Uncertain Supply Chain Management 11 (2023) 411–422

Contents lists available at GrowingScience

Uncertain Supply Chain Management

homepage: www.GrowingScience.com/uscm

Factors affecting e-supply chain management systems adoption in Jordan: An empirical study

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A B S T R A C T

Article history:
Received November 10, 2022
Received in revised format December 22, 2022
Accepted March 12 2023
Available online March 12 2023

Keywords:
Electronic Supply Chain Management System (eSCMS)
Adoption Intentions (AI)
Technology
Organization
Environment (TOE) framework
Jordan

Recently, there have been a growing number of articles focusing on the benefits of adopting e-SCM systems and the value of such systems in supply chain performance. However, less academic research was devoted to understanding factors affecting the adoption intention of such systems. This study uses the technology, organization, and environment (TOE) framework to examine factors that affect the adoption of e-SCM systems in Jordan, where limited research has been conducted in this country. Through an online survey filled by 251 participants via the LinkedIn website, the study shows that perceived relative advantage, financial resources, employee competency, top management support, competitive pressures, and customer pressure positively impact the adoption intention of e-SCM systems. The findings confirm the association between variables embedded in the TOE framework and the adoption intention of innovative supply chain systems and solutions and support earlier findings. According to the study findings, e-SCM systems providers should focus on the relative advantage these systems offer to increase the likelihood of their adoption.

1. Introduction

The world of business is witnessing a considerable shift to a digital economy. Manufacturing and services firms are undergoing a digital transformation to improve their current business activities. As a result, it is unsurprising that new intelligent technologies and networks have emerged to help business leaders pursue digitization. Regarding supply chain management, the continuous development of intelligent technologies continues to affect how web-based information transfers between companies, their suppliers, and their customers, increasing the role of information management in creating effective supply chains (Mukherjee & Chittipaka, 2021). Hence, the electronic supply chain management system (eSCMS) has been defined as an approach in which organizations use internet and information technologies and systems to integrate various supply chain partners, including suppliers, manufacturers, retailers, and customers, to improve service level and supply chain performance (Antoni & Akbar, 2019). Presently, there are many technologies used in various supply chain sectors, such as radio frequency identification (RFID), electronic resource planning (ERP), and electronic data interchange (EDI). Indeed, these technologies assist supply chain managers in reducing operational costs and improving supply chain performance (Lin, 2017; Hamadneh et al., 2021). Likewise, more recent intelligent systems have emerged to improve the performance of e-

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doi: 10.5267/j.uscm.2023.3.008

supply chain systems, such as Multi-Agent Systems (MAS), Artificial Neural Networks (ANN), Genetic Algorithms (GA), and Fuzzy Logic (FL) (Alzoubi, 2018).

Extant research on e-SCM systems focuses on how IT tools and intelligent systems improve supply chain performance (Wu and Chang, 2012), enhance SC processes (Gimenez and Lourenço, 2008), and improve competitiveness (Erceg and Damoska-Sekulowska, 2019). However, a few studies (e.g., Lin 2014) investigated the idea of e-SCM adoption. This is surprising because the current research acknowledges that adopting e-SCM systems entails many internal and external challenges regarding the financial investment required, organizational aspects, and the environmental contexts (Pulevska-Ivanovska & Kaleshovska, 2013; Lin 2014; Aityassine et al., 2022). Hence, understanding how these aspects may affect the adoption intention of e-SCM systems is relevant and important.

The study by Lin (2014) offers valuable insights into the key determinants that influence e-SCM systems adoption in Taiwanese manufacturing firms. The same author points out the need to conduct further studies in different countries and cultural contexts to examine the main factors affecting e-SCM systems adoption. Hence, this study aims to extend our understanding of the main factors affecting supply chain managers' ability to adopt e-SCM systems effectively. With this in mind, the study focuses on a unique context, particularly the Jordanian manufacturing sector. We selected Jordan as a developing country in this study because, according to Shaar et al. (2022), its industrial supply chains are yet in the early stages of growth. These authors highlighted that more investment is needed to enhance supply chain integration and green innovation in Jordanian's supply chain state. Further, according to Marei et al., (2021) only 27.6 of firms utilize e-procurement systems in Jordan, which suggests that there might be some hesitance in adopting e-SCM systems in Jordan. Therefore, understanding the factors which affect e-SCM systems adoption can help identify the key prerequisites for such adoption among supply chain practitioners in Jordan. Managerially, the results of this study will help e-SCM systems providers to understand the main factors which can affect the adoption intention of these systems among Jordanian firms and therefore approach them more effectively.

The paper is structured as follows. First, we review previous literature on e-SCM systems and the technology, organization, and environment (TOE) framework. Subsequently, we discuss the research design and data collection and analysis techniques adopted in the study. Next, we present the empirical findings, highlight the theoretical and managerial contribution, and offer further avenues for future research.

