Teece and Pisano, 1994; Wang and Ahmed, 2007), stakeholder theory (STK) (Parmar *et al.*, 2010) and institution theory (IST) (DiMaggio and Powell, 1983). In addition, the collaborative structure (Chong and Zhou, 2014) was assembled into the TOE framework to crucially strengthen the supply chain collaboration perspectives, which were lacking from the original TOE framework.

Furthermore, the current literature on the adoption of any new technology mainly purely focused on either attitude or intention as a dependent variable. Only a few studies brought both attitude and intention into the same model. It is important to consider the relationship between both of them in a single model, so academicians, business practitioners and service providers could have more insights and gain a deeper understanding of the factors that directly impact the intention and that mediates through attitude. As a consequence, the authors fulfil this gap in the adoption of QM IoT in food supply chain research with the third research objective which is to construct the model and explore the relationship of both attitude as a mediator to intention and intention as an independent variable.

2. Literature review

2.1 Quality management Internet of Things

Some research on the QM IoT in the food supply chain has been conducted in the current literature. The authors illustrated its application and benefits in five main areas, including source, make, deliver, return and plan. For sourcing, the optical noninvasive sensors could be used for phenotyping and plant disease detection (Wahabzada *et al.*, 2016). In addition, the electric nose was used in quality control to accept or refuse incoming raw materials, such as coffee, tea, fish and fruit, while some applications could even determine the origin of olive oil and orange (Peres *et al.*, 2007). Furthermore, the electronic cattle ear tags could collect and provide the data, such as an ear tag number, ear tag image, (including barcode and identification number in human-readable format), biometric identifiers (retinal scan), herd details (name and address), date of birth, GPS of premises, scan date and time stamp, device ID (serial number) and operator ID via an online database among the supply chain networks (Shanahan *et al.*, 2009). It could also improve searching efforts on the authentication information of Halal ingredients (Ahmad Tarmizi *et al.*, 2020).

For making, the automation and quality control in the cheese fabrication process could be made via the use of QM IoT. The attached RFID on the individual cheese could determine the humidity, temperature, product handling, mold growing, biological contamination, acid corrosion, ammoniacal gases, ripening status, kind of milk, manufacturer, batch and batch qualification. The data was collected automatically as a numerical value in the RFID, while the manual recording method was removed (Pérez-Aloe *et al.*, 2007). Furthermore, a biosensor was used to monitor the residual peroxide during the on-line disinfection processes in the food and beverage industry (Moody *et al.*, 2001). It could also be used for the detection of mycotoxins, bactericides, allergens and contaminating microbes (Aarnisalo *et al.*, 2007).

For delivering, sensors in a power-safe mode, called Flexible Tag Datalogger (FTD) that are attached to the wine bottles could monitor the quality of the wine during transporting, storing and vending. The FTD wrapped around the bottleneck to effectively sense the environmental changes, such as temperature, humidity and light, during the processes in the wine logistics chain in real-time. Consumers could also easily check those data by filling in the identification number (ID) on the website (Mattoli *et al.*, 2009). In addition, the quality of perishable foods, such as deep-frozen goods, fish and meat and vegetables, could also be captured in real-time (Aung and Chang, 2014; Wilson and Clarke, 1998). Once environmental changes exceeded the standard, such as a higher amount of heat and carbon dioxide emission, QM IoT could identify the problem location, raise the alarm and calculate the remaining shelf life automatically (Jedermann *et al.*, 2009).

For returning, the return in the food supply chain could be determined as recalling the product back to the original locations or scraping areas due to quality concerns. During the crisis, the food products that were sent to the downstream networks could be immediately realized and recalled (Kumar and Budin, 2006). The traceback or traceforward investigation of the contamination and distribution locations could be done immediately through the use of QM IoT (Aung and Chang, 2014). Recalling might efficiently happen for partial products instead of massive calls due to the use of this technology, while consumers and supply chain networks could exchange the data that synchronized via QM IoT in real-time (Kumar and Budin, 2006; Xu, 2011). In addition, the food supply chain could use the dynamic expiration date (DED) on a food package that could control the quality of the products when distributed along the supply chain. The earliest expiry date items could be determined and sent to the nearest distributor, while the longer ones for further routes. Therefore, firms could reduce food waste, recalls and returns (Heising *et al.*, 2017).

For planning, IoT could act as predictive analytic tools that helped make a decision in supply chain planning, such as in re-stocking, distributing and retrieving the estimated time to complete the process (Rey *et al.*, 2021). In addition, (re)planning, booking, cancelling processes through the information of the container and vessel space availability could be completed in real-time with less manual work through the use of cloud-based platform, such as via FIspace platform in the fresh fish distribution in Norway (Verdouw *et al.*, 2016). The planning activity could also be done via QM IoT in agricultural contexts, such as calculating the amount and period to apply the fertilizers, pesticides and water, while it could also automatically perform the site-specific weather forecast, yield projections and probability maps for diseases and disasters through the accumulated data via QM IoT (Wahabzada *et al.*, 2016; Walter *et al.*, 2017). In addition, the individualized feeding ratio of livestock could be planned via the use of remote-sensing signals, sensors or actuators attached to the livestock (Walter *et al.*, 2017).

Using QM IoT could promote efficiency, quality management, performance tracking, decision-making and automatic notification for the users. This was not limited to the single users but rather shared important information with the upstream and downstream partners in the supply chain. The end consumers could also benefit from the usage of QM IoT in the food supply chain.

2.2 Technological–organizational–environmental framework and related theories

The TOE framework has been to examine the adoption of innovation of information system or technology in three context groups, including technological, organizational and environmental contexts (Tornatzky *et al.*, 1990). TOE framework was used to analyze the adoption factors in various industries, such as in semiconductor industry (Hwang *et al.*, 2016), SME's e-business (Chong *et al.*, 2009), logistic service provider (Hsu and Yeh, 2017; Rey *et al.*, 2021), healthcare industry (Karahoca *et al.*, 2018), e-learning platform (Huang *et al.*, 2020) and so on. The application of the TOE framework was relatively limited in food-related industry studies. Some were found in agriculture (Lin *et al.*, 2016; Shi and Yan, 2016); however, there was a scarcity of applying the TOE framework in the food manufacturing supply chain.

Also, there was a controversy over the use of the TOE framework due to its own limit on the generalization and vagueness of the constructed factors (Gangwar *et al.*, 2015; Hwang *et al.*, 2016). Therefore, the authors brought in several theories to support and strengthen the model in each context explained as followed.

Under the technological context, the authors brought in four technological-related theories to strengthen this context, including the diffusion of innovation theory (DOI), technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT) and privacy calculus theory (PVC). First, DOI indicated the fundamental approach to investigate the new technology diffusion through certain channels among social members over time, such as the adoption of Nintendo video games and home computers. There were five factors that predict the innovation's rate of adoption, including relative advantage, compatibility, complexity, trialability and observability (Rogers, 1995). Therefore, these five factors were included in the technological context as it helped investigate the new technology diffusion. Second, TAM was also included in the technological context as it proposed important determinants for the potential users to use or not use the new technology. TAM was applied as a predictor of intention in using a diverse set of technologies with two factors, including perceived usefulness and perceived ease of use (Davis, 1989). However, these two factors from TAM were essentially similar to the relative advantage and complexity of DOI, respectively (Fichman, 1992). Therefore, they were combined and presented as relative advantage and complexity in this study. Third, UTAUT was another expanding theory from TAM. It was used to understand the drivers of acceptance of the new technology. It consisted of four direct determinants of intention and usage behaviors, including performance expectancy, effort expectancy, social influence and facilitating condition (Venkatesh *et al.*, 2003). However, those factors from UTAUT showed similarity over the adoption factors from TAM and DOI used in this study. For example, performance expectancy pertained to the relative advantage of DOI and perceived usefulness from TAM, effort expectancy was associated with the complexity of DOI and perceive ease of use from TAM, and facilitating condition was embodied in the compatibility factor from DOI (Venkatesh *et al.*, 2003). Therefore, they were combined and presented as the relative advantage, complexity and compatibility, respectively. Fourth, PVC raised concerns about risk beliefs. It showed two inhibitors of willingness to provide information, including the perceived risk and privacy concerns. PVC was previously used to examine the wiliness to provide information, such as via e-commerce (Dinev and Hart, 2006). As QM IoT was the new technology that captured tremendous private information from each firm in the supply chain, these two factors were presented as the sixth and the seventh factors under the technological context. Therefore, this research selected seven adoption factors from four theories, including DOI, TAM, UTAUT and PVC under the technological context. Based on their similarity, those factors included relative advantage, compatibility, complexity, trialability, observability, perceived risks and privacy concerns.

There were several research that pressed importance or indicated challenges of the technological factors on the attitude toward IoT adoption and IoT adoption intention, such as in Chinese agricultural supply chain (Lin *et al.*, 2016), Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020) and fish supply chain network (Verdouw *et al.*, 2016), Taiwanese retailer (Hong *et al.*, 2011), India retail supply chain (Kamble *et al.*, 2019b), the cheese supply chain network (Jedermann *et al.*, 2009), in food retail value chain in Sweden (Carlström and Silander Hahström, 2017), business e-learning in Taiwan (Lee *et al.*, 2011), healthcare industry (Karahoca *et al.*, 2018), agriculture in USA (Jayashankar *et al.*, 2018), electronic bill payment (Featherman and Pavlou, 2003) and home service in Korea (Sung and Jo, 2018). The definition, detailed current literature and hypothesis of each factor under the technological context were presented in section 2.3.

Under the organizational context, the theory of dynamic capability (TDC) indicated the way to better use of resources distinctively in a competitive and dynamic environment (Teece and Pisano, 1994; Wang and Ahmed, 2007) were also embedded in the model. The stakeholder theory (STK) was introduced to the model. Executive support was perceived as an important stakeholder that could influence the adoption of this theory (Parmar *et al.*, 2010). Hence, the constructed factors under the organizational context were based on its similarity and appropriateness, including firm size, adaptive capability, absorptive capability, innovative capability and executive support.

Several research concluded that the organizational factors impacted the attitude toward IoT adoption and IoT adoption intention, such as in agriculture (Lin *et al.*, 2016; Shi and Yan, 2016), Irish SMEs (Carcary *et al.*, 2014), Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020), food supply chain (Jedermann *et al.*, 2009), smart farm development (Walter *et al.*, 2017), Greek Fresh produce supply chain (Manos and Manikas, 2010), Italy transportation and logistics (Rey *et al.*, 2021), Indian food retail (Kamble *et al.*, 2019b) and manufacturing firms (Chan and Chong, 2013). In Section 2.4, the definition, current literature and hypothesis of each factor under the organizational context were explained.

Under the environmental context, the institution theory (IST) which provided the mechanism to explain the external environmental pressures was included in the model (DiMaggio and Powell., 1983). In addition, a factor under UATUT (Venkatesh *et al.*, 2003) was also added to this context. Based on their similarities in definition, this study included five factors from three theories under the environmental context, including competitive pressure, value chain partner pressure, social pressure, presence of the service provider and government regulation.

There were several research revealed the challenges and importance of environmental factors on the attitude toward IoT adoption and IoT adoption intention, such as in the logistics industry (Hsu and Yeh, 2017), agriculture (Lin *et al.*, 2016), electrical and electronic organization (Chong and Ooi, 2008), Malaysian SMEs (Chong *et al.*, 2009), mobile supply chain manufacturers in Malaysia (Chan and Chong, 2013), India food retail (Kamble *et al.*, 2019b) and smart farm (Walter *et al.*, 2017). Their studies explored that those firms could be influenced by the environmental factors in their specific sectors. The definition, current literature and hypothesis of each factor under the environmental context were presented in Section 2.5.

It could be seen that some research focused only on some contexts or some factors. However, this research integrated all factors supported by several theories previously mentioned. Therefore, the overall views on all three contexts were captured. In addition to the TOE context, the collaborative structure was added to the model to expand the importance of the supply chain networks instead of focusing only on one party in the supply chain. The collaborative structure, including information sharing and trust, was introduced to construct the conceptual framework and to determine the relationship between the supply chain members on the QM IoT adoption in this research. The collaborative structure would help extend the focus on how collaboration in the food manufacturing supply chain members does impact the QM IoT adoption.

