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Understanding the Determinants of Construction Robot Adoption: Perspective of Building Contractors

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Abstract: Construction robots have emerged as a revolutionary technology for buildings. However, real-world adoption is still limited. Little is known how the decision of adopting construction robots or not is made in organizations, which inhibits the benefits of robots from being fully realized. This paper aims to investigate the determinants affecting construction robot adoption for building works at organizational level. Drawing on the technology-organization-environment framework, a research model with eleven hypotheses on determinants was developed, and empirically evaluated via a survey with 94 typical building contractors in Hong Kong using partial least squares structural equation modeling technique. The results indicate that relative advantage, top management support, organizational readiness, market competitive pressure, and high costs are significantly related to the adoption, among which top management support is most influential. A two-stage conceptual framework is derived that provides theoretical insights on the determinants and reveals the complexities and influence dynamics of determinants on the adoption during technology development. The findings offer useful suggestions for the effective development of robots for building works and lay a foundation for construction innovation adoption in a wider context.

Keywords: construction robots; innovation adoption; building; technology-organization-environment

Introduction

Construction robots have emerged as a revolutionary technology for buildings that have the potential to reform and renovate the building sector. The development is manifold, ranging from upgraded construction equipment with robotic features (e.g., robotic excavators, robotic cranes), derived robots from other industries (e.g., welding robots, robotic drones), to construction specific robots (e.g., facade installation robots, integrated robotized construction sites) (Bock 2015). Despite the increasing demand and futuristic ambition towards robots in the construction industry (World Economic Forum 2018), real-world adoption is still quite limited (Saidi et al. 2016). To invigorate the uptake of construction robots and enable their transformation power to the industry, it is critical to well understand the decisions pertain to adoption at organizational level. Although there is some literature on the opportunities and barriers of construction robots (e.g., Mahbub 2008; Bogue 2018), little is known how the decision of adopting construction robots or not is made in organizations, especially contractors who are directly responsible for the building works. This knowledge gap also inhibits the realization of the full benefits of construction robots for buildings.

Therefore, this study aims to investigate the determinants affecting the adoption of construction robot for buildings at organizational level, from the perspective of building contractors. A research model with hypothesized relationships between determinants and adoption was developed, grounded in the technology-organization-environment (TOE) framework, which is a generic organizational innovation theory (Tornatzky and Fleischer 1990). The hypotheses were then empirically evaluated with a sample of 94 typical contractors in the Hong Kong building sector, using partial least squares structural equation modeling (PLS-SEM). The results and findings lead to the derivation of a two-stage model for understanding the determinants of construction robot adoption, thereby offering suggestions to promote the development and implementation of construction robots and contributing to the knowledge of construction innovation adoption in a wider context.

The remainder of this paper is organized as follows. Background section sequentially discusses the relevant background of the study, followed by the theoretical model and hypotheses on determinants proposed in the research model and hypotheses section. Research methods section then introduces the measurement and data for testing the hypotheses, and the data analysis method. Results and analyses section presents the results of the hypothesis testing using PLS-SEM. Discussion section discusses the findings and provides theoretical and practical insights for the future development and implementation of construction robots. Conclusions section concludes the paper and comments on future research directions.

Background

Construction robot adoption

There are years of technological research efforts to speed up the breakthrough of construction robots (Bock and Linner 2016). In the 1980s and 1990s, many early adoption cases were reported on single-task construction robots, such as mobile handling robots, concrete finishing robots, plastering robots, ceiling board installation robots, and fireproofing robots (Cousineau and Miura 1998; Bock and Linner 2016). Most of them involved prototype robots stem from research projects, but many failed to be commercialized (Mahbub 2008). Except the areas of off-site prefabrication, pipe maintenance and demolition (Bock and Linner 2016), the real-world take-up of construction robots to date still remains limited (Saidi et al. 2016).

There is a wide variety of research on construction robots led by academia. For example, researchers in ETH Zurich developed a mobile robotic system named 'In situ Fabricator' for fabricating building elements on the site (Giftthaler et al. 2017). A prototype cable-driven parallel robot to build, repair and maintain a building facade is under development by academics from Technical University of Munich (Taghavi et al. 2018). A research team from the University of Michigan is developing modeling techniques for adaptive and autonomous manipulation of construction robots (Lundeen et al. 2017; Lundeen et al. 2019). Besides, a growing number of start-ups with commercialized robots has been witnessed in recent years, such as the bricklaying robot SAM100 by Construction Robotics and Hadrian X by Fastbrick Robotics for onsite masonry construction (Bogue 2018), the ceiling drilling robot by nLink for precise and continuous drilling of holes in concrete ceilings (nLink 2018). There are also increasing development efforts from research institutes, such as a humanoid robot prototype HRP-5P by Japan's Advanced Industrial Science and Technology (2018). Although there are some adoption cases, many of these innovative robots are still discussed as a future technology with limited real-world adoption yet (World Economic Forum 2018). Some examples of worldwide development are provided in **Fig. 1**.

Innovation adoption theory

Construction robots are essentially innovation to the building sector, which elicits strategic concerns of adoption decisions from an organizational perspective. Therefore, the construction robot adoption is related to the research field of innovation adoption, which has attracted intense research interest among different sectors. Fundamentally, innovation adoption is considered as '*a decision to make full use of an innovation as the best course of action*' (Rogers 2010), and organizational adoption of innovation is commonly intended to contribute to the performance or effectiveness of the adopting organization (Damanpour 1991). There are a variety of theoretical models proposed to examine and understand innovation adoption in organizations, and to summarize factors at multiple levels that potentially influence the adoption process in different fields (Hameed et al. 2012). Specifically, diffusion of innovations (DOI) theory is applicable for the analysis at both individual and organizational levels; theory of reasoned action, theory of planned behavior and technology acceptance model are generally applied at the individual level of analysis; and the technology-organization-environment (TOE) framework is adopted for the organizational level of analysis (Hameed et al. 2012). It has been noted that the TOE framework overlaps with the innovation characteristics in the DOI theory (Oliveira et al. 2014). Therefore, many studies on organizational innovation adoption are grounded in the TOE framework while incorporating the DOI theory (Thiesse et al. 2011; Oliveira et al. 2014).

Basically, the TOE framework (Tornatzky and Fleischer 1990) describes that the adoption of technological innovations for a company is influenced by the technology, organization, and external environment context. The technology context refers to the technological attributes that can affect the decision to adopt the innovation, the organization context describes the organizational characteristics that can inhibit or facilitate innovation adoption, and the environment context concerns factors external to the organization that can present challenges and opportunities to the adoption of innovation (Tornatzky and Fleischer 1990; Thiesse et al. 2011; Oliveira et al. 2014; Pan and Pan 2019).

