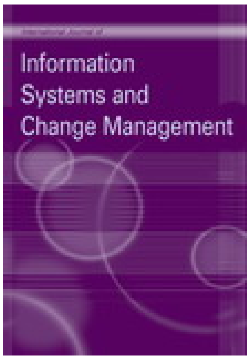

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AI and organisational learning: exploring the impact of IoTs and innovation management on the organisational learning process with moderation of perceived risk

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Abstract: Organisational learning is crucial for adapting to change, fostering innovation, and improving organisational performance. Artificial intelligence (AI) plays a vital role in various sectors that revolutionise industries and drive innovation in a productive way. This study examines the nexus among the Internet of Things (IoT), innovation management (IM), and organisational learning (OL) from the perspective of China. First, the outcomes confirmed a positive connection between IoT technologies and OL. Second, the study found a positive connection between innovation management and organisational learning. Finally, the study affirmed a positive moderating connection of perceived risk among IoT, IM, and OL. The study endows with insights that by focusing on IoT and IM, organisations can enhance learning capabilities, adapt to changing environments, and drive sustainable growth through the implementation of new technologies. IoT and innovation management empower organisations to embrace a learning mindset, stay agile, and seize opportunities for growth in today's dynamic and competitive business landscape.

Keywords: artificial intelligence; organisational learning; internet-of-things; innovation management; structure equation modelling.

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Biographical notes: Xue Zhao is now working in Personal Department at Binzhou Polytechnic. She is dedicated to publishing more papers in similar fields. Her main research fields are related to management and organisation.

1 Introduction

Learning organisations (LO) are institutions which hold the acquisition, retention, and application of knowledge in order to improve their performance and adapt to changes (Meher et al., 2024; Schulz, 2017). It entails a culture which places priority on continuous learning, and that enables every employee to advance his or her skills and knowledge. OL is essential as it is the one way for companies to remain competitive as the business world is continuously changing. The proponents of the OL believe its effectiveness is based on diverse activities and strategies such as training seminars, workshops, and mentoring programs that can develop firm capabilities. OL offers businesses to unlock their employees' knowledge, to share their colleagues' intelligence and to fight as one team under the flag of knowledge management (Argote and Todorova, 2007; Farrukh and Waheed, 2015). A suitable ambience is required for learning in which educators are given the space to give their own knowledge, try new things and make mistakes in the process can help the organisation to learn sufficiently. OL may be enabled by an array of capacities involving communication channels which are strong, development and training resources and motivating constructive feedback (Argote and Todorova, 2007; Zhang et al., 2023).

The methodical and systematic approach towards facilitating and promoting the process of innovation inside corporations is termed as innovation management (Taghavi et al., 2023; Zennouche et al., 2014). It means the development of an environment that provides an atmosphere for all those who think freely, who are creative, and who come up with and utilise new ideas. Resource allocation, risk assessment, and innovation initiative monitoring are the parts IM (Alkhatib and Valeri, 2024). Organisations may be able to stay ahead of the market competition, be flexible to environmental change and realise sustainable growth with good integrated management (IM) (Adams et al., 2006). It promotes teamwork across functions and departments, works to problem solve, and then delivers new products, services and business models. In the same sense AI means the creation of technical machines that can imitate the human mind and to perform the tasks that typically require the human cognitive abilities (Hamet and Tremblay, 2017). It is made of a wide range of methods: machine learning, natural language processing, and computer vision. AI has a massive potential across various industries that eventually enable numerous capabilities such as automation, data analysis, and decision-making process. AI has multiple applications in different areas and sphere of human life which include healthcare, transportation, customer services, and productivity related operations of the organisations (Cockburn et al., 2018). Therefore, to explore the insights into these variables such as AI, innovation, Internet of Things (IoT), and learning organisations may provide another productive and interesting outcome from the domain of China.

