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A conceptual model for the adoption of autonomous robots in supply chain and logistics industry

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The arrival of the era of robots and autonomous machines is undisputable. It is anticipated that the future business environment will be characterized by a variety of intelligent systems and autonomous robots. In 2017, the International Federation of Robotics reported that momentum gained by robotic technologies is strong and that the sales volumes of both service and industrial robots is expected to grow. Building on this projection, the present study proposes a set of prerequisites or key determinants for the adoption of autonomous robots in the supply chain and logistics industry: technological context (i.e., relative advantage, complexity, and cost), organizational context (i.e., management support, financial support and employee competence) and environmental context (i.e., competitive pressure, customer pressure and vendor support). The study adapts a quantitative research design and uses an online survey to collect the needed data to test the conceptual framework and hypotheses proposed. Part of the study results confirms the association between the cost of digital technologies and the adoption of autonomous robots. However, the study found no evidence that the perceived relative advantage positively impacts supply chain and logistics firms' adoption of autonomous robots. The study offers some managerial advices to supply chain mangers and marketers of the digital technologies and tools that can be applied in the supply chain setting.

1. Introduction

Robotic systems have been inspired by authors of science fiction and directors of films for decades. These prophecies have begun to materialize as the sales of service and industrial robots are projected to increase exponentially in the coming years (International Federation of Robotics, 2017). Robots have gradually evolved from single-function automatons to intelligent systems with versatile features (Savela et al., 2018). An autonomous robot denotes a type of intelligent machine that conducts assigned tasks with a high degree of autonomy (e.g., absence of human control or influence). In recent years, innovations have increased people's acquaintance with robots as part of their daily lives (Gnambs & Appel., 2019). The momentum gained by robotics is strong and evident in various industries. For example, in the car industry a combination of artificial intelligence and robotics has given birth to driverless cars (Wakabayashi, 2017). Autonomous robots are used in the healthcare sector for surgery and care of the elderly (Kachouie et al., 2014; Savela et al., 2018), for emotional and social companionship (Piçarra & Giger, 2018) and in educational fields (Reich-Stiebert & Eyssel, 2015). In surveillance, autonomous robots are used for dangerous tasks, monitoring and spying (Carlsen et al., 2014), used as assistants for administration, touring and guidance in a shopping mall (Destephe et al., 2015; Šabanović, 2014), and lastly deployed in

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agriculture (Hansen, 2015). Although firms worldwide, such as General Electric, Amazon and Alibaba, have come to rely increasingly on autonomous robots, the supply chain and logistics industry has received very little attention from empirical research (Hofmann *et al.*, 2019), Thus, providing additional space for more research.

Critics of autonomous robotics point out concerns about the effects of robotics on the workforce and employment (Manyika et al., 2017). On the other hand, advocates argue that such systems will enhance individuals' activities and wellbeing and serve as a source of economic growth for firms. Nevertheless, the use of autonomous robots can represent vulnerability for industrial and service firms (Gnambs, & Appel, 2019; Savela et al., 2018), for the reliance on the Internet, internal expertise, data management, data privacy and challenges related to software and hardware availability. The weighing of the pros and cons regarding the technological, organizational, and environmental scope leads to firms being uncertain about the value of adopting autonomous robots. Building on this premise, the present study proposes a conceptual model denoting how technological factors (i.e., relative advantage, complexity and cost), organizational factors (i.e., management support, financial support and employee competence) and environmental factors (i.e., competitive pressure, customer pressure and vendor support) can boost the adoption of autonomous robots in the supply chain and logistics industry.

2. Theoretical background

2.1. Technological context

The technological context describes any technology that is either being used by the organization or that is available and is known to be potentially useful but has not yet been deployed. The technological context in supply chain management includes important internal and external technologies (i.e., those adopted by a supply chain and logistics firm and those available in the marketplace but not yet exploited) (Baker, 2011; Alshurideh et al., 2019; Hamadneh et al., 2021; Joghee et al., 2021). Adoption of technological innovations is strongly contingent upon several characteristics of the focal technology (Alaali et al., 2021; Alshurideh et al., 2021; Al Kurdi et al., 2020). These characteristics subsume the net benefits of the technology against its cost, and its contribution toward increased efficiency, effectiveness and productivity (Gu, Cao & Duan, 2012; Alshurideh et al., 2019; Alzoubi et al., 2021; Naqvi et al., 2021). That is, technological adoption is largely motivated by the perceived benefits of the focal technology, technically known as relative advantage (Obeidat et al., 2021; Zu'bi et al., 2012).

According to Rogers (2010), relative advantage is defined as the extent to which potential adopters see a technological innovation as better than the alternatives. Scholars have assessed the chain of association between relative advantage and intention to adopt technology in various contexts. For instance, relative advantage was found to boost e-procurement adoption in developing countries (e.g., Aboelmaged, 2010), website use intention (Ramayah et al., 2016), online sales channel among SMEs (Li et al., 2011; Al Dmour et al., 2014; Al-Khayyal et al., 2021; Sweiss et al., 2021), and mobile marketing adoption by SMEs (Maduku et al., 2016; Al-Hamad et al., 2021; Alshurideh et al., 2021). Building on the extant arguments, the relative advantage of autonomous robots in the supply chain and logistics industry denotes the expected utility which firms can derive from using such technologies, because decision makers are likely to adopt autonomous robots if they perceive incremental benefits in operation over existing tools. Drawing on this line of reasoning, the following hypothesis is proposed:

***Hypothesis 1a**. Perceived relative advantage has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

Complexity and ease of use associated with technology or innovation are polar in nature (Akour et al., 2021; Kurdi et al., 2021). According to Chuang, Nakatani and Zhou (2009), complexity is defined as the extent to which a technological innovation is characterized as relatively difficult to comprehend and use. Maduku et al. (2016) show that complexity tends to inhibit the adoption of a technology or innovation. As the levels of complexity associated with a technology increase, the more likely is it that users will be discouraged from using it. The inhibiting factor is that it requires more mental effort, consumes time, and gives rise to frustration (Naicker & Van Der Merwe, 2018). Moreover, only a handful of researchers have tested this association at the organizational level (e.g., Maduku et al., 2016; Tsai et al., 2010). This paper addresses this gap from the supply chain and logistics perspective in the context of autonomous robots' adoption. Drawing on this line of reasoning, the following hypothesis is proposed:

***Hypothesis 1b**. Perceived complexity has a negative impact on supply chain and logistics firms' adoption of autonomous robots.*

Cost perception illustrates how potential users of an innovation or technology assess and consider price relative to their purchasing power (Moore & Benbasat, 1991, p. 194). Perceived cost is the extent to which users believe that using a technology or innovation will cost money. Yu and Buahom (2013) extend the TAM model by adding perceived cost to examine the user's concerns about the required cost for mobile commerce. The assumption that perceived cost can accelerate and/or decelerate the adoption of technological innovation has received support from several researchers (Lin & Wang, 2005; Maduku et al., 2016; Naicker & Van Der Merwe, 2018; Yadav et al., 2016). In both private and public sectors, the central idea of using intelligent machines and autonomous robots is to save costs and improve efficiency. Thus, in the context of supply chain and logistics, cost saving, and adoption of autonomous robots are believed to be associated. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 1c. *Perceived cost has a negative impact on supply chain and logistics firms' adoption of autonomous robots.*