Previous studies on construction innovation adoption

The construction industry is always considered as a low-tech sector with poor innovation performance (Martínez-Román et al. 2017). One fundamental reason is pertained to the nature of the business, as it is project-oriented and requiring collaboration and interaction among multiple stakeholders and specialists over the whole project life cycle, resulting in considerable difficulties for innovation adoption agreement among different groups (Dubois and Gadde 2002). Furthermore, the construction process of buildings or other civil engineering structures is complicated, and often, the major barriers for innovation adoption are: 1) the uncertainties in ascertaining the benefits of adoption and, 2) the lack of clear understanding of how innovation can be best integrated into existing processes (Blayse and Manley 2004). Consequently, construction practitioners are always blocked in conventional construction methods and reluctant to innovation and changes.

Therefore, researchers have long been interested in understanding and explaining the adoption and management of innovation in the construction industry (Ozorhon and Oral 2016). Great attention has been paid to information and communication technologies such as virtual reality (Whyte 2002), building information modelling (BIM) (Bin Zakaria et al. 2013; Lee and Yu 2015), as well as many other tools for construction project management (Ahuja et al. 2009). There are also studies in innovative construction methods, like off-site production (Pan et al. 2012). However, research is limited to new construction technologies in terms of tools and equipment (Sepasgozar et al. 2018), which include robotics. Therefore, discussions on construction robots could contribute to this knowledge gap in construction innovation adoption.

Research model and hypotheses

The TOE framework, integrating characteristics from the DOI theory, has been applied as the theoretical basis to explore the determinants of construction robot adoption in this study. TOE is a generic theory for innovation adoption at the organizational level of analysis that has been successfully adopted in a wide variety of research fields to explore and examine adoption determinants of innovative technologies (Thiesse et al. 2011; Hameed et al. 2012; Oliveira et al. 2014). Besides, the three contexts of the TOE framework echo with issues considered in many construction innovation adoption studies (Mitropoulos and Tatum 1999; Taylor 2007). The previous study of robot adoption determinants in off-site construction (Pan and Pan 2019) also demonstrated the feasibility of applying TOE in this exploratory study regarding robot adoption for on-site building works.

It has been noticed that project-based firms, like construction companies, can learn from general innovation literature if findings and research are focused on firms (Martínez-Román et al. 2017). Therefore, concerns from previous relevant studies in innovation adoption and construction robots were considered together. Based on the TOE framework and literature review, a research model is developed and illustrated in **Fig. 2**. There are twelve constructs in the model, including the eleven determinants in the TOE contexts as independent variables, and the construction robot adoption as the dependent variable. The examined determinants are based on the previous study for robot adoption in off-site construction (Pan and Pan, 2019), while supported by the reviewed studies in adoption of other innovation in construction or other disciplines (e.g. Grandon and Pearson 2004; Thiesse et al. 2011; Chong and Chan 2012; Oliveira et al. 2014; Wang et al. 2016). The descriptions of the eleven determinants are summarized in **Table 1**. The model graphically presents the hypothesized relationships between the determinants and adoption (constructs) and these hypotheses are detailed in the following subsections.

Hypotheses of the technology context

Perceived relative advantage refers to the degree to which adopting construction robots are perceived as providing benefits to the organization. It has been generally agreed that the perceived relative advantage of an innovation is positively related to the rate or extent of adoption (Thiesse et al. 2011; Oliveira et al. 2014). Regarding construction robots, the potential to provide environmental, economic and social benefits to organizations and projects has been widely explored (Pan et al. 2018). Relative advantage offered by construction robots to replace or assist human in conducting dull, dirty, and dangerous works is a critical driver for adoption (Lim et al. 2012; Skibniewski and Zavadskas 2013). It is therefore hypothesized that:

H1. Perceived relative advantage will positively influence construction robot adoption.

Compatibility between the innovation and firm's culture, values, and practices is widely recognized as an influential determinant of the innovation adoption (Thiesse et al. 2011; Chong and Chan 2012; Oliveira et al. 2014; Wang et al. 2016). Perceived compatibility has also been identified as a vital issue in adopting robots for off-site production (Pan and Pan 2019). As for the general on-site building works, the compatibility issue could be even more problematic in terms of unique project characteristics, changing site environment, and human interaction. It is therefore hypothesized that:

H2. Perceived compatibility will positively influence construction robot adoption.

Perceived complexity often inhibits the adoption of new technology (Grandon and Pearson 2004; Chong and Chan 2012; Wang et al. 2016). In this study, complexity is considered the degree to which construction robots are perceived to be difficult to understand and use. Complexity is deemed to cause the uncertain future adoption of some construction robots (Bogue 2018). Adopting construction robots can be challenging to companies that lack technological expertise, which is often the situation in many construction companies with expertise only in their own trade fields. It is therefore hypothesized that:

H3. Perceived complexity will negatively influence construction robot adoption.

Previous studies have widely discussed that high costs would deter technology adoption (Lin 2014). With respect to construction robots, high costs have been long discussed to retard their real-world adoption, owing to the high capital cost, operation and maintenance cost (Cousineau and Miura 1998; Mahbub 2008; Bock and Linner 2016). High costs are also attributed to the lack of economic justification for the utilization of construction robots (Pan et al. 2018). It is therefore hypothesized that:

H4. Perceived high costs will negatively influence construction robot adoption.

Hypotheses of the organization context

Top management support is identified as crucial in many innovation adoption studies of information systems, as it creates a positive environment to influence employees and provides organizational commitment (Oliveira et al. 2014). Its importance has also been emphasized for innovation adoption in the construction industry (Ozorhon and Oral 2016). Construction robots as the innovation to be applied at the organizational level, top management support primarily refers to the degree to which top management understands the importance of adopting construction robots and the extent to provide sufficient support in making the adoption decision. It is therefore hypothesized that:

H5. Top management support will positively influence construction robot adoption.

Firm size is an important organizational factor established in previous research that can affect the adoption of many new technologies (Lin 2014; Wang et al. 2016). Large firms are more likely to adopt new technologies than small ones, as they have more flexibility, resources, and risk tolerance. Previous studies have demonstrated the influence of firm size for the construction innovation adoption, such as prefabrication (Pan et al. 2012) and BIM (Bin Zakaria et al. 2013). It is therefore hypothesized that:

H6. Firm size will positively influence construction robot adoption.

Organizational readiness is considered as the readiness of the organization in terms of financial resources and technological knowledge (Grandon and Pearson 2004; Chong and Chan 2012), to adopt an innovation. Many construction robots require trials and additional development before real-world implementation. Sufficient financial resources, professional knowledge, and technological capability in the construction companies are the fundamental concerns to guarantee the research and development efforts, and the adoption, on construction robots (Pan and Pan 2019). It is therefore hypothesized that:

H7. Organizational readiness will positively influence construction robot adoption.