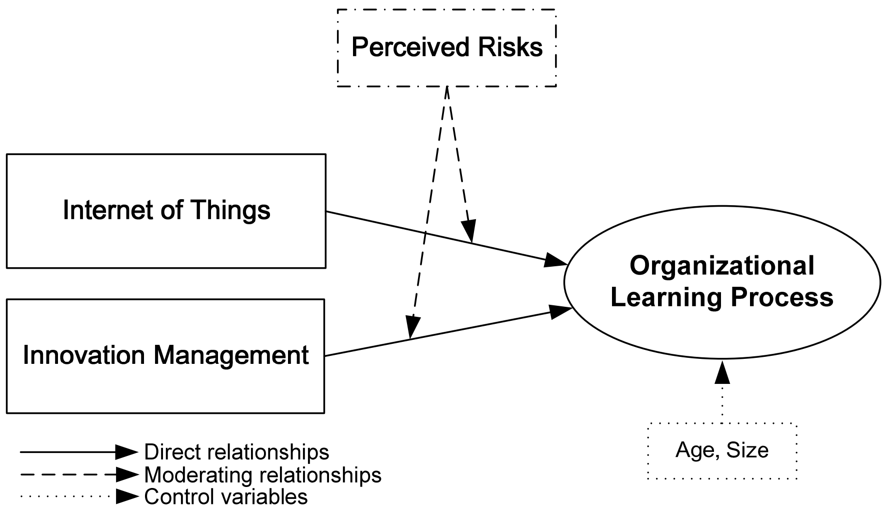
To conduct more research on the theme of IoT, innovation management (IM), and organisational learning (OL) is crucial for the organisations due to several reasons. First of all, this research would help the organisations to disclose multiple new insights, trends, and best practices which can enable the organisations to stay informed about latest technological developments (Hakansson and Waluszewski, 2003). Secondly, this study attempts to provide a foundation for evidence-based decision-making that ultimately will permit the organisations to make informed choices with respect to IoT-based adoption of technologies by implementing the effective innovative strategies to optimise organisational OL processes (Adams et al., 2006; Argote and Todorova, 2007; Cockburn et al., 2018). In addition, the research supports to recognise challenges, certain risks, and suitable solutions that enable organisations to steer complexities in order to maximise the benefits. This study drives progress, fosters innovation, and adds to the improvement of organisations in an ever-changing business landscape through utilising IoT-based technologies and IM. Because of research on the area of IoT, IM, and OL can foster a deeper understanding and synergies that uncover opportunities for organisations to weight IoT-based technologies for improving OL practices within Chinese market. China, the world's most populous country, holds a rich cultural heritage and a rapidly growing economy (Tao et al., 2023). It has made remarkable advancements in technology, manufacturing, and infrastructure development. China plays a significant role in global trade, and its policies and actions have a significant impact on international relations and the global economy (Agarwal and Wu, 2004). It is worth mentioning to explore the nexus among IoT-based technologies, innovation management, and organisational learning process based on the certain objectives as follows.

First, the study investigates the impact of IoTs on the organisational learning process. Second, the aim is to unveil the connection of innovation management toward the organisational learning process. Third, a moderation of perceived risk was examined among the connection of IoT, innovation management, and organisational learning. This study is organised based on the following outlines. First, this study discusses theoretical framework as well as hypotheses. Subsequently, we conferred the methods of the study, including sampling procedure, collection procedure, and analysis procedure. The part of the discussion along with implications are reported accordingly. The final part consists of limitations and future opportunities for worldly scholars.

2 Theoretical framework and hypotheses

There are several theories related to technology acceptance that aim to explain and predict how individuals adopt and use technology. Such theories such as technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), innovation diffusion theory, social cognitive theory, and expectation confirmation theory provide insights into the factors that influence people's acceptance and utilisation of new technological innovations (Hossain and Quaddus, 2012; Venkatesh et al., 2012; Wani and Ali, 2015). Our study currently emphasises TAM which is a comprehensive model that integrates various factors influencing technology acceptance (Holden and Karsh, 2010; Klaic et al., 2024). TAM accounts for individual differences and organisational support that provides valuable insights into technology adoption and utilisation (Masrom, 2007). TAM incorporates facilitating conditions such as the availability of resources and support for the organisation (King and He, 2006). TAM has been widely employed in research and has practical implications for designing interventions to promote successful technology adoption and usage (Legris et al., 2003). However, many studies independently researched each variable within distinct contextualisation other than organisational learning over the past (Holden and Karsh, 2010; King and He, 2006; Masrom, 2007). Therefore, it is worth mentioning to uncover the nexus of IoT-based technologies and innovation management with respect to learning organisations based on TAM supporting model, as shown in Figure 1.