2.2. Organizational context

Organizational context represents a variety of conditions spanning from top management support, adequate financial resources, to employee capability. These conditions are known to facilitate innovation adoption. The implementation and deployment of new technology in organizations usually comes in a top-down style (i.e., from the top management's decisions to the bottom of the organizational hierarchy). Ragu-Nathan et al. (2004) defined top management support "as the degree to which top management understands the importance of the IS function and the extent to which it is involved in IS activities". This support is also crucial for building a supportive environment and providing adequate resources to aid the adoption of new technologies (Maduku et al., 2016). Existing research findings (i.e., Hasani, Bojei & Dehghantanha, 2017; Ahmad, Abu-Bakar & Ahmad, 2019; AlSharji, Ahmad, & Abu Bakar, 2018) have documented that top management and/or decision makers are more likely to adopt an innovation if its benefits surpass the existing technology and outweigh the risks of its adoption. For instance, a study revealed that perceived benefit causes supply chain and logistics firms to adopt big data analytics (Lai, Sun, & Ren, 2018). Top management support has been shown to be an indicator for adoption of innovation (AlSharji et al., 2018; Gangwar, 2018; Oliveira et al., 2019; Kurdi et al., 2020). This theorizes that top management support and adoption of autonomous robots can be associated in the context of supply chain and logistics. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 2a. *Top management support has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

The second organizational factor influencing the adoption of new technology is the availability of financial resources. Resource availability symbolizes the availability and willingness of an organization to give up the resource to adopt a technological innovation. According to Tornatzky and Fleischer (1990), organizational resources can be classified into two: financial and human. First, Financial resources signify monetary resources available to cover the costs associated with the purchase, implementation, and maintenance of technological innovations (Kim & Garrison, 2010). Lai, Sun and Ren (2018) added that financial support and its availability highlight organizational ability and readiness to pay for the cost of a new system's implementation, training and integration. Thus, in the context of supply chain and logistics, availability of financial resources may enhance the adoption of autonomous robots. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 2b. *Financial support has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

Second**,** human resources signify qualified personnel to work and leverage the benefits of technological innovations. Qualified employees with competent learning capabilities is a prerequisite step for technological adoption (Tornatzky & Fleischer, 1990). Personnel with learning capabilities are more likely to assimilate and learn through training programmes and are less likely to resist innovation (Lin & Ho, 2011). In this study, we refer to this dimension as perceived employee capability. Technological competence is a driver for adoption, therefore, the extent to which organizations and their entities are receptive to new ideas will influence their propensity to adopt new technologies (Lin & Ho, 2011). Accordingly, Oliveira et al. (2019) stated that technology competence encompasses the technical infrastructure and human knowledge that can influence the firm's adoption of an innovation**.** Thus, in the context of supply chain and logistics, organizations that perceive their employees as competent are more likely to adopt autonomous robots. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 2c. *Employee competence has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

2.3. Environmental context

The environmental context represents the actors in the ecosystem in which the organization operates, implying competitive strategies, industrial structure, customers, rivals, partners and government regulations (Tornatzky & Fleicher, 1990). Competitive pressure describes the degree of rivalry within an industry, triggered by factors including globalization, the development of new technology and knowledge use. It is important to note that external pressures can push companies to adopt new technologies even without a full understanding of their benefits (Hasani et al., 2017). In a more competitive environment, organizations tend to innovate (AlSharji et al., 2018). Mimetic pressures reflect the act of imitating rivals' strategies and activities (Oliveira et al. 2019). Prior studies found that perceived competitive pressure has a strong influence on the adoption of technological innovation (Hasani et al., 2017; Lai et al., 2018; Borgman et al., 2014). This paper theorizes that perceived competitive pressure is likely to encourage firms to adopt autonomous robots in their operations in the context of supply chain and logistics. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 3a. *Competitive pressure has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

Customer pressure encompasses consumer demands and behaviours that make companies adopt new technologies (Hasani et al., 2017). External pressure, especially from consumers, forces firms to adopt technological innovations in an attempt to remain competitive and/or retain their market share (Eze et al., 2019; Wu & Lee, 2005). According to Wang et al. (2016), pressure from consumers has encouraged hotels to adopt mobile CRM and reservation systems. Thus, in the context of supply chain and logistics, perceived customer pressure is likely to encourage firms to adopt autonomous robots in their operations. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 3b. *Customer pressure has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

Research shows that the adoption of innovation is influenced by support from vendors (Al-Qirim, 2007). From a pragmatic point of view, there is a shortage of IS experts, and hiring consultant experts is expensive. Ghobakhloo et al. (2011) added that absence of support from technology vendors may hinder adoption. Perceived vendor support has been found to be an important antecedent for big data analytics adoption (Gangwar, 2018). Thus, in the context of supply chain and logistics, technology vendors can be considered as the main source of external IS expertise and a significant determinant of autonomous robots' adoption. Drawing on this line of reasoning, the following hypothesis is proposed:

Hypothesis 3c. *Vendor support has a positive impact on supply chain and logistics firms' adoption of autonomous robots.*

3. The proposed conceptual model

Fig. 1 depicts the proposed conceptual model which clarifies the relationship among the selected variables and appendix Table 1 shows the main independent and dependent variables' items used.

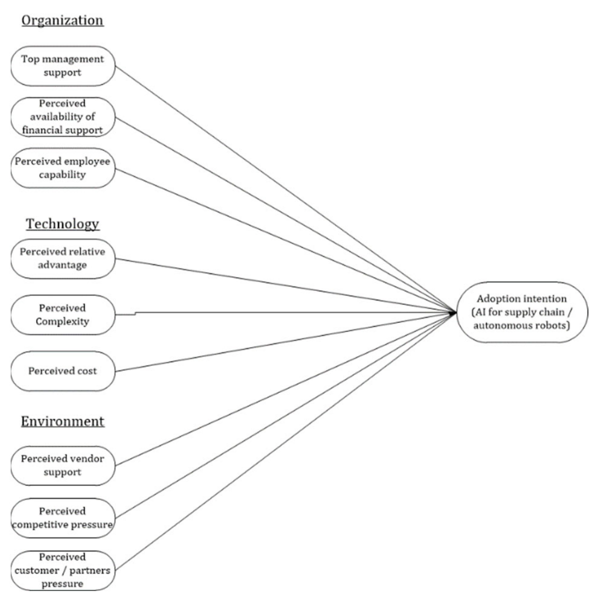

Fig. 1. Proposed conceptual model

4. Methodology and Data analysis

This study is based on the results of a survey carried out through the LinkedIn website during 2020. The survey aimed at supply chain managers and senior people working in the logistics field to offer rich information concerning the purpose of this study, with participation being entirely voluntary. Participants had various experiences and operated in different entities of within the supply chain field (e.g., producers, vendors, warehouse, transportation companies, distribution centres and retailers) In total, there were 314 participants who filled the survey. Overall, participants had an average of 9 years of experience in various areas of the supply chain. A survey instrument was utilized to a test conceptual model which identifies the key prerequisites for the adoption of autonomous robots in the supply chain and logistics industry. The survey consisted of 38 items for measuring the theoretical constructs presented in this study. The source of the constructs of the first ten questions related directly to previous theories and frameworks concerning the supply chain management and information technology areas (see appendix Table 1).