Some studies indicated challenges and influence of collaborative factors on the attitude toward IoT adoption and IoT adoption intention, such as in agriculture supply chain (Lin *et al.*, 2016) and food distribution (Shi and Yan, 2016), fish supply chain (Verdouw *et al.*, 2016), Malaysian SME (Chong *et al.*, 2009) and Greek fresh produce supply chain (Manos and Manikas, 2010). The definition, current literature and hypothesis of each factor under the collaborative structure were presented in Section 2.6.

Furthermore, the majority of current research focused on either the attitude toward IoT adoption or IoT adoption intention. However, this research crucially expanded the scope to study the impact of the attitude toward IoT adoption on the QM IoT adoption intention. Therefore, it could help cover the current literature gap and increase the understanding of the business practitioners on its role. Also, the conceptual model proposed in this research included both attitude and intention as mediating factor and as final independent variable, respectively. The hypothesis was shown in Section 2.7.

2.3 The technological context

2.3.1 Relative advantage. Relative advantage refers to the degree to which potential adopters rate the innovation's advantage as higher or lower than the current way of performing the same task. It could be measured economically – financial performance – or socially – satisfaction, reputation and convenience (Hwang *et al.*, 2016). Some research indicated that the relative advantage positively influenced IoT adoption, including the study in the Chinese agricultural supply chain (Lin *et al.*, 2016), Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020) and fish supply chain network (Verdouw *et al.*, 2016). The measure for IoT and cloud-based computing capabilities used for the fish supply chain network included potential saving, remote managing in real-time and efficient operations (Verdouw *et al.*, 2016), while the relative advantage from Taiwanese retailers focused on the period and amount from the return of investment (Hong *et al.*, 2011). As relative advantage showed its importance on IoT adoption in several industries, the following hypotheses have been proposed:

H1a. Relative advantage has a positive influence on attitude toward QM IoT adoption.

H1b. Relative advantage has a positive influence on QM IoT adoption intention.

2.3.2 Compatibility. Compatibility refers to the degree to which an innovation is perceived by the potential adopters to be consistent with the current values, previous experiences and needs (Rogers, 1995). In other words, the previous system or technology is perceived to be matched with the innovation (Liu *et al.*, 2014). Some research indicated that compatibility could positively influence or have a challenge in IoT adoption. For example, the hardware and bandwidth of cold chain firms might not be able to handle huge volume of data and implement monitoring systems (Jedermann *et al.*, 2009). In addition, the standardization of a common platform and transferring of own legacy systems and procedures on different platforms by the India retail supply chain (Kamble *et al.*, 2019b), standardization of traceability system for the cheese supply chain network (Jedermann *et al.*, 2009) and standardization of format in exchanging of information between various links in their network were other challenges for the IoT adoption (Aung and Chang, 2014). Furthermore, some research, including the Chinese agricultural supply chain (Lin *et al.*, 2016), was shown that compatibility positively influenced IoT adoption. Therefore, the following hypotheses have been proposed:

H2a. Compatibility has a positive influence on attitude toward QM IoT adoption.

H2b. Compatibility has a positive influence on QM IoT adoption intention.

2.3.3 Complexity. Complexity refers to the degree to which the potential adopters determine the understanding and difficulty of innovation usage. It had a negative correlation with the rate of adoption (Hwang *et al.*, 2016). Complexity showed a negative influence on IoT adoption in several food supply chains, including in the agricultural area (Lin *et al.*, 2016). In addition, the fish supply chain network members needed to deal with the virtually complexed dimensions, including their networks, objects, processes and controls (Verdouw *et al.*, 2016). In Malaysian Halal agro-food SMEs, they perceived that complexity was negatively and statistically significant in adopting IoT (Ahmad Tarmizi *et al.*, 2020). Several research on another innovation, such as Software-as-a-Service (SaaS), indicated that the complexity had a negative influence on its adoption by IT enterprises (Safari *et al.*, 2015) and in Indonesia (Mangula *et al.*, 2014). Another research also indicated that the complexity had a negative influence on cloud computing by higher education institutions in Saudi Arabia (Tashkandi and Al-Jabri, 2015). However, there was a controversy that the complexity was not found to be a significant factor that affected the adoption of cloud computing by high-tech industry firms (Low *et al.*, 2011). In this research, the following hypotheses have been proposed:

H3a. Complexity has a negative influence on attitude toward QM IoT adoption.

H3b. Complexity has a negative influence on QM IoT adoption intention.

2.3.4 Trialability. Trialability is the degree to which the innovation might be experimented with, where it can be done in a small portion (Hwang *et al.*, 2016). However, it was difficult for a firm to have a small pilot as a representative for the whole system since IoT referred to the system devices of large scales (Carlström and Silander Hahström, 2017). There were several controversies about the impact of IoT adoption depending on the industry. For example, Carlström and Silander Hahström (2017) addressed that trialability was one of the challenges of IoT adoption in the food retail value chain in Sweden. Thus, the trialability positively impacted IoT adoption. This positive impact on the adoption intention of trialability was also similar to the study of the technology adoption in the e-learning business in Taiwan (Lee *et al.*, 2011). However, trialability showed no significant impact on IoT adoption in the healthcare industry (Karahoca *et al.*, 2018). In this study, we expected that trialability could play an important role in QM IoT adoption therefore, the following hypotheses have been proposed:

H4a. Trialability has a positive influence on attitude toward QM IoT adoption.

H4b. Trialability has a positive influence on QM IoT adoption intention.

2.3.5 Observability. Observability is the degree to which the results of the innovation can be easily observed, discussed and represented among others (Hwang *et al.*, 2016; Liu *et al.*, 2014). Firms could observe and monitor the financial and operational results in real-time and with different measurable parameters from the IoT solutions. Observability, which showed good proof of IoT solutions, could influence the adoption of IoT in the food retail value chain (Carlström and Silander Hahström, 2017). In addition, observability was indicated as a positive indicator in the adoption of another innovation, such as SaaS by IT enterprises (Mangula *et al.*, 2014; Safari *et al.*, 2015). Another confirmation of the positive influence of observability in the adoption of innovation applied to the cloud computing service adoption in enterprises in Taiwan (Hsu and Lin, 2016). Even though the observability of the QM IoT adoption in a food supply chain was quite limited, the research in other innovation adoption reported it as a positive influencing factor. Therefore, the following hypotheses have been proposed:

H5a. Observability has a positive influence on attitude toward QM IoT adoption.

H5b. Observability has a positive influence on QM IoT adoption.

2.3.6 Perceived risk. Perceived risk refers to the transactions associated with the requirement for personal information disclosure (Dinev and Hart, 2006) and to the uncertainty regarding the possible consequences of utilizing a product or service (Featherman and Pavlou, 2003). The research in several contexts confirmed that perceived risk had a negative relationship with IoT adoption, such as in agriculture in the USA (Jayashankar *et al.*, 2018) and in the Internet-based bill payment services (Featherman and Pavlou, 2003). Perceived risk also negatively influenced both attitude toward home service IoT and intention to use it in Korea (Sung and Jo, 2018). Therefore, the following hypotheses have been proposed:

H6a. Perceived risk has a negative influence on attitude toward QM IoT adoption.

H6b. Perceived risk has a negative influence on QM IoT adoption intention.

2.3.7 Privacy concerns. Privacy concerns refers to the beliefs about who can access the information that is disclosed, and how it is used (Dinev and Hart, 2006). Security and privacy concerns were important for firms to determine when developing the IoT (Sheng *et al.*, 2010). The security and privacy of the IoT devices could not be compromised since attackers could abuse the information retrieved from IoT. For example, the attackers might gain access to private data from the sensors on IoT devices, such as light, magnetic and audio sensors if proper security are not put in place. Thus, these sensors could disperse a triggering message of malware or alter data types and storage locations (Sikder *et al.*, 2018). Apart from the front-end sensors and equipment security mentioned previously, the attackers could steal or change the communication of the information, such as modifying, inserting, deleting or replaying the user communication information (Du and Chao, 2010). The privacy concerns was also shown to be a challenge for the firms to adopt cloud computing (Al-Hujran *et al.*, 2018; Aqeel-ur-Rehman *et al.*, 2016). Therefore, the following hypotheses, in the food manufacturing context, have been proposed:

H7a. Privacy concerns has a negative influence on attitude toward QM IoT adoption.

H7b. Privacy concerns has a negative influence on QM IoT adoption intention.

2.4 The organizational context

2.4.1 Firm size. Firm size was originally shown in the TOE framework (Tornatzky *et al.*, 1990). Some research showed that the bigger the firm size, the higher chance that the firm would adopt IoT in the supply chain (Olushola, 2019), such as in the agricultural product distribution industry and supply chain in China (Lin *et al.*, 2016; Shi and Yan, 2016) and in the Irish SMEs that a larger firm tended to have more skills, time and staff to effectively adopt the IoT (cloud computing) than the smaller ones (Carcary *et al.*, 2014). However, there was a controversy among Malaysian Halal agro-food SMEs, which concluded that firm size was not reliable to determine the adoption of IoT (Ahmad Tarmizi *et al.*, 2020). In this study, we believed that firm size might play an essential role in adopting QM IoT in the food manufacturing supply chain. Therefore, the following hypotheses have been proposed:

H8a. Firm size has a positive influence on attitude toward QM IoT adoption.

H8b. Firm size has a positive influence on QM IoT adoption intention.

2.4.2 Adaptive capability. Adaptive capability refers to the firm's flexibility in the available resources and in applying these resources (Sanchez, 1995). Oktemgil and Greenley (1997) showed that a firm with high adaptive capability could respond and allocate resources to the changing market condition fast. Some research showed that some food supply chain members faced difficulty in allocating resources. For instance, firms need to prepare capital expenses for IoT installation and start-ups at the early stage, such as RFID gate reader (Jedermann *et al.*, 2009) and smart farm development (Walter *et al.*, 2017). Also, the operational expenses for day-to-day operations and technical support thereafter (Hong *et al.*, 2011) were another example that firms struggled with resource issues. In addition, education and training for the IoT was another challenge (Walter *et al.*, 2017). The research showed that small-scale producers from less developed countries encountered difficulty in adopting traceability systems due to the cost barrier. However, high-valued or high-risk food products could gain more benefits than the operations and installation costs of a traceability system (Aung and Chang, 2014). Therefore, the following hypotheses have been proposed:

H9a. Adaptive capability has a positive influence on attitude toward QM IoT adoption.

H9b. Adaptive capability has a positive influence on QM IoT adoption intention.

2.4.3 Absorptive capability. Absorptive capability is the ability of a firm to recognize the value of new information, assimilate it with firm's prior related knowledge and apply it through commercial ends (Cohen and Levinthal, 1990). Absorptive capability brought challenges for the firm to adopt the IoT. For instance, the higher the technical knowledge and skills of IoT, the higher chance the IoT adoption could be influenced in Chinese agricultural supply chain (Lin *et al.*, 2016), smart farming (Walter *et al.*, 2017) and Greek Fresh produce supply chain's traceability system (Manos and Manikas, 2010). Apart from the knowledge itself, the availability of skilled employees, such as the percentage of graduates in science technology engineering and mathematics (STEM) out of the total number of employees in Italy's transportation and logistics (Rey *et al.*, 2021), the analytical capability of employees in the Indian food retail supply chain block chain (Kamble *et al.*, 2019b), number of IT professionals to implement new technology available in the firms (Martins *et al.*, 2016) also positively impacted the IoT adoption. In addition, the study of US manufacturing firms also confirmed that the absorptive capacity facilitated the firms to integrate and implement the new technology (Liao *et al.*, 2010). However, Malaysian Halal agro-food SMEs perceived that firm size is not statically significant in adopting IoT (Ahmad Tarmizi *et al.*, 2020). Even though there was controversy on the role of absorptive capability in influencing the adoption of innovation, we believed that there might be an impact of it in this research. Therefore, the following hypotheses have been proposed:

H10a. Absorptive capability has a positive influence on attitude toward QM IoT adoption.