Figure 1 Research model



2.1 IoTs and organisational learning (OL)

The relationships between the IoT and OL can be conceptualised in various ways such as follows. IoT technologies enable the collection of vast amounts of data from various sources within an organisation whereby a higher utilisation of IoT leads to improved data collection and analysis that eventually improves organisational learning (Brous et al., 2020; Ehie and Chilton, 2020). IoT devices allow real-time monitoring of processes, equipment, and environments which enable corporate learning with respect to timely feedback and corrective actions (Brous et al., 2020). IoT provides a platform for experimentation, testing new ideas, and piloting innovative solutions whereby such experimentation mindset can foster a culture of learning within the organisation (Alwahedi et al., 2024; Clarysse et al., 2022). IoT allows organisations to gather real-time data on market trends, customer preferences, and environmental changes (Clarysse et al., 2022; Rath et al., 2024). IoT-based technologies can contribute toward OL by enabling proactive responses to dynamic market situations (Ehie and Chilton, 2020). It is also advocated by the researchers that use of IoT for OL engagement can foster a learning culture which eventually encourages experimentation (Al-Emran et al., 2020; Brous et al., 2020). The organisational culture which indeed values learning and knowledge sharing can defiantly enable the integration of IoT into learning processes (Shahzad et al., 2012). IoT integration for organisational learning can help the organisations to improve problem-solving capabilities (Brous et al., 2020). A real-time data processing as well as analytics as provided by IoT devices might be better helpful to identify patterns and for informed decision-making (Croushore, 2011). Therefore, exploring more aspects related to IoTs, innovation management, and organisational learning could provide additional empirical evidence (Al-Emran et al., 2020; Zhang et al., 2023). Based on the massive significance of IoT in terms of the organisational learning, we currently assumed the following propositions to empirically validate from China.

H1: IoT positively optimises organisational learning process.

2.2 Innovation management and OL

Innovation management (IM) refers to the systematic planning, coordination, and implementation of strategies, processes, and activities aimed at fostering innovation within an organisation (Adams et al., 2006; Wu et al., 2009). The relationship between innovation management and OL can be formulated as follows. IM practices, i.e., idea generation, research, and development as well as collaboration with external partners help to foster the creation and acquisition of new knowledge that eventually fuels organisational learning processes (Chanal, 2004). An active engagement in IM encourages OL through experiential learning which involves new ideas, processes, and technologies (Hidalgo and Albors, 2008; Wu et al., 2009). According to scholars, IM practices promote knowledge sharing within the organisation (Lee, 2016). IM encourages feedback mechanisms, evaluation of outcomes, and iterative improvements that provides several opportunities for organisational learning (Hidalgo and Albors, 2008; Zhang et al., 2023). IM and OL are intricately linked in several ways whereas an effective IM practice can drive OL by promoting a culture of curiosity, openness to new ideas, and continuous improvement (Eason, 2010). OL also provides valuable insights that inform and shape innovation management strategies that eventually ensuring that future innovation efforts are more targeted and successful (Chanal, 2004). Furthermore, OL can lead to the development of knowledge management systems and processes that support IM by capturing, sharing, and applying knowledge gained from past experiences (Argote and Todorova, 2007; Farrukh and Waheed, 2015). Hence, IM and OL are interrelated processes that mutually reinforce each other. It is important to empirically examine these hypothesised relationships in specific organisational contexts to validate their significance and understand the underlying mechanisms through which IM influences OL. Therefore, based on the massive significance of innovation management in terms of the OL, we currently assumed the following propositions to empirically validate from China.

H2: Innovation management within organisations positively optimises OL.