4.1 Analysis Coding

Table 1 shows the main study variables' codes used.

Table 1: Analysis Coding

	Dimensions	Independent	Dependent
ADVT	Relative advantage	Organizational	Autonomous AUTO
CMPX	Complexity		
COST	Cost		
SPRT	Top management support	Technological	
FINC	Availability financial support		
CAPA	Employee capability		
VEND	Vendor support	Environmental	
CMTV	Competitive pressure		
CUST	Customer pressure		

4.2 Descriptive statistics

Table 2 presents the descriptive statistics of the latent variables. The variables were measured using a 5 point Likert scale ranging from strong negative to strong positive. An average of 3 signifies a lack of opinion, an average lower than 3 signifies a negative opinion about the construct while an average greater than 3 signifies a positive opinion about the latent construct. Reading from table one, on average, respondents had a positive opinion about the all the latent construct given that the minimum observed average was 3.85.

Table 2
Latent Variable Descriptive statistics

	Mean	Median	Min	Max	Std Dev
ADVT	3.870	4.000	1.253	5.000	0.791
CMPX	3.888	4.016	1.274	5.000	0.736
COST	3.861	4.000	1.475	5.000	0.770
SPRT	3.894	4.125	1.000	5.000	0.816
FINC	3.857	3.812	1.000	5.000	0.845
CAPA	3.804	4.000	1.378	5.000	0.792
VEND	3.952	4.001	1.000	5.000	0.822
CMTV	3.911	4.025	1.336	5.000	0.811
CUST	3.924	4.036	1.000	5.000	0.844
AUTO	3.989	4.224	1.266	5.000	0.832

4.3 Measurement model assessment

Fig. 2 shows the detailed measurement model assessment.

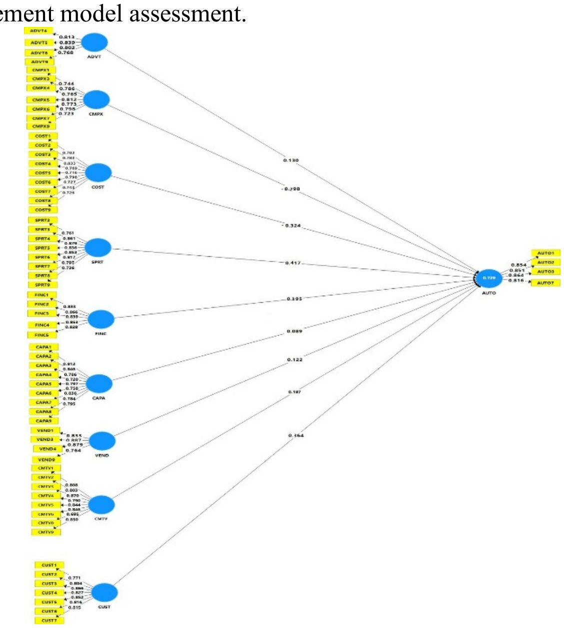

Fig. 2. The measurement model assessment

4.4 Construct Validity and Reliability

Table 3 presents all the measures for construct validity and reliability. The first step in assessing the reliability of a reflective latent construct is to assess indicator reliability. Indicator reliability is assessed using the indicator outer loadings. According to Hair et al., 2016, an indicator is reliable if it has a loading of 0.7 and above. Additionally, indicators can be removed from the model if they load more to other latent constructs than to the latent construct to which it primarily belongs. As part of the measurement model, five items were removed from the latent construct ADVT (ADVT1, ADVT2, ADVT3, ADVT6 and ADVT7). Four items were finally retained for the latent variable ADVT. These items had a composite reliability of 0.881 and a Cronbach's Alpha of 0.820 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. Convergent validity is the extent to which the indicators belonging to one latent variable actually measure the same construct. The average variance extracted (AVE), typically used to assess convergent validity. The AVE for ADVT was 0.649 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). To assess the validity and reliability of the latent variable CMPX, two items were removed from the latent construct CMPX (CMPX2, CMPX8). seven items were finally retained for the latent variable CMPX. These items had a composite reliability of 0.912 and a Cronbach's Alpha of 0.887 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. Convergent validity is the extent to which the indicators belonging to one latent variable actually measure the same construct. The average variance extracted (AVE), typically used to assess convergent validity. The AVE for CMPX was 0.596 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). Also, to assess the validity and reliability of the latent variable COST, all items were retained because neither of them had an indicator loading lower than 0.7 or had indicators loading more to other latent constructs. These items had a composite reliability of 0.927 and a Cronbach's Alpha of 0.911 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. The AVE for COST was 0.585 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). To assess the validity and reliability of the latent variable SPRT, one item was removed from the latent construct SPRT (SPRT1). 8 items were finally retained for the latent variable SPRT. These items had a composite reliability of 0.942 and a Cronbach's Alpha of 0.929 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. Convergent validity is the extent to which the indicators belonging to one latent variable actually measure the same construct. The average variance extracted (AVE), typically used to assess convergent validity. The AVE for SPRT was 0.670 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). In addition, to assess the validity and reliability of the latent variable SPRT, one item was removed from the latent construct SPRT (SPRT1). 8 items were finally retained for the latent variable SPRT. These items had a composite reliability of 0.942 and a Cronbach's Alpha of 0.929 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. Convergent validity is the extent to which the indicators belonging to one latent variable actually measure the same construct. The average variance extracted (AVE), typically used to assess convergent validity. The AVE for SPRT was 0.670 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell and Lacker (1981).

For the assessment of the validity of FINC, four items were removed from the latent construct FINC (FINC6- FINC9). 5 items were finally retained for the latent variable FINC. These items had a composite reliability of 0.925 and a Cronbach's Alpha of 0.899 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. Convergent validity is the extent to which the indicators belonging to one latent variable actually measure the same construct. The average variance extracted (AVE), typically used to assess convergent validity. The AVE for FINC was 0.712 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). Furthermore, to assess the validity of CAPA, all its items met all requirements to be considered as truly belonging to the latent variable CAPA therefore, all of them were retained. These items had a composite reliability of 0.939 and a Cronbach's Alpha of 0.927 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. Convergent validity is the extent to which the indicators belonging to one latent variable actually measure the same construct. The average variance extracted (AVE), typically used to assess convergent validity. The AVE for CAPA was 0.630 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell and Lacker (1981).