Hypotheses of the environment context

Market competitive pressure drives organizations in all industries to seek competitive advantages by adopting new technologies (Lin 2014; Oliveira et al. 2014; Wang et al. 2016). Accordingly, competitive pressure is widely discussed as an important determinant in the adoption of new systems or technologies (Oliveira et al. 2014). This study defines market competitive pressure as pressure resulting from the practices of competitors and a need to gain competitive advantage. The building sector is quite competitive, fraught with various difficulties and challenges like low productivity and labor shortage (Pan et al. 2018). Construction robots as a disruptive innovation are expected to support early adopters to compete for successfulness in the highly competitive market. It is therefore hypothesized that:

H8. Market competitive pressure will positively influence construction robot adoption.

The influence of market demand on innovation has been highlighted from the market pull perspective in innovation studies, especially in the innovation generation (Di Stefano et al. 2012). As for construction robots, the adoption intention has also been reckoned to meet the market demands for workforce replenishment, productivity improvement, and environmental impact reduction (Pan et al. 2018). It is therefore hypothesized that:

H9. Market demand will positively influence construction robot adoption.

Regulatory support refers to the support from the government or its authority to encourage the adoption of an innovation (Thiesse et al. 2011; Oliveira et al. 2014). Regulatory policies and standards could facilitate innovation adoption by reward schemes or mandatory regulations (Ozorhon and Oral 2016). In the building sector, the role of the government is critical for innovation adoption, not only to formulate regulation and guidance, but also as the largest client. It is therefore hypothesized that:

H10. Regulatory support will positively influence construction robot adoption.

Trading partners across the supply chain can be positively related to the adoption of technological innovations (Thiesse et al. 2011). Pressure from trading partners from both upstream and downstream supply chain is a key impetus that the powerful partners may request or persuade the company to adopt the new technology (Wang et al. 2010). Trading partners are also influential in construction as a project-based community (Sepasgozar 2018). Besides, the construction robot application would initiate a new stakeholder group – robot vendors. A close relationship with robot vendors is necessary for construction companies to make decisions on adopting robots (Pan and Pan 2019). It is therefore hypothesized that:

H11. Trading partner support will positively influence construction robot adoption.

Research methods

To assess the hypotheses developed above, a questionnaire survey was conducted among typical building contractors in Hong Kong. The questionnaire included demographic information on the participant, an open-ended question for those have experience of construction robots to specify the area of applications, and pertinent questions regarding determinants of the construction robot adoption. The overall research methodology is presented in **Fig. 3** and described in the subsections below.

Measurement of determinants

The questionnaire items to measure the constructs in the research model (relative advantage, compatibility, complexity, high costs, top management support, firm size, organizational readiness, market demand, market competitive pressure, regulatory support, trading partner support, and construction robot adoption) were based upon published literature (see **Table 2**). To be consistent with the sources, the constructs were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree", except those noted otherwise. To test the research instrument, a pilot study was conducted with ten relevant experts from academia and industry by inviting them to complete the questionnaire and provide comments. The results were not included in the main survey since some of the invited experts do not currently work for a contractor. The pilot study verified that the questionnaire is understandable and easy to fill.

Research participants

The questionnaire was emailed to qualified individuals (CEOs, directors, senior managers) at 800 contractors for building works in Hong Kong, attached with an editable PDF file and an online filled link. The potential contractors were identified using publicly available databases supplemented by the networks of the researchers. Examples of the databases included: Development Bureau's (2018) list of approved contractors, Building Department's (2018) list of registered contractors, and Hong Kong Trade Development Council's (HKTDC 2018) database of contractors. In total, 94 valid questionnaires were returned out of 800 sent out, yielding an overall response rate of 11.8%, which is comparable to other studies as an internet-based survey in the construction field (Zhao et al. 2018). Profiles of questionnaire participants are shown in **Table 3**. The respondents were experienced and qualified individuals, indicating a good quality of data. The Harman's one-factor (or single-factor) test (Podsakoff et al. 2003) was used to examine the common method bias that the majority of the variance in the model (>50%) cannot be explained by a single factor, and no significant common method bias was found in the returned data set as a single factor accounted for 37.9 % from the test.

Data analysis

Variance-based structural equation modeling (SEM) was adopted to evaluate the research model, using partial least squares (PLS) for the analysis, which is namely the partial least squares structural equation modeling (PLS-SEM) technique. The primary motivations for choosing PLS-SEM instead of other covariance-based SEM methods (Hair et al. 2016) is the consideration of the relatively small sample size, non-normal data, as well as nature of this exploratory research. Previous studies have also illustrated the usefulness of PLS-SEM in exploratory studies in the construction field (Yap et al. 2018). Particularly, SmartPLS was used as a tool for analysis.

Although PLS-SEM has a relatively lower requirement for sample size than covariance-based SEM, it has minimum sample size requirements to ensure the effectiveness of using PLS-SEM for analysis. Many studies follow the ten times rule by Barclay et al. (1995) that the minimum sample size should be ten times the largest number of, either indicators used to measure one construct, or structural paths directed at a latent construct in the structural model. However, this guideline has received many debates recently (Hair et al. 2016) and regarded as a rough estimation, while a more scientific way to decide sample size should be based on model complexity and data characteristics (Hair et al. 2016). Hair et al.'s (2016) suggestion for the rules of thumb by Cohen (2013) recommends the minimum sample size for PLS-SEM based on the required statistical power level, pre-specified significance level, the population effect size and the number of arrows pointing at a construct in the path model, which can also be calculated by G*Power (Faul et al. 2007). The sample size in this study consists of 94 contractors, which satisfies both Barclay et al.' (1995) ten times rule (the minimum sample size should be 60) and Cohen's (2013) recommendation considering a 90% power level, 0.05 significance level and small effect size (R^2=0.25) (the minimum sample size should be 67 for 11 determinants). Variance inflation factors (VIFs) were calculated to detect potential multicollinearity, which occurs when there is a strong linear correlation among items for measuring constructs. According to the requirement that VIF should be lower than the threshold of 5 to avoid multicollinearity (Oliveira et al. 2014), two items, CB4 (VIF=5.762) and CB5 (VIF=7.133) for measuring the compatibility were deleted.

There are a set of criteria to assess partial model structures in a two-step process, including the assessment of the measurement (the outer) model and the assessment of the structure (the inner) model (Hair et al. 2016), which are explained as follows.