2.3 Moderation of perceived risk (PR)

Perceived risk (PR) generally refers to a subjective assessment of the potential negative outcomes, uncertainties, or losses associated with a particular decision, action, or situation (Mitchell, 1999; Sohaib et al., 2018). In the scenario of IoT, innovation management, and organisational learning, perceived risk has major importance in terms of new technology adaptation and implementation (Chanal, 2004; Masrom, 2007; Mitchell, 1999). Nevertheless, it is important to note that the specific nature and impact of risks as a moderating factor can vary across organisations and contexts (Casidy and Wymer, 2016; Huy Tuu et al., 2011; Parayitam et al., 2020). Agencies that have an extreme overhaul of risk may end up being very cautious about adopting IoT technologies because of the perceived risks and uncertainties associated with their implementation (Parayitam et al., 2020). The ones that handle risks associated with IoT precariously as well as mitigate the risks can provide an environment for learning that will be safer and conducive for learning (Lu et al., 2016). Risk perceptions within the organisation can be decisive on how issues of IoT adoption and put to use are handled (Power, 2004). Risk perception is likely to bring in more careful decision making or a slower integration of IoT initiatives that might slow down the speed and rate of OL (Lee, 2020; Malik and Singh, 2019). In addition to this, risk can influence the associations between internet and virtual reality in different ways as presented below. Organisations that engage with high risks are more willing to experiment and innovate (Malik and Singh, 2019; Mirhosseini et al., 2021; Wani and Ali, 2015). Organising failures as learning opportunity may sometimes not work for organisations that are perceptual on higher level of risks as this may limit the extent to which IM initiatives add value to the organisational learning (Casidy and Wymer, 2016). Following the suggestions of the experts, IS varies with respect to the level of risk. Risk propensity and risk mitigation can be the determining factors to increase the efficiency of IM and OL (Manuel, 2017; Meher et al., 2024). These decisions can influence both the risk perception and resource allocation, so innovation can truly enable organisational learning (Manuel, 2017). However, risk is the most important element in relationships of IoT, IM, and organisational learning. Therefore, it is crucial to comprehend how risk moderates the relationships among IoT, IM, and organisational learning. To that end, we assumed the following propositions to empirically validate the assumption from Chinese market.

H3: PR moderates the connection between IoT and LO.

H4: PR moderates the connection between IM and LO.

3 Methodologies

3.1 Data gathering and sampling.

In this research, eleven thousand questionnaires were carefully distributed to the concerned managers within the Chinese corporates to get feedback. A few procedures were carried out during the data collection procedure, such as online circulation by means of WeChat and emails as well as personal visits were made with the help of Chinese colleagues. We currently focused on the Chinese market to affirm additional empirical evidence from this market on how smart cities could play an essential role in Chinese market. The participants were separately invited for the surveys and 893 responses were successfully got back. Finally, a total of eight hundred and twenty-one questionnaires were considered for the aim of data analysis after evaluating and scrutinising improperly filled information along with other critical issues such as incomplete responses just to ensure the feedback authenticity. A seven-point Likert scale was majorly employed by inspiring previously published studies of scholars (Mehmood et al., 2019; Shahid et al., 2022; Wu et al., 2022; Younas et al., 2017). Furthermore, the main inquiry statements consisted of forty-nine questions while respondents' profiles were assessed using 5 characteristics (see Table 1).

Furthermore, it is important to work on pilot testing before conducting a survey on a large scale to assess better and more fruitful results (Thabane et al., 2010). A total of 45 ($n = 45$) questionnaires were treated for this purpose and results are evaluated based on the suggested criteria of the statisticians (Black and Babin, 2019; Hair, 2011). The present values are normal where IoT stood at 0.745, IM stood at 0.745, perceived Risk at 0.810, and organisational learning stood at 0.748, respectively (Hair, 2011).

Table 1 Descriptive findings (N = 821)

	Male		*Female*	
	Freq.	*%*	*Freq.*	*%*
Gender	*510*	*62.10*	*311*	*37.90*
Qualification				
Bachelor	109	21.37	039	12.54
Master	111	21.76	111	35.69
PhD	160	31.37	102	32.80
Others	130	25.49	058	18.65
Age in years				
17–20	085	16.67	045	14.47
21–23	135	26.47	098	31.51
24–27	185	36.27	108	34.73
>28	105	20.59	059	18.97
Work experience in years				
<3 years	077	15.10	095	30.55
4–8 years	130	25.49	081	26.05
9–13 years	194	38.04	075	24.12
>14 years	109	21.37	060	19.29

3.2 Measures

IoT and innovation management (IM) variables are used as an independent measure, while organisational learning (OL) is a dependent variable. Moreover, perceived risk (PR) was taken as a moderating factor among IoT, IM, and OL. First, IoT was accessed using 10-items as adopted from the past study (Mashayekhy et al., 2022). Second, IM was measured using 6 items, as adopted by (Kalay and Gary, 2015). Third, OL was measured using the 10-item adopted from (Tseng, 2010). Finally, PR was measured using 4 items being assessed from the past study (Venkatesh et al., 2019).