For the assessment of the validity of VEND, five items were removed from the latent construct VEND (VEND1, VEND5- VEND8). four items were finally retained for the latent variable VEND. These items had a composite reliability of 0.907 and a Cronbach's Alpha of 0.862 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. The AVE for VEND was 0.710 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). Moreover, for the assessment of the validity of CMTV, one item was removed from the latent construct CMTV (CMTV7). eight items were retained for the latent variable CMTV. These items had a composite reliability of 0.940 and a Cronbach's Alpha of 0.927which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. The AVE for CMTV was 0.664 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell and Lacker (1981). To assess the validity of CUST, all its seven items met all requirements to be considered as truly belonging to the latent variable CUST therefore, all of them were retained. These items had a composite reliability of 0.936 and a Cronbach's Alpha of 0.920 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. The AVE for CAPA was 0.676 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981). Additionally, for the assessment of the validity of AUTO, five items were removed from the latent construct AUTO (AUTO4- AUTO5, AUTO8– AUTO9). Five items were retained for the latent variable AUTO. These items had a composite reliability of 0.910 and a Cronbach's Alpha of 0.868 which is greater than the threshold of 0.7 as recommended by Hair et al., 2016. The AVE for VEND was 0.716 which surpasses the threshold of 0.5 set by Chin (2010) and Fornell & Lacker (1981).

Table 3
Construct Validity and Reliability

Latent Variables	Indicators	ADVT	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
ADVT	ADVT4	0.813	0.820	0.820	0.881	0.649
	ADVT5	0.839				
	ADVT8	0.802				
	ADVT9	0.768				
CMPX	CMPX1	0.744	0.887	0.887	0.912	0.596
	CMPX3	0.786				
	CMPX4	0.765				
	CMPX5	0.812				
	CMPX6	0.773				
	CMPX7	0.798				
	CMPX9	0.723				
COST	COST1	0.783	0.911	0.915	0.927	0.585
	COST2	0.783				
	COST3	0.833				
	COST4	0.769				
	COST5	0.716				
	COST6	0.798				
	COST7	0.727				
	COST8	0.743				
	COST9	0.726				
SPRT	SPRT2	0.761	0.929	0.933	0.942	0.670
	SPRT3	0.861				
	SPRT4	0.879				
	SPRT5	0.836				
	SPRT6	0.853				
	SPRT7	0.817				
	SPRT8	0.797				
	SPRT9	0.736				
FINC	FINC1	0.833	0.899	0.901	0.925	0.712
	FINC2	0.866				
	FINC3	0.839				
	FINC4	0.853				
	FINC5	0.828				
CAPA	CAPA1	0.812	0.927	0.932	0.939	0.630
	CAPA2	0.846				
	CAPA3	0.786				
	CAPA4	0.720				
	CAPA5	0.797				
	CAPA6	0.758				
	CAPA7	0.836				
	CAPA8	0.784				
	CAPA9	0.795				
VEND	VEND1	0.833	0.862	0.869	0.907	0.710
	VEND3	0.887				
	VEND4	0.879				
	VEND9	0.764				
CMTV	CMTV1	0.808	0.927	0.931	0.940	0.664
	CMTV2	0.803				
	CMTV3	0.870				
	CMTV4	0.790				
	CMTV5	0.844				
	CMTV6	0.846				
	CMTV9	0.850				
CUST	CUST1	0.771	0.920	0.924	0.936	0.676
	CUST2	0.804				
	CUST3	0.866				
	CUST4	0.827				
	CUST5	0.852				
	CUST6	0.816				
	CUST7	0.815				
AUTO	AUTO1	0.854	0.868	0.868	0.910	0.716
	AUTO2	0.851				
	AUTO3	0.864				
	AUTO7	0.816				

4.5 Discriminant Validity Following the Fornell-Larcker Criterion

Table 4
Discriminant Validity Following the Fornell-Larcker Criterion

	ADVT	CMPX	COST	SPRT	FINC	CAPA	VEND	CMTV	CUST	AUTO
ADVT	**0.806**									
CMPX	0.775	**0.772**								
COST	0.798	0.781	**0.765**							
SPRT	0.760	0.767	0.746	**0.819**						
FINC	0.622	0.675	0.708	0.672	**0.844**					
CAPA	0.742	0.703	0.737	0.755	0.621	**0.793**				
VEND	0.752	0.778	0.720	0.751	0.604	0.698	**0.842**			
CMTV	0.740	0.777	0.753	0.734	0.655	0.699	0.830	**0.815**		
CUST	0.755	0.769	0.761	0.734	0.648	0.775	0.787	0.806	**0.822**	
AUTO	0.749	0.756	0.797	0.706	0.666	0.653	0.743	0.769	0.737	**0.846**

Table 4 assesses discriminant validity following the Fornell-Larcker Criterion. According to this criterion, the square root of the AVE for a variable should be greater than the correlation of the latent construct to any other latent construct for discriminant validity to be established Fornell & Lacker (1981) and Hair et al. (2014). Looking at the table, discriminant validity was not established for CMPX and COST. All other combinations of latent variables established discriminant validity.

4.6 Discriminant Validity Following the Cross Loadings

For discriminant validity to be established according to the cross-loading criterion, the loading of an item to its parent latent construct should be higher than its loading to all other latent constructs (Fornell & Lacker, 1981; Hair et al., 2014). According to Table 5, discriminant validity is established following the cross-loading criterion.

