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Determinants of Collaborative Robots Innovation Adoption in Small and Medium-Sized Enterprises: An Empirical Study in China

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Abstract: With the rapid development of industry 4.0 and the boom of large-scale product customization, the adoption of collaborative robots' innovation becomes a hot topic in research. Previous studies have mainly focused on individuals, but few on enterprises, and in particular, there has been a lack of empirical research on the enterprise level. Based on the combined model of Technology-Organization-Environment Framework (TOE) and Diffusion of Innovations Theory (DOI), this study investigated 373 small and medium-sized enterprises (SMEs) in Guangdong Province, China, to explore the determinants of SMEs' adoption of collaborative robot innovation in technology, organization, and environment. The result shows that the technical factors of relative advantage, compatibility, observability, and trialability have a significant positive correlation with the adoption of collaborative robots, while complexity has a significant negative correlation with the adoption. Among the organizational factors, top management support and organizational readiness have a significant positive correlation with the adoption of collaborative robots. Among the environmental factors, agent support is positively and significantly correlated with adoption. The findings will help practitioners develop appropriate strategies for the adoption of collaborative robot innovation.

Keywords: small and medium-sized enterprises; collaborative robots; innovation adoption; technology-organization-environment framework; diffusion of innovations theory

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1. Introduction

With the rapid development of industry 4.0, diversified and customized production has significantly increased the demand for robots. Traditional industrial robots are gradually unable to meet the market demand. Firstly, traditional industrial robots have many deficiencies in technical intelligence and flexibility [1]. Secondly, the entry barriers such as the high price of traditional industrial robot equipment, the pre-installation and post-maintenance costs, professional operating skills, etc. have become major obstacles to adoption [2]. As a new type of industrial robot [3,4], the collaborative robot can greatly expand the application scenarios of robots, remove the necessary protective measures when working with traditional industrial robots, and truly realize the collaborative operation between humans and robots [5,6]. Humans and robots can conduct human-machine interaction within a short distance in shared spaces so that production can become more intelligent. Humans play a dominating role in the production process and achieve a higher level of large-scale customization [1,3,7].

Small and medium-sized enterprises (SMEs) are the primary target market for collaborative robots [8]. Collaborative robots are safe, low-cost, and easy to use (plug-and-play can be achieved in most workplaces) [9–11], which are suitable for SMEs to produce small batch, customized, and short-term products and pay attention to the return on investment (ROI) [12,13]. SMEs account for about 90% of the world's enterprises and are significant drivers of global economic growth and the creation of jobs [14,15]. Considering the large size of the potential user base, the growth of the entire collaborative robot industry market is expected to be very high, but the current adoption of collaborative robots by SMEs is still at an early stage [4,16,17].

For a long time, operational efficiency and ergonomics, and human factors have been considered the main determinants of the adoption of collaborative robots [6,18]. Early articles pointed out that collaborative robots can increase productivity while minimizing the trauma caused by repetitive or overloaded movements in workers' material handling [19]. A large number of recent studies have explored that collaborative robots can take over workers' repetitive and heavy tasks, to reduce the incidence of workers' musculoskeletal diseases (MSDS), and improve ergonomic working conditions [20–22]. However, while collaborative robots continue to take over workers' tasks and effectively improve the operation efficiency of enterprises (such as improving production efficiency, improving product quality, and meeting customized needs), workers' concerns about being displaced by robots and losing their jobs can affect the adoption of collaborative robots [23]. Therefore, many studies have also proposed numerous solutions to address the problem of human-machine trust [24–26] and the ethical issues of human-machine cooperation [27] in collaborative robot adoption. However, the existing research mainly focuses on the individual level to explain the determinants of the adoption of collaborative robots by enterprises, and there is a lack of research on the determinants of the adoption of collaborative robots at the enterprise level [28]. Although a recent study has explored the willingness to adopt collaborative robots at the enterprise level, there is a lack of further discussion in empirical research [29], especially for SMEs, the main target customers of collaborative robots.

Therefore, this study raises the following research questions:

RQ1: What are the enterprise-level determinants for SMEs to adopt collaborative robot innovation?

RQ2: What are the impacts of enterprise-level determinants on SMEs' adoption of collaborative robot innovation?

To figure out the above problems, this study draws on the Diffusion of Innovations Theory (DOI) and the Technology-Organization-Environment (TOE) framework to develop a model, and the structural equation model (SEM) based on SmartPLS 3.0 was used to conduct an empirical analysis. In terms of managerial implications, the results of this study fill the gap in empirical research on determinants of collaborative robot adoption at the enterprise level, broaden the research on innovation factors in innovation adoption, and extend the combined model of TOE and DOI to the field of innovation adoption in SMEs.

2. Theoretical Background

2.1. Diffusion of Innovations Theory (DOI)

The Diffusion of Innovations Theory (DIO) is put forward by Everett Rogers, who defines innovation as an idea, technology, or thing that is considered novel by individuals or other adopters [30]. The collaborative robot is regarded as an innovation by scholars [24,29,31] as a new and safe human-assisted robot designed to reduce the cost of traditional industrial robots [32].