H10b. Absorptive capability has a positive influence on QM IoT adoption intention.

2.4.4 Innovative capability. Innovative capability's dimension refers to a firm's ability to develop new products or services, new markets, new processes and methods of production and/or new sources of supply through their strategic innovative orientation (Wang and Ahmed, 2007). In the context of transportation and logistics, innovation capacity refers to the firm's ability to innovate in long term through intangible assets, such as research and development expenses, patents and publications to adopt the new technology in the competitive markets (Rey *et al.*, 2021). Surprisingly, the results from some research showed that innovativeness showed no statistical significance in wireless Internet service via mobile technology (Lu *et al.*, 2005) and in the transportation and logistics context (Rey *et al.*, 2021). However, the result of the QM IoT in the food supply chain context might not be similar to other mentioned industries. Therefore, the following hypotheses have been proposed:

H11a. Innovative capability has a positive influence on attitude toward QM IoT adoption.

H11b. Innovative capability has a positive influence on QM IoT adoption intention.

2.4.5 Executive support. Executive support is the factor retrieved from the stakeholder theory. It has been widely applied to technology adoption research. It is important for firms to better enhance and promote this support since executive support positively impacted the adoption of IoT in the Chinese agricultural supply chain (Lin *et al.*, 2016) and in manufacturing firms (Chan and Chong, 2013). In addition, industrial experts, logistics service providers and academic scholars with logistics experience in Taiwan showed that executive support was the most essential factor that influenced IoT adoption since it helped increase organizational readiness and the expected benefits (Hsu and Yeh, 2017). Therefore, the following hypotheses have been proposed:

H12a. Executive support has a positive influence on attitude toward QM IoT adoption.

H12b. Executive support has a positive influence on QM IoT adoption intention.

2.5 The environmental context

2.5.1 Competitive pressure. Competitive pressure encourages a firm to adopt new technology to improve services, gain more competitive advantage (Lian *et al.*, 2014) or at least to survive in the competitive market (Al-Hujran *et al.*, 2018). Several studies showed that competitive pressure positively influenced the adoption of IoT. For example, competitive pressure could influence IoT adoption in the Taiwanese logistics industry (Hsu and Yeh, 2017). In addition, competitive pressure levels in the agricultural product distribution industry and supply chain in China showed significant positive relationship on the RFID adoption (Lin *et al.*, 2016; Shi and Yan, 2016). In this research, we expected that competitive pressure would exercise the same power, Therefore, the following hypotheses have been proposed:

H13a. Competitive pressure has a positive influence on attitude toward QM IoT adoption.

H13b. Competitive pressure has a positive influence on QM IoT adoption intention.

2.5.2 Value chain partner pressure. Value chain partner pressure receives from two main trading partners, including suppliers and customers. The supplier and customer's pressures were the convincing or compulsory powers that can influence the adoption of technological innovation (Chan and Chong, 2013; Hart and Saunders, 1997). The studies showed that the value chain partner pressure positively influenced the IoT adoption in the Chinese agricultural supply chain (Lin *et al.*, 2016). The partner's power positively impacted the adoption of an interorganizational system standards in the supply chain of Malaysian electrical and electronic organizations (Chong and Ooi, 2008). Additionally, some trading partners might restrict their suppliers to use technology, such as Electronic Data Interchange (EDI) to maintain a certain sales level. Thus, the power between partners could be fiercely based on buyer-imposed conditions (Hart and Saunders, 1997). However, there was a controversy on the influenceable impact of trading partners on the e-business adoption in Malaysian SMEs (Chong *et al.*, 2009) and on the mobile supply chain management systems in manufacturers in Malaysia (Chan and Chong, 2013). In this research, the authors insisted on testing the influencing pressure of value chain partner pressure on the QM IoT adoption. Therefore, the following hypotheses have been proposed:

H14a. Value chain partner pressure has a positive influence on attitude toward QM IoT adoption.

H14b. Value chain partner pressure has a positive influence on QM IoT adoption intention.

2.5.3 Social pressure. Not only do consumers keep eye on food safety, social pressure from the Food and Agriculture Organization of the United Nations (FAO) and the World Health Organization (WHO) can also influence and support global food safety and protect consumer's health along the food production chain from the farm to the end consumers (Food and Agriculture Organization of the United Nations, 2021). In addition, the Codex Alimentarius has collected internationally adopted food standards, guideline and codes of practice in a uniform manner to ensure the food are safe in respect of food hygiene, food additives, residues of pesticides and veterinary drugs, contaminants, labelling and presentation, methods of analysis and sampling and import and export inspection and certification. The standards from Codex would guide and facilitate international trade and harmonize the requirements (Codex Alimentarius Commission, 2021). In Thailand, the Food and Drug Administration (FDA) under the Ministry of Public Health could take legal actions for food manufacturers that did not comply with Good Manufacturing Process (GMP) law under section 6(7) of the Food Act B.E.2522 (Food and Drug Administration, 2021). Therefore, the food supply chain could be influenced by social pressure (Lin *et al.*, 2016) and needed to comply with quality management principles (Al-rub, 2020; Food and Drug Administration, 2021; International Organization for Standardization, 2015). Then, the following hypotheses have been proposed:

H15a. Social pressure has a positive influence on attitude toward QM IoT adoption.

H15b. Social pressure has a positive influence on QM IoT adoption intention.

2.5.4 Presence of the service provider. Presence of the service provider refers to the skilled labor, consultants or the suppliers of the technology service availability in the market (Rees *et al.*, 1984). A study showed that the majority of the visualization applications from IoT focused on monitoring and event management in a high level; however, the lower-level management and its integrated software solutions were still scarce (Verdouw *et al.*, 2016). Firms need to ensure both service provider availability and applications or systems that match with firms' requirement together. The study on cloud computing adoption in Jordan concluded that the cloud service provider needed to provide the benefits of technology that value the firm's executives. In addition, the service level agreement had to mutually benefit both parties as they need to rely on one another (Al-Hujran *et al.*, 2018). We could see that presence of service provider is an important factor to adapt new technology. Therefore, the following hypotheses have been proposed:

H16a. Presence of the service provider has a positive influence on attitude toward QM IoT adoption.

H16b. Presence of the service provider has a positive influence on QM IoT adoption intention.

2.5.5 Government support. Government support could be such as providing tax advantages and regulating the trustworthy business platform (Zhu *et al.*, 2003); however, the government can also pass the constraint to the firms instead (Borgman *et al.*, 2013). Some studies showed that when the government is supportive toward IoT-related projects, such as the Chinese agricultural supply chain (Lin *et al.*, 2016), pilot research on food traceability as appointed by the Taiwanese government (Hong *et al.*, 2011) and IoT adoption in the logistics industry in Taiwan (Hsu and Yeh, 2017), the IoT adoption would increase. In addition, the finding on the adoption of IoT in India's food retail supply chain showed that government interventions in the development of policies and regulations played an important role in the adoption (Kamble *et al.*, 2019b). The governments also played an important role in establishing the regulatory architecture to support the use of smart farm IoT and foster additional laws to regulate and monitor the use of those data (Walter *et al.*, 2017). In this research, we examined the impact of government support on QM IoT adoption in the food manufacturing supply chain. Therefore, the following hypotheses have been proposed:

H17a. Government regulation has a positive influence on attitude toward QM IoT adoption.

H17b. Government regulation has a positive influence on QM IoT adoption intention.

2.6 Collaborative structure

2.6.1 Trust. Trust is an important facilitator for collaborative activities, and it influences the adoption of inter-organizational system (Yang and Jarvenpaa, 2005). Some research showed that trust positively influenced QM IoT adoption in several industries, including the agriculture supply chain (Lin *et al.*, 2016) and food distribution (Shi and Yan, 2016). Moreover, the challenge of trust in the fish supply chain's network was also addressed since the data must be shared via cloud-based platform among sea carriers, freight forwarders and cargo owners (Verdouw *et al.*, 2016). In this research, we believed that trust would play an important role in influencing the firms in the food supply chain to adoption QM IoT. Therefore, the following hypotheses have been proposed:

H18a. Trust has a positive influence on attitude toward QM IoT adoption.

H18b. Trust has a positive influence on QM IoT adoption intention.

2.6.2 Information sharing. Information sharing was an important source to achieve supply chain integration, improve coordination among the supply chain networks and improve supply chain performance (Lyons *et al.*, 2005). Using information systems and technology could help advance information sharing to achieve collaboration and integration in real-time. Thus, the appropriate information sharing and information architecture could improve the supply chain quality operations (Xu, 2011). Information sharing was found to have a significant effect on the adoption of inter-organization systems, such as e-business adoption in Malaysian SMEs (Chong *et al.*, 2009). Besides, the study of the Greek fresh produce supply chain showed that the ephemeral dynamic collaboration blocked transparency with regard to the exchange of information among the supply chain members (Manos and Manikas, 2010). Therefore, the following hypotheses have been proposed:

H19a. Information sharing has a positive influence on attitude toward QM IoT adoption.

H19b. Information sharing has a positive influence on QM IoT adoption intention.

2.7 Attitude toward QM IoT adoption

The 19 factors discussed previously could directly influence the attitude toward QM IoT adoption and QM IoT adoption intention. In this section, the authors expanded the role of the attitude as a mediator between those 19 factors and intention. This is crucially important because firms may or may not actually have the adoption intention on the QM IoT even though their attitude toward adoption was high. Therefore, the following hypotheses have been proposed:

H20. The attitude toward QM IoT adoption has a positive influence on QM IoT adoption intention.

The conceptual model was proposed in Figure 1. The details of indicators of each factor were later explained in Table 1.

3. Research methodology

3.1 Target population

The target population was the 326 food processing manufacturers registered with the Food Processing Industry Club, the Federation of Thai Industry (Food Processing Industry Club, 2021). The Food Processing Industry Club strengthened performance of the members and worked closely with the government to solve and prevent the food-related issues. Therefore, these firms are indicated as good representatives in doing this research on QM IoT. A list of members' emails and phone numbers were provided on the federation website. The emails with a Google Form link were sent to all members, and the phone calls were also made to all members to ensure the reception of emails and as reminders. The researchers clearly stated in the email that a supervisor, assistant manager, manager or higher-level employees in the supply chain, logistics, operations, production, quality, information technology or related functions that work closely with operations was a representative for his or her firm. After four months of the survey, 201 distinct firm respondents answered the questionnaires via the Google Form. These sets of data were enough to analyze the structural equation modeling (SEM) (Barclay *et al.*, 1995; Hair *et al.*, 2011). Four sets of data were screened out due to data incompletion. Hence, 197 sets of data were used for further analysis.

3.2 Questionnaire development

In this research, there were two parts of the questionnaires, including general questions in Part 1 and QM IoT adoption questions in Part 2.

In Part 1, the general questions, including gender, age, education, current field of work, job level, total year of experience after graduated, company age, turnover per year, number of employees, company nationality, foreign shareholder(s) and foreign management. The respondents were asked to fill in their firm's names. However, the names would not be revealed in this research but just to ensure that there would be no duplication of answers from the same firm.