The measurement model was assessed in terms of reliability and validity. The reliability of each item for measuring constructs could be examined with loadings. Considering that a latent variable (items) should explain a substantial part (usually at least 50%) of each indicator's variance (Hair et al. 2016), the items with loading less than 0.7 ($\approx \sqrt{0.5}$) should be removed. The internal consistency reliability is traditionally assessed by Cronbach's α. Another measure, composite reliability (CR) is proposed as a more suitable assessment criterion for reliability in PLS-SEM (Hair et al. 2016). For both reliability coefficients, the satisfactory value is considered as above 0.7 in early research stages and above 0.8 or 0.9 in more advanced research stages (Nunnally and Bernstein 1994). The validity is usually examined with convergent validity and discriminant validity (Hair et al. 2016). The convergent validity using average variance extracted (AVE) should higher than 0.50. The discriminant validity could be assessed using Fornell–Larcker criterion and cross-loadings. Specifically, the Fornell–Larcker criterion postulates that the square root of AVE should be larger than the correlations between the constructs (Fornell and Larcker 1981). The cross-loadings criterion requires that the loading of each construct should be larger than all item cross-loadings (Chin 1998).

The structure model was then tested to verify the hypotheses in the research model. The effect size was calculated by Cohen's f^2 that 0.02, 0.15, 0.35 are considered for weak, moderate, strong effects for the evaluated variables (Hair et al. 2016). The f^2 should therefore larger than 0.02 in order to have meaningful explanation. The significance level (p) of standardized paths were calculated, with resampling using bootstrapping was conducted, to estimate path coefficients for hypotheses testing. The explanatory power of the model to explain all the data was measured by R^2 value.

Table 4 summarizes the above-mentioned criteria and rules of thumb adopted in this study for evaluating data, measurement model and structure model.

Results and Analyses

In general, the results demonstrated the currently minimal adoption of construction robots by contractors in Hong Kong with only 8.5 % indicated the adoption stage as “have already adopted”. For those adopters, the details about their adopted robots were asked using an open-ended question. The identified applications included robot for excavation and bricklaying, automated guided vehicle, lifter, robotic gantry, exoskeleton suit, robotic arms for drilling holes, concrete breaker, demolition robot, drones and robots for maintenance, monitoring, and inspection. Besides, the intention was also mentioned by some respondents to adopt some new types of robots, such as cable-driven parallel robots, collaborative robots, and three-dimensional printing. Some examples of the mentioned construction robots that are adopted or under trials in Hong Kong are presented in **Fig. 4**.

The assessment of the measurement model and the structure model are presented in the following subsections.

Assessment of the measurement model

From the measurement model in this research, the reliability of each item was first tested, where four items were removed, remaining those with loadings above 0.7 and statistically significant at the 0.01 level formulated a revised model. The mean, standard deviation (SD), Cronbach’s α, CR and AVE of constructs in the revised model were calculated and shown in **Table 5**. The internal consistency reliability and convergent validity were satisfied. As for discriminant validity, both Fornell–Larcker criteria (see **Table 6**) and cross-loadings criteria were also satisfied. Therefore, all the required criteria were met for a reliable and valid measurement of constructs in the revised model.

Assessment of the structural model

In this step, the hypothesized relationships between the constructs were estimated via the assessment of the structural model. The estimation indicated that two constructs, market demand (H9) and trading partner support (H11), have very low f^2 value (<0.02) to support a meaningful explanation (Cohen, 2013). Therefore, these two were removed in further analysis. To evaluate the significance of standardized paths in the structural model, the bootstrapping method of 5000 re-samples was used. The results are presented in **Table 7** and **Fig. 5**. The hypotheses for relative advantage (H1) ($p < 0.05$), high costs (H4) ($p < 0.05$), top management support (H5) ($p < 0.001$), organizational readiness (H7) ($p < 0.1$), market competitive pressure (H8) ($p < 0.05$) are confirmed, while compatibility (H2) is oppositely confirmed. Complexity (H3), firm size (H6), and regulatory support (H10) are not statistically supported at a significant level. R^2 value is 0.57, showing the whole research model explains 57% of adoption potential of construction robots.

Discussion

Hypotheses discussion

The results revealed the limited adoption of construction robots in Hong Kong. The evaluation of the research model confirmed the hypotheses of five determinants to affect the adoption of construction robots: relative advantage, high costs, top management support, organizational readiness, and market competitive pressure. The results further indicated a singularity regarding the influence of compatibility. All the results of hypotheses are discussed as follows.

From the technology context, relative advantage (H1) is found to positively influence the adoption of construction robots among contractors. This finding is consistent with previous arguments made by construction robot researchers (Lim et al. 2012; Skibniewski and Zavadskas 2013). It further echoes Pan et al. (2018)'s argument that the advantage of construction robots in terms of environmental, economic and social benefits could be the possible trigger for the future large-scale adoption of robots for building works. Unexpectedly, the influence of compatibility (H2) is confirmed but in the opposite direction, which means that the result indicates the negative influence of compatibility on the adoption. This might because that those potential or existing adopters are facing the compatibility issues during adoption, while non-adopters are not very concerned about this problem in their planning. The influence of complexity (H3), concerned by previous studies (Bogue 2018), is not found to negatively influence the adoption at a significant level. High cost (H4) is confirmed to negatively influence the adoption, which is also consistent with prior studies that perceived high costs is a key inhibitor for construction robot adoption (Cousineau and Miura 1998; Mahbub 2008; Bock and Linner 2016).

From the organization context, the study unravels that top management support (H5) is the most influential determinant in explaining the adoption of construction robots. It could positively influence the adoption, with the highest path coefficient value and f-value among all tested determinants. This result confirmed the importance of top management, which is also consistent with studies in other innovation adoption in construction (Whyte et al. 2002; Bin Zakaria et al. 2013). Firm size (H6) is not found to significantly influence the adoption. This might because some surveyed contractors considered its firm size from an industry-wide concern while some subcontractors may compare it to others in the same trade. Organizational readiness (H7) is confirmed as a positive determinant to the adoption, which also reflects the need for financial and human resources in construction robot adoption.

From the environment context, market competitive pressure (H8) is found to positively influence the adoption. This is consistent with the findings on robot adoption in off-site precast production (Pan and Pan 2018), as well as the argument on the initial driving force of construction robot adoption in Japan (Mahbub 2008). Regulatory support (H10) is not identified to have a noticeable influence on adoption. This is might because there is still no explicit regulation or financial support for construction robots, and therefore regulatory support is not a powerful driver for the current adopters or potential adopters. Market demand (H9) and trading partner support (H11) are not found to have a significant influence on the adoption. A possible explanation is that the lack of knowledge and unclear vendors for construction robots limit the understanding of two determinants from the survey participants.

The results together indicate that the adoption of construction robots is influenced by the factors from the technology, organization, and environment contexts, while the top management support has the most decisive effect. More investigations are needed for these unsupported hypotheses. The implications to theory and practice are summarized as follows.

Theoretical implications

Construction innovation has not yet received much attention in the field of innovation adoption, and particularly, there is a research need to understand technology adoption in construction especially for tools and equipment (Sepasgozar et al. 2018). The study contributes to this knowledge field by exploring the determinants of the adoption of construction robots for the building sector. It also supplements many previous qualitative studies on construction innovation adoption (e.g., Whyte et al. 2002; Bin Zakaria et al. 2013; Pan and Pan 2019) by a quantitative investigation based on structural equation modeling.