The adaptation of innovation by individuals or other organizations is determined by many factors, one of which is the cognitive attributes of innovation (including comparative advantage, compatibility, complexity, observability, and trialability) that directly affect the degree of innovation adoption [30,33]. The cognitive attributes of collaborative robot innovation are characterized by safety, low cost, and easy use (plug and play can be achieved in most workplaces) [9–11]. Compared with traditional industrial robots, collaborative robots not only have the comparative advantages of being safer, more economical, and more flexible [34,35], but also are easier to install and use, and are far less complex than traditional industrial robots [5,11,36]. In terms of compatibility, collaborative robots and traditional industrial robots are complementary today and can be compatible with the existing production lines of enterprises [29]. In previous research on innovation adoption, scholars generally believed that comparative advantage, compatibility, and complexity were applicable to explain innovation adoption, while observability and trialability were not extensive in research on innovation adoption [37–40]. Collaborative robots are small, lightweight, and plug-and-play in most workplaces [23,41,42], which facilitates collaborative robot manufacturers (or vendors) to display and are convenient for enterprises with intentions to conduct on-site trials.

2.2. Technology–Organization–Environment Framework (TOE)

The Technology-Organization-Environment Framework (TOE), is a theoretical framework put forward by Louis G. Tornatzky and Mitchell Fleischer in 1990 to explain the adoption of innovation by enterprises and describe how the process of innovation adoption is affected by technology, organization, and environment [43,44]. Technical factors mainly refer to the characteristics of the technology itself that has been adopted or will be adopted related to the enterprise, such as the technical factors of collaborative robot innovation as new technology (comparative advantage, compatibility, complexity, observability, and trialability). Organizational factors mainly refer to the organizational characteristics of an enterprise, generally including enterprise scale, management structure, and human resources. Environmental factors need to consider the political, economic, and cultural environment in which the enterprise is located, such as competitors in the industry, technology suppliers, and government support.

The TOE framework provides an excellent theoretical perspective for the study of enterprise innovation adoption. It has been widely used in the study of information system innovation adoption, such as enterprise resource planning (ERP) system adoption [45], RFID adoption [46], adoption of e-commerce applications [47], electronic supply chain management system (e-SCM) adoption [48], etc. In recent years, researchers have also applied the TOE framework to other innovative adoption studies. For example, they have used the TOE framework to explore the adoption of artificial intelligence in public organizations [49], and identified the determinants of Unmanned Aerial Vehicle technology adoption based on the TOE framework. Technical, organizational, and environmental factors of the TOE framework, as predictive factors of innovation adoption, can help enterprises figure out the determinants of adoption [50,51]. The TOE framework is flexible to accommodate different factors, such as technology, organization, and environmental factors, to explain the adoption of enterprise innovation.

3. Models and Assumptions

To better explain the determinants of SMEs' adoption of collaborative robot innovation, this study uses the combined model of the TOE and DOI (as shown in Figure 1). The combination of the TOE and the DOI is considered to be the most prominent adoption model at the enterprise level [52], and has been widely used in the field of innovation adoption [39,53–55]. The analysis at the enterprise level of the TOE framework in this research model uses the five cognitive attributes of innovation in the DOI theory. At the organizational level, the TOE framework can explain that the internal features of the organizational structure and the external features of the organization are crucial prerequisites for the enterprise to adopt innovation [52]. In addition, the TOE framework complements the deficiency that the DOI theory does not consider the environmental aspect and therefore better explains the adoption of internal innovation in enterprises [52].

3.1. The Technological Context

Technical factors mainly refer to the cognitive attributes of the new technology to be adopted by the enterprise (including comparative advantage, compatibility, complexity, observability, and trialability). Comparative advantage means that enterprises adopt innovations when they realize that there are potential benefits of using innovation. Compared with traditional industrial robots, collaborative robot innovation has the comparative advantages of low investment costs, high safety, ergonomics, and high flexibility [34,35]. Compatibility indicates the coexistence degree of innovation and existing technology. At this stage, collaborative robots and traditional industrial robots are complementary and can coexist well with the existing technologies of enterprises [29]. Comparative advantage and compatibility have long been considered the necessary conditions for innovation to be adopted [30]. For instance, the data analysis result of a sample of 200 SMEs in Malaysia shows that comparative advantage and compatibility have a significant impact on the adoption of e-commerce [56]. In addition, another study on the determinants of e-commerce adoption by Romanian SMEs confirms that the main factor determining e-commerce adoption is the comparative advantage brought by e-commerce activities, while the main obstacle is the lack of compatibility between e-commerce activities and the business patterns of SMEs [57].

