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# Synergistic Relationship, Agent Interaction, and Knowledge Coupling: Driving Innovation in Intelligent Construction Technology

**Wei Chen [1,2], Mingyu Yu [1,2,*] and Jia Hou [1,2]**

[1] School of Civil Engineering and Architecture, Wuhan University of Technology, Wuhan 430070, China; iamhappychen@163.com (W.C.); houjia@whut.edu.cn (J.H.)
[2] Sanya Science and Education Innovation Park, Wuhan University of Technology, Sanya 572000, China
* Correspondence: yumingyu@whut.edu.cn

**Abstract:** The core driving force behind innovation in intelligent construction technology is synergistic relationships. It has become common practice to promote synergistic innovation through agent interaction and knowledge coupling in the development of intelligent construction technology. Drawing upon synergetics, social network theory, and the knowledge base view as theoretical frameworks, this research examines the impact of synergistic relationship, agent interaction, and knowledge coupling on innovation in intelligent construction technology. An empirical analysis of 186 questionnaires revealed the following: (1) regarding synergistic relationships, both horizontal synergy and vertical synergy significantly positively impact innovation in intelligent construction technology. (2) Concerning agent interaction, strong interaction serves as a mediator between horizontal synergy and innovation in intelligent construction technology, while weak interaction serves as a mediator between vertical synergy and innovation in intelligent construction technology. (3) Knowledge coupling has a positive moderating effect on innovation in intelligent construction technology under a strong interaction and a negative moderating effect on innovation in intelligent construction technology under a weak interaction. This study contributes to expanding the theory of synergistic relationships and its application in the context of intelligent construction technology. Furthermore, it provides practical insights and guidance for construction companies seeking to enhance innovation in intelligent construction technology through the utilization of agent interaction and knowledge coupling.

**Keywords:** intelligent construction technology; innovation; synergistic relationship; agent interaction; knowledge coupling



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## 1. Introduction

In the future development of the construction industry, characterized by intelligence, digitalization, and informatization [1], construction companies must completely transform their fragmented and rudimentary construction practices. They should increase the utilization of information technology, such as artificial intelligence [2], architectural robotics [3], big data [4], and the Internet of Things [5]. Additionally, they need to adapt to the goals of achieving carbon peaking and carbon neutrality [6], ensure high-quality development [7], and lead the transformation and upgrading of the construction industry through scientific and technological innovation. Intelligent construction differs from traditional construction technology and practices in the construction industry. It represents an innovative engineering approach that involves the integration of multiple technologies and **interdisciplinary majors** [8,9]. This complexity necessitates continuous adaptation through technological innovation for construction companies to achieve a sustainable competitive advantage, despite potential cognitive misunderstandings and practical challenges [10–13].

The breadth and depth of the **innovation in intelligent construction technology (IICT)** are expected to expand with the further development of industrial integration platforms such as the global Internet of Things [14], cloud computing [15], and big data [16]. This expansion will result in an enhanced industry chain synergy within the construction industry, including vertical integration and synergistic development from the upstream to the midstream and downstream [17]. Additionally, there will be closer technological fusion between related industries and the construction industry through cross-fertilization and a multi-source infiltration of technologies like information, sensing, new energy, and new materials [18]. To achieve the full potential of intelligent construction technology in the process of **agent interaction (AI)** and **knowledge coupling (KC)** value added, innovative elements within the system must flow smoothly and innovative resources must be aggregated [19], enabling the integration of multi-disciplinary advanced intelligent construction technology. This accelerates the transformation of the intelligent construction field from the individual innovation of single-point technology and single-product independent development to the systematic innovation of diversified technology and multi-industry integration [1].