Table 5

Discriminant Validity Following the Cross Loadings

	ADVT	CMPX	COST	SPRT	FINC	CAPA	VEND	CMTV	CUST	AUTO
ADVT4	**0.813**	0.620	0.707	0.621	0.522	0.659	0.566	0.584	0.639	0.625
ADVT5	**0.839**	0.619	0.704	0.590	0.512	0.663	0.622	0.594	0.640	0.585
ADVT8	**0.802**	0.662	0.606	0.675	0.476	0.547	0.657	0.632	0.595	0.622
ADVT9	**0.768**	0.595	0.553	0.556	0.494	0.519	0.575	0.571	0.557	0.580
CMPX1	0.602	**0.744**	0.669	0.596	0.591	0.618	0.547	0.572	0.660	0.588
CMPX3	0.564	**0.786**	0.576	0.574	0.519	0.542	0.628	0.607	0.570	0.618
CMPX4	0.613	**0.765**	0.566	0.597	0.501	0.527	0.543	0.608	0.552	0.579
CMPX5	0.593	**0.812**	0.601	0.614	0.556	0.517	0.630	0.652	0.614	0.594
CMPX6	0.616	**0.773**	0.623	0.604	0.490	0.572	0.610	0.554	0.588	0.543
CMPX7	0.586	**0.798**	0.594	0.600	0.489	0.539	0.659	0.614	0.587	0.568
CMPX9	0.616	**0.723**	0.595	0.559	0.495	0.484	0.583	0.586	0.580	0.589
COST1	0.675	0.665	**0.783**	0.615	0.552	0.580	0.634	0.657	0.639	0.658
COST2	0.637	0.678	**0.783**	0.607	0.550	0.547	0.595	0.683	0.649	0.673
COST3	0.680	0.681	**0.833**	0.619	0.606	0.650	0.599	0.625	0.647	0.665
COST4	0.605	0.578	**0.769**	0.561	0.555	0.625	0.569	0.535	0.597	0.536
COST5	0.549	0.491	**0.716**	0.511	0.492	0.553	0.472	0.454	0.507	0.494
COST6	0.577	0.548	**0.798**	0.554	0.545	0.606	0.485	0.508	0.580	0.525
COST7	0.573	0.571	**0.727**	0.559	0.501	0.551	0.510	0.529	0.515	0.550
COST8	0.602	0.620	**0.743**	0.610	0.536	0.529	0.628	0.625	0.560	0.678
COST9	0.570	0.501	**0.726**	0.479	0.527	0.452	0.426	0.510	0.522	0.638
SPRT2	0.668	0.627	0.683	**0.761**	0.521	0.744	0.579	0.529	0.657	0.551
SPRT3	0.666	0.658	0.602	**0.861**	0.556	0.621	0.666	0.670	0.623	0.642
SPRT4	0.645	0.680	0.655	**0.879**	0.570	0.672	0.651	0.631	0.650	0.630
SPRT5	0.633	0.608	0.628	**0.836**	0.572	0.568	0.651	0.603	0.581	0.584
SPRT6	0.637	0.632	0.630	**0.853**	0.554	0.594	0.646	0.640	0.605	0.621
SPRT7	0.621	0.641	0.648	**0.817**	0.560	0.666	0.541	0.582	0.599	0.542
SPRT8	0.569	0.622	0.531	**0.797**	0.543	0.536	0.636	0.606	0.571	0.546
SPRT9	0.527	0.549	0.504	**0.736**	0.532	0.547	0.536	0.535	0.521	0.483
FINC1	0.438	0.550	0.535	0.521	**0.833**	0.427	0.454	0.553	0.480	0.530
FINC2	0.542	0.616	0.590	0.593	**0.866**	0.461	0.558	0.630	0.572	0.603
FINC3	0.520	0.567	0.638	0.562	**0.839**	0.589	0.508	0.490	0.575	0.527
FINC4	0.559	0.579	0.629	0.589	**0.853**	0.590	0.514	0.528	0.556	0.553
FINC5	0.558	0.534	0.597	0.566	**0.828**	0.555	0.509	0.553	0.547	0.588
CAPA1	0.645	0.694	0.634	0.670	0.535	**0.812**	0.664	0.637	0.666	0.606
CAPA2	0.628	0.588	0.614	0.626	0.554	**0.846**	0.576	0.571	0.635	0.549
CAPA3	0.529	0.503	0.538	0.578	0.473	**0.786**	0.496	0.518	0.580	0.484
CAPA4	0.574	0.558	0.511	0.654	0.489	**0.720**	0.578	0.635	0.576	0.585
CAPA5	0.548	0.521	0.583	0.558	0.416	**0.797**	0.490	0.468	0.587	0.456
CAPA6	0.482	0.444	0.519	0.452	0.394	**0.758**	0.400	0.379	0.478	0.382
CAPA7	0.603	0.515	0.614	0.600	0.461	**0.836**	0.515	0.502	0.620	0.452
CAPA8	0.656	0.618	0.621	0.618	0.567	**0.784**	0.642	0.642	0.701	0.607
CAPA9	0.562	0.480	0.604	0.549	0.468	**0.795**	0.520	0.521	0.628	0.426
VEND1	0.605	0.621	0.554	0.586	0.469	0.585	**0.833**	0.721	0.660	0.586
VEND3	0.653	0.680	0.639	0.678	0.510	0.592	**0.887**	0.712	0.680	0.665
VEND4	0.635	0.692	0.647	0.657	0.538	0.615	**0.879**	0.723	0.671	0.675
VEND9	0.644	0.624	0.580	0.605	0.518	0.561	**0.764**	0.643	0.644	0.571
CMTV1	0.611	0.667	0.621	0.658	0.566	0.583	0.672	**0.808**	0.660	0.647
CMTV2	0.543	0.569	0.566	0.571	0.498	0.504	0.643	**0.803**	0.607	0.562
CMTV3	0.633	0.717	0.674	0.593	0.564	0.584	0.699	**0.870**	0.658	0.698
CMTV4	0.556	0.629	0.578	0.570	0.528	0.523	0.692	**0.790**	0.644	0.601
CMTV5	0.610	0.648	0.587	0.639	0.495	0.560	0.673	**0.844**	0.637	0.603
CMTV6	0.579	0.625	0.589	0.602	0.548	0.571	0.680	**0.846**	0.661	0.652
CMTV8	0.647	0.534	0.656	0.541	0.493	0.651	0.598	**0.695**	0.620	0.541
CMTV9	0.645	0.657	0.642	0.609	0.568	0.591	0.745	**0.850**	0.760	0.686
CUST1	0.630	0.633	0.583	0.602	0.540	0.624	0.669	0.707	**0.771**	0.565
CUST2	0.593	0.638	0.576	0.591	0.558	0.565	0.685	0.674	**0.804**	0.640
CUST3	0.690	0.714	0.641	0.660	0.583	0.615	0.725	0.760	**0.866**	0.690
CUST4	0.611	0.597	0.650	0.605	0.502	0.709	0.595	0.581	**0.827**	0.524
CUST5	0.636	0.684	0.684	0.638	0.549	0.652	0.667	0.697	**0.852**	0.664
CUST6	0.587	0.574	0.635	0.567	0.482	0.657	0.575	0.588	**0.816**	0.579
CUST7	0.589	0.558	0.613	0.551	0.500	0.663	0.591	0.603	**0.815**	0.541
AUTO1	0.646	0.672	0.736	0.622	0.567	0.562	0.644	0.670	0.634	**0.854**
AUTO2	0.617	0.635	0.679	0.616	0.563	0.527	0.662	0.659	0.622	**0.851**
AUTO3	0.622	0.602	0.673	0.557	0.544	0.566	0.597	0.629	0.609	**0.864**
AUTO7	0.651	0.650	0.606	0.590	0.579	0.555	0.611	0.644	0.626	**0.816**

4.7 Discriminant Validity Following the Heterotrait-Monotrait Ratio (HTMT)

According to Kline (2011) and Gold et al. (2001), the HTMT is the most appropriate measurement of discriminant validity. For discriminant validity to be established following the HTMT ratio, the ratio has to be lower than 0.85 (ideal) or 0.9 (acceptable). Inferring from table 6, discriminant validity was not established for CMPX and ADVT (HTMT=0.909), ADVT & COST (HTMT=0.918) and VEND & CMTV (HTMT=0.930). All other combination of variables established discriminant validity.