The study builds upon the TOE framework to integrate various perspectives into a proposed research model. The model considers the determinants from technology, organization, and environment contexts that underlie the adoption of construction robots. Reliability and validity tests have verified the revised measurement for constructs used in this study. Therefore, the research model and the measurement could provide a sound foundation for understanding the determinants of construction robot adoption and might be applicable for other construction innovation studies.

Compared with the prior study for construction robot adoption in precast concrete production (Pan and Pan 2019), the findings have further theoretical implications on the adoption determinants for robots in different technology readiness levels (the maturity of technology). In particular, construction robots in precast concrete production have entered the market since the early 1990s which are well-developed technologies with a high technology readiness level (Pan and Pan 2019). Nine of the examined determinants in this study were considered important and highly correlated in determining adoption decisions of robots for precast concrete production, with compatibility identified as a primary reason for non-adoption (Pan and Pan 2019). While construction robots for general on-site building works, as the focus of this study, are mainly in research and development stages with a low technology readiness level. The discussion on hypotheses in the above subsection indicates that significant determinants of construction robot adoption identified in this study somehow differ from the off-site context, as reported by Pan and Pan (2019). Consequently, a two-stage conceptual framework is derived for understanding the determinants of construction robot adoption (**Fig. 6**). For the early stage of construction robot, like most of the robots for on-site building works discussed in this study, determinants at the organizational context, especially the top management support, are the most decisive ones, while the determinants at the external environment are not quite influential. For the later stage, like robots for off-site construction that are mature and established (Pan and Pan 2019), determinants at the technological and environment contexts might exert greater influence on the adoption decision. Along with the technology development, the compatibility could be an increasingly important concern for adoption, since technology adaptation is often necessitated in the adoption of construction robots. Trading partner support (Sepasgozar 2018;

Pan and Pan 2019) might be influential when robots have reached a high technology readiness level. Besides, the correlation between technology, environment, and organization contexts could be increased, indicating the growing complexities for the adoption at the later stage of technology development. Therefore, the framework reveals the complexities of determinants and their influence dynamics on the construction robot adoption during technology development. This framework should also be applicable to explain and understand the determinants of adopting other technological innovation in construction, and further validation studies are needed.

Practical implications

The findings also provide important practical implications to both contractors and robot developers to promote the future development and adoption of construction robots. Although the empirical data were collected in Hong Kong, some implications are irradiative to other regions. The generality of findings requires further studies in other cities or countries.

First, the perceived relative advantage is currently the main driver while perceived high costs is the main barrier for construction robot adoption in the technological context. Construction robots could offer the relative advantages of productivity, quality, safety, and sustainability improvement as well as economic benefits in reducing the cost of expensive labor (Pan et al. 2018). However, perceived high costs associated with construction robots themselves inhibit the adoption intention. These concerns require the decision-makers to clearly define all the trade-offs in a dialectical systems manner to make proper decisions. Besides, cooperation with partners via cost-sharing agreements could reduce the cost impacts on the adoption decision (Thiesse et al. 2011).

Second, compatibility has been noticed as an issue for some adopters and potential adopters, which is attributable to the nature of uniqueness of building projects that increase the difficulties for the real-world adoption of construction robots. Comparatively, complexity might not be a significant concern for the adoption of construction robots. For the future adopters and robot developers, great attention should be paid on the adaption of construction robots to fit for the project-based construction companies and address the compatibility issues. In this regard, robot developers and vendors could also exploit business opportunities in addressing compatibility of robots with other emerging themes in construction, such as modular integrated construction (Pan and Hon 2018).

Third, the study emphasized the importance of top management support in the construction robot adoption. For the contractors, the top management should be mindful of possible promises and pitfalls of the available construction robots in making the appropriate adoption decisions. To accelerate the adoption process, it is essential for robot developers and vendors to actively building up the awareness and acknowledgment of construction robots among the top management in the construction companies.

Fourth, market competitive pressure in the environmental context was found as a driver to construction robot adoption, which has also been identified as a facilitator for robot implementation in the off-site construction (Pan and Pan 2019). Such driving forces might be progressively significant along with the increasing technology readiness and market maturity of construction robots in the future.

Conclusions

This paper has investigated the determinants of construction robot adoption from the perspectives of building contractors. A research model was developed in the technology, organization, and environment contexts, with embedded hypothesized relationships between determinants and adoption. The hypotheses were empirically evaluated based on a questionnaire survey with 94 typical contractors for building works in Hong Kong using partial least squares structural equation modeling. The results indicate that the four determinants, namely, relative advantage, top management support, organizational readiness, and market competitive pressure, are significantly positively related to construction robot adoption, while one determinant, high costs, is significantly negatively related to the adoption. Top management support was identified as the most influential determinant for the adoption. Compatibility is unexpectedly found to negatively influence the adoption, revealing that the potential or existing adopters are still fraught with compatibility issues that however are less noticed by non-adopters. Complexity, firm size, market demand, market competitive pressure, regulatory support, and trading partner support are found to have no statistically significant influence, since the relevant hypotheses are not supported. For them, further investigation is necessary to reach more definitive insights.

A two-stage conceptual framework of the determinants of construction robot adoption is derived, which paints an insightful picture of what determines the adoption of construction robots at different stages of technology development. The framework conceptualizes the complexities and influence dynamics of determinants on the adoption. Practical suggestions are offered for contractors to make thoughtful decisions towards the successful implementation of available construction robots, as well as for robot developers and vendors to address issues stem from important determinants for the effective development of future construction robots for buildings. The framework and findings also lay a good foundation for future research into other technology adoption for the construction industry. Further research can examine the complexities of, correlation between, and influence power on the determinants of construction robot adoption or other innovation, which should elicit more insightful findings to further improve and contextualize the two-stage framework, as well as to support technology development and deployment.

Data Availability Statement

All data, models, or code generated or used during the study are available from the corresponding author by request.

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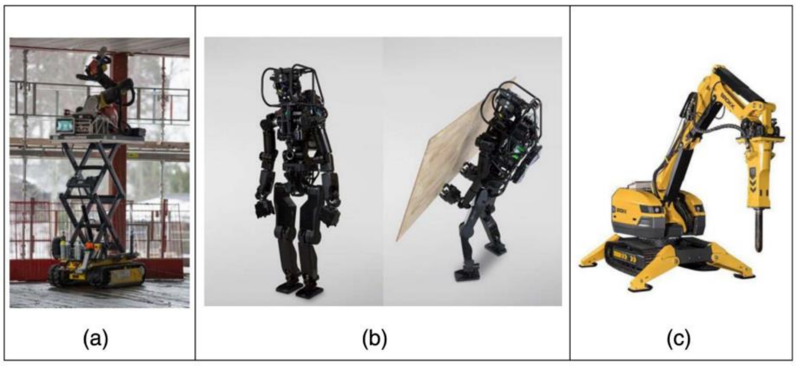

Fig. 1. Examples of worldwide development on construction robots: (a) ceiling drilling robot (image courtesy of nLink); (b) humanoid robot prototype HRP-5P (images courtesy of AIST); and (c) demolition robot (image courtesy of BROKK).