In Part 2, the total of 71 questions on the adoption factors tested with five experts in supply chain, industrial engineer, quality and IT fields were asked. All of them were developed from the literature as shown in Table 1. However, three social pressure questions (SCP02-SCP04) were developed by the authors together with the experts in food supply chain fields, and three of the presence of service providers questions (SPV01-SPV03) were developed by the expert from a well-known IoT firm. Five-point Likert scale was used since it can easily utilize the verbal response descriptors (Dawes, 2008) and reduce the frustration level of the respondents (Babakus and Mangold, 1992). The double translation (Mcgorry, 2000) was used, in which the first translator translated the questionnaires from English to Thai; then, the second

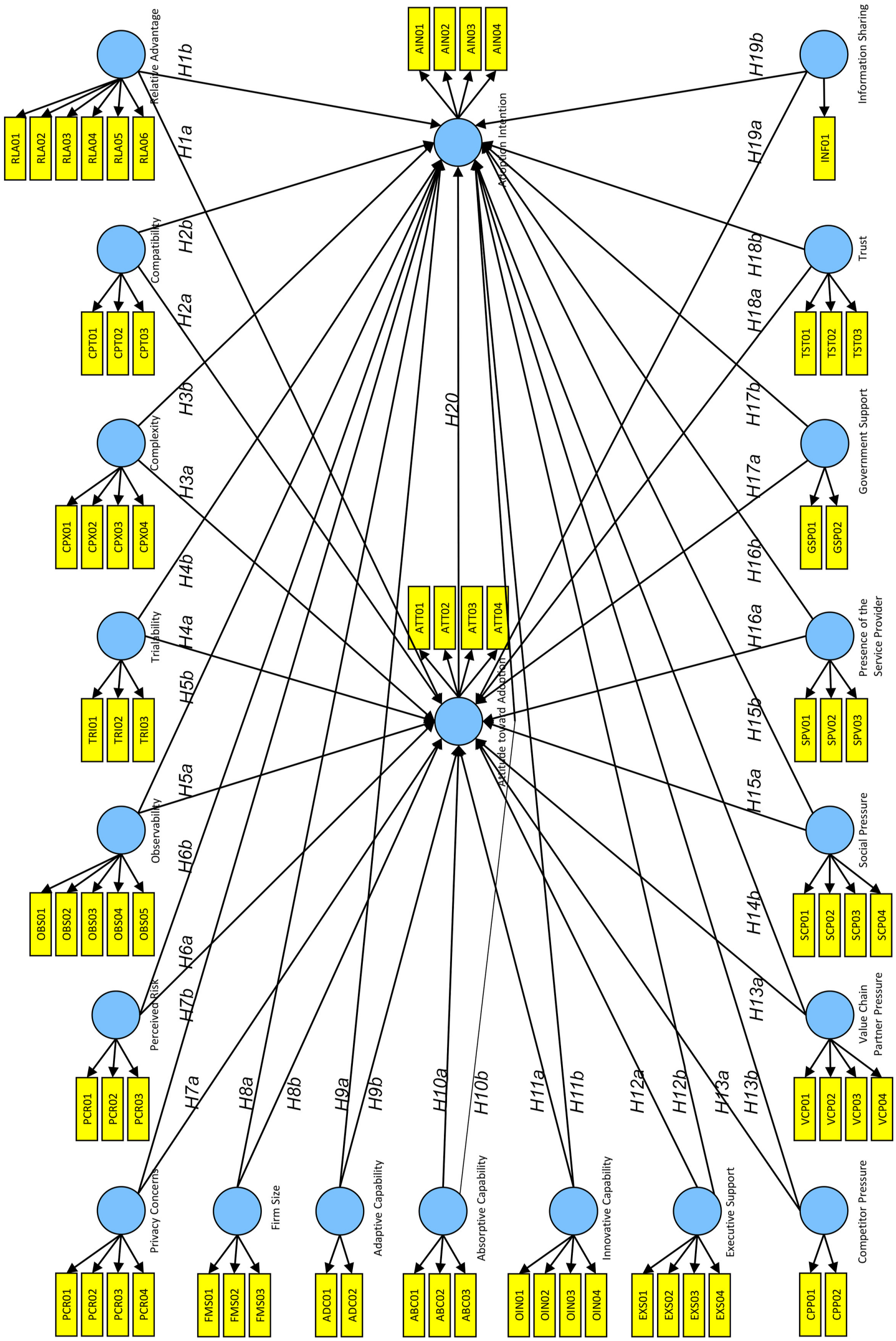

Figure 1.
Theoretical framework and hypothesis

Factors	Questionnaires	Reference
Relative advantage	RLA01 – QM IoT can make supply chain more transparent and visualization RLA02 – QM IoT can reduce the manpower cost RLA03 – QM IoT can improve the operating efficiency, enhance the speed of response and save time RLA04 – QM IoT can improve and support service RLA05 – QM IoT can improve reliability and delivery of products and services RLA06 – QM IoT can improve inventory turnover	Chong and Zhou (2014), Kamble *et al.* (2019a), Lin *et al.* (2016)
Compatibility	CPT01 – QM IoT can blend in the business flows in my supply chain well CPT02 – QM IoT can be compatible with other existing information systems (ERP, WMS, etc.) in my supply chain CPT03 – QM IoT can be compatible with the work content in my supply chain	Chong and Zhou (2014), Lin *et al.* (2016)
Complexity	CPX01 – QM IoT system is clear and understandable (Reverse) CPX02 – It easy to use QM IoT system do what I want them to do (Reverse) CPX03 – It is easy to learn and perform tasks using QM IoT system (Reverse) CPX04 – Using QM IoT should be easier compared to the conventional practices of managing supply chains. (Reverse)	Chong and Zhou (2014), Kamble *et al.* (2019a)
Trialability	TRI01 – My firm would like to trial QM IoT before deciding on whether or not to adopt TRI02 – My firm would like to properly trial QM IoT before deciding on whether or not to adopt TRI03 – My firm would have a chance to try QM IoT long enough to see what it can do	Karahoca *et al.* (2018)
Observability	OBS01 – My firm can easily see other firms using QM IoT in their work OBS02 – My firm has an opportunity to see other firms using QM IoT OBS03 – The benefits of QM IoT on my firm are obvious OBS04 – It is easy to find others sharing and discussing the usage of QM IoT with other firms OBS05 – My firm has seen the demonstrations and applications of QM IoT	Huang *et al.* (2020), Liu and Li (2010), Park and Chen (2007)
Perceived risk	PCR01 – My firm's information submitted via QM IoT can be misused PCR02 – My firm's information shared via QM IoT can be made available to others without my knowledge PCR03 – My firm's information shared via QM IoT can be inappropriately used	Dinev *et al.* (2006), Dinev and Hart (2006)
Privacy concerns	PVC01 – My firm is concerned that the information submitted on the QM IoT can be misused PVC02 – My firm is concerned about submitting information on the QM IoT, because of what others might do with it PVC03 – My firm is concerned about submitting information on the QM IoT, because it can be used in a way I did not foresee PVC04 – My firm is concerned that my firm's private information can show up on the QM IoT	Dinev *et al.* (2006)
Firm size	FMS01 – My firm is large enough to have more willingness to implement QM IoT FMS02 – My firm is large enough to have more resources to implement QM IoT FMS03 – My firm is large enough to have bigger chance to be successful in implementing QM IoT	Lin *et al.* (2016)

(*continued*)

Table 1. Questionnaire development

Factors	Questionnaires	Reference
Adaptive capability	ADC01 – Adopting the QM IoT technology will increase hardware equipment cost. (Reverse) ADC02 – Adopting the QM IoT technology will increase operating cost and maintenance cost. (Reverse)	Lin *et al.* (2016)
Absorptive capability	ABC01 – Supply chain firm has QM IoT related technical knowledge such as RFID, cloud storage and other IoT-related programs ABC02 – Supply chain firm has QM IoT technology-related professionals ABC03 – My firm is dedicated to ensuring that employees are familiar with QM IoT	Chan and Chong (2013), Lin *et al.* (2016)
Innovative capability	OIN01 – It would be beneficial for the firm to look for ways to experiment with new technology, such as QM IoT OIN02 – Among peers, my firm is usually the first to explore new technologies OIN03 – My firm likes to experiment with new technologies, such as QM IoT OIN04 – In general, I am hesitant to try out new technologies (Reverse)	Lu *et al.* (2005)
Executive support	EXS01 – Top management actively participates in establishing a vision and formulating strategies for utilizing QM IoT plan EXS02 – Top management communicates its support (manpower, money, etc.) for the use of QM IoT plan EXS03 – Top management is likely to take risk involved in implementing QM IoT plan EXS04 – Senior staffs seems encourage employees to plan applying QM IoT in daily work	Chan and Chong (2013), Lin *et al.* (2016)
Competitor pressure	CPP01 – My firm experiences competitive pressure to implement QM IoT CPP02 – My firm will have competitive disadvantage if we do not implement QM IoT	Chan and Chong (2013), Chong and Zhou (2014), Lin *et al.* (2016)
Value chain partner pressure	VCP01 – My firm's suppliers can encourage the implementation of QM IoT VCP02 – My firm's customers can encourage the implementation of QM IoT VCP03 – Incentive from trading partners will encourage us on implementing QM IoT VCP04 – If a firm has more bargaining power, it is able to demand its trading partners to implement QM IoT	Chan and Chong (2013), Chong and Zhou (2014), Lin *et al.* (2016)
Social pressure	SCP01 – Social factors such as culture, trend, other norms affect the adoption of QM IoT technology SCP02 – Legal factors, such as Food Act on the Good Manufacturing Process, encourage my firm to implement QM IoT SCP03 – Pressure from Non-Governmental Organization, such as from World Health Organization, Food and Agriculture Organization of the United Nations, CICOT or GS1 encourages my firm to implement QM IoT SCP04 – The pressure from trading agreement, such as from World Trade Organization and ASEAN Economic Community encourages my firm to implement QM IoT	Lin *et al.* (2016) and added by authors from pre-test
Presence of the service provider	SPV01 – Types of available technology (hardware and software) are important to implement QM IoT technology SPV02 – Product quality, such as the durability of hardware and reliability of software is important to implement QM IoT technology SPV03 – Before and after sales service is important to implement QM IoT technology	Added by authors from pre-test

Table 1.

(*continued*)

Factors	Questionnaires	Reference
Government support	GSP01 – The Thai Government provides financial support to the development of QM IoT technology GSP01 – The Thai Government publishes related policies to strongly support the development of QM IoT technology	Lin *et al.* (2016)
Trust	TST01 – There are good benefit distribution plans or mechanisms between my supply chain firms to realize benefit sharing TST02 – There are good risks sharing plans or mechanisms between my supply chain firms TST03 – My upstream and downstream supply chain firms help each other to promote the adoption of QM IoT technology	Lin *et al.* (2016)
Information sharing	INF01 – My firm is comfortable sharing our business operation information with trading partners and customers	Chong and Zhou (2014)
Attitude	ATT01 – From the firm's perspective, it is desirable to use QM IoT in the supply chain ATT02 – From the firm's perspective, it will be good for the supply chain to use QM IoT ATT03 – Overall, my firm's attitude toward QM IoT is favorable ATT04 – The firm's employees will feel happy if the firm implements QM IoT	Kamble *et al.* (2019a)
Intention to use	AIN01 – Our firm will use QM IoT in the future AIN02 – Our firm have a plan to try out QM IoT within the next year AIN03 – Predictively, our firm will use QM IoT on a regular basis in the future AIN04 – Our firm expects to use QM IoT for supply chain transactions	Kamble *et al.* (2019a), Lin *et al.* (2016)

Table 1.

translators translated them back from Thai to English; and finally, the authors compared both versions and adjusted the inconsistencies.

3.3 Partial least square structural equation modeling (PLS-SEM) assessment

This research used the SEM. Two main types of SEMs, including covariance-based SEM (CB-SEM) and partial least square SEM (PLS-SEM), have been widely applied to research. CB-SEM is more suitable for the confirmatory of the existing structural theory, while PLS-SEM is suitable for the exploratory or extension of an existing structural theory. Hence, PLS-SEM was more suitable as exploratory theory was the essence of this research. There are two assessment criteria for PLS-SEM, including the reflective measurement model assessment and the structural model assessment as shown in Figure 2.

Each assessment included four steps as explained thereafter. The reflective measurement model assessment included indicator reliability, internal consistency reliability, convergent validity and discriminant validity. The structural model assessment included collinearity assessment, explanatory power (R^2), predictive relevance (Q^2) and path coefficients' relevance and significance of the structural model relationship, respectively. The criteria and results were explained together with the finding in Section 4.2.