Table 6
Discriminant Validity Following the Heterotrait-Monotrait Ratio (HTMT)

	ADVT	CMPX	COST	SPRT	FINC	CAPA	VEND	CMTV	CUST	AUTO
ADVT										
CMPX	**0.909**									
COST	**0.918**	0.862								
SPRT	0.868	**0.845**	**0.807**							
FINC	**0.723**	**0.755**	**0.781**	**0.736**						
CAPA	**0.839**	**0.761**	**0.801**	**0.802**	**0.669**					
VEND	0.896	0.889	**0.805**	**0.837**	**0.685**	**0.765**				
CMTV	**0.850**	0.854	**0.812**	**0.791**	**0.715**	**0.739**	**0.930**			
CUST	0.867	**0.846**	**0.828**	**0.793**	**0.709**	**0.835**	0.882	0.868		
AUTO	0.887	0.860	0.883	**0.782**	**0.752**	**0.710**	0.857	0.855	**0.817**	

4.8 Correlation of Latent Variables

Table 7 presents the correlation of the latent variables. The Pearson's product moment correlation coefficient was used to test the correlations between latent variables. All variables are positively related to each other and significant at 1%.

Table 7
Correlation of Latent Variables

Relationship	ADVT	CMPX	COST	SPRT	FINC	CAPA	VEND	CMTV	CUST
CMPX	0.775**								
COST	0.798**	0.781**							
SPRT	0.760**	0.767**	0.746**						
FINC	0.622**	0.675**	0.708**	0.672**					
CAPA	0.742**	0.703**	0.737**	0.755**	0.621**				
VEND	0.752**	0.778**	0.720**	0.751**	0.604**	0.698**			
CMTV	0.740**	0.777**	0.753**	0.734**	0.655**	0.699**	0.830**		
CUST	0.755**	0.769**	0.761**	0.734**	0.648**	0.775**	0.787**	0.806**	
AUTO	0.749**	0.756**	0.797**	0.706**	0.666**	0.653**	0.743**	0.769**	0.737**

Note *** Correlation is significant at 1%

4.9 Model Fit

Table 8 presents the measure fit indices used to measure the quality of the model. From the table, the SRMR of 0.065 which is lower than 0.085 provides evidence for an acceptable model fit (Hu & Bentler, 1999). SRMR as an approximate measure of model fit.

Table 8
Model Fit

Fit Indices	Value	95%	99%
SRMR	0.068	0.046	0.048
d_ULS	9.791	4.486	4.844
d_G	**4.571**	3.49	3.84

4.10 SEM Results

Table 9 shows the adjusted R^2 the degree of variation in adoption intention that can be explained by variations in Adoption of Autonomous Robots. Inferring from the adjusted R^2 (Coefficient of multiple determination), 71.7% of variations in the Adoption intention is accounted for or explained by variations in Adoption of Autonomous Robots. 28.3% of variations in Adoption intention are accounted for by variations in other variables different from Adoption of Autonomous Robots (influence of the extraneous variables). This shows that the independent variables have a substantial effect on the dependent variable. (Hair, Ringle, & Sarstedt, 2011; Henseler et al., 2009; Shamout, 2020a,b). The predictive relevance of the model was assessed using the (q^2). Given a value of (0.51), this implies that the model has a large predictive relevance in predicting the adoption intention of autonomous robots in the supply chain and logistics industry (Hair et al., 2014).

Table 9
SEM Results

	Coef	Std Err	T Stat	P Values	F2	L95% BC CI	U95% BC CI
R square	0.729	0.742	21.034	**0.000**		0.647	0.779
Adj R Square	0.717	0.036	19.848	**0.000**		0.632	0.769
Q Square	**0.51**						
ADVT	0.130	0.078	1.663	**0.097**	0.016	-0.018	0.288
CMPX	-0.298	0.073	3.341	**0.018**	0.039	-0.052	0.427
COST	-0.324	0.077	4.225	**0.000**	0.093	-0.166	0.457
SPRT	0.417	0.075	3.224	**0.023**	0.056	0.063	0.565
FINC	0.395	0.066	4.443	**0.015**	0.084	0.029	0.419
CAPA	0.089	0.071	1.255	**0.210**	0.009	0.217	0.048
VEND	0.122	0.075	1.622	**0.106**	0.013	-0.024	0.274
CMTV	0.187	0.076	2.664	**0.014**	0.029	0.048	0.340
CUST	0.364	0.084	2.766	**0.044**	0.074	0.019	0.332

4.11 Hypothesiss results

4.11.1 Hypothesis 1a. Perceived relative advantage has a positive impact on supply chain and logistics firms' adoption of autonomous robots (ADVT)

Perceived relative advantage has a positive but insignificant effect on Adoption intention all other variables being constant. For each unit increase in the Perceived relative advantage, Adoption intention increases by 13.00%. Inferring from the significance of the t statistic of 1.663 we will be taking a 9.70% risk in assuming that the Perceived relative advantage has a significant effect on the Adoption intention which is greater than the level of significance of 5%. Furthermore, the effect size of perceived relative advantage is 0.016 which is lower than the threshold of 0.02 (Cohen, 1988). We therefore conclude that the Perceived relative advantage has a positive but insignificant effect on the Adoption intention.

4.11.2. Hypothesis 1b. Perceived complexity has a negative impact on supply chain and logistics firms' adoption of autonomous robots

Perceived Complexity has a negative and significant effect on Adoption intention all other variables being constant. For each unit increase in the Perceived Complexity, Adoption intention increases by 29.8%. Inferring from the significance of the t statistic of 3.341 we will be taking a 1.8% risk in assuming that the Perceived Complexity have a significant effect on the Adoption intention which is less than the level of significance of 5%. Furthermore, the affect size associated to the coefficient of 0.039 is greater than the threshold of 0.02, this confirms that perceived complexity actually has a significant effect on the adoption of autonomous robots in the supply chain and logistics industry. We therefore reject the null hypothesis; the risk to reject the null hypothesis while it is true is 1.8%.

4.11.3. Hypothesis 1c. Perceived cost has a negative impact on supply chain and logistics firms' adoption of autonomous robots

At a 99% confidence interval, perceived cost has a negative and significant effect on Adoption intention of automotive robots in the supply chain and logistics industry all other variables being constant. For each unit increase in the Perceived cost, Adoption intention decreases by 32.40%. Inferring from the significance of the t statistic of 4.225 we will be taking a 0.00% risk in assuming that the Perceived cost have a significant effect on the Adoption intention which is lower than the level of significance of 5%. Given an effect size of 0.09 which is greater than the minimum of 0.02, this confirms that perceived cost actually has a significant effect on the adoption of autonomous robots in the supply chain and logistics industry. We therefore reject the null hypothesis and retain the alternative. The risk to reject the null hypothesis while it is true is lower than 0.01%.

4.11.4. Hypothesis 2a. Top management support has a positive impact on supply chain and logistics firms' adoption of autonomous robots

Top management support has a positive and significant effect on adoption intention all other variables being constant. For each unit increase in the top management support, adoption intention increases by 41.7%. Inferring from the significance of the t statistic of 3.224 we will be taking a 2.30% risk in assuming that the top management support has a significant effect on the adoption intention which is less than the level of significance of 5%. We therefore conclude that the top management support brings a significant amount of information in explaining the adoption intention of autonomous robots in the supply chain and logistics industry. We therefore reject the null hypothesis and retain the alternative. The risk to reject the null hypothesis while it is true is lower than 0.02%.