Currently, intelligent construction technology (ICT) is still facing some pressing problems in the process of innovation, such as insufficient R&D support, slow transformation of achievements, and an imperfect innovation mode. Synergistic innovation provides an effective approach to the development of ICT. Synergetics believe that in a complex open system, subsystems can produce the synergistic effect of "1 + 1 > 2" through interactions [20]. Compared with traditional cooperative innovation, **synergistic relationship (SR)** focuses on specific risks, challenges, and benefits involved in innovation activities, providing a wider range of strategic choices and risk-sharing possibilities [21,22]. It is widely accepted in the academic community that building a high-level technological synergistic innovation network can generate a chain reaction, which is conducive to a spiral innovation effect [23–26]. The need for synergistic innovation in ICT is particularly evident given the high degree of intersectionality, complexity, and interconnectedness inherent in the intelligent construction industry, which requires high levels of access to innovative resources and the integration of innovative technologies.

The interaction mechanism is the key to the development of synergistic innovation in ICT, which is also reflected in the mixed evidence from current research [26–28]. AI can bring all kinds of innovation agents of ICT into the synergistic system, form a fit by association, change the discrete innovation situation of scattered and independent agents, and then form a close cooperation mechanism, a suitable learning organization, and an overall innovation model. In the process of adopting, absorbing, and applying ICT, interactive relationships are formed to promote the flow and aggregation of various types of innovative resources, achieve synergistic advantages and efficient innovation output, and unleash the synergy of IICT. These mixed shreds of evidence also lead to an ongoing debate [28] on what intensity of AI should be used to promote technological innovation under different SRs.

KC refers to the promotion of collaborative interaction and technological innovation through the combination of knowledge elements among subjects [29–31]. From this perspective, the degree of KC in the form of AI is the key factor [32], and the performance of technological innovation activities is inevitably affected by this factor. Although some studies have found that KC is a key factor in technological innovation and have shown that the coupling between different knowledge fields can lead to new knowledge creation and, thus, innovation [33–35], most of the existing studies only discuss its role in technological innovation [36–38], and it is rare to explore the mechanism of KC from the perspective of different interaction intensities under different collaborative relationships.

This study followed the logical framework of "characteristics-behaviors-results" in organizational behavior, integrated AI as a mediating factor to explore the impact of SR on the IICT, and considered the moderating role of KC to enhance the study. While existing studies demonstrate the effects of SR, AI, and KC on technological innovation, there remains a lack of consensus on their comprehensive roles, hindering a clear answer. Therefore, the main contributions of this study are as follows: (1) introducing the mediating variable of AI into the traditional SR study, classifying SR into **horizontal synergy (HS) and vertical synergy (VS)**, and classifying AI into **strong interaction (SI) and weak interaction (WI)**; this study compares and analyzes the different impacts of the two SRs on the IICT through the two states of AI to enrich the study on the impact of SR on IICT; (2) further introducing the moderating variable of KC and proposing a technological innovation analysis model based on "SR-AI-KC" to expand the research paradigm of technological innovation. The conclusions of the empirical study not only expand existing research results but also provide a new research perspective and analysis model for the field of technological innovation, offering a basis for intelligent construction-related companies to optimize the SR and manage the AI and KC effectively.

The rest of the paper is organized as follows: in Section 2, we offer a succinct overview of the current state of research in the field of intelligent construction. Specifically, we delve into the topics of SR, AI, and KC. Moreover, we present our research hypotheses and theoretical model in this section. Moving on to Section 3, we provide a comprehensive discussion on the research methodology, emphasizing the logical steps, measuring instruments, and data collection techniques employed. Section 4 is dedicated to describing the research process with a specific focus on data analysis and hypothesis testing procedures. In Section 5, we unveil our findings and carefully examine their implications for both theory and practice in the field. Lastly, in Section 6, we conclude the paper by summarizing the key insights and highlighting potential avenues for future research.

## 2. Literature Review

### *2.1. IICT*

Intelligent construction, at its core, leverages artificial intelligence to replace complex human labor in the design, production, construction, and maintenance of buildings and infrastructure, achieving a high level of automation in the construction industry [39]. Drawing on the works of Han, Z. [40] and Li, T. [10], this study defines intelligent construction as a novel production mode utilizing advanced information technology and industrialized construction to fulfill the functional and individual needs of engineering projects. It integrates information, aligns business operations across the entire industry chain throughout the life cycle of engineering projects, establishes an intelligent environment for project construction and operation, and enhances energy efficiency while maximizing resource value.