2. Literature review and hypothesis development

2.1 Electronic Supply Chain Management (e-SCM)

Supply Chain Management (SCM) is an approach that seeks to efficiently integrate suppliers, business partners, and warehouses so products are produced in the right quantity, distributed to the appropriate locations, and at the right time to minimize costs and satisfy customer needs (Stadtler, 2008). E-SCM is a new concept derived from the former SCM concept and emerged because of the evolution of information technologies and re-engineering of the organizations' business processes towards partners cooperation enabled by the Internet (Pulevska-Ivanovska & Kaleshovska, 2013). E-SCM has been defined as an approach in which organizations use internet and information technologies and systems to integrate various supply chain partners, including suppliers, manufacturers, retailers, and customers to improve service level and supply chain performance (Antoni & Akbar, 2019). In this sense, e-SCM systems enable supply chain partners to connect among them digitally and also via various digital networks enabled by intelligent systems such as Multi Agent System (MAS), Artificial Neural Network (ANN), Genetic Algorithms (GA), and Fuzzy Logic (FL) (Alzoubi, 2018).

In recent years, many authors have explored the effect of e-SCM on systems on supply chain performance. These studies have argued that e-SCM of an organization helps a network of supply chain partners to identify and respond quickly to changing customer demand, thus providing higher possibilities for achieving competitive advantage (Kasemsap 2015). Similarly, Valverde & Saadé (2015) showed that e-SCM positively affected the electronic manufacturing services industry, mainly because it leads to higher profitability and improved communications.

2.2 *Technology, Organisation and Environment (TOE) Framework*

The technology-organization-environment (TOE) of Tornatzky and Fleischer (1990) is considered a suitable theoretical foundation for studying, adopting and implementing new intelligent technologies and systems. The framework has been used widely among SCM scholars (e.g., Shaik & Abdul-Kader, 2013; Lin, 2014; Chittipaka et al., 2022). In line with the previous studies, this study employs the TOE framework to examine factors that affect the adoption intention of e-SCM systems among Jordanian manufacturing firms. Tornatzky and Fleischer (1990) identified three institutional contexts of the TOE framework, including the technological, organizational, and environmental contexts, which impact the adoption and implementation of technological innovations, such as e-SCM systems. We present the TOE framework in the following subsections.

2.2.1 Technological Context (TC)

The technological context relates to ICT infrastructure and the ICT skills of employees. It also includes the technological tools currently being applied by firms or those yet to be deployed. It has been reported that the internet and IT technologies can help improve supply chain activities such as planning and forecasting, procurement, logistics and information sharing (Hua,

& Cong, 2011). The study by Ercegand and Damoska-Sekulowska (2019) concluded that using advanced logistics and eSCM systems can help firms increase their competitiveness in today's fast-changing markets.

Understanding how technology is adopted becomes increasingly important when predicting whether individuals will use a specific technology. Adopting new technologies relies heavily on perceiving their benefits or relative advantage among users. When potential adopters view a specific technology or innovation as better than other alternatives, they are more likely to adopt it (Rogers, 2010). It is now well established from various studies that PRA is a strong predictor of adopting technologies, such as online marketing channels among SMEs Li et al., 2011; Masa'deh et al., 2023, e-procurement (e.g., Aboelmaged, 2010), website use intention (Ramayah et al., 2016; Alzoubi et al., 2022) and mobile marketing by SMEs (Maduku et al., 2016). Similar results were found in the literature, which suggests that supply chain managers are more willing to adopt and implement new e-SCM systems when they realize their advantages (Lin, 2014). Thus, the following hypothesis is proposed:

Hypothesis (H_{1a}): *PRA has a positive impact on the AI of eSCMS.*

Another factor related to the technological element is the perceived complexity experienced when adopting innovations or technologies. Complexity has been conceptualized as the degree to which individuals perceive the new technology as difficult to use and understand (Chuang, Nakatani and Zhou 2009). Complexity was found to be one of the most important causes of the slower rate of the adoption of technology (Premkumar and Ramamurthy 1995). In contrast, trialability and observability have been perceived as important factors enabling innovative IT systems adoption (Premkumar and Ramamurthy 1995; Kurdi et al., 2022). Hence, it can be proposed that:

Hypothesis (H_{1b}): *Complexity has a negative impact on the AI of eSCMS.*

Another variable that may affect the adoption intention of innovative technologies is the cost associated with acquiring these technologies. Perceived costs, or how much a new technology or system would cost, can enable or hinder the adoption intention of technological innovation (Lin & Wang, 2005; Maduku et al., 2016; Naicker & Van Der Merwe, 2018). Although several articles argued that adopting e-SCM systems can save large amount of money for supply chain actors (Antoni & Akbar, 2019; Taghipour et al., 2021), the cost of investing and implementing eSCM systems can be high, thus impeding firms from acquiring such systems (Lin, 2014).