4. Research finding

4.1 Respondent profile

The respondents were female (58.4%), male (41.1%) and not specified (0.5%) with the major ages ranged between 35 and 45 (50.3%) and 25–35 (42.6%). The respondents mostly held a bachelor's degree (43.1%) and higher (56.9%). The top five fields of work were supply chain (27.4%), quality (23.9%), production (14.2%), operations (9.1%) and logistics (7.1%) with the

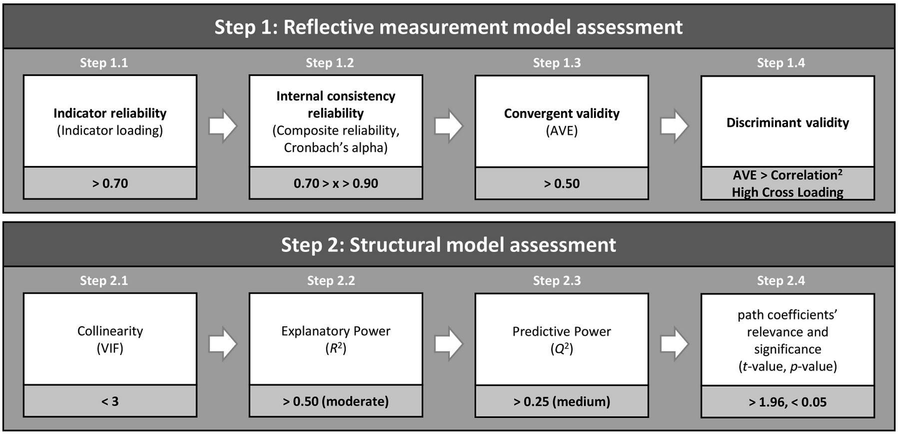

Figure 2.
PLS-SEM assessment criteria and steps

top three job levels, including manager (42.1%), supervisor (22.8%) and assistant manager (16.2%). The total year of experience after graduating between 6 and 10 (28.4%), 11–15 (25.95) and 16–20 (21.8%) years were the top three ranges. Majority of the company age was 15 years above (64.5%) with a turnover of 1,001–5,000 (25.9%), 501–1,000 (18.3%), and 101–500 (16.2%) million Thai Baht represented as the top three ranges. The firms mostly had employees ranged between 201 and 1,000 (39.6%); 1,001 and 5,000 (17.8%); and 51 and 200 (15.2%) people. More than half of the respondents' firms had Thai nationality (56.9%), Thai shareholders (59.4%) and no foreign management (58.9%); the rest was spreading throughout several foreign nationalities, shareholders and management.

4.2 Reflective measurement model assessment

First, the indicator reliability was assessed through the indicator loadings with the minimum requirement of 0.70 as it is indicated that the construct explained more than 50% of the indicator's variance (Hair *et al.*, 2019). After all indicators were measured, 54 indicators' loadings exceeded the minimum requirement, while nine indicators, including RLA02, CPX01, OBS04, OBS05, ADC01, OIN02, OIN04, EXS01 and VCP01, were dropped out as exhibited loadings below 0.70 since it would have adverse effects on the measures' convergent validity and internal consistency reliability (Sarstedt *et al.*, 2014).

Second, the internal consistency reliability was measured through the composite reliability and Cronbach's alpha with the recommended acceptable value between 0.70 and 0.90. However, the minimum value could be 0.60 in the exploratory research, and the maximum value could be 0.95 to avoid indicator redundancy which could compromise the content validity (Hair *et al.*, 2019). Majority of the composite reliabilities for all reflectively measured constructs were between 0.70 and 0.95 as shown in Table 2; however, four composite reliabilities from privacy concerns (PVC), adaptive capability (ADC), government supports (GSP) and information sharing (INF) were exceeded the 0.95, which might indicate redundancy; however, this research retained all of them in the model due to the reasons as followed. For PVC and GSP, the composite reliabilities showed 0.953 and 0.974, respectively. However, if we monitored the Cronbach's slpha for these two constructs, they showed the values at 0.938 and 0.947, respectively. Therefore, both were kept as their Cronbach's alphas were below the maximum requirement at 0.950. Besides, there was only one question in each ADC and INF construct. For ADC, one of two indicators was removed from the indicator reliability assessment. For INF, solely one question was asked to the respondents; thus,

	Indicator	Composite reliability	Cronbach's alpha	AVE	VIF (ATT)	VIF (AIN)
RLA	Relative advantage	0.908	0.876	0.665	2.070	2.070
CPT	Compatibility	0.891	0.818	0.732	1.760	1.830
CPX	Complexity	0.843	0.724	0.642	1.460	1.460
TRI	Trialability	0.915	0.861	0.781	1.630	1.690
OBS	Observability	0.860	0.768	0.673	1.610	1.630
PCR	Perceived risk	0.941	0.908	0.842	2.150	2.150
PVC	Privacy concerns	0.953	0.938	0.835	2.400	2.400
FMS	Firm size	0.931	0.890	0.819	1.760	1.760
ADC	Adaptive capability	1.000	1.000	1.000	1.250	1.280
ABC	Absorptive capability	0.913	0.867	0.777	1.620	1.620
OIN	Innovative capability	0.870	0.703	0.770	1.840	2.010
EXS	Executive support	0.872	0.778	0.694	1.540	1.580
CPP	Competitor pressure	0.831	0.653	0.715	1.350	1.350
VCP	Value chain partner pressure	0.874	0.786	0.697	1.740	1.780
SCP	Social pressure	0.891	0.837	0.673	1.590	1.620
SPV	Presence of the service provider	0.914	0.859	0.779	1.610	1.720
GSP	Government support	0.974	0.947	0.949	1.330	1.360
TST	Trust	0.912	0.854	0.776	1.710	1.710
INF	Information sharing	1.000	1.000	1.000	1.470	1.660
ATT	Attitude toward adoption	0.877	0.812	0.641	–	2.790
AIN	Adoption intention	0.911	0.868	0.719	–	–

Table 2. Composite reliability, Cronbach's alpha, AVE, and VIF

reporting number as 1.000 had no redundant issue for ADC and INF. Furthermore, the Cronbach's alpha for all constructs passed the minimum requirement at 0.70, except CCP valued slightly lower than 0.70 at 0.653. This construct was kept as its composite reliability indicated the satisfied value at 0.831. ADC and INF values showed at 1.000 were not an issue as a prior explanation.

Third, the convergent validity was measured through the average variance extracted (AVE) values. The criteria of 0.50 or higher indicated that the construct explained at least 50% of the variance of its items (Hair *et al.*, 2019). All AVE values for this model exceeded 0.5 for the reflective constructs as shown in Table 2; therefore, all constructs indicated convergent validity.

Fourth, the discriminant validity was then assessed. All AVE values of each latent construct in Table 2 were higher than the construct's highest squared correlation with any other latent construct (Fornell–Larcker criterion) (Hair *et al.*, 2011) in Table 3. In addition, all indicator's loadings for each construct were higher than its cross-loading (Hair *et al.*, 2011) as shown in Table 4. Therefore, each construct was empirically distinct from other constructs.

4.3 Structural model assessment

First, the collinearity was assessed by means of the VIF. The VIF values of 3 or less would be ideal to confirm that there was no collinearity issue (Hair *et al.*, 2019). There was no collinearity issue since all VIFs valued less than 3 under both ATT and AIN dependent variable tests as shown in Table 2.

Second, the explanatory power (R^2) measures the model's explanatory power value with the range from 0 to 1, where the higher value represents greater explanatory power. The value of 0.75, 0.50 and 0.25 is considerate as substantial, moderate and weak, respectively (Hair *et al.*, 2019). Both endogenous constructs indicated 0.642 for the attitude toward QM IoT

Table 3. The construct's highest squared correlation with any other latent construct

	RLA	CPT	CPX	TRI	OBS	PCR	PVC	FMS	ADC	ABC	OIN	EXS	CPP	VCP	SCP	SPV	GSP	TST	INF
RLA	1.000																		
CPT	0.321	1.000																	
CPX	0.135	0.116	1.000																
TRI	0.170	0.040	0.083	1.000															
OBS	0.122	0.117	0.203	0.108	1.000														
PCR	0.012	0.025	0.002	0.001	0.002	1.000													
PVC	0.002	0.005	0.010	0.000	0.000	0.463	1.000												
FMS	0.030	0.103	0.078	0.026	0.088	0.011	0.006	1.000											
ADC	0.003	0.007	0.005	0.016	0.002	0.041	0.097	0.001	1.000										
ABC	0.004	0.032	0.014	0.008	0.075	0.002	0.001	0.191	0.010	1.000									
OIN	0.193	0.101	0.087	0.206	0.113	0.005	0.014	0.110	0.000	0.005	1.000								
EXS	0.049	0.047	0.017	0.075	0.075	0.006	0.022	0.065	0.000	0.095	0.169	1.000							
CPP	0.017	0.010	0.010	0.006	0.036	0.007	0.013	0.087	0.000	0.046	0.043	0.021	1.000						
VCP	0.102	0.040	0.035	0.047	0.119	0.007	0.022	0.080	0.009	0.019	0.153	0.019	0.174	1.000					
SCP	0.066	0.061	0.044	0.028	0.074	0.005	0.020	0.097	0.007	0.006	0.059	0.014	0.062	0.201	1.000				
SPV	0.177	0.035	0.041	0.166	0.043	0.006	0.002	0.028	0.030	0.008	0.141	0.035	0.002	0.103	0.108	1.000			
GSP	0.002	0.001	0.001	0.004	0.007	0.040	0.006	0.017	0.005	0.003	0.002	0.016	0.001	0.001	0.026	0.001	1.000		
TST	0.039	0.065	0.038	0.006	0.051	0.018	0.010	0.096	0.000	0.070	0.051	0.112	0.041	0.054	0.126	0.057	0.119	1.000	
INF	0.032	0.050	0.048	0.027	0.038	0.000	0.030	0.061	0.002	0.026	0.057	0.019	0.021	0.010	0.089	0.063	0.013	0.150	1.000