Currently, intelligent construction primarily advances industrial chain development through technology empowerment and data-driven processes. Typical features at various stages include digitization of surveys, standardization of designs, modularization of production, prefabrication of construction, integration of interior finishing, intelligent maintenance, and promotion of data and information management [41]. This has led to the identification of four core sub-industries: integrated design, prefabricated construction, intelligent home/property, and building internet. Each core sub-industry incorporates key intelligent construction technologies, outlined below:

(1) BIM and simulation

Leveraging BIM technology [42], the entire building can be modeled in three dimensions. This modeling allows for simulating stress characteristics, the entire construction process, and the interaction with the surrounding environment, as well as storing information data.

(2) Prefabrication and 3D print

Using digitized geometric information, components are automatically machined [43] and shaped using numerical control equipment or 3D printing technology. This application of prefabricated machining technology facilitates both modular production and on-site prefabrication.

(3) Mechanization and robot

Computer-controlled mechanical equipment or intelligent construction robots are used for high-precision component prefabrication and construction installation through human–machine cooperation on site, following the specific construction process [44].

(4) Precision measurement and control

Utilizing GPS, 3D laser scanners [45], and other advanced measuring instruments, the construction space is rapidly positioned and monitored in real time through surveying, design, and information data.

(5) Structural safety and health monitoring

By utilizing sensing technology, data acquisition, system identification, and damage localization techniques, the analysis covers the strength, safety, integrity, and reliability of the building structure. It also predicts the impact of damage for early repairs [46].

(6) Construction environment perception

With reliance on the Internet of Things, big data, and cloud computing technology, it analyzes and identifies the construction environment, determines location, matches perception, provides real-time predictions, and enables intelligent early warnings [8].

(7) Personnel safety and health monitoring

Via the use of the wearable intelligent terminal [47], it monitors the physiological indicators of the construction personnel, locates their location information, and provides warning guidance for their construction behavior to ensure their safety and health technology.

(8) Information management

Besides the aforementioned technical system, intelligent construction incorporates information management technology based on BIM technology, big data platforms, artificial intelligence, and knowledge ontology in the construction field [48]. This includes a project information management platform, a multi-party collaborative work network platform, a 4D construction management system, and an on-site information acquisition system. These systems enable intelligent management of the multi-party, dynamic information involved in the construction process.

Based on the aforementioned analyses pertaining to the domain of intelligent construction, this paper defines the concept of the intelligent construction company that is the concern of this study. It refers to a construction and management company that utilizes advanced technologies and intelligent tools to digitize and automate the entire construction process [1,10,49]. Further, it narrows down to technological innovation. ICTI mainly involves horizontally integrating and vertically developing through the industrial chain to achieve dynamic breakthroughs in industrial technology modules [50]. HS realizes the integration of value networks within sub-industries [51], and VS enables the flow of information resources between sub-industries [52]. In short, it is necessary to organically combine the various interconnected technology modules to implement innovation, as depicted in Figure 1.

### *2.2. The Direct Effect of SR on IICT*

Haken, H. first defined "synergy" as a composite system that contains multiple subsystems and generates synergistic effects through non-linear interactions [53]. Later, this concept was applied in the innovation system theory, and the SR usually appeared in two ways: HS and VS [54–56]. HS refers to inter-organizational synergy within the same link of the industry chain [51], whereas VS refers to organizational synergy in different links of the industry chain [52]. Synergistic innovation is typically described as a process in which two or more industry chain members, such as raw material suppliers, builders, sellers, and customers, jointly plan and implement knowledge-related activities in the industry chain network [57–59]. Building on the research of Xue, X. [60] and Lindsay, C. [61], this study defines synergistic innovation as cooperative behaviors and processes aiming for technological breakthroughs, utilizing knowledge management as the means, and involving multi-subject, multi-factor, and multi-stage collaborative interactions at the center, which are complementary, comprehensive, and in-depth. Scholars generally agree that synergistic innovation represents a model that bridges closed and open innovation. It incorporates the openness of breaking boundaries and accessing resources while maintaining the focus and protection of knowledge flow. This unique approach promotes technological breakthroughs [62].