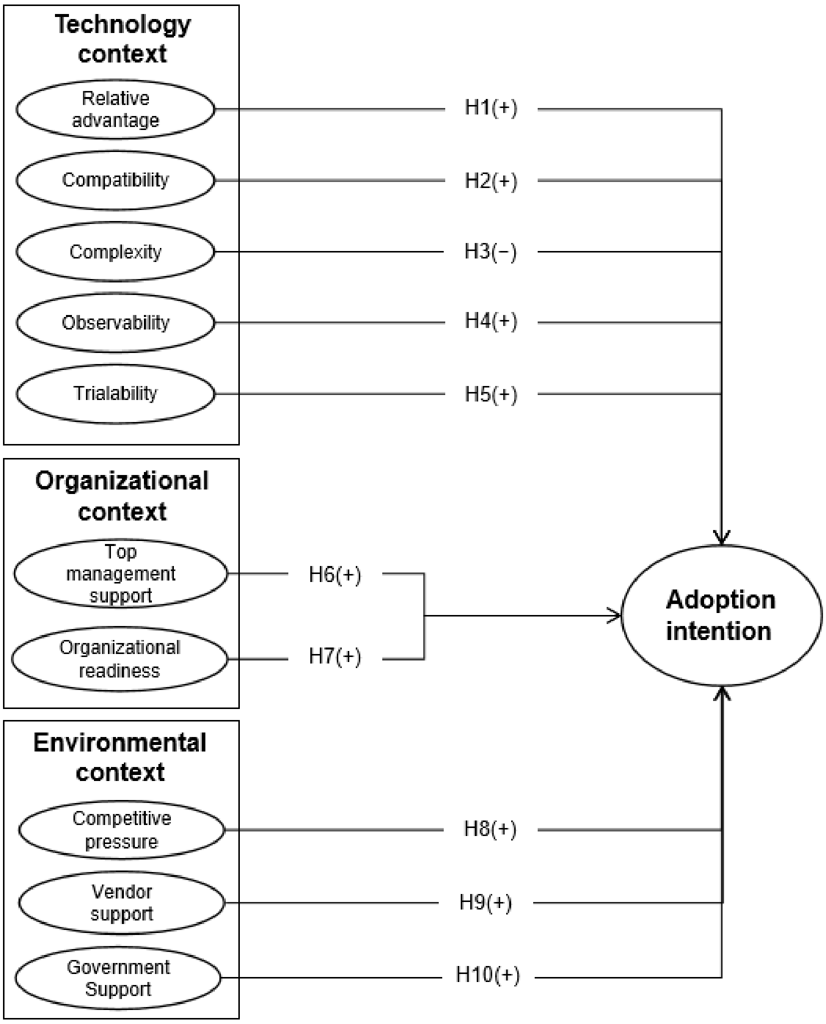

Figure 1. Research Model.

Complexity refers to the degree to which innovation is hard to comprehend and use, and is generally considered to be negatively correlated with adoption [30,39,58,59]. Collaborative robots are far less complex than traditional industrial robots, mainly in terms of simple programming, convenient installation, and flexible deployment [5,11,36].

As previously mentioned, observability and trialability have not been widely studied in innovation adoption. However, the collaborative robot has the advantages of being small in size, lightweight, and plug-and-play [23,41,42], which makes it easy for collaborative robot manufacturers (or vendors) to display robots in an exhibition hall and for enterprises to conduct on-site trials [29], reflecting the observability and trialability of the collaborative robot. Based on the above, the following hypotheses are proposed:

H1. *The comparative advantage of collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

H2. *The compatibility of collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

H3. *The complexity of collaborative robot innovation is negatively correlated with the adoption intention of SMEs.*

H4. *The observability of collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

H5. *The trialability of collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

3.2. The Organization Context

In addition to technical and environmental factors, the adoption of any innovation is affected by a number of specific organizational environmental factors. Such as company size [37], absorptive capacity [48], management barriers [60], organizational readiness [61], human resources [62] and top management support [63]. In this study, we consider top management support and organizational readiness as organizational environmental factors for adopting collaborative robot innovation in organizations.

Top management support is considered to be an essential factor for organizations to adopt innovations [48,64,65]. SMEs have a simple and highly centralized structure, and the role of senior managers is crucial to the enterprise because their decisions affect the activities of all companies [64,66]. Many studies have shown that the adoption of innovation in SMEs is directly affected by the support of top management. For instance, in a survey of the key predictors of cloud computing technology adoption in SMEs, top management support has a significant impact on the adoption [64]. In an empirical study on the adoption of Green Supply Chain Management (GSCM) technology by SMEs in Malaysia, top management support has also been proven to be a significant factor affecting the adoption [65].

Organizational readiness is divided into two aspects: the availability of financial resources and human resources. The availability of financial and human resources is necessary for an organization to adopt an innovation [48,67,68]. Adopting innovation usually involves vast upfront costs, e.g., investment in R & D, production, sales, staff training, etc. [69,70]. The literature shows that most enterprises, especially SMEs, lack financial and human resources [71–74]. Therefore, having the financial and human resources for innovation can stimulate the willingness of SMEs to adopt collaborative robots. Based on the above, this study proposes the following hypotheses:

H6. *The top management support for collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

H7. *The organizational readiness for collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

3.3. The Environmental Context

The environmental context consists of the industry's scale and structure, the company's competitors, technical service provider support, macroeconomic context, and regulatory environment [44]. Ref. [29] divides environmental factors into the inter-organizational environment and socio-political environment. In the inter-organizational environment, the adoption of innovation by organizations is usually caused by the competitive pressure caused by the adoption or imminent adoption of similar organizations [75]. The literature suggests that competitive pressure has always been regarded as the driving force for the adoption of organizational innovation, prompting organizations to seek competitive advantage through the adoption of innovation [48,76]. SMEs tend to postpone innovation adoption due to a lack of expertise in innovation adoption [77,78]. In general, innovation providers can help organizations bridge the knowledge gaps associated with innovation adoption. For instance, vendor support affects the decision to use accounting software [79], IS vendor support has a positive impact on the adoption of Internet/e-commerce technology by Canadian SMEs [80], and vendor support helps SMEs implement ERP systems [81].

In the socio-political environment, government support is considered to play a significant role in the adoption of innovation by organizations [82,83]. The government supports the adoption of organizational innovation by providing organizations with government subsidies [84], public technology development [85], technical training [86], etc. Based on the above, the following hypotheses are proposed:

H8. *The competitive pressure of collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

H9. *The vendor support for collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

H10. *The government support for collaborative robot innovation is positively correlated with the adoption intention of SMEs.*

4. Empirical Research

In this study, the method of field investigation is used to test the research model. Firstly, a questionnaire is developed to measure the research structure of the model. Secondly, pre-test the questionnaire. Thirdly, the demographic analysis of the survey respondents is carried out to obtain the demographic data table. Finally, the structural equation model (SEM) based on SmartPLS 3.0 is used to test the relationship between various structures of collaborative robot adoption intention.