Hypothesis (H_{1c}): *Perceived cost has a negative impact on the AI of eSCMS.*

Hypothesis (H_1): *Technological Context has a significant impact on the AI of eSCMS.*

2.2.2 Organizational Context

Organizational context involves top management's support, financial, and human resources. These elements are crucial to facilitate innovation adoption. Top management support refers "to the degree to which top management understands the importance of the IS function and the extent to which it is involved in IS activities" (Ragu-Nathan et al., 2004). It has been argued that top management support is necessary for creating a supportive business environment to facilitate the adoption of new technologies (Maduku et al., 2016). Previous research has found that top management support enables adopting eSCM systems in Taiwan (Lin, 2014). Current research findings have conclusively shown that top management support is an indicator of adoption of innovation (Gangwar, 2018; Oliveira et al., 2019; Marei et al., 2021). As a result, it can be proposed the following hypothesis:

Hypothesis (H_{2a}): *Top management support has a positive impact on the AI of eSCMS.*

Organizational resources can be divided into either financial or human (Tornatzky and Fleischer, 1990). Monetary resources are essential to consider because the availability of such resources can fund purchasing and maintaining new technological innovations and systems (Kim & Garrison, 2010). Hence, it can be stated that the availability of financial resources will increase the financial readiness of firms to invest in e-SCM systems. In other words,

Hypothesis (H_{2b}): *FR has a positive impact on the AI of eSCMS.*

Second, human resources are related to employees' competencies, enabling them to derive value from using new systems or innovations. It has been argued that human resource power is the drive for organizational activities in business, which helps to achieve the organization's vision, mission, and goals (Duncan,1995). Further, competent and knowledgeable employees are more likely to learn new things and thus reduce the likelihood of new adoption resistance (Lin & Ho, 2011). In short:

Hypothesis (H_{2c}): *Employees competency has a positive impact on the AI of eSCMS.*

Hypothesis (H_2): *Organizational Context has a positive impact on the AI of eSCMS.*

2.2.3 Environmental Context

The environmental context refers to the organization's environment, such as the industry's structure, competitive advantage, and government support (Tornatzky & Klein, 1982). Competitive pressure (CMP) is fundamentally important variable to understand how the environment context support adopting new innovations (Mukherjee & Chittipaka, 2021). CMP can be viewed in terms of the competitive environment within an industry and disruptive technologies that can redefine industries. It has been noted that that external pressures can increase the likelihood of adopting new technologies and systems (Tashkandi

& Al-Jabri, 2015; Hasani et al., 2017). In the context of e-SCM**,** CMP was found to have a significant impact on adopting eSCM systems in Taiwan (Lin, 2014). Indeed, the rapid digitisation of industry, is trending in supply chain management (Schniederjans et al., 2020) and therefore supply chain executives perceive investing in e-SCM systems is critical to move forward their operations especially after the Covid-19 pandemic (Faiz et al., 2023; Zhou et al., 2023). Results from earlier studies show a strong and consistent association between perceived competitive pressure and the adoption of technological innovation (Glowalla & Sunyaev 2012; Hasani et al., 2017; Lai et al., 2018). Hence, we propose the following hypothesis:

Hypothesis (H_{3a}): *CMP has a positive impact on the AI of eSCMS.*

Customer pressure (CSP) entails consumer expectations and behaviors that affect firms' intention to adopt and use new technological solutions (Hasani et al., 2017; Al Kurdi et al., 2022; Nuseir et al., 2023). Earlier research argued that the key driver to shift to e-SCM is the constant change in customers' needs and expectations (Ross, 1998; Valverde and Saadé, 2015; Alzoubi, 2018). Hence, such external pressure will probably influence firms' decision to adopt technological innovations to sustain their competitive position in their respective industries (Eze et al., 2019; Wu & Lee, 2005). In other words, perceived customer pressure will likely put more pressure on supply chain executives to adopt e-SCM systems (Lee et al., 2022). In short:

Hypothesis (H_{3b}): *CSP has a positive impact on the AI of eSCMS.*

Hypothesis (H_3): *Environmental Context has a positive impact on the AI of eSCMS.*

Fig. 1 below presents the research farmwork based on the preceding review and clarifies the relationships between the study variables.