4.11.5: Hypothesis 2b. Financial support has a positive impact on supply chain and logistics firms' adoption of autonomous robots

Perceived availability of financial support has a positive and significant impact on adoption intention all other variables being constant. For each unit increase in the perceived availability of financial support, Adoption intentions increases by 39.5%. Inferring from the significance of the t statistic of 4.443 we will be taking a 1.00% risk in assuming that the Perceived availability of financial support have a significant effect on the adoption intention of autonomous robots which is less than the level of significance of 5%. We therefore conclude that the perceived availability of financial support brings a significant amount of information in explaining the adoption intentions of autonomous robots. We therefore reject the null hypothesis and retain the alternative. The risk to reject the null hypothesis while it is true is lower than 0.02%.

4.11.6. Hypothesis 2c. Employee competence has a positive impact on supply chain and logistics firms' adoption of autonomous robots

Perceived employee competence has a positive but insignificant effect on adoption intentions of autonomous robots in the supply chain and logistics industry**.** For each unit increase in the perceived employee competence, Adoption intentions of autonomous robots increases by 8.90%. Inferring from the significance of the t statistic of 1.255 we will be taking a 21.00% risk in assuming that the perceived employee capability has a significant effect on the adoption intention which is greater than the level of significance of 5%. We therefore conclude that the perceived employee capability does not bring a significant amount of information in explaining the adoption intentions of autonomous robots in the supply chain and logistics industry.

4.11.7. Hypothesis 3a. Competitive pressure has a positive impact on supply chain and logistics firms' adoption of autonomous robots

At a 95% confidence interval, perceived competitive pressure has a positive and significant effect on adoption intention all other variables being constant. For each unit increase in the perceived competitive pressure, adoption intention increases by 18.70%. Inferring from the significance of the t statistic of 2.664 we will be taking a 1.40% risk in assuming that the perceived competitive pressure has a significant effect on the adoption intention which is lower than the level of significance of 5%. We therefore conclude that the perceived competitive pressure has a positive and significant effect on the adoption intention.

4.11.8. Hypothesis 3b. Customer pressure has a positive impact on supply chain and logistics firms' adoption of autonomous robots

At a 95% confidence interval, perceived customer pressure has a positive and significant effect on adoption intention all other variables being constant. For each unit increase in the Perceived customer pressure, Adoption intention increases by 36.4%. Inferring from the significance of the t statistic of 2.766 we will be taking a 4.40% risk in assuming that the perceived customer pressure has a significant effect on the adoption intention which is less than the level of significance of 5%. We therefore conclude that the perceived customer pressure has a positive and significant effect on the Adoption intention.

4.11.9. Hypothesis 3c. Vendor support has a positive impact on supply chain and logistics firms' adoption of autonomous robots

Perceived vendor support has a positive but insignificant effect on adoption intention intentions of autonomous robots in the supply chain and logistics industry all other variables being equal. For each unit increase in the perceived vendor support, adoption intention increases by 12.20%. Inferring from the significance of the t statistic of 1.622 we will be taking a 10.60% risk in assuming that the perceived vendor support has a significant effect on the adoption intention which is greater than the level of significance of 5%. We therefore conclude that the perceived vendor support has a positive but insignificant effect on the adoption intentions of autonomous robots in the supply chain and logistics industry.

4.11 Summary of supported Hypothesis

Table 10 shows the summary of hypotheses testing.

Table 10
Summary of supported Hypothesis

	Coef	Std Err	T Stat	P Values	F2	L95% BC CI	U95% BC CI	Hypothesis summary
CMPX	-0.298	0.073	3.341	**0.018**	0.039	-0.052	0.427	Supported
COST	-0.324	0.077	4.225	**0.000**	0.093	-0.166	0.457	Supported
SPRT	0.417	0.075	3.224	**0.023**	0.056	0.063	0.565	Supported
FINC	0.395	0.066	4.443	**0.015**	0.084	0.029	0.419	Supported
CMTV	0.187	0.076	2.664	**0.014**	0.029	0.048	0.340	Supported
CUST	0.364	0.084	2.766	**0.044**	0.074	0.019	0.332	Supported

5. Discussion

Earlier research has demonstrated the potential of adopting robots in various sectors and fields such as the healthcare sector (Kachouie et al., 2014; Savela et al., 2018), for emotional and social companionship (Piçarra & Giger, 2018), for educational purposes (Reich-Stiebert & Eyssel, 2015) and in surveillance (Carlsen et al., 2014). However, there is a dearth of research in adopting such autonomous robots in the field of supply chain and logistics (Hofmann *et al.*, 2019). Therefore, the purpose of this study was to develop and test a conceptual model which identifies the key prerequisites for the adoption of autonomous robots in the supply chain and logistics industry. In particular, the study tested some hypotheses to understand how technological factors (i.e., relative advantage, complexity and cost), organisational factors (i.e., management support, financial support and employee competence), and environmental factors (i.e., competitive pressure, customer pressure and vendor support) can boost the adoption of autonomous robots in the supply chain and logistics industry. Indeed, these factors have been recognised widely as an important predictor of technological innovations adoption (e.g., AlSharji et al., 2018; Gangwar, 2018; Maduku et al., 2016; Oliveira et al., 2019). With this in mind, a multi-dimensional framework that considers technological, organizational and environmental factors in determining the adoption of autonomous robots in the supply chain and logistics sector is proposed (see Fig. 1).

At the technological level, the study found that perceived complexity has a negative and significant impact on supply chain and logistics firms' adoption of autonomous robots. Complexity is defined as the extent to which technological innovation is characterized as relatively difficult to comprehend and use. This finding is consistent with Naicker & Van Der Merwe (2018), who found that people are less likely to adopt novel technologies if they perceive them to be highly complex. Similarly, the study demonstrated that perceived cost has a negative and significant impact on supply chain and logistics firms' adoption of autonomous robots. This result confirms the association between the cost of digital technologies and the adoption level (Yadav et al., 2016). However, the study found no evidence that the perceived relative advantage positively impacts supply chain and logistics firms' adoption of autonomous robots. While this is a surprising result considering the potential value that digital technologies can bring to supply chains (Hofmann *et al.*, 2019), it shows that supply chain decision-makers may not necessarily realize the usefulness of using autonomous robots in supply chain activities.

At the organisational level, the study demonstrated that top management support has a positive and significant impact on supply chain and logistics firms' adoption of autonomous robots. This result is in line with the previous findings from information technology adoption literature which have suggested that top management support can serve as an enabler of adopting new technologies (AlSharji et al., 2018; Gangwar, 2018; Oliveira et al., 2019). Another crucial organisational factor that was found to have a positive and significant impact on adopting autonomous robots in the supply chain context is the availability of financial resources. This is an expected finding as having high financial resources increases firms' ability to invest in technological solutions (Lai, Sun and Ren, 2018). However, there was not enough evidence to suggest that employees' technical competence would impact autonomous robots' adoption. This result can be explained by the fact that robotic solutions can function autonomously and therefore does not require a high level of technical competence to adopt such tools.