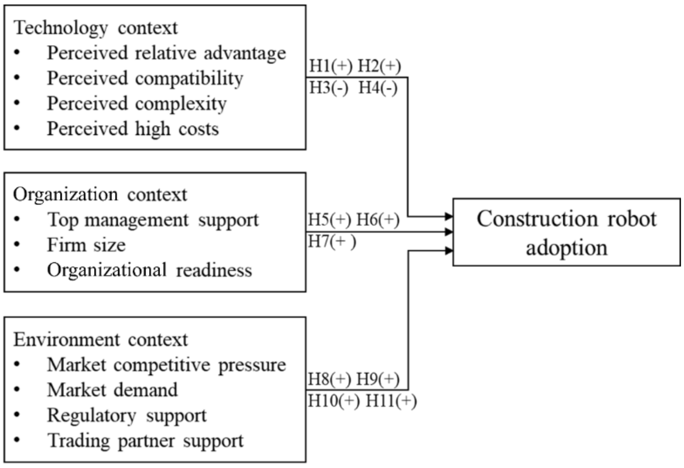

Fig. 2. The research model for contractors' adoption of construction robots

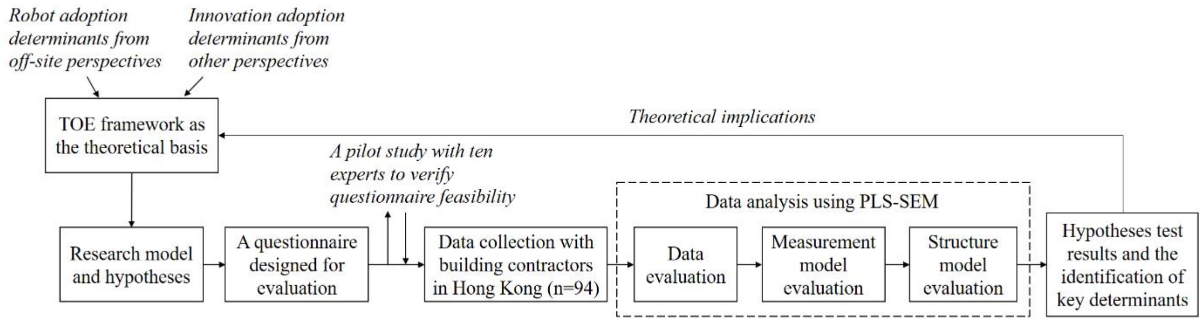

Fig. 3. The overall research methodology

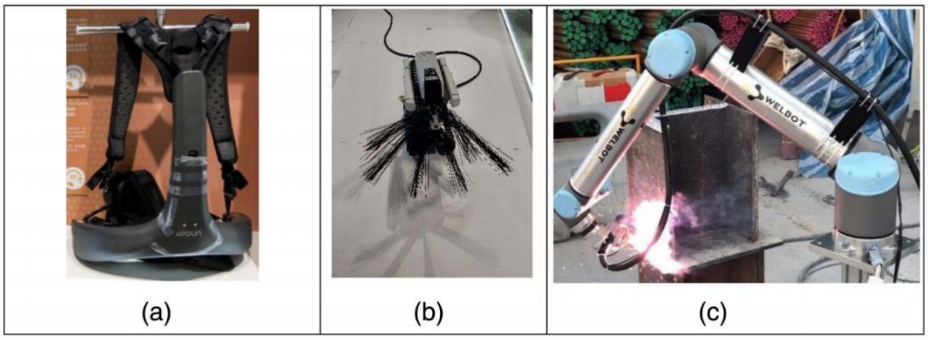

Fig. 4. Examples of applications of construction robots in Hong Kong: (a) exoskeleton suit exhibited by Atoun at Construction Innovation and Technology Application Centre (CITAC); (b) indoor air quality (IAQ) disinfection robot for maintenance exhibited by Gammon at CITAC; and (c) adaptive welding robot for onsite construction works. [Images in (a and b) by authors; image in (c) courtesy of Welbot Technology Limited.]