4.1. Questionnaires and Surveys

The questionnaire items come from published literature (see Appendix A). To be consistent with the literature source, all measurement items (relative advantage, compatibility, complexity, trialability, observability, top management support, organizational readiness, government support, vendor support, competitive pressure, and adoption intention) were measured with the Likert scale, from "strongly disagree" (1) to "strongly agree" (5). They have been revised to fit the research context—that is, to evaluate the intention to adopt collaborative robots from the perspective of SMEs. All questions were mandatory. If the question was not answered, the questionnaire cannot be submitted. Since the questionnaire was conducted in China, the English version of the questionnaire was translated into Chinese. To ensure the validity of the questionnaire, three language experts proficient in English and Chinese and two experts in this research field were responsible for the review. After that, we conducted a preliminary pre-test on the managers of 50 SMEs.

The questionnaire of this study is distributed online through social networks. Before issuing the questionnaire, we consulted the Scientific Ethics Committee of Yeungnanm University to ensure that there were no ethical issues in the questionnaire. The questionnaire was filled out anonymously, and the content and purpose of the survey were explained to the participants at the beginning of the questionnaire, which did not involve personal privacy information, and the data collected from the survey was only used for this study, and the participants were free to choose to answer or not to answer the questionnaire. The International Federation of Robotics (IFR) predicts that cooperative robots will continue to replace traditional industrial robots and take the lead in the robot industry. The IFR report shows that since 2016, China's industrial robot market has become the world's largest industrial robot market. In 2019, China's industrial robot market holdings nearly tripled from 2016, accounting for about 48% of the world's top 10 markets [87,88]. Therefore, China will dominate the market for collaborative robots [89], and Guangdong Province is the largest industrial manufacturing base in China [90]. Thus, in the field survey, the sample of this study is from the SMEs in Guangdong Province, China. The survey lasted two months from March 2022 to May 2022. A total of 373 questionnaires were distributed, and 242 responded effectively, with a response rate of 60.5%.

4.2. Analytical Method

In this study, SPSS was used for demographic analysis, and then VB-SEM and PLS-SEM 3.0 were used to verify the hypotheses proposed in this study. There are two kinds of SEM, one is CB-SEM, and the other is VB-SEM. VB-SEM is more suitable than CB-SEM for analyzing small sample data, non-normal distribution data, and models with more than 6 variables [91]. The sample size of this study is small, and there are 10 variables, and through the website calculator (https://webpower.psychstat.org/) (accessed on 16 June 2022) test, the result shows that Mardia's multivariate skewness $\beta = 191.064$, $p > 0.05$ and multivariate kurtosis $\beta = 1329.877$, $p < 0.01$, which suggests multivariate non-normality [92]. Therefore, it is appropriate to use VB-SEM (PLS-SEM) in this study.

4.3. Demographic and Bias Test

The demographic details of the respondents are shown in Table 1. Among them, 165 (68%) are male respondents and 77 (32%) are female respondents. The respondents' ages are mainly between 31–40 years old (38%), followed by 40–50 years old (31.4%). The education level is mainly a bachelor's degree (39%), followed by high school and below (34.3%). The respondents' positions are mainly middle management (40.5%), followed by top management (34.3%).

Table 1. Demographic Details of Respondents.

Respondent Characteristics	N = 242	%
Gender		
Female	77	32
Male	165	68
Age (in years)		
<30	32	13.2
30–40	92	38.0
41–50	76	31.4
51–60	36	14.8
>60	6	2.4
Education		
High school, technical school, and below	83	34.3
Junior college	28	11.6
Bachelor degree	95	39.0
Master's degree and above	36	14.9
Job position		
First-line managers	61	25.2
Middle managers	98	40.5
Top Management	83	34.3

To avoid the non-response bias of demographic data, a paired t-test is adopted to test the data filled in by the top and bottom 25 people who submitted the questionnaire. According to the verification results, there are no noteworthy differences between the two groups.

Common method bias is a common problem in the questionnaire survey. This study uses two methods to measure common method bias. First, the single factor analysis by Harman was performed [93]. The results showed that the percentage of extracted variables was 12.720% (less than 40%). Then, the common method bias in PLSSEM was measured according to FLL-VIF [94,95], and all VIF values were lower than 3.3. The results of the two test methods show that the common method bias in this study is not a serious problem.

4.4. Measurement Model Test

This study tests the measurement model by assessing composite reliability (CR), average variance extracted (AVE), discriminant validity, and outer loading. As shown in Table 2 and Figure 2, each variable's CR value is over 0.7, and Cronbach's a is likewise greater than 0.7, indicating that the internal consistency of the research data is qualified. Besides, each structure's AVE value is above 0.5 and outer loading is greater than 0.7 as well, indicating the standard for convergent validity is met [96]. The R square of technology, organization, and environmental factors on the intention to adopt collaborative robots is 0.516.