3.3 Data analysis tools and tactics

First, we applied descriptive statistics to calculate the basic information about the participants' profiles. Subsequently, a correlation testing approach was applied to understand the interrelationships among variables of the study. Third, discriminant validity was calculated and examined based on two methods such as Fornell and Larcker along with Heterotrait-Monotrait (HTMT) methods (Ab Hamid et al., 2017; Fornell and Larcker, 1981). Likewise, convergent validity approach was carried out as per suggested methods such as average variance extracted (AVEs), loadings, and by evaluation of reliability (Russell, 1978). Structure equation modelling (SEM) using SmartPLS software was eventually applied to affirm the directional relationships among the variables. It is critical to calculate the values of normed fit index (NFI) and standardised (NIF) and root mean square residual (SRMR) to confirm the authenticity of the model, SEM (Hu and Bentler, 1999). The advised criteria for each analysis and indices are reported as follows. For instance, values should be between –1 to +1 in Pearson testing (Cohen et al., 2009; Hair, 2011), loading and AVEs outcome values should be lower than 0.5 (Hu and Bentler, 1999), reliability values should be higher than 0.7 (Hair et al., 2011), values should <0.9 in HTMT (Henseler et al., 2015), the outcomes of Square roots of AVEs should be higher than the following interrelationships in discriminant validity (Henseler et al., 2015), values of NFI should be higher than 0.9 (Hu and Bentler, 1999)**,** and finally the outcomes of SRMR should lower than 0.08 (Hair, 2011; Hu and Bentler, 1999)**.**

4 Results

4.1 Validity and reliability

Table 2 confirms the validity as well as reliability values along with other descriptions of means and standard deviations. As reported above, loadings and AVEs outcome values should be lower than 0.5 as well as reliability values should be higher than 0.7 (Hair et al., 2011).

Table 2 Validity process

Coding	*Mean value*	*SD value*	*Loadings value*	*AVE value*	*Reliability value*
Internet-of-Things (*IoTs*)				0.655	0.802
IoT-I1	5.134	1.351	0.555		
IoT-I2	4.982	1.021	0.634		
IoT-I3	5.189	1.540	0.633		
IoT-I4	5.134	1.351	0.555		
IoT-I5	4.982	1.021	0.634		
IoT-I6	5.189	1.540	0.633		
IoT-I7	4.982	1.021	0.555		
IoT-I8	5.189	1.540	0.634		
IoT-I9	5.134	1.351	0.633		
IoT-I10	4.982	1.021	0.555		
Innovation Management (*IM*)				0.658	0.851
IM-I1	5.134	1.351	0.555		
IM-I2	4.982	1.021	0.634		
IM-I3	5.189	1.540	0.633		
IM-I4	5.134	1.351	0.555		
IM-I5	5.189	1.021	0.633		
IM-I6	5.134	1.540	0.555		
Perceived risk (*PR*)				0.782	0.812
PR-I1	5.134	1.351	0.555		
PR-I2	4.982	1.021	0.634		
PR-I3	5.189	1.540	0.633		
PR-I4	5.134	1.351	0.555		

Table 2 Validity process (continued)

Coding	*Mean value*	*SD value*	*Loadings value*	*AVE value*	*Reliability value*
Learning organisation				0.801	0.788
LO-I1	5.134	1.021	0.633		
LO-I2	4.982	1.540	0.555		
LO-I3	5.189	1.351	0.634		
LO-I4	4.982	1.021	0.633		
LO-I5	5.134	1.021	0.633		
LO-I6	4.982	1.540	0.555		
LO-I7	5.189	1.351	0.634		
LO-I8	4.982	1.021	0.633		
LO-I9	5.189	1.540	0.555		
LO-I10	5.134	1.021	0.634		

*Items removed having <0.5 AVEs and loadings.

4.2 Analysis of Pearson's correlation

Table 3 indicates the outcome values of correlation analysis to affirm the relationships among proposed variables of this study. The values should be between –1 to +1 where negative values affirm a negative connection, lower values affirm a lower connection and higher values assure a higher connection (e.g., Fornell and Larcker, 1981; Hair et al., 2019; Kline, 2005). The results are reported below.

Table 3 Analysis of Pearson correlation

	*IoT**	*IM**	*PR***	*OL****
IoT*	1.000			
IM*	0.254	1.000		
PR**	0.185	0.424	1.000	
OL***	0.352	0.227	0.203	1.000

IoT = Internet of Things; IM = innovation management; PR = perceived risk; OL = organisational learning; *independent, **moderating, and ***dependent factors; values evaluation between –1 to + 1.