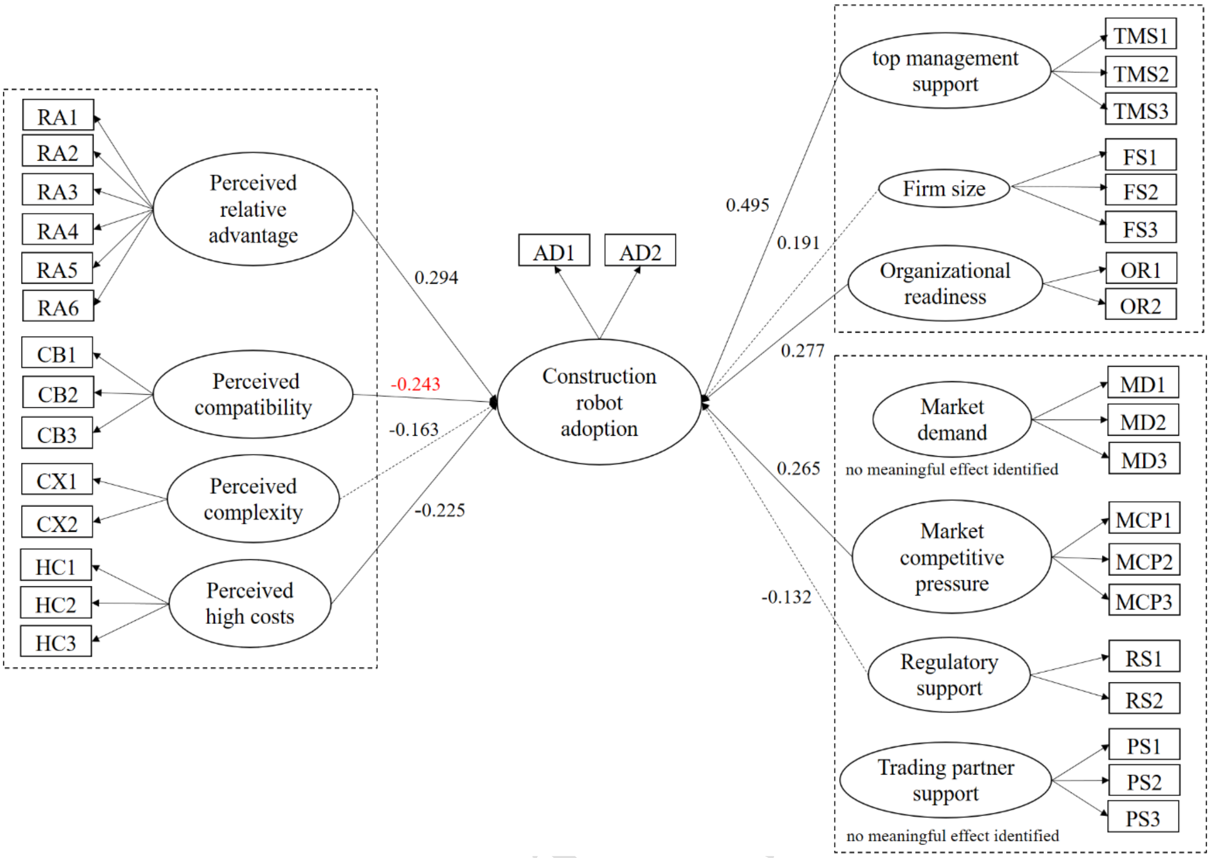

Fig. 5. Results of structural model evaluation for the hypothesized relationships

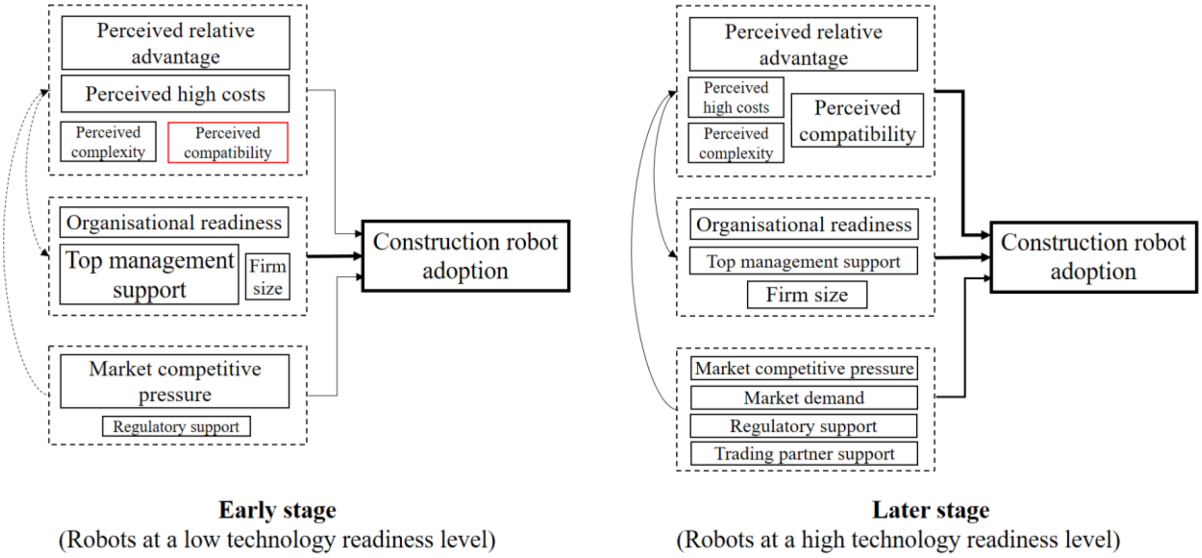

Fig. 6. A two-stage conceptual framework for understanding the determinants of construction robot adoption

List of Tables

Table 1. Descriptions of determinants in the research model

Determinant	Description
Relative advantage	The degree to which adopting construction robots are perceived as providing benefits to the organization
Compatibility	The degree to which construction robots are perceived to be compatible with the needs, existing practices, and other technologies
Complexity	The degree to which construction robots are perceived to be difficult to understand and use
High costs	The perceived high costs (capital cost, operation and maintenance cost) of adopting construction robots
Top management support	The degree to which top management understands the importance of adopting construction robots and the extent to provide sufficient support in making the adoption decision
Firm size	The size of the organization
Organizational readiness	The readiness of the organization in terms of financial resources and technological knowledge to adopt construction robots
Market competitive pressure	The pressure resulting from the practices of competitors and a need to gain competitive advantage from adopting construction robots
Market demand	The market demands
Regulatory support	The support from the government or its authority to encourage the adoption of construction robots
Trading partner support	The support and pressure from trading partners from both upstream and downstream supply chain to adopt construction robots

Note: the organization refers to the potential adopter of construction robots

Table 2. Measurement items for constructs

Constructs	Items	Refereed sources
Relative advantage (RA)	RA1: My company expects construction robots to help improve project productivity performance	(Thiesse et al. 2011; Chong and Chan 2012; Oliveira et al. 2014; Wang et al. 2016)
	RA2: My company expects construction robots to help reduce construction cost (labor-saving, material saving)	
	RA3: My company expects construction robots to help improve project environmental performance	
	RA4: My company expects construction robots to help improve project quality performance	
	RA5: My company expects construction robots to help improve worker safety & healthy performance	
	RA6: My company expects construction robots to secure the technological lead	
Compatibility (CB)	CB1: Construction robots are compatible with existing practices in my company	(Grandon and Pearson 2004; Thiesse et al. 2011; Chong and Chan 2012; Oliveira et al. 2014; Wang et al. 2016)
	CB2: Construction robots are compatible with the typology of buildings (the implementation situation)	
	CB3: Construction robots fit with the existing values of my company	
	CB4: Construction robots are compatible with the task to perform	
	CB5: Construction robots are compatible with existing equipment and other technologies in my company	
Complexity (CX)	CX1: My company believes that construction robots are complex to use	(Grandon and Pearson 2004; Chong and Chan 2012; Wang et al. 2016)
	CX2: My company believes that construction robots are bulkiness, heavy and high-power	
	CX3: My company believes that the implementation of construction robots is a complex process	
High costs (HC)	HC1: Construction robots have high initial costs	(Lin 2014)
	HC2: Construction robots have high operating and maintenance costs	
	HC3: Lead time to complete testing and training before starting to construction robots is long.	
Top management support (TMS)	TMS1: My top management is likely to invest funds in construction robots	(Chong and Chan 2012; Lin 2014; Wang et al. 2016)
	TMS2: My top management is willing to take risks involved in the adoption of construction robots	
	TMS3: My top management is likely to consider the adoption of construction robots as strategically important	
Firm size (FS)	FS1: The capital of my company is high compared to the industry	(Wang et al. 2010; Chong and Chan 2012; Lin 2014; Wang et al. 2016)
	FS2: The revenue of my company is high compared to the industry	
	FS3: The number of employees at my company is high compared to the industry	
Organizational readiness (OR)	OR1: Our company has the financial resources to adopt construction robots	(Grandon and Pearson 2004; Chong and Chan 2012)
	OR2: Our company has recruited/is recruiting the robot-related professionals	
	OR3: Training and education related to construction robots are provided to employees	