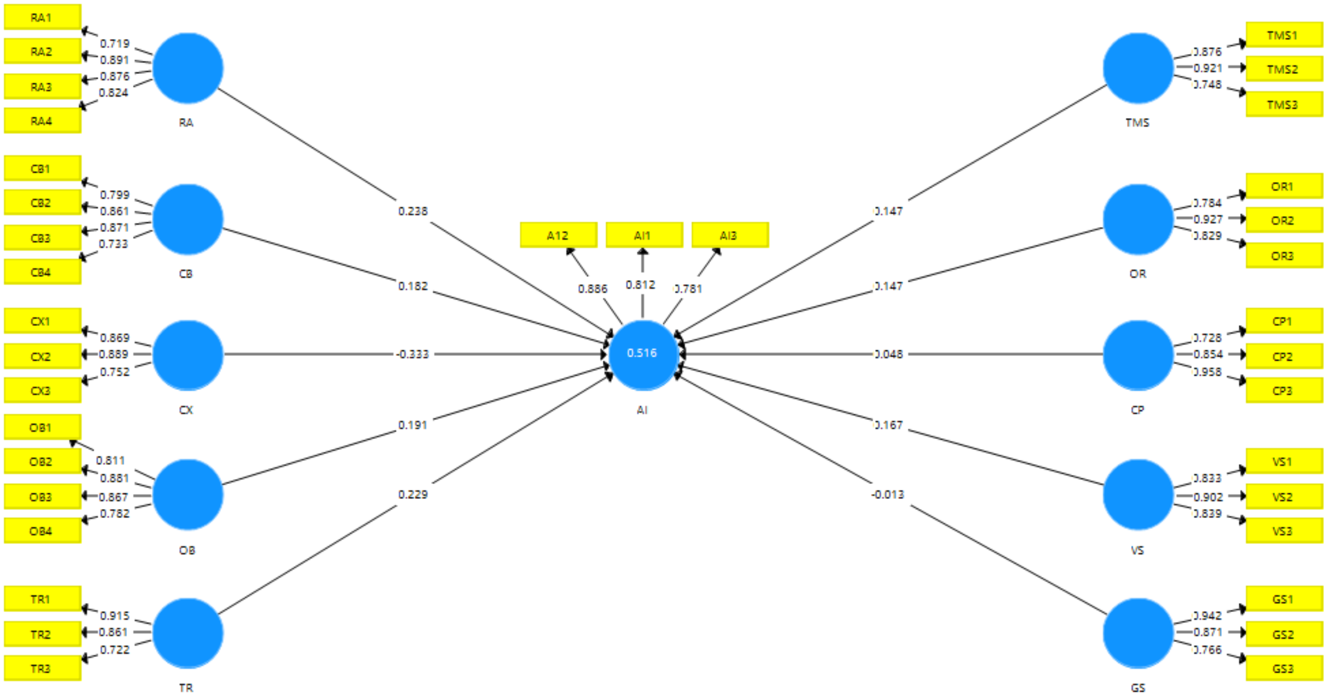

Figure 2. R square of the Collaborative Robots Innovation Adoption.

Table 2. Reliability and Validity Coefficients for Constructs.

Latent Variable	Item	Loading	Mean (SD)	Cronbach's α	CR	AVE
RA	RA1	0.719	3.044 (0.970)	0.850	0.898	0.690
	RA2	0.891				
	RA3	0.876				
	RA4	0.824				
CB	CB1	0.799	3.120 (0.980)	0.834	0.889	0.669
	CB2	0.861				
	CB3	0.871				
	CB4	0.733				
CX	CX1	0.869	2.870 (0.791)	0.802	0.876	0.704
	CX2	0.889				
	CX3	0.752				
OB	OB1	0.811	2.924 (1.030)	0.856	0.903	0.699
	OB2	0.881				
	OB3	0.867				
	OB4	0.782				

Table 2. *Cont.*

Latent Variable	Item	Loading	Mean (SD)	Cronbach's α	CR	AVE
TR	TR1	0.915	2.986 (1.049)	0.802	0.874	0.700
	TR2	0.861				
	TR3	0.722				
TMS	TMS1	0.876	3.065 (1.009)	0.819	0.887	0.725
	TMS2	0.921				
	TMS3	0.748				
OR	OR1	0.784	2.995 (0.964)	0.803	0.885	0.720
	OR2	0.927				
	OR3	0.829				
CP	CP1	0.728	3.057 (1.065)	0.867	0.887	0.726
	CP 2	0.854				
	CP 3	0.958				
VS	VS1	0.833	3.116 (1.025)	0.821	0.894	0.737
	VS2	0.902				
	VS3	0.839				
GS	GS1	0.942	2.993 (1.113)	0.845	0.897	0.744
	GS2	0.871				
	GS3	0.766				
AI	AI1	0.886	3.533 (0.752)	0.770	0.867	0.685
	AI2	0.812				
	AI3	0.781				

Note: RA—Relative Advantage, CB—Compatibility, CX—Complexity, OB—Observability, TR—Trialability, TMS—Top Management Support, OR—Organizational Readiness, CP—Competitive Pressure, VS—Vendor Support, GS—Government Support, AI—Adoption Intention.

As shown in Table 3, Fornell and Larcker's Test and Heterotrait-Monotrait ratio (HTMT) test were used to measure the discriminant validity of this study. The HTMT value between variables was lower than the threshold of 0.85, and the square root of AVE of each variable was also greater than the correlation with its variables [96].