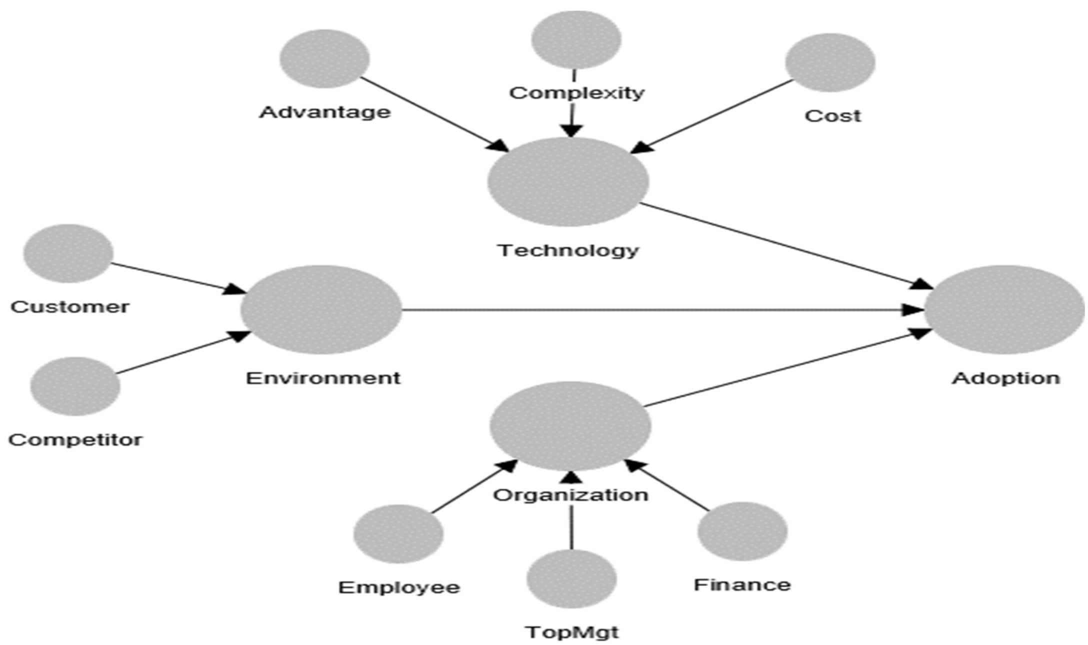

Fig. 1. Research Model

3. Methodology

The professional website LinkedIn was used to send online survey to collect data in this study during 2022. The survey aimed at supply chain managers and individuals working in the logistics and supply chain field to achieve the study aim, with participation being entirely voluntary. There were 251 participants who filled the survey. As it was seen from their LinkedIn profiles, participants had a diverse experience as they held different roles and responsibilities throughout their careers. Table 1 shows that 61.4% of the respondents (n = 251) were males (n = 154) and 38.6% were females (n = 97). Majority of the participants (35.1%, n = 88) were aged between 41-50 years. Most of the participants (n = 148, 59%) had bachelor's degree as the highest educational qualification. While 48.2% (n = 121) of the participants had 1-5 years' work experience, which was actually most of the participants.

With respect to the central tendency and variability of the data or the responses with respect to the perceptions of the participants on the study variables, we calculated the means (M), standard deviation (DV) of the study variables. We also estimated the correlations among the study variables so determine that how strongly those were associated with each other and what was the type of those associations e.g., moderate and positive association, for details see Table 2.

Table 1
Demographics Analysis

Characteristic	Frequency	Percent
	Gender	
Male	154	61.4
Female	97	38.6
Total	251	100.0
	Age	
18-30 years	74	29.5
31-40 years	58	23.1
41-50 years	88	35.1
Above 50 years	31	12.4
Total	251	100.0
	Educational Qualification	
High School	25	10.0
Bachelors	148	59.0
Masters	74	29.5
PhD	4	1.6
Total	251	100.0
	Work Experience	
1-5 years	121	48.2
6-10 years	54	21.5
11-15 years	48	19.1
Above 15 years	28	11.2
Total	251	100.0

N = 238

Table 2
Mean, SD and Correlations

	M	SD	TC	PRA	COMPX	PC	OC	TMS	FR	EC	ENV	CMP	CSP	AI
TC	2.93	0.38	1											
PRA	3.02	0.83	.295*	1										
COMPX	2.96	0.71	.565*	-.305*	1									
PC	2.80	0.82	.620*	-.332*	.240*	1								
OC	3.05	0.65	-.173*	.587*	-.377*	-.511*	1							
TMS	3.12	0.94	-.137*	.503*	-.308*	-.435*	.826*	1						
FR	3.12	0.66	-.130*	.412*	-.241*	-.390*	.789*	.453*	1					
EC	2.92	0.78	-.156*	.503*	-.362*	-.415*	.820*	.464*	.565*	1				
ENV	2.99	0.69	.112	.089	.047	.027	.152*	.143*	.188*	.047	1			
CMP	3.19	1.26	-.079	.284*	-.246*	-.186*	.422*	.388*	.286*	.338*	.670*	1		
CSP	2.79	1.08	.236*	-.218*	.347*	.252*	-.297*	-.270*	-.093	-.334*	.499*	-.310*	1	
AI	3.31	0.57	-.214*	.486*	-.384*	-.460*	.629*	.503*	.509*	.525*	.169*	.311*	-.147*	1

N = 251, *p < .05

4. Data Analysis

We had mixed ordered constructs i.e., lower order constructs (LOC) e.g., TMS in OC and higher order constructs (HOC) e.g., OC and TC, in both types i.e., reflective and formative. So, aligned with the recommendations of Sarstedt, Hair, Cheah, Becker and Ringle (2019) we chose the Type-II Reflective-Formative typology for our model for the assessment of measurement and structural models. We further followed Sarstedt at al., (2019) by using the two-stage extended / repeated indicators approach as that is easy to implement and understand.