4.3 Model of discriminant validity

Table 4 shows the values for discriminant analysis being used for validation of the dataset. Researchers have suggested the criteria for this analysis. For example, the outcomes of square roots of AVEs should be higher than the following interrelationships in discriminant validity (Fornell and Lacker, 1981). The bold values given in the first row of each column represent the square roots of AVEs, and non-bold values show interrelationships.

Table 4 Model of discriminant validity

	*IoT**	*IM**	*PR***	*OL****
IoT*	**0.841**			
IM*	0.352	**0.722**		
PR**	0.122	0.284	**0.855**	
OL***	0.228	0.198	0.203	**0.885**

IoT = Internet of Things; IM = innovation management; PR = perceived risk; OL = organisational learning; *independent, **moderating, and ***dependent factors; values evaluation by comparing bold with nonbold values.

4.4 Heterotrait–monotrait (HTMT)

Other than Fornel and Lacker (1981) analysis, another technique is HTMT which affirms the validity of the data exploring the similarities. As per the recommendation by Henseler et al. (2015), values should be <0.9 in HTMT analysis. Therefore, the present results confirmed the HTMT validity in the data based on the following accuracy of the results as mentioned in Table 5.

Table 5 HTMT

	*IoT**	*IM**	*PR***	*OL****
IoT*				
IM*	0.225			
PR**	0.450	0.332		
OL***	0.202	0.200	0.113	

*independent, **moderating, and ***dependent factors; values should be less than 0.9.

4.5 Path relationships using SEM.

Table 6 shows the directions of major paths that were evaluated based on beta values through a model of SEM. It is recommended that CFI and SRMR should be observed to discover and analyse the authenticity of the SEM model. For example, the values of NFI should be higher than 0.9 and SRMR should be lower than 0.08 (Hu and Bentler, 1999**).** The present values are best fit as per recommendations where NFI stood at 0.922 and SRMR at 0.0352.

5 Discussion

(IM), perspective risk (PR), and organisational learning (e.g., employee training metrics, knowledge retention, knowledge sharing, adaptability, performance improvement, feedback mechanisms, knowledge management systems, learning cultural assessment, benchmarking, and retention of intellectual capital) from the mainstream of China. It was propositioned in hypothesis one (H1), IoTs are positively correlated with OL. A structural approach confirmed a positive linkage between IoTs and OL at (β = 0.233***; 0.000). Therefore, hypothesis one is supporting now which confirms a direct relationship of IoTs toward OL. Second, it was propositioned in hypothesis two (H2), IM is positively correlated with OL. A structural approach confirmed a positive linkage between IM and OL at ($\beta = 0.452$***; 0.000). Therefore, hypothesis one is supporting which confirms a direct relationship of IM on OL. On the other side, the results are supporting past studies in which experts suggested a positive connection various IoT-based technologies and learning organisation from numerous perspectives, worldwide (Al-Emran et al., 2020; Brous et al., 2020; Clarysse et al., 2022; Croushore, 2011; Ehie and Chilton, 2020; Hamet and Tremblay, 2017; Lee, 2020; Schulz, 2017; Shahzad et al., 2012). However, it was proposed in hypothesis three (H3) that PR moderates the associations between IoTs and OL. A structural approach confirmed a positive moderation of PR between IoTs and OL at ($\beta = 0.235$***; 0.001). Therefore, hypothesis three is supporting. Finally, it was assumed in hypothesis four (H4) that PR moderates the associations between IM and OL. A structural approach confirmed a positive moderation of PR between IM and OL at ($\beta = 0.118$***; 0.001). However, the results are supporting past studies in which experts suggested a positive connection of perceived risk taking into account IoT-based technologies and learning organisation from numerous perspectives, worldwide (Casidy and Wymer, 2016; Chanal, 2004; Farrukh and Waheed, 2015; Huy Tuu et al., 2011; Kalay and Gary, 2015; Malik and Singh, 2019; Manuel, 2017; Power, 2004).

Table 6 SEM model results

Directions	*ES*	*Direct*	*Moderating*	*Sig.*	*S.E*	*Decision*
H1: IoT → OL	±	0.223***	–	0.000	0.021	Supported
H2: IM → OL		0.452***		0.000	0.018	Supported
H3: IoT*PR → OL			0.235***	0.001	0.025	Supported
H4: IM*PR → OL	±	–	0.118***	0.001	0.038	Supported
	Model fitness					
		NFI	0.922			
		SRMR	0.0352			
AGE[a]		–	–	–	–	–
SIZE[a]		–	–	–	–	–

***$p < 0.05$.

IoT = Internet of Things; IM = innovation management; PR = perceived risk; OL = organisational learning; *independent, **moderating, and ***dependent factors; values should be less than 0.9.