4.5. Structural Model Test

First, the collinearity problem is tested. The VIFs of variables are less than 5, which indicates this study does not have collinearity problems. After ensuring the reliability, validity, and collinearity of the model, the structural model is analyzed to verify the relationship between hypotheses. The path coefficient of the structural model and the overall explanatory power are shown in Table 4. It can be seen that comparative advantage ($\beta = 0.231$, $p < 0.001$) and compatibility ($\beta = 0.184$, $p < 0.001$) have significant positive impacts on the intention of SMEs to adopt collaborative robots; thus, H1 and H2 are supported. Complexity ($\beta = -0.326$, $p < 0.001$) has a significant negative effect on the intention of SMEs to adopt collaborative robots; thus, H3 is supported. Observability ($\beta = 0.192$, $p < 0.001$) and trialability ($\beta = 0.227$, $p < 0.001$) have significant positive impacts on the intention of SMEs to adopt collaborative robots; thus, H4 and H5 are supported. Top management support ($\beta = 0.150$, $p < 0.005$) and organizational readiness ($\beta = 0.149$, $p < 0.005$) have significant positive impacts on the intention of SMEs to adopt collaborative robots; thus, H6 and H7 are supported. Vendor support ($\beta = 0.181$, $p < 0.001$) has a significant positive effect on the intention of SMEs to adopt collaborative robots; thus, H9 is supported. However, competitive pressure ($\beta = 0.047$, $p > 0.05$) and government support ($\beta = -0.006$, $p > 0.05$)

have no significant impacts on the intention of SMEs to adopt collaborative robots; thus, H8 and H10 are not supported. This study also measured the impact of control variables (gender, age, education, Job position) on the intention of SMEs to adopt collaborative robots. The results show that there was no significant impact.

Table 3. Discriminant Validity.

Fornell-Larcker Criterion											
	AI	**CB**	**CP**	**CX**	**GS**	**OB**	**OR**	**RA**	**TMS**	**TR**	**VS**
AI	0.827										
CB	0.228	0.818									
CP	0.080	−0.011	0.852								
CX	−0.496	−0.098	0.034	0.839							
GS	0.058	−0.011	0.055	−0.037	0.863						
OB	0.239	0.006	0.059	−0.062	−0.031	0.836					
OR	0.207	−0.087	−0.052	−0.138	0.006	0.003	0.849				
RA	0.325	−0.001	−0.035	−0.101	−0.022	0.128	0.052	0.830			
TMS	0.199	−0.006	0.048	−0.060	0.194	−0.070	0.057	0.133	0.851		
TR	0.349	0.104	0.124	−0.199	0.108	−0.001	0.002	0.074	0.001	0.837	
VS	0.261	0.017	0.091	−0.220	0.086	0.070	0.011	−0.065	0.003	0.073	0.859
Heterotrait-Monotrait Ratio											
	AI	CB	CP	CX	GS	OB	OR	RA	TMS	TR	VS
AI											
CB	0.277										
CP	0.081	0.083									
CX	0.588	0.133	0.063								
GS	0.062	0.045	0.074	0.069							
OB	0.279	0.069	0.063	0.096	0.058						
OR	0.256	0.122	0.073	0.149	0.060	0.032					
RA	0.378	0.086	0.075	0.114	0.042	0.159	0.087				
TMS	0.219	0.054	0.045	0.071	0.210	0.095	0.087	0.154			
TR	0.399	0.129	0.156	0.200	0.114	0.062	0.052	0.135	0.070		
VS	0.320	0.053	0.106	0.256	0.098	0.101	0.050	0.078	0.040	0.081	

Note: RA—Relative Advantage, CB—Compatibility, CX—Complexity, OB—Observability, TR—Trialability, TMS—Top Management Support, OR—Organizational Readiness, CP—Competitive Pressure, VS—Vendor Support, GS—Government Support, AI—Adoption Intention.

Table 4. Assessment of the structural model.

Hypothesis	β	STDEV	T Statistics	*p* Values	Result
H1: RA → AI	0.231	0.043	5.423	0.000	Support
H2: CB → AI	0.184	0.043	4.277	0.000	Support
H3: CX → AI	−0.326	0.050	6.521	0.000	Support
H4: OB → AI	0.192	0.046	4.169	0.000	Support
H5: TR → AI	0.227	0.045	5.075	0.000	Support
H6: TMS → AI	0.150	0.048	3.111	0.002	Support
H7: OR → AI	0.149	0.049	3.056	0.002	Support

Table 4. *Cont.*

Hypothesis	β	STDEV	T Statistics	*p* Values	Result
H8: CP → AI	0.047	0.053	0.895	0.371	Reject
H9: VS → AI	0.181	0.047	3.854	0.000	Support
H10: GS → AI	−0.006	0.052	0.118	0.906	Reject
Gender	−0.021	0.045	0.480	0.632	-
Age	0.064	0.042	1.511	0.131	-
Education	−0.079	0.045	1.757	0.079	-
Job position	−0.012	0.044	0.279	0.780	-

Note: RA-Relative Advantage, CB-Compatibility, CX-Complexity, OB-Observability, TR-Trialability, TMS-Top Management Support, OR-Organizational Readiness, CP-Competitive Pressure, VS-Vendor Support, GS-Government Support, AI-Adoption Intention.

In this study, model fit is measured by the standardized root mean square residuals (SRMR) value. In PLS-SEM, an SRMR value less than 0.08 is considered to be an acceptable model fit [97].

5. Discussion and Conclusions

5.1. Key Findings

With the arrival of the industry 5.0 era, collaborative robot innovation technology will become the leading robot technology in the future [98], and this innovative technology will also bring significant benefits to the development of enterprises [35]. Firstly, this study explains the first research question by using a combined model of the TOE framework and DOI theory at three levels: technical, organizational, and environmental. Comparative advantage, compatibility, complexity, observability, and trialability at the technical level, top management support and organizational readiness at the organizational level, and competitive pressure, vendor support, and government support at the environmental level are the enterprise-level determinants of collaborative robot innovation adopted by SMEs.