Finally, at the environmental level, in line with the previous studies (e.g., Hasani et al., 2017; Lai et al., 2018), this study suggests that competitive pressure has a positive and significant impact on supply chains and logistics firms' adoption of autonomous robots. Furthermore, Customers' pressure was found to positively and significantly impact supply chain and logistics firms' adoption of autonomous robots. As customers have high expectations for the speedy delivery and high service levels, supply chain decision-makers become more encouraged to adopt innovative solutions to improve the supply chain performance (Hofmann *et al.*, 2019).

6. Conclusion and implications

The current study aimed to develop and test a conceptual framework that identifies the key determinants that can affect the adoption of autonomous robots in the supply chain and logistics sector. First, by drawing on the previous streams of research in supply chain management, information technology, and artificial intelligence, the study developed several hypotheses that affect supply chain managers' decision to adopt autonomous robots (Fig. 1). Second, the study tested the hypotheses included the study model to examine the relationship between various variables and the adoption of autonomous robots. Overall, the study results confirm the association between the cost of digital technologies and the adoption level of autonomous robots. However, the study found no evidence that the perceived relative advantage positively impacts supply chain and logistics firms' adoption of autonomous robots.

The study makes a theoretical contribution by responding to the lack of research on the mechanism of supply chain adoption of autonomous robots (Hofmann *et al.*, 2019). It lays out the key prerequisites and drivers that facilitate the adoption of autonomous robots in the supply chain and logistics sector. Managerially, Fig. 1 should help managers understand the key drivers they need to consider when adopting autonomous robots in their supply chains. Further, the study showed no evidence to suggest that the perceived relative advantage (e.g., usefulness) of autonomous robots will encourage decision-makers to adopt such robots. This result suggests that supply chain actors may not necessarily be cognizant of the latest innovative solutions which can improve supply chain performance. Hence, the manufacturing firms and marketers of these technologies should approach supply chain managers, demonstrate the value of such technologies, and explain why supply chain actors should adopt these innovative tools. In particular, producers of such autonomous robots should work closely with decision-makers to understand today's supply chains challenges (e.g., consumers' pressures for speedy delivery, risings costs, increasing service levels) to meet current and future needs. Given the scarcity of research in applying autonomous robots in the supply chain and logistics field, one of the interesting future research areas is conducting case study research to document the value of using autonomous robots in the supply chain and logistics sector. This is important as it will add to our knowledge into which areas in the logistics these robots are deployed and where this can be expanded. Further, future research can focus on how novel technologies, in general, can help to address supply chain challenges.

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Appendix

Table 1
Proposed research instruments

Instruments	Sources
Perceived relative advantage 1. "AI for supply chain / autonomous robots would enable our enterprise to market our products/services in a better way" 2. "AI for supply chain / autonomous robots would enable our enterprise to communicate with our customers / partners effectively" 3. "We would be able to serve our customers / partners timeously with AI for supply chain / autonomous robots" 4. "AI for supply chain / autonomous robots would assist us to develop better relationships with our customers / partners"	Ghobakhloo et al. (2011); Lian et al. (2014)
Perceived Complexity 1. "The use of AI for supply chain / autonomous robots would require a lot of mental effort" 2. "The use of AI for supply chain / autonomous robots would be frustrating" 3. "AI for supply chain / autonomous robots would be too complex for our inventory and supply chain activities" 4. "The skills needed to use AI for supply chain / autonomous robots would be too complex for employees of our enterprise"	Ghobakhloo et al. (2011); Lian et al. (2014)
Perceived cost 1. "The costs involved in the adoption of AI for supply chain / autonomous robots would be far greater than the expected benefits" 2. "The cost of maintaining AI for supply chain / autonomous robots would be very high for our enterprises" 3. "The cost involved in providing support systems for AI for supply chain / autonomous robots would be too high" 4. "The amount of money invested in training employees to use AI for supply chain / autonomous robots would be very high"	Lai et al. (2014); Lian et al. (2014)
Top management support 1. "Top management would provide resources necessary for the adoption of AI for supply chain / autonomous robots" 2. "Top management would provide necessary support for the adoption of AI for supply chain / autonomous robots" 3. "Top management would support the use of AI for supply chain / autonomous robots" 4. "Top managers would be enthusiastic about adopting AI for supply chain / autonomous robots"	Borgman et al. (2014); Lian et al. (2014);
Perceived availability of financial support 1. "Our enterprise would have the financial resources for adopting AI for supply chain / autonomous robots" 2. "Our budgets would be significant enough to support the adoption of AI for supply chain / autonomous robots" 3. "It would be easy to obtain financial support for AI for supply chain / autonomous robots' adoption from local banks and/or other financial institutions" 4. "Our enterprise would take AI for supply chain / autonomous robots more seriously because of the adequate financial support we receive from local banks"	Lai et al. (2014); Ifinedo (2011)
Perceived employee capability 1. "Our employees would be capable of learning AI for supply chain / autonomous robots related technologies easily" 2. "Our employees would be capable of using AI for supply chain / autonomous robots to solve our supply chain and inventory problems easily" 3. "Our employees would be capable of using AI for supply chain / autonomous robots to interact with our partners and customers" 4. "Our employees would be capable of providing new ideas on AI for supply chain / autonomous robots use for our enterprise"	Lin and Ho (2011)
Perceived vendor support 1. "Vendors actively market the use of AI for supply chain / autonomous robots" 2. "There would be adequate technical support for AI for supply chain / autonomous robots provided by vendors" 3. "Training for AI for supply chain / autonomous robots would be adequately provided by vendors & other training service providers" 4. "AI for supply chain / autonomous robots' vendors are encouraging our enterprise to adopt it by providing us with free training sessions"	Ghobakhloo et al. (2011); Al-Qirim (2007)
Perceived competitive pressure 1. "Our choice to adopt AI for supply chain / autonomous robots would be strongly influenced by what competitors in the industry are doing" 2. "Our enterprise is under pressure from competitors to adopt to AI for supply chain / autonomous robots" 3. "Our enterprise has would adopt AI for supply chain / autonomous robots in response to what competitors are doing"	Ghobakhloo et al. (2011); Ifinedo (2011)
Perceived customer pressure 1. "Many of our customers/partners would expect our enterprise to adopt AI for supply chain / autonomous robots" 2. "Our customers / partners would demand that we establish relationships with them using AI for supply chain / autonomous robots" 3. "Our relationship with our major customers /partners would suffer if we did not adopt AI for supply chain / autonomous robots" 4. "Our customers /partners would consider us to be forward thinking by adopting AI for supply chain / autonomous robots"	Wu and Lee (2005);
Adoption intention 1. "Our enterprise intends to adopt AI for supply chain / autonomous robots" 2. "Our enterprise intends to start using AI for supply chain / autonomous robots regularly in the future" 3. "Our enterprise would highly recommend AI for supply chain / autonomous robots for other enterprises to adopt"	Mishra, Akman, and Mishra (2014)