Measurement Model Assessment – LOC Reflective: When endogenous variables of a construct are intercorrelated it is called a reflective model. Reflective part of a measurement model can be assessed through by the means of factor loadings (FL) which are required to be > .05 (Hair, Black, Babin & Anderson, 2019), as shown in Figure 2 that FL for all of the reflective constructs were above 0.5, which indicated the confirmation of the reliability of the study measures. Cronbach's alpha (CA) values > 0.7 (Hair et al., 2019) confirm the internal consistency, Table 3 detailed that CA values were > 0.7. Additionally, composite reliability (CR) was also examined to rule out the underestimation of CA, as seen in Table 3 that CR values were also > 0.7. Convergent validity of a construct is established when its AVE value is > 0.5 (Hair et al., 2019). Table 3 showed that AVE of all constructs were > 0.5. HTMT ratios were consulted to confirm the discriminant validity of the constructs, Table 3 shows that assumption of discriminant validity was also established as all HTMT ratios were < 0.85 (Hair et al., 2019). Towards the end of assessing the LOC-reflective model we examined the predictive relevance with the help of predictive validity, which is calculated as by utilizing the values of communality (H^2), all of those H^2 values were positive for all blocks (see Table 3), hence ensuring the predictive relevance of our measurement model.

Table 3
Measurement Model Assessment – LOC Reflective

	CA	CR	AVE	H^2	HTMT								
					PRA	COMPX	PC	TMS	FR	EC	CMP	CSP	AI
PRA	.778	.857	.602	.346	-								
COMPX	.826	.884	.657	.426	.382	-							
PC	.817	.880	.648	.411	.418	.293	-						
TMS	.768	.851	.588	.320	.650	.389	.546	-					
FR	.753	.845	.582	.326	.538	.310	.496	.599	-				
EC	.758	.851	.595	.346	.656	.459	.521	.612	.749	-			
CMP	.861	.915	.782	.534	.354	.281	.228	.495	.351	.391	-		
CSP	.897	.936	.829	.618	.260	.404	.287	.327	.155	.404	.378	-	
AI	.816	.866	.525	.355	.605	.460	.562	.632	.641	.661	.411	.171	-

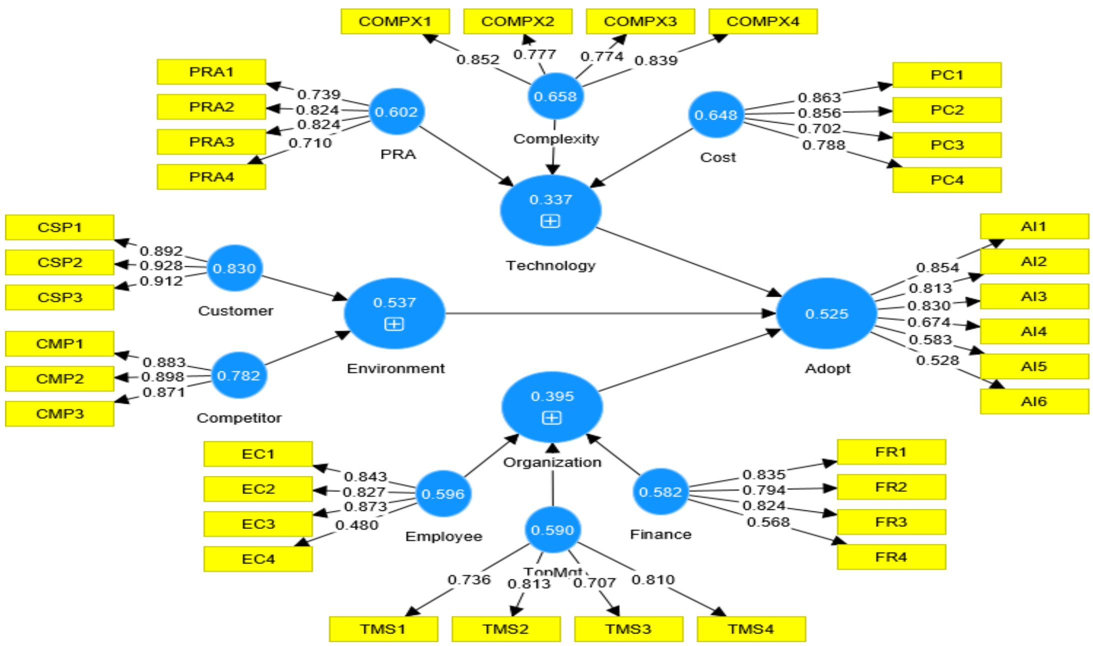

Fig. 2. Measurement Model Assessment

Measurement Model Assessment – HOC-Formative: A measurement model is known to formative when its endogenous variables or the indicator items are uncorrelated, but they can cause the exogenous variable e.g., CSP and CMP. Formative model doesn't require CA, AVE or HTMT etc. as the indicator variables are uncorrelated, rather it's assessed through the collinearity of the indicators of a formative construct, if the VIF values are < 3 then indicators are assumed to have ignorable collinearity (Hair et al., 2019). Appendix-1 shows that VIF all indicators were < 3. Then outer weights (OW) of the indicators are examined, if any outer weight (OW) is insignificant then the relevant indicator can be considered for removal, but its final removal is done on the basis of its outer loading (Hair et al., 2019). Appendix-1 shows that all OW were significant. Lastly, relevance of the indicators is examined to establish the reliability and validity of formative construct. Relevance of FL is established on the basis of their sizes, larger the size more the relevance. All FL along with the OW were significant, so all of them were retained. Normally FL > 0.5 is deemed relevant (Hair et al., 2019), and as per this criteria all FL were relevant, see Appendix-1.