	RLA	CPT	CPX	TRI	OBS	PCR	PVC	FMS	ADC	ABC	OIN	EXS	CPP	VCP	SCP	SPV	GSP	TST	INF
RLA01	0.792	0.441	−0.275	0.255	0.344	−0.172	−0.048	0.161	−0.021	0.070	0.216	0.145	0.097	0.232	0.219	0.293	0.016	0.152	0.107
RLA03	0.778	0.413	−0.255	0.365	0.163	−0.033	−0.002	0.078	−0.100	−0.042	0.399	0.125	0.020	0.237	0.218	0.349	0.047	0.144	0.130
RLA04	0.819	0.474	−0.330	0.369	0.280	−0.170	−0.030	0.111	−0.104	0.071	0.323	0.136	0.103	0.242	0.192	0.342	−0.015	0.109	0.143
RLA05	0.841	0.458	−0.343	0.326	0.305	−0.124	−0.109	0.147	−0.015	0.011	0.361	0.153	0.069	0.314	0.196	0.370	0.038	0.137	0.124
RLA06	0.846	0.510	−0.297	0.362	0.321	−0.005	0.009	0.181	−0.013	0.130	0.443	0.286	0.204	0.267	0.225	0.355	0.056	0.228	0.198
CPT01	0.453	0.859	−0.278	0.183	0.330	−0.194	−0.075	0.329	0.063	0.166	0.260	0.216	0.009	0.146	0.233	0.124	0.018	0.236	0.181
CPT02	0.431	0.849	−0.301	0.103	0.272	−0.143	−0.079	0.265	0.109	0.170	0.263	0.166	0.117	0.153	0.211	0.097	0.047	0.231	0.188
CPT03	0.562	0.859	−0.297	0.223	0.278	−0.073	−0.036	0.233	0.044	0.125	0.290	0.172	0.133	0.212	0.191	0.252	0.008	0.190	0.204
CPX02	−0.276	−0.311	0.781	−0.179	−0.401	0.049	0.045	−0.195	−0.115	−0.097	−0.191	−0.080	−0.090	−0.100	−0.175	−0.119	−0.055	−0.205	−0.158
CPX03	−0.252	−0.328	0.829	−0.159	−0.372	0.086	0.121	−0.292	−0.077	−0.158	−0.237	−0.168	−0.173	−0.199	−0.201	−0.133	0.020	−0.170	−0.159
CPX04	−0.349	−0.196	0.793	−0.339	−0.321	−0.031	0.072	−0.182	0.006	−0.031	−0.271	−0.060	0.011	−0.141	−0.131	−0.220	−0.057	−0.109	−0.207
TRI01	0.358	0.197	−0.255	0.894	0.253	−0.014	−0.064	0.180	−0.048	−0.121	0.454	0.274	0.091	0.233	0.138	0.387	−0.065	0.094	0.165
TRI02	0.351	0.132	−0.266	0.887	0.291	0.039	0.000	0.140	−0.159	−0.005	0.359	0.216	0.093	0.160	0.182	0.351	−0.028	0.062	0.177
TRI03	0.385	0.197	−0.246	0.870	0.334	0.064	0.066	0.099	−0.145	−0.098	0.379	0.229	0.019	0.172	0.127	0.337	−0.066	0.046	0.094
OBS01	0.197	0.159	−0.365	0.210	0.826	0.007	−0.001	0.182	−0.049	0.196	0.241	0.199	0.174	0.268	0.247	0.107	0.070	0.152	0.167
OBS02	0.163	0.208	−0.344	0.205	0.842	0.002	−0.083	0.190	0.005	0.251	0.222	0.284	0.050	0.191	0.219	0.087	0.141	0.218	0.193
OBS03	0.427	0.405	−0.386	0.349	0.792	0.075	0.093	0.317	−0.051	0.222	0.332	0.195	0.216	0.354	0.207	0.265	0.014	0.180	0.131
PCR01	−0.119	−0.155	0.042	0.000	0.060	0.909	0.612	−0.045	−0.167	−0.002	−0.044	−0.019	0.087	0.103	0.114	0.066	0.156	0.198	0.031
PCR02	−0.074	−0.101	−0.017	0.044	0.027	0.903	0.621	−0.120	−0.172	−0.064	−0.065	−0.105	0.034	0.070	0.060	0.060	0.229	0.101	0.017
PCR03	−0.100	−0.162	0.064	0.047	0.025	0.941	0.643	−0.132	−0.215	−0.076	−0.079	−0.099	0.092	0.059	0.012	0.084	0.184	0.060	−0.033
PVC01	−0.055	−0.068	0.091	−0.016	0.013	0.649	0.936	−0.063	−0.260	−0.031	−0.145	−0.154	0.105	0.159	0.135	0.034	0.101	0.097	−0.191
PVC02	−0.058	−0.036	0.058	−0.006	0.004	0.638	0.905	−0.073	−0.227	−0.019	−0.095	−0.114	0.125	0.107	0.156	−0.020	0.084	0.099	−0.172
PVC03	−0.022	−0.094	0.130	−0.005	0.029	0.603	0.942	−0.063	−0.376	−0.020	−0.095	−0.111	0.107	0.119	0.125	0.059	0.045	0.090	−0.132
PVC04	−0.012	−0.041	0.059	0.041	0.006	0.637	0.869	−0.138	−0.204	−0.083	−0.070	−0.205	0.080	0.174	0.108	0.082	0.060	0.079	−0.143
FMS01	0.155	0.269	−0.220	0.156	0.280	−0.003	0.020	0.902	−0.073	0.388	0.299	0.237	0.274	0.263	0.263	0.166	−0.144	0.284	0.260
FMS02	0.073	0.268	−0.268	0.091	0.251	−0.114	−0.113	0.900	0.023	0.452	0.227	0.201	0.241	0.241	0.297	0.072	−0.058	0.308	0.162
FMS03	0.220	0.329	−0.275	0.175	0.271	−0.171	−0.135	0.912	−0.005	0.360	0.358	0.249	0.280	0.259	0.291	0.200	−0.138	0.256	0.237
ADC02	−0.055	0.083	−0.070	−0.127	−0.041	−0.203	−0.311	−0.024	1.000	−0.102	0.012	0.018	−0.003	−0.094	−0.085	−0.174	0.072	−0.014	−0.047
ABC01	0.087	0.184	−0.106	−0.050	0.292	−0.008	0.029	0.347	−0.116	0.879	0.059	0.280	0.159	0.137	0.023	−0.045	0.061	0.219	0.082
ABC02	0.019	0.102	−0.142	−0.123	0.225	−0.005	−0.002	0.383	−0.128	0.854	0.010	0.168	0.219	0.118	0.078	−0.132	0.036	0.199	0.084
ABC03	0.051	0.158	−0.089	−0.088	0.213	−0.084	−0.086	0.424	−0.057	0.910	0.081	0.307	0.205	0.115	0.107	−0.091	0.044	0.262	0.210
OIN01	0.433	0.326	−0.254	0.399	0.230	−0.127	−0.083	0.265	0.004	0.011	0.857	0.277	0.142	0.361	0.186	0.381	−0.078	0.177	0.080
OIN03	0.347	0.239	−0.264	0.399	0.351	−0.002	−0.120	0.314	0.016	0.103	0.897	0.433	0.218	0.329	0.236	0.286	−0.007	0.218	0.322
EXS02	0.199	0.205	−0.154	0.204	0.264	0.008	−0.041	0.258	−0.083	0.343	0.367	0.848	0.121	0.188	0.208	0.188	0.148	0.336	0.160

(*continued*)

Table 4.
Cross loading

	RLA	CPT	CPX	TRI	OBS	PCR	PVC	FMS	ADC	ABC	OIN	EXS	CPP	VCP	SCP	SPV	GSP	TST	INF
EXS03	0.153	0.126	−0.071	0.281	0.252	−0.096	−0.144	0.187	−0.006	0.256	0.373	0.876	0.217	0.114	0.077	0.100	0.045	0.272	0.095
EXS04	0.200	0.209	−0.092	0.200	0.161	−0.108	−0.195	0.190	0.148	0.161	0.282	0.772	0.021	0.032	−0.007	0.179	0.121	0.220	0.089
CPP01	−0.019	0.038	0.010	−0.024	0.144	0.161	0.151	0.216	−0.100	0.310	0.053	0.126	0.716	0.249	0.186	−0.125	0.001	0.265	0.105
CPP02	0.173	0.112	−0.131	0.106	0.177	0.037	0.082	0.281	0.037	0.140	0.238	0.131	0.958	0.420	0.235	0.108	−0.035	0.146	0.137
VCP02	0.232	0.101	−0.134	0.151	0.290	0.090	0.125	0.187	−0.132	0.137	0.322	0.117	0.345	0.809	0.241	0.275	0.007	0.126	0.074
VCP03	0.349	0.160	−0.160	0.268	0.344	0.017	0.088	0.229	−0.166	0.105	0.312	0.152	0.334	0.851	0.382	0.323	−0.016	0.152	0.078
VCP04	0.216	0.223	−0.170	0.120	0.235	0.111	0.157	0.278	0.041	0.113	0.347	0.079	0.367	0.845	0.463	0.212	0.061	0.282	0.095
SCP01	0.314	0.271	−0.292	0.137	0.275	−0.047	0.083	0.235	−0.065	0.109	0.294	0.107	0.165	0.386	0.729	0.255	0.082	0.271	0.173
SCP02	0.183	0.224	−0.092	0.137	0.217	0.078	0.133	0.231	−0.028	0.049	0.231	0.091	0.192	0.455	0.835	0.282	0.101	0.218	0.189
SCP03	0.163	0.156	−0.167	0.148	0.189	0.088	0.102	0.266	−0.082	0.036	0.137	0.107	0.233	0.289	0.870	0.255	0.176	0.361	0.339
SCP04	0.171	0.137	−0.128	0.123	0.196	0.115	0.151	0.298	−0.114	0.063	0.104	0.075	0.229	0.309	0.841	0.278	0.179	0.331	0.301
SPV01	0.367	0.202	−0.185	0.348	0.217	0.096	0.012	0.180	−0.186	−0.049	0.327	0.174	0.106	0.311	0.315	0.896	0.029	0.229	0.305
SPV02	0.356	0.133	−0.150	0.367	0.150	0.066	0.033	0.109	−0.095	−0.108	0.309	0.178	−0.020	0.219	0.262	0.892	0.058	0.196	0.177
SPV03	0.396	0.156	−0.199	0.367	0.174	0.036	0.072	0.152	−0.177	−0.090	0.361	0.140	0.022	0.319	0.289	0.859	−0.027	0.206	0.164
GSP01	0.073	0.054	−0.058	−0.046	0.107	0.203	0.105	−0.112	0.048	0.048	−0.049	0.089	−0.026	0.029	0.166	0.037	0.968	0.346	0.128
GSP02	0.011	0.005	−0.019	−0.071	0.061	0.189	0.054	−0.139	0.087	0.059	−0.041	0.151	−0.028	0.017	0.148	0.014	0.980	0.328	0.098
TST01	0.243	0.243	−0.215	0.116	0.201	0.170	0.101	0.238	0.012	0.159	0.238	0.273	0.172	0.224	0.350	0.291	0.324	0.914	0.323
TST02	0.168	0.245	−0.185	0.070	0.183	0.146	0.135	0.328	−0.053	0.202	0.187	0.292	0.204	0.220	0.358	0.214	0.315	0.934	0.369
TST03	0.091	0.176	−0.099	0.006	0.222	0.012	0.012	0.255	0.009	0.381	0.170	0.335	0.161	0.161	0.211	0.103	0.269	0.788	0.337
INF01	0.178	0.224	−0.220	0.164	0.196	0.003	−0.174	0.248	−0.047	0.160	0.239	0.139	0.144	0.100	0.299	0.251	0.114	0.387	1.000
ATT01	0.313	0.346	−0.295	0.424	0.328	−0.021	−0.144	0.330	0.120	0.091	0.555	0.337	0.210	0.308	0.263	0.334	0.178	0.341	0.452
ATT02	0.490	0.390	−0.260	0.442	0.384	−0.044	−0.048	0.221	0.001	0.029	0.538	0.281	0.133	0.367	0.264	0.518	0.024	0.242	0.362
ATT03	0.374	0.355	−0.178	0.331	0.305	−0.007	−0.069	0.250	0.001	0.078	0.481	0.444	0.093	0.230	0.081	0.404	0.135	0.275	0.351
ATT04	0.331	0.297	−0.238	0.323	0.303	−0.005	−0.082	0.249	0.055	0.161	0.375	0.267	0.241	0.336	0.293	0.308	0.016	0.228	0.251
AIN01	0.329	0.319	−0.248	0.401	0.330	−0.056	−0.095	0.359	0.074	0.085	0.535	0.319	0.271	0.290	0.133	0.307	−0.019	0.210	0.337
AIN02	0.089	0.252	−0.128	0.091	0.320	−0.014	−0.128	0.373	0.150	0.279	0.339	0.409	0.277	0.186	0.218	0.041	0.166	0.345	0.307
AIN03	0.280	0.359	−0.292	0.327	0.358	0.055	−0.071	0.320	0.157	0.227	0.478	0.382	0.275	0.303	0.276	0.285	0.106	0.370	0.460
AIN04	0.302	0.341	−0.190	0.409	0.298	0.019	−0.061	0.293	0.102	0.086	0.557	0.338	0.200	0.249	0.188	0.323	0.029	0.293	0.386

Table 4.

adoption and 0.598 for the QM IoT adoption intention. The explanatory power for both constructs was considered as moderate since the values were above 0.5.

Third, the predictive relevance (Q^2) was measured by using blindfolding to obtain cross-validated redundancy to measure the PLS path model's predictive accuracy with the criteria of 0, 0.25 and 0.50 as small, medium and large predictive relevance of the PLS-path model, respectively (Hair *et al.*, 2019). Some researchers indicated that 0.35 already showed large predictive relevance (Chin, 2010). The value of 0.409 for the attitude toward QM IoT adoption and 0.423 for the QM IoT adoption intention was calculated in this research. Therefore, the exogenous constructs had large predictive relevance for both endogenous constructs.

Finally, the bootstrapping technique was used to assess the path coefficients' relevance and significance of the structural model relationship. The t value higher than 1.96 ($p \leq 0.05$) showed statistical significance (Kock, 2016). The results revealed that 12 out of 39 structural relationships are significant ($p \leq 0.05$). It included eight factors that significantly impacted the attitude toward adoption (ATT), three factors that showed a direct impact on the adoption intention (AIN), and attitude toward adoption (ATT) significantly impacted the adoption intention (AIN) as shown in Table 5.