Secondly, to address the second research question, this study aims at China, the world's largest collaborative robot market, and conducts an empirical analysis of the impact of enterprise-level determinants on SMEs' adoption of collaborative robot innovation.

Among the determinants of technology, absolute advantage and compatibility have significant positive impacts on SMEs' adoption of collaborative robot innovation. This finding is consistent with the previous research results on e-commerce adoption factors of SMEs in Malaysia and Romania [56,57]. It shows that SMEs have begun to recognize the potential benefits of collaborative robot innovation and are ready to adopt it, which meets the necessary conditions for innovation to be adopted [30]. At the same time, this study finds that complexity has a significant negative impact on SMEs' adoption of collaborative robot innovation. This result is consistent with the results of earlier studies that complexity is negatively correlated with adoption [30,39,58,59]. This shows that SMEs will have concerns and anxiety about the knowledge and skills required for collaborative robot innovation when considering collaborative robot innovation, such as the complexity of programming [4]. In addition, the trialability and observability factors in this study have significant positive impacts on SMEs' adoption of collaborative robot innovation. This result is consistent with previous studies, such as the adoption of big data analysis innovation by SMEs in Iran [78], the adoption of enterprise application (EA) innovation by SMEs in England [99], and the adoption of e-commerce (EC) innovation by Brunei SMEs [100]. A possible explanation is that the collaborative robot has the advantages of being small in size, lightweight, and plug-and-play [23,41,42], which eases the operational difficulty for SMEs to perceive the observability and trialability of collaborative robot innovation.

Among the organizational determinants, top management support has a significant positive impact on the adoption of collaborative robot innovation by SMEs, and this result is consistent with the finding in the previous research on the adoption of cloud computing by SMEs and green supply chain management innovation [64,65]. In addition, in a recent interview study on the innovation adoption of collaborative robots, thirteen interviewees believed that top management played an important role in supporting the adoption of collaborative robot technology [29]. The organizational readiness factors in this study are divided into two parts: the availability of financial resources and human resources. The results suggest that organizational readiness has a significant positive effect on the adoption of collaborative robot innovation in SMEs. This finding is consistent with the research results on the adoption of e-commerce and industrial Internet of Things by SMEs [56,101]. There are two possible explanations. On the one hand, SMEs have recognized the importance of future collaborative robot innovation, thus increasing the financial and human resources for collaborative robot innovation. On the other hand, collaborative robot innovation requires few financial and human resources, which is convenient for SMEs to adopt.

Among the environmental determinants, vendor support has a significant positive impact on SMEs' adoption of collaborative robot innovation. This result is consistent with the finding in the previous study that vendor support has a positive effect on SMEs' adoption of Internet/e-commerce innovation and ERP innovation [80,81]. This is consistent with the preceding part of this paper that SMEs lack expertise in innovation adoption and need innovation vendors to help bridge the knowledge gap related to innovation adoption. However, the other two environmental determinants, competitive pressure, and government support have no significant impact on SMEs' intentions to adopt collaborative robots. This result is inconsistent with previous studies [48,76,82,83]. A possible explanation is that although China is the largest collaborative robot market in the world, the adoption of collaborative robot innovation by SMEs is in the early stage of innovation adoption [4,16,17], so SMEs have not felt the competitive pressure of competitors adopting collaborative robot innovation. In terms of government support, the Chinese government has issued a number of policies to support technological innovation, however, to achieve the optimal allocation of resources, policy resources are mostly inclined toward large enterprises [102].

5.2. Theoretical Implications

This study has four contributions to the existing literature. First of all, this study conducts research on the innovative adoption of collaborative robots at the enterprise level and successfully analyzes the determinants of collaborative robots' innovation adoption in SMEs in China. Most of the previous research focuses on the adoption at the individual level. This study enriches the research on adopting collaborative robot innovation at the enterprise level.

Secondly, this research adopts the empirical analysis method. Through the empirical research on the innovation of collaborative robots in China's SMEs, this paper objectively reflects the factors of enterprises' adoption of collaborative robots innovation. It fills the gap in the empirical research on the determinants of collaborative robot adoption at the enterprise level.

Thirdly, this study introduces the observability and trialability elements that are not widely used in previous studies, empirically analyze the significant positive effects on the innovation adoption of collaborative robots, and broadens the research on innovation elements in innovation adoption.

Finally, this research extends the most prominent combination model of TOE and DOI at the organizational level to the innovative adoption of collaborative robots in SMEs. In previous studies, the combined model of TOE and DOI has been widely used to explain innovation adoption. This study creatively uses the combined model of TOE and DOI to explore the innovative adoption of collaborative robots in SMEs. Specifically, this study extends the combined model of TOE and DOI to the research of collaborative robots, exploring the determinants of SMEs' adoption of collaborative robot innovation from the perspective of technology, organization, and environment. In general, this research provides a theoretical perspective, which can well explain the response of SMEs to the adoption of collaborative robots' innovation.

5.3. Practical Implications

This study analyzes the determinants of collaborative robot innovation adopted by SMEs in three aspects: technology, organization, and environment. It is proved that the five elements of innovation within the technology aspect, top management support and organizational readiness within the organization aspect, and vendor support within the environment aspect have significant impacts on the adoption of collaborative robot innovation by SMEs. With the continuous spread and popularization of collaborative robot innovation, it is necessary to provide some practical suggestions for managers.