***Structural Model Assessment*:** This tests the relationships between constructs and related theories based on existing literature (Hair et al., 2019), our model had direct effects only. We utilized bias corrected 95% confidence intervals to test out direct effect hypotheses.

***Hypotheses Testing*:** H1 was approved as TC had a negative and significant impact on AI (β = -.343, t = 5.597, p < .001), with Cohen's (1988) small effect size (F^2 = .119). TC had an aggregated negative impact as two of its dimensions i.e., COMPX and PC had individual negative effects on AI. As shown in Table 4 that PRA had a positive and significant impact on AI (β = .148, t = 2.434, p = .015), with a small effect size AI (F^2 = .029), so H1a was supported. H1b was also supported as COMPX had a negative and significant impact on AI (β = -.181, t = 3.532, p <.001), along with a small effect size at F^2 = .052. Similarly, H1c was also supported as PC was impacting the AI negatively and significantly (β = -.185, t = 3.298, p = .001), the effect size was small (F^2 = .051), see Figure 3 as well.

Table 4
Hypothesis Testing

Path	Estimate	T	P	F^2	R^2	Q^2	VIF	Status
TC → AI	-.343	5.597	.000	.119			1.905	H1: Supported
PRA → AI	.148	2.434	.015	.029			1.565	H1a: Supported
COMPX → AI	-.181	3.532	.000	.052			1.283	H1b: Supported
PC → AI	-.185	3.298	.001	.051			1.379	H1c: Supported
OC → AI	.418	5.697	.000	.180			1.911	H2: Supported
TMS → AI	.134	2.062	.040	.021	.519	.256	1.788	H2a: Supported
FR → AI	.174	2.847	.005	.037			1.685	H2b: Supported
EC → AI	.160	2.283	.023	.027			1.937	H2c: Supported
ENV → AI	.000	0.005	.996	.000			1.293	H3: Not Supported
CMP → AI	.153	2.374	.018	.037			1.313	H3a: Supported
CSP → AI	.146	2.336	.020	.033			1.331	H3b: Supported

H2 received an obvious support when OC caused a positive and significant impact on AI (β = .418, t = 5.697, p < .001), with a medium effect size (F^2 = .180). H2a was also supported as TMS impacted the AI positively and significantly (β = .134, t = 2.062, p = .040), TMS also had a small effect on AI (F^2 = .021). FR was also having a positive and significant impact on AI (β = .174, t = 2.847, p = .005), with a small effect size at F^2 = .037, hence it confirmed the approval of H2b. H2c was also supported as EC had a positive and significant impact on AI (β = .160, t = 2.283, p = .027), with a small effect size (F^2 = .027).