The eight factors that significantly impacted the attitude toward QM IoT adoption (ATT) were summarized as followed. First, compatibility (β: 0.1703; t-stat: 2.730; p-value $\leq$ 0.01) and trialability (β: 0.1662; t-stat: 2.711; p-value $\leq$ 0.01) were two significant factors under the technological context. Therefore, H2a and H4a were accepted. Second, adaptive capability (β: 0.0711; t-stat: 2.349; p-value $\leq$ 0.05), innovative capability (β: 0.2249; t-stat: 3.662; p-value $\leq$ 0.001) and executive support (β: 0.1270; t-stat: 2.330; p-value $\leq$ 0.05) were three significant factors under the organizational context. Therefore, H9a, H11a and H12a were accepted. Third, value chain partner pressure (β: 0.1034; t-stat: 2.139; p-value $\leq$ 0.05) and presence of the service provider (β: 0.1561; t-stat: 3.412; p-value $\leq$ 0.001) were two significant factors under the environmental context. Therefore, H14a and H16a were accepted. Finally, information sharing (β: 0.2265; t-stat: 3.727; p-value $\leq$ 0.001) was the sole significant factor in the collaborative context. Therefore, H19a was accepted. The rest of the hypothesis, including H1a, H3a, H5a, H6a, H7a, H8a, H10a, H13a, H15a, H17a and H18a were rejected.

There were three factors that showed a direct impact on the QM IoT adoption intention (AIN). First, there was no technological factor that directly impact the adoption intention. Second, adaptive capability (β: 0.0661; t-stat: 2.166; p-value $\leq$ 0.05) and innovative capability (β: 0.2287; t-stat: 2.986; p-value $\leq$ 0.01) showed a direct impact on the adoption intention under the organizational context. Therefore, H9b and H11b were accepted. Third, there was no environmental factor that directly impact the adoption intention. Finally, information sharing (β: 0.0785; t-stat: 2.819; p-value $\leq$ 0.01) was the sole factor showing a direct impact on the adoption intention under the environmental context. Therefore, H19b was accepted. In addition, the attitude toward adoption (ATT) (β: 0.3765; t-stat: 3.422; p-value $\leq$ 0.001) significantly impacted the adoption intention (AIN). Therefore, H20 was accepted. The rest of the insignificant factors and rejected hypothesis, including H1b, H2b, H3b, H4b, H5b, H6b, H7b, H8b, H10b, H12b, H13b, H14b, H15b, H16b, H17b and H18b, were shown in Table 5.

5. Discussion

In this section, the significant factors that impacted the attitudes toward QM IoT adoption and QM IoT adoption intention were discussed in Sections 5.1 and 5.2, respectively.

5.1 Factors impacted the attitude toward QM IoT adoption

There were two technological factors, including compatibility and trialability that were essential for the attitude toward QM IoT adoption for the food supply chain in Thailand.

Table 5.
Path coefficients' relevance and significance

Abbreviation	Factors	Attitude toward adoption (ATT) t stat	Path coefficient	Hypothesis	Adoption intention (AIN) t stat	Path coefficient	Hypothesis
RLA	Relative advantage	0.353	−0.0213	H1a	1.357	−0.1647	H1b
CPT	Compatibility	2.730	0.1703 **	H2a	1.572	0.1483	H2b
CPX	Complexity	0.995	0.0400	H3a	0.809	0.0392	H3b
TRI	Trialability	2.711	0.1662 **	H4a	1.473	0.0825	H4b
OBS	Observability	1.539	0.1032	H5a	1.192	0.0734	H5b
PCR	Perceived risk	0.031	0.0351	H6a	0.612	0.0848	H6b
PVC	Privacy concerns	0.118	−0.0535	H7a	0.118	−0.0637	H7b
FMS	Firm size	0.812	0.0161	H8a	1.270	0.0328	H8b
ADC	Adaptive capability	2.349	0.0711 *	H9a	2.166	0.0661 *	H9b
ABC	Absorptive Capability	0.485	−0.0499	H10a	0.234	0.0043	H10b
OIN	Innovative capability	3.662	0.2249 ***	H11a	2.986	0.2287 **	H11b
EXS	Executive support	2.330	0.1270 *	H12a	1.481	0.0528	H12b
CPP	Competitor pressure	0.322	0.0361	H13a	1.803	0.1287	H13b
VCP	Value chain partner pressure	2.139	0.1034 *	H14a	0.006	−0.0420	H14b
SCP	Social pressure	1.289	−0.0908	H15a	0.633	−0.0358	H15b
SPV	Presence of the service provider	3.412	0.1561 ***	H16a	0.175	−0.0540	H16b
GSP	Government support	1.341	0.0921	H17a	0.132	0.0043	H17b
TST	Trust	0.021	0.0258	H18a	0.493	0.1270	H18b
INF	Information sharing	3.727	0.2265 ***	H19a	2.819	0.0785 **	H19b
ATT	Attitude toward adoption				3.422	0.3765 ***	H20

Note(s): *$p \leq 0.05$, **$p \leq 0.01$, ***$p \leq 0.001$

Similar to previous research in the agricultural supply chain (Lin *et al.*, 2016), cold chain firms (Jedermann *et al.*, 2009) and India retail supply chain (Kamble *et al.*, 2019b), compatibility also indicated as an important factor on the attitude toward QM IoT adoption among food supply chain firms in Thailand. In addition, the role of trialability also aligned with the research in the Swedish food retail chain (Carlström and Silander Hahström, 2017) and in Taiwanese e-learning technology (Lee *et al.*, 2011). However, it was contrasted with the healthcare industry (Karahoca *et al.*, 2018).

There were three organizational factors, including adaptive capability, innovative capability and executive support that significantly impacted the attitude toward QM IoT adoption for the food supply chain in Thailand. The result of adaptive capability was crucially important as the previous studies, such as in cold chain transportation (Jedermann *et al.*, 2009) and smart farm development (Walter *et al.*, 2017). In addition, innovative capability was an essential factor that could influence the attitude toward QM IoT adoption for the food supply chain in Thailand. It was not consistent in its role with previous research, such as in transportation and logistics (Rey *et al.*, 2021) and wireless Internet service via mobile technology (Lu *et al.*, 2005). Furthermore, the role of executive support was as important as previous studies in the Chinese agricultural supply chain (Lin *et al.*, 2016), manufacturing firms (Chan and Chong, 2013) and logistics areas in Taiwan (Hsu and Yeh, 2017).

There were two environmental factors, including the value chain partner pressure and the presence of the service provider that were essential for the attitude toward QM IoT adoption for the food supply chain in Thailand. The value chain partner pressure was an important determinant in previous studies, such as in the Chinese agricultural supply chain (Lin *et al.*, 2016) and supply chain in Malaysian electrical and electronic organizations (Chong and Ooi, 2008). However, there was a controversy on the influenceable impact of trading partners on e-business adoption in Malaysian SMEs (Chong *et al.*, 2009) and the mobile supply chain management systems in manufacturers in Malaysia (Chan and Chong, 2013). Besides, the presence of the service provider was an important determinant on the attitude toward QM IoT adoption. It was consistent with previous technology-related studies, such as in integrated software solutions (Verdouw *et al.*, 2016) and cloud computing adoption in Jordan (Al-Hujran *et al.*, 2018).

Information sharing was the only factor under the collaborative structure that could influence the attitude toward QM IoT adoption for the food supply chain in Thailand. It was consistent with previous studies, such as e-business adoption in Malaysian SME (Chong *et al.*, 2009) and the Greek fresh produce supply chain (Manos and Manikas, 2010).

5.2 Factors impacted the QM IoT adoption intention

Apart from the attitude toward adoption, this research also extended to the QM IoT adoption intention in food supply chain in Thailand. There were two organizational factors and one collaborative factor, including the adaptive capability, innovative capability and information sharing, respectively, that were essential for the QM IoT adoption intention for the food supply chain in Thailand. Adaptive capability was indicated as an important factor that could directly affect the adoption intention for the food supply chain in Thailand as in the previous studies, such as in the agricultural context (Lin *et al.*, 2016). In addition, the innovation capacity was another strong factor that directly impacted the adoption intention. It was not consistent in its role with previous research, such as in transportation and logistics (Rey *et al.*, 2021) and wireless Internet service via mobile technology (Lu *et al.*, 2005). In addition, information sharing was also important and consistent with previous studies, such as e-business adoption in Malaysian SMEs (Chong *et al.*, 2009) and Greek fresh produce supply chain (Manos and Manikas, 2010). The attitude toward QM IoT adoption had a positive influence on QM IoT adoption intention. As a result, it mediated compatibility, trialability, adaptive capability, organizational innovativeness, executive support, value chain partner pressure, presence of the service provider and information sharing on adoption intention significance. It was aligned with the previous study on the essential influence of attitude on intention, such as in the blockchain adoption intention (Kamble *et al.*, 2019a).

5.3 Factor showing no impact on attitude or intention

There were several factors that did not impact the attitude toward QM IoT and QM IoT adoption intention. The five factors under the technological context were firstly discussed. The result for the relative advantage was not consistent with some research, such as in agricultural supply chain (Lin *et al.*, 2016), Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020) and fish supply chain (Verdouw *et al.*, 2016). However, this research aligned with some research, including the adoption of big data in the fashion industry (Chen *et al.*, 2015) and the adoption of e-commerce in the hotel industry (Mndzebele, 2013). The relative advantage was not a sufficient condition for the firm in the food processing supply chain to adopt QM IoT even though the firms understand that QM IoT could provide benefits. In addition, the result of the complexity contrasted with the previous studies that showed a negative influence on the Chinese agricultural supply chain (Lin *et al.*, 2016), the fish supply chain (Verdouw *et al.*, 2016) and Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020). The result of the complexity also contrasted with other research on the adoption of SaaS (Mangula *et al.*, 2014; Safari *et al.*, 2015) and cloud computing (Tashkandi and Al-Jabri, 2015) that showed a negative impact on the adoption of innovation. However, the result aligned with the high-tech industry firms that the complexity reported as an insignificant factor in adopting cloud computing (Low *et al.*, 2011). Instead of recreating the entire business process, the firm could enhance the existing business process under several areas by using pre-built IoT software (Oracle, 2021). QM IoT could actually reduce the complexity by better managing assets and devices, ingesting and analyzing data and reducing risks (O'Connor, 2016). IoT could collect data, monitor the processes and product quality, and adjust the interaction between connected things with minimal human intervention (Oracle, 2021). Therefore, it could be seen that QM IoT could make things easier for firms. Furthermore, the result of the observability contradicted other research, such as in food retail value chain (Carlström and Silander Hahström, 2017), in IT enterprises to adopt SaaS (Mangula *et al.*, 2014; Safari *et al.*, 2015), and in the firms to adopt the cloud computing service (Hsu and Lin, 2016). The reason could be that each firm needed to select both hardware and software based on their preferred capabilities under their different conditions. Therefore, only observation might not be enough to adopt QM IoT, instead the appropriate testing needed to be distinctly performed prior to the adoption.

Interestingly, both perceived risk and privacy concerns did not influence the adoption in this research. Some research indicated a negative relationship between perceived risk in the adoption of technology, such as in the IoT adoption in agriculture in USA (Jayashankar *et al.*, 2018), in Internet-based bill payment services (Featherman and Pavlou, 2003) and in-home service IoT in Korea (Sung and Jo, 2018). However, the risk factors and cybersecurity could be already accounted for during the normal design of the system at all stages of development (Asplund and Nadjm-Tehrani, 2016). Therefore, firms in the food supply chain might already have started to hold certain confidence in using the QM IoT. Although there were also privacy concerns challenge to the adoption of IoT in other research, such as in cloud computing adoption (Al-Hujran *et al.*, 2018; Aqeel-ur-Rehman *et al.*, 2016). However, it did not show a significant influence on the QM IoT adoption in this research. As IoT connected a large number of devices together, the security and privacy might be concerned. The security and privacy preferences could actually be evaluated and reported to the service provider on its appropriate security level before connecting any device with the IoT (Aqeel-ur-Rehman *et al.*, 2016). The privacy concerns could be enhanced by several technologies, such as by increasing the transport layer security, enabling encryption and authentication or using a virtual private network (Perera *et al.*, 2020; Weber, 2010). Therefore, the food supply chain might be well acknowledged on these but did not see them as a challenge in QM IoT adoption.