First and foremost, SME managers need to weigh the potential risks and benefits before adopting collaborative robot innovation. It is necessary to not only consider the economic benefits brought by collaborative robot innovation but also avoid excessive adoption based on the actual situation of the enterprise.

Second, managers of SMEs need to broaden their horizons, understand the cutting-edge technologies of industry development, and constantly deepen their understanding of innovation. Besides, it is suggested to actively raise funds and recruit talents to prepare for the implementation of innovation.

Third, collaborative robot vendors need to continuously publicize the comparative advantages of innovation. In the early stage of the adoption of collaborative robot innovation, it is recommended to use the means of mass communication for dissemination, such as live streaming. At the same time, continuous technical improvements are made to improve the usability of collaborative robots, such as the development of a collaborative robot AI voice system to achieve real-time conversation-based human-machine collaboration. In addition, it is suggested to develop high-quality benchmark customers in various regions, take full advantage of the role of opinion leaders in innovation diffusion, and facilitate the display of innovation achievements to intended customers. At the same time, free trials can also be provided to intended customers to facilitate transactions.

Finally, government deciders need to fully understand there is a lack of support for innovation policies for SMEs and need to formulate independent innovation policies for SMEs, such as formulating a series of laws and regulations applicable to the needs of SMEs at different stages, and creating innovation support funds, etc.

5.4. Limitations and Future Research

This study has several limitations. One is that this study only collected data from the Guangdong Province of China. Regional differences may lead to differences in the determinants of SMEs' adoption of collaborative robots, which challenges the universality of the results of this study. In future research, different regions or countries should be tested and compared. In addition, although this study explains the determinants of SMEs' adoption of collaborative robots from three aspects: technology, organization, and environment, other factors may also affect SMEs' adoption of collaborative robots, such as the ethics and safety of human-machine collaboration.

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Appendix A

Factors	Serial Num.	Item	Reference
Relative Advantage (RA)	RA1	Adoption of collaborative robot innovation will enable our companies to increase productivity	[47]
	RA2	Adopting collaborative robot innovation will enable our company to improve work performance	
	RA3	Adopting collaborative robot innovation will enhance the image of our company	
	RA4	Adopting collaborative robot innovation will increase our company's profitability	
Compatibility (CB)	CB1	The adoption of collaborative robots' innovation is in line with the work style of our company	[39]
	CB2	The adoption of collaborative robot innovation is fully compatible with our current production operations	
	CB3	The adoption of collaborative robot innovation is compatible with our company's corporate culture and value system	
	CB4	The adoption of collaborative robots' innovation will be compatible with our existing hardware and software	
Complexity (CX)	CX1	The skills required to adopt collaborative robot innovation are too complex for our company	[46]
	CX2	The skills required to adopt collaborative robot innovation are too complex for our employees	
	CX3	It will be a challenge to adopt collaborative robot innovation in our current work practice	
Trialability (TR)	TR1	We are allowed to try out the collaborative robot in our company for a period of time, long enough to understand how it fits the company	[78]
	TR2	Before adopting collaborative robot innovation, our company has the opportunity to adopt collaborative robots in actual production to confirm whether they can reflect the company's requirements	
	TR3	Before adopting collaborative robot innovation, our company was allowed to use collaborative robots for a long enough time to fully understand their functions.	
Observability (OB)	OB1	The benefits of collaborative robot innovation are obvious.	[78]
	OB2	It is easy to see the benefits of a partner's adoption of collaborative robots.	
	OB3	Many people in our company know about collaborative robots.	
	OB4	It is observed that companies in the same industry are adopting collaborative robot innovation.	
Top management support (TMS)	TMS1	Our top management supports the adoption of collaborative robot innovation.	[46]
	TMS2	The top management of our company hopes to make our company a leader in the field of using collaborative robot innovation.	
	TMS3	The top management of our company is prepared to bear the risks associated with adopting collaborative robot innovation (financial and organizational).	

Factors	Serial Num.	Item	Reference
Organizational readiness (OR)	OR1	Our company has the financial and human resources to adopt collaborative robot innovation.	[101]
	OR2	Our company can bear the pressure of financial resources for collaborative robot innovation.	
	OR3	Our company can bear the pressure of human resources for collaborative robot innovation.	
Government support (GS)	GS1	Our company is pushed by some government agencies to adopt collaborative robot innovation.	[80]
	GS2	The government is encouraging us to adopt collaborative robot innovation.	
	GS3	The government is actively conducting collaborative robot innovation training to help our company adopt collaborative robot innovation.	
Vendor support (VS)	VS1	Vendors actively market collaborative robot innovation to our company.	[47]
	VS2	The vendor has provided sufficient technical support for the adoption of our company's collaborative robot innovation.	
	VS3	The vendor has provided sufficient technical training for the adoption of collaborative robot innovation in our company.	
Competitive pressure (CP)	CP1	Our company believes that the adoption of collaborative robot innovation has an impact on the competition in the industry.	[39]
	CP2	Our company is facing pressure from competitors. It is challenging to survive in the fierce competition without using collaborative robot innovation.	
	CP3	Some of our competitors have started to adopt collaborative robot innovation.	
Adoption Intention (AI)	AI1	Our company plans to spend resources on the adoption of collaborative robot innovation.	[101]
	AI2	The production activities of our company need to adopt collaborative robot innovation.	
	AI3	Collaborative robot innovation is required in all functional areas of our company.	

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