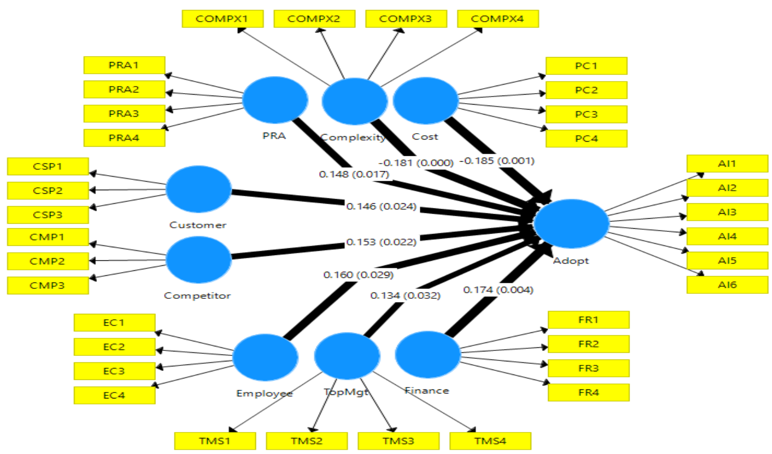

Fig. 3. Structural Model – LOC Reflective

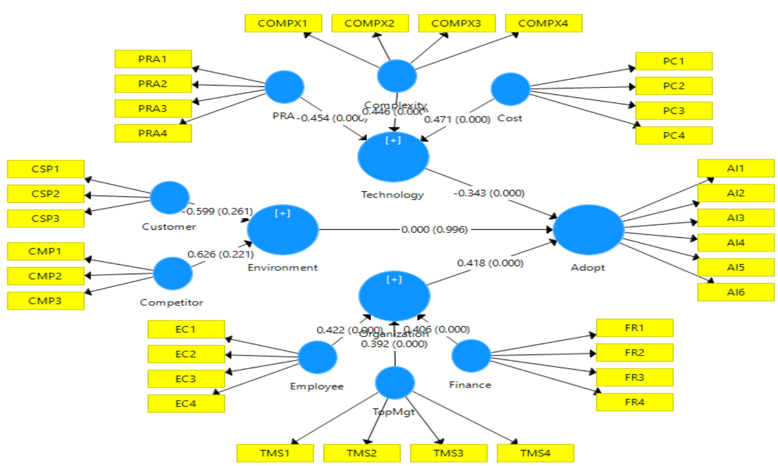

Fig. 4. Structural Model – HOC Formative

H3 was somehow not approved, as there was literally no aggregate effect of ENV on AI (β = .000, t = .005, p = .996, F^2 = .000). Nonetheless, H3a at the individual level was supported as CMP impacted the AI positively and significantly (β = .153, t = 2.374, p = .018), CMP also had a small effect on AI (F^2 = .037). Similarly, H3b was also support as CSP was also having a positive and significant impact on AI (β = .146, t = 2.336, p = .020), with a small effect size at F^2 = .033. Figure 3 and Figure 4 along with Table 4 for the details on hypothesis testing.

Predictive Quality of the Structural Model: On account of predictive quality of the structural model we consulted the Q^2 and R^2 values. Positive value of Q^2 (> 0) in Table 4 indicated the good predictive relevance of the structural model. R^2 is the measure of overall effect size, as indicated in Table 4 that 51.9% AI was explained by the overall model. Whereas F^2 has already been explained with hypotheses results. We also examined the VIF values as additional quality measure and as shown in Table 4 that existence path collinearity which could possibly contaminate the structural model was overruled (Kock, 2015).

5. Discussion and conclusions

Electronic supply chain management (e-SCM) concept has been defined as an approach in which organizations utilize internet and information technologies and systems to integrate various supply chain partners including suppliers, manufacturers, retailers and customers to improve service level and supply chain performance (Antoni & Akbar, 2019). Earlier research has focused intensively on the benefits got from acquiring and implanting e-SCM systems and its role on the supply chain performance (Gimenez & Lourenço, 2008; Wu & Chang, 2012; Erceg & Damoska-Sekulowska, 2019). However, few studies were conducted to examine factors that affect the adoption intention of e-SCM systems. In particular, such research in the Middle East, specifically Jordan, is limited. Hence, the primary aim of this study was to understand the main factors that affect the adoption intention of e-SCM systems in Jordan. In light of prior studies (e.g., Shaik & Abdul-Kader, 2013; Lin, 2014; Chittipaka et al., 2022), this study adopted the TOE framework to predict factors which affect supply chain actors' willingness to adopt e-SCM systems. To achieve the study aim, an online survey was sent through the professional site LinkedIn to collect data from supply chain practitioners working in Jordan.

At the technological level, the perceived relative advantage was found to have a positive impact on the adoption intention of e-SCM systems in Jordan. This result matches the one observed in Taiwan and support earlier findings (Lin, 2014). Further, the perceived complexity and perceived cost were found to have a negative impact on the adoption intention of e-SCM systems. The more complex e-SCM systems are, the less likely are to be adopted. Further, when supply chain managers perceive the costs of such systems high, they might become more hesitant about acquiring and implementing e-SCM systems. This result is consistent with the earlier findings of Lin (2014).

However, it is important to stress that these results can also be explained from a cultural perspective too. For instance, Jordan is an Arab country and according to the influential cultural theorist Hofstede (2001), Arab nations scored high in the uncertainty avoidance, meaning it can be even harder for them to adopt innovative systems and solutions. As the study results show that perceived relative advantage had a positive impact on the adoption intention of e-SCM systems, e-SCM systems providers need to focus on this point and show the benefits of these systems when approaching their potential buyers to get them to adopt e-SCM systems. The results of this study also confirmed the association between top management support, financial resources and employees' competencies and the adoption intention of e-SCM systems. These findings are in line with previous studies that have investigated the impact of these variables on adopting new innovations (e.g., Aboelmaged, 2010; Lin, 2014; Oliveira et al., 2019). Finally, the results also showed competitive pressure and customer pressures perceived by supply chain actors can increase the likelihood of adopting e-SCM systems. In short, these findings reinforce earlier outcomes by confirming the association between variables selected in Fig 1 and the adoption intention of new and innovative supply chain systems and solutions (Lin, 2014; Shamout et al., 2022).

The study contributes theoretically by expanding our understanding of the factors affecting the adoption intention to e-SCM systems, where a few studied focused on this area as noted by (Lin, 2014). Further, the study was conducted in a unique context where there has been little research about e-SCM systems in the Middle East particularly, Jordan.

6. Limitations and Future research

The study adopted a quantitative research design, which does not allow offering in-depth insights into the variables tested. Hence, future academic research may adopt qualitative techniques to uncover more insights regarding adopting and implementing e-SCM systems. For instance, future research is needed to understand what challenges supply chain actors face when adopting e-SCM systems. Further, to what extent does national culture and organisational culture can impact the adopting and implanting e-SCM system? Second, the study focused only on one country, Jordan. Future studies may replicate the research framework to test the results in other countries.