Under the organizational context, there were two factors that showed no significant influence on the QM IoT adoption in this research. First, the result of the firm size was not consistent with some studies, such as in the agricultural product distribution industry (Shi and Yan, 2016), in agricultural supply chain (Lin *et al.*, 2016) and in the Irish SMEs (Carcary *et al.*, 2014), while it was consistent with some studies, such as Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020). Each firm could specify the scope of QM IoT needs depending on the current operational conditions. Large firms may be interested in more hardware equipment and more sophisticated software, while smaller ones can reduce the scale to match their requirement. Therefore, all sizes of businesses could still access this opportunity. Second, the result of absorptive capability was contrasted with the studies on the Chinese agricultural supply chain (Lin *et al.*, 2016), smart farming (Walter *et al.*, 2017) and the Greek fresh produce supply chain's traceability system (Manos and Manikas, 2010), while it was consistent with some studies, such as in Malaysian Halal agro-food SMEs (Ahmad Tarmizi *et al.*, 2020). Instead of having a strong absorptive capability (having high numbers of employees in QM IoT expertise) to adopt the QM IoT, it is more critical for the firm to work with the vendors that have the capability to deliver an IoT platform, the truly holistic solution and the world-leading communications technology as their partners (O'Connor, 2016; Things on Net, 2022). Therefore, the service provider could enable the business outcomes and be a turnkey way of knowledge to the firms.

There were another three factors under the environmental context that did not show significant influence on the QM IoT adoption. First, the result of competitive pressure was not consistent with some studies, such as in the Taiwanese logistics industry (Hsu and Yeh, 2017), in the agricultural product distribution industry (Shi and Yan, 2016) and in the supply chain in China (Lin *et al.*, 2016). A benchmark retrieved from competitors in the same category as a good practice to improve a firm's competencies. However, the attitude and intention to adopt QM IoT were not determined by the competitors' practice. To illustrate, although the competitors might currently have the newest technology, the firm might not need to actively follow that practice if it does not create any competitive advantage or bring more value to their customers or consumers. Second, the result of social pressure was also not consistent with some studies, such as in the Chinese agricultural supply chain (Lin *et al.*, 2016). The reason might be that the firms in the food supply chain did not have high pressure from the social generally; however, the pressure would mainly come from the end consumers instead. The pressure from the non-profit organization might not intervene in the adoption of QM IoT if the consumers do not highly value it. Third, the result of the government support was not consistent with some studies, such as in Chinese agricultural supply chain (Lin *et al.*, 2016), pilot research on food traceability as appointed by the Taiwanese government (Hong *et al.*, 2011), IoT adoption in the logistics industry in Taiwan (Hsu and Yeh, 2017), in India food retail supply chain (Kamble *et al.*, 2019b) and in smart farm IoT (Walter *et al.*, 2017). Even though the Thai government has promoted the policy and long-term plan for digital economy improvement (Digital Economy Promotion Agency, 2017) and Thailand 4.0 (National Broadcasting and Telecommunications Commission, 2017), it is still not visible and attractive yet to the management in the food industry. Therefore, the government should intensively promote more campaigns to make the adoption of QM IoT more attractive.

The trust was the solely factor under the collaborative structure that found no significant influence on the QM IoT adoption in this research. It was not consistent with some studies, such as in the agriculture supply chain (Lin *et al.*, 2016) and in the food distribution

(Shi and Yan, 2016). However, when dealing with corporations locally or globally, trust could be reinforced through contracts. The justifications of contract law implicitly carried the notions of trust or at least supported its existence (Bukspan, 2006). In today's business world, contracts were created between parties in their supply chain to define social and economic engagement. As a result, trust was not an important factor that directly influenced firms or firms' attitude or intention to adopt QM IoT in their food supply chain since the contract itself implicitly carried the notion of trust already.

6. Implication

6.1 Theoretical implications

The IoT has been introduced to various industries and household for quite a few years. Several research quantitatively and qualitatively studied and published its usage and benefits in various areas. This research advances the literature in three ways.

First, no studies have so far empirically tested the adoption of the QM IoT in the food supply chain, in which quality is the most crucial part for the food-related manufacturers and its supply chain partners. Therefore, the authors filled this crucial gap where QM IoT played an important role in the food supply chain.

Second, this study brought in several theories to strengthen the TOE framework which was criticized for its limitation toward the generalization and vagueness in constructing the adoption factors (Gangwar *et al.*, 2015; Hwang *et al.*, 2016). Therefore, the traditional adoption theories, such as DOI, TAM, UTAUT, PVC, TDC, STK and IST were brought in to strengthen the factors under the technological, organizational and environmental constructions. Also, the collaborative structure was brought into the model to expand the focus to the supply chain area. The theoretical implications for each context were explained as follows.

Even though several studies showed that all five factors from DOI showed their influencing power on the innovation adoption. However, only two factors from DOI, including compatibility and trialability, showed a significant impact on the QM IoT adoption, while the remainingthree factors, including relative advantage, complexity and observability did not indicate this. Thereby, two factors from TAM (perceived usefulness and perceived ease of use) and another two factors from UTAUT (performance expectancy and effort expectancy) were also revealed as having no significant impact on the QM IoT adoption as they were similar to the relative advantage and complexity, respectively. Only one factor from UATUT (facilitating condition) showed significant impact on the QM IoT adoption as it was similar to the compatibility. Interestingly, both two factors under PVC, including perceived risk and privacy concerns, did not show influencing power on the QM IoT adoption. Therefore, two technological-related factors, including compatibility and trialability should be first considered for future research in a similar context. In addition, TDC and STK theories strengthened the organizational construct. Two factors from TDC, including the adaptive capability and innovative capability, showed a significant influence on QM IoT adoption, while the absorptive capability did not reveal. The executive support factor from STK also indicated the influencing power on the QM IoT adoption, while firm size from the original TOE factor did not show the influencing result. Thus, the adaptive capability and innovative capability should be firstly prioritized in the organizational context for future research in a similar study field. Furthermore, IST and UTAUT tightened the environmental construct. There were two factors, including the value chain partner pressure from IST and presence of service provider from TOE showed significant results, while the rest of the factors, including the competitive pressure, social pressure and government support from IST and UTAUT did not show significant impact on the QM IoT adoption. Therefore, these two significant environmental factors, including value chain partner pressure and presence of service provider should be emphasized in a similar context for future research. Likewise, the collaborative structure reinforced the TOE framework on the supply chain collaboration perspectives where they were lacking from the original TOE framework. The information sharing indicated influencing power on the QM IoT adoption, while the other factor (trust) did not reveal. Therefore, trust should be emphasized in the collaborative context for future research.

Third, current studies on the adoption of new technology purely focused on either attitude or intention. Only a few studies brought in both attitude and intention and considered their relationship. This study considered this important point as it brought more benefits to the practitioner and fulfilled this gap in the adoption of QM IoT in the food supply chain. The statistically validated model indicated tentatively high explanatory power (R^2 = 0.642 for ATT and 0.598 for AIN) and large predictive relevance (Q^2 = 0.409 for ATT and 0.423 for AIN).

6.2 Managerial implication

The results of this research have significant implications for the food supply chain practitioners, employees and executives to emphasize the factors that are important for their firms and their supply chain to adopt the QM IoT in the future. In addition, the QM IoT service providers can also increasingly understand the crucial requirement of the firms in the food supply chain. The implications were suggested in four contexts, including technological, organizational, environmental and collaborative contexts.

Under the technological context, food supply chain firms should pay high attention to compatibility and trialability. For compatibility, the firms might not be able to amend the current IT infrastructure since they already existed in the firms. However, the firms could actively participate in setting technology standards that allow for expanded modularity and interoperability among and within applications and devices (Wee *et al.*, 2015). In addition, the firms could seek a vendor who can retrofit the existing supply chain infrastructure and systems and who could provide trialability on the prototype systems that can be easily plugged in and out as needed in case it does not fit with the requirement. Hence, the trialability would then be importantly to consider together with the compatibility.

Under the organizational context, innovativeness and executive support were also important for the firms. Creativity and innovation among employees could be promoted through the organizational characteristics, such as communication, control mechanisms and organizational and management support (Antoncic, 2007). In addition, the firms should also empower their employees to develop a good relationship between employees and the organization which can potentially help create higher innovation, such as developing newer, faster and better processes and methods in the supply chain. To enable this innovativeness, the executive should support the employees to look for better methods and options, such as setting stretch goals and should not discourage their creativity. In addition, they should encourage employees to participate in an innovative community where employees in diverse fields can share their ideas and promote the willingness to change. Besides, executives could consider different organizational structures where IT function is no longer only back-end supports but rather synergizes with the operations team as technology is not embedded in everything businesses do. These strategies or directions could be supported by the executive team since they are the ones who set it up.

In addition, the firms in the food supply chain needed to consider both capital and operational expenses to strengthen their adaptive capability. It is difficult to precisely predict the IT project cost; however, the estimated budgets need to be assessed prior to the implementation of a project, not in the current year but for the long-term view. Once the budget for the software, hardware and maintenance is actively considered and flexible enough for allocation, the adoption rate could possibly be accelerated.

Under the environmental context, value chain partner pressure and the presence of service provider were crucially important for the firms. For value chain partner pressure, the firms should seek a long-term contract with a limited number of partners and integrate them as part of the firm's operations, especially those from downstream since they can exercise higher pressure than the upstream ones. Therefore, the long-term relationship could potentially enhance the firm's readiness for large investment, such as IT and information sharing. For the presence of service provider, the firms should prepare to seek for service providers who can provide preferred solutions and provide compatibility with the current infrastructure. In addition, those providers should be able to evaluate and implement technology with customer's requirement together with the standard ones, such as security and privacy. Hence, the firms will have a higher potential to adopt QM IoT faster when they have better preparation with the value chain partners and the service providers.

Under the collaborative context, information sharing is important for the firms in the food supply chain to adopt the QM IoT. Similar to value chain partner pressure, the firms in the food supply chain should build a long-term relationship with the partners because it helps enhance the level of information sharing among their supply chain partners. Thus, a good collaboration in sharing the information could fasten the QM IoT adoption for food supply chain firms.

7. Conclusion, limitation and future research

The research found that eight factors, including compatibility, trialability, adaptive capacity, innovative capability, executive support, value chain partner pressure, presence of service provider and information sharing significantly impacted the attitude toward QM IoT adoption, while three factors, including adaptive capability innovative capability and information sharing also significantly impacted the QM IoT adoption intention. In addition, the attitude toward QM IoT adoption positively influenced the QM IoT adoption intention. The results were essential for the academicians due to three aspects. First, the study on the QM IoT was expanded in the food supply chain, in which the current literature had not yet been explored into. Second, the generalization and vagueness of TOE framework had been resolved by integrating several traditional adoption theories into the model. Therefore, precise and broader adoption factors had been covered. In addition, the collaborative structure had been added to the model to cover collaborative aspects in the adoption of QM IoT in the food supply chain. Third, considering both attitude toward adoption and adoption intention could provide intense results of the influencing factors. Also, the firms' executives could get insights from this study to prepare and accelerate the adoption of the QM IoT in the future, while the service providers could also be aware on the essential factors that firms in the food supply chain are looking for, so the service provider could better prepare and provide additional alternative services.

This research collected the data from the food supply chain firms that are registered with the Food Processing Industry Club, the Federation of Thai Industry. Thus, the framework was specifically developed for the food industry. The concluded results might be varied from research in another industry. Therefore, it is a good opportunity for future research to consider this model to be tested in other industries, especially in the adoption of QM IoT in hospitals or healthcare centers where the quality management is also crucial for their patients. Not only patients but also the medical staff could benefit from the IoT in fastening the process, ensure security and precisely tracking symptoms.

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