NFI must be >0.9; SRMR must <0.08; *a* = control variables.

6 Implications

From a theoretical standpoint, this work adds to the body of literature by showing insights into IoTs, innovation management (IM), perceived risk (PR), and organisational learning (OL). This study additionally adds in the literature showing empirical outcomes regarding risk how it moderates the nexus IoTs, innovation management (IM), and organisational learning (OL) within the market of China, a developing nation. From managerial domain, IoT technologies such as IoT sensors, smart operational solutions, predictive maintenance, machine learning, blockchain, robotics, edge computing, IoT-enabled communication, augmented reality, and quality control sensors offer significant managerial implications for organisational learning. Embracing IoT requires a shift towards fostering a culture of continuous learning, as employees must adapt to evolving digital landscapes. Managers need to invest in training programs to enhance employees' digital literacy and ensure seamless integration of IoT into daily operations. Further, firms could implement the security policies, wherein the IoT data can be utilised successfully for the purpose of informed decision making.

The innovations management within the organisations requires a specific focus on organisational learning (OL). It must become the related management to form a culture stimulating the advancement of research and knowledge sharing. Hence, iterative development is also promoted, with special emphasis on turning the failures into learning experiences. Towards this, consistent guidance programs would be developed to improve employee's skills by ensuring implementation of certain developing technologies including IoT-based technologies. Also, managers should draft feedback loops to pick up insights related to innovation through helping in building in the new knowledge for future innovation projects. The method is purposefully created to build in the organisation the ability to adapt to innovation as a pioneer. Furthermore, management must recognise innovative efforts by motivating employees to actively contribute to the learning process of the organisations.

It is advised to the management that implementing responsive methodologies can better aid adaptation toward a changing market. It stated that regularly upgradation of innovation strategies based on organisational learning can better ensure relevance. A holistic method toward innovation management is deeply rooted in organisational learning that eventually propels the organisation in achieving sustained success in today's evolving business world. Moreover, an effective management of risk requires proactive strategies therefore the concerned managers must prioritise transparent communication to address uncertainties and to build trust along with sustainable relationships with the stakeholders. It is advocated that a regularly assessing risk management strategies allows the organisations for timely adjustments that indeed enhance resilience of the organisations. An adoption of IoT technologies could supports both capabilities such as organisational learning and innovation management. As IoT can better provide a real-time data by fostering a continuous learning culture within the organisation. The interconnected nature of IoT-based devices can better promote collaboration and learning of organisations. It is also worth mentioning thar IoT-based data can productively empower IM through enabling the organisations to detect trends and proactively respond to evolving opportunities. Therefore, management is suggested to embrace IoT not only to improve operational efficiency, but it additionally helps to management the dynamic environment that support towards sustained learning and innovation.

7 Conclusion

It is concluded that IoT-based technologies for OL can better provide real-time data by fostering learnt decision-making and adaptability. It is concluded that such kind of dynamic learning environment can productively improve the operational efficiency of the organisations. Innovation management is paramount for organisational survival and growth. It fuels adaptability, fosters a culture of creativity, and positions businesses to meet evolving market demands. Embracing innovation ensures that organisations remain agile, competitive, and resilient, driving success in dynamic and challenging business landscapes. Understanding risk is indispensable for effective decision-making and organisational resilience. It enables proactive mitigation, safeguards against potential threats, and fosters a culture of preparedness. Recognising the importance of risk comprehension empowers businesses to navigate uncertainties, ensuring long-term viability and success in an ever-changing and unpredictable model. This study reached the above decision by concluded a positive connection IoTs and OL along moderation of perceive risk.

7.1 Limitations and future possibilities

On the other hand, there are certain limitations of the study that future researchers can consider understanding insights into IoTs, innovation management (IM), perceived risk (PR), and organisational learning (OL). First, the sample size was small which restricts its generalisation. Second, only one developing country was focused that is China. Third, the study ignored considering any mediation variable among the connections of IoTs, innovation management (IM), perceived risk (PR), and organisational learning (OL) to ensure the relational strength of the variables. Therefore, with consideration of these drawbacks, researchers may carry out additional studies to validate the current outcome from other nations with different assumptions.

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