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Appendix

Measurement Model Assessment – HOC Formative

	VIF	FL	FL – P value	OW	OW – P value
CMP1	2.156	0.883	.000	0.382	.000
CMP2	2.373	0.898	.000	0.384	.000
CMP3	2.077	0.871	.000	0.365	.000
COMPX1	2.022	0.852	.000	0.334	.000
COMPX2	1.644	0.777	.000	0.278	.000
COMPX3	1.647	0.774	.000	0.281	.000
COMPX4	1.918	0.839	.000	0.336	.000
CSP1	2.382	0.892	.000	0.363	.000
CSP2	3.274	0.928	.000	0.376	.000
CSP3	2.933	0.912	.000	0.359	.000
EC1	1.935	0.843	.000	0.348	.000
EC2	1.884	0.827	.000	0.339	.000
EC3	2.028	0.873	.000	0.378	.000
EC4	1.136	0.480	.000	0.201	.000
FR1	1.789	0.835	.000	0.363	.000
FR2	1.665	0.794	.000	0.324	.000
FR3	1.679	0.824	.000	0.362	.000
FR4	1.156	0.568	.000	0.249	.000
PC1	2.433	0.863	.000	0.335	.000
PC2	2.389	0.856	.000	0.342	.000
PC3	1.418	0.702	.000	0.271	.000
PC4	1.672	0.788	.000	0.290	.000
PRA1	1.478	0.739	.000	0.301	.000
PRA2	1.923	0.824	.000	0.318	.000
PRA3	1.800	0.824	.000	0.349	.000
PRA4	1.317	0.710	.000	0.321	.000
TMS1	1.530	0.736	.000	0.284	.000
TMS2	1.747	0.813	.000	0.354	.000
TMS3	1.401	0.707	0.000	0.289	0.000
TMS4	1.639	0.810	0.000	0.370	0.000

Questionnaires

Technology	**Perceived Relative Advantage** (adopted from Lin, 2014)		
	1	PB1	Our company sale revenue increasing recently
	2	PB2	Our company expanding in new markets for existing products or services
	3	PB3	We have improving coordination with suppliers and customers
	4	PB4	We feel we're generating competitive advantage
	Perceived Complexity (adopted from Atkinson, 2007)		
	5	COMPX1	Everyone in our company understand the way e-Supply chain operate
	6	COMPX2	All technical aspects of e-Supply chain are understood
	7	COMPX3	Everyone able to participate of the e-Supply chain implementation
	8	COMPX4	Our company able to adopt & customize e-Supply chain activates
	Perceived Costs (adopted from Lin, 2014)		
	9	PC1	Lead time for e-Supply chain implementation is reasonable
	10	PC2	e-Supply chain implementation has rational setup cost
	11	PC3	e-Supply chain implementation has rational operating & maintenance cost
	12	PC4	e-Supply chain implementation has rational training cost
Organization	**Top Management Support** (adopted from Lin, 2014)		
	13	TS1	Our top management are supporting & interested in the implementation of e-SCM
	14	TS2	Our top management is aware of all processes of e-SCM implementation
	15	TS3	Top management has allocated adequate financial and other resources for e-SCM implementation
	16	TS4	Top management leading our company to success through e-SCM implementation
	Financial Resources (adopted from Roxas & Chadee, 2012)		
	17	FR1	Our company has adequate financial resources to support the e-SCM implementation
	18	FR2	Our company has financial commitment to our projects that allocated in the budget
	19	FR3	Our company has adequate financial resources to support training of e-SCM implementation
	20	FR4	Our company can afford any expenses related to e-SCM implementation
	Employee Competence (adopted from Antoni & Akbar, 2019)		
	21	EC1	We had skilled employees that match the e-SCM requirements
	22	EC2	Our employees had the technical ability to implement and use e-SCM
	23	EC3	Our employees had the interdisciplinary knowledge that support the e-SCM implementation
	24	EC4	Our employees able to integrate and innovate many ways of operating e-SCM
Environment	**Perceived Competitive Pressure** (adopted from Lin, 2014)		
	25	CMP1	Our company experienced competitive pressure to adopt e-SCM
	26	CMP2	Our company aware how to deal with competitive pressure to adopt e-SCM
	27	CMP3	Our company experienced to manage & control competitive pressure to adopt e-SCM
	Perceived Customer Pressure (adopted from Gualandris, & Kalchschmidt, 2014).		
	28	CSP1	Our company aware to the customers preference regarding dealing with the e-SCM
	29	CSP2	Our company bridging & connecting with its customers
	30	CSP3	Our company design its processes based on its customers preferences
Adoption Intention	**Adoption Intention** (adopted from Wu & Chang, 2012)		
	31	AI1	Our company considers using e-SCM to improve the overall performance of the company
	32	AI2	Our company believe they can adopt e-SCM in the company
	33	AI3	Our company believe they can integrate e-SCM in its processes
	34	AI4	Our company believe that e-SCM adoption will enhance the customer satisfaction
	35	AI5	Our company believe that e-SCM adoption will enhance its financial situation
	36	AI6	Our company believe that e-SCM adoption will enhance its competitive & market position