	OR4: Our company has the technical knowledge and skills to adopt construction robots	
Market competitive pressure (MP)	MP1: My company experiences competitive pressure to adopt construction robots	(Lin 2014; Oliveira et al. 2014; Wang et al. 2016)
	MP2: Construction robots are being adopted by my competitors	
	MP3: My company would have experienced a competitive disadvantage if not adopt construction robots	
Market demand (MD)	MD1: The industry is faced with an urgent need to improve occupational safety and health	(Pan and Pan 2019)
	MD2: The industry is faced with an urgent need to provide sustainable construction	
	MD3: The industry is faced with serious shortages in skilled labor in the field of my company's business/practice	
	MD4: The industry is faced with a significantly aging workforce problem	
Regulatory support (RS)	RS1: Government provides financial support for adopting construction robots (e.g., incentives and R&D support)	(Thiesse et al. 2011; Oliveira et al. 2014)
	RS2: Government adopts the adoption of construction robots in public project	
	RS3: Government provides technical guidance for adopting construction robots	
Trading partner support (TPS)	TPS1: The important trading partner recommended the adoption of construction robots	(Wang et al. 2010)
	TPS2: My company has a close relationship with the vendor and research institutes of possible robotic technologies	
	TPS3: Technical support and training are provided by the robot vendor	
	TPS4: The client recommended/promoted the adoption of construction robots	
Construction robot adoption (AD)	AD1: At what stage is the company currently engaged regarding the adoption of possible construction robots in the field of my company's business/practice? Not considering; Currently evaluating; Have evaluated, but do not plan to adopt; Have evaluated and plan to adopt; Have already adopted. AD2: If anticipating that my company will adopt possible construction robots in the future. How will it happen? Not considering; More than 10 years; Between 5 and 10 years; Between 3 and 5 years; Between 1 and 3 years; Less than 1 year; Have already adopted.	(Thiesse et al. 2011; Oliveira et al. 2014)

Note: All items are based on the 5-point scale except those noted otherwise.
The items CB4, CB5 were deleted in the final analysis due to multicollinearity issue tested by variance inflation factor (VIF, >5); The items CX3, OR3, OR4, MD4, RS3, TPS4 were deleted in the final analysis due to low loading (<0.7).

Table 3. Profiles of questionnaire participants (n=94)

Items	Descriptions	Number	Percentage
Years of work experience	6-9 years	6	6.4%
	10-19 years	20	21.3%
	20-29 years	36	38.3%
	30-39 years	24	25.5%
	More than 40 years	8	8.5%
	Total	94	100%
Positions	CEO, chairman, director	42	44.7%
	Head of department, manager	39	41.5%
	Senior engineer, senior staff	13	13.8%
	Total	94	100%

Table 4. Adopted criteria and rules of thumb for PLS-SEM method

Criterion	**Rules of thumb**
Data issues	
Sample size	Ten times rule as rough requirement, and considering the required statistical power level, pre-specified significance level, the population effect size and the number of arrows pointing at a construct in the path model
Multicollinearity	Variance inflation factor (VIF) < 5
Measurement (outer) model evaluation	
Item reliability	Standardized item loadings $\geqslant 0.7$
Construct reliability	Cronbach's $\alpha \geqslant 0.7$ or Composite reliability (CR) $\geqslant 0.7$
Convergent validity	Average variance extracted (AVE) $\geqslant 0.5$
Discriminant validity	Fornell–Larcker criterion: the square root of AVE should be larger than the correlations between the constructs Cross-loadings: the loading of each construct should be larger than all item cross-loadings
Structure (the inner) model evaluation	
Effect size	Cohen's f^2: 0.02, 0.15, 0.35 for weak, moderate, strong effects, and less than 0.02 indicates no effect
Path coefficient estimation	The significance level (p) of standardized paths < 0.1
R^2	Research context determines the acceptable value

Table 5. Mean, standard deviation and reliability indicators for the constructs

Constructs	Item	Mean	SD	Cronbach's α	AVE	CR
RA	6	3.68	0.90	0.940	0.769	0.952
CB	3	3.17	1.00	0.901	0.835	0.938
CX	2	3.23	0.90	0.723	0.738	0.846
HC	3	3.76	0.87	0.931	0.877	0.955
TMS	3	3.28	0.96	0.902	0.836	0.938
FS	3	3.09	1.01	0.929	0.873	0.954
OR	2	2.93	1.04	0.778	0.818	0.900
MCP	3	2.99	1.03	0.857	0.777	0.913
MD	3	3.80	0.91	0.811	0.726	0.888
RS	2	3.52	1.07	0.863	0.874	0.932
PS	3	3.14	1.07	0.808	0.719	0.884
AD	2	2.66	1.56	0.767	0.811	0.896

Table 6. Correlations and the square roots of the average variance extracted

Constructs	RA	CB	CX	PC	TMS	FS	OR	MCP	MD	RS	PS	AD
RA	**0.88**											
CB	0.71	**0.91**										
CX	0.35	0.24	**0.86**									
HC	0.35	0.22	0.57	**0.94**								
TMS	0.72	0.68	0.13	0.10	**0.91**							
FS	0.49	0.54	0.19	0.13	0.63	**0.93**						
OR	0.49	0.60	0.13	-0.02	0.70	0.79	**0.90**					
MCP	0.65	0.68	0.43	0.29	0.57	0.50	0.48	**0.88**				
MD	0.55	0.40	0.24	0.35	0.45	0.44	0.32	0.40	**0.85**			
RS	0.37	0.32	0.30	0.06	0.31	0.14	0.21	0.40	0.27	**0.94**		
PS	0.48	0.59	0.31	0.05	0.47	0.37	0.49	0.68	0.34	0.58	**0.85**	
AD	0.47	0.37	-0.13	-0.19	0.64	0.38	0.52	0.37	0.20	0.09	0.27	**0.90**

Note: The square roots of the AVE are diagonal in bold.

Table 7. Structural model evaluation results

Hypotheses	Constructs	Path coefficients	t-values	Hypothesis supported
H1	Relative advantage	0.294	2.298**	yes
H2	Compatibility	-0.243	2.193**	no
H3	Complexity	-0.163	1.331	no
H4	High costs	-0.225	2.133**	yes
H5	Top management support	0.495	3.511***	yes
H6	Firm size	0.191	1.286	no
H7	Organizational readiness	0.277	1.68*	yes
H8	Market competitive pressure	0.265	1.959**	yes
H10	Regulatory support	-0.132	1.263	no
		R^2=0.57		

*significance at p<0.1, significance at **p<0.05, significance at ***p<0.001
H9 and H11 have no meaningful effect identified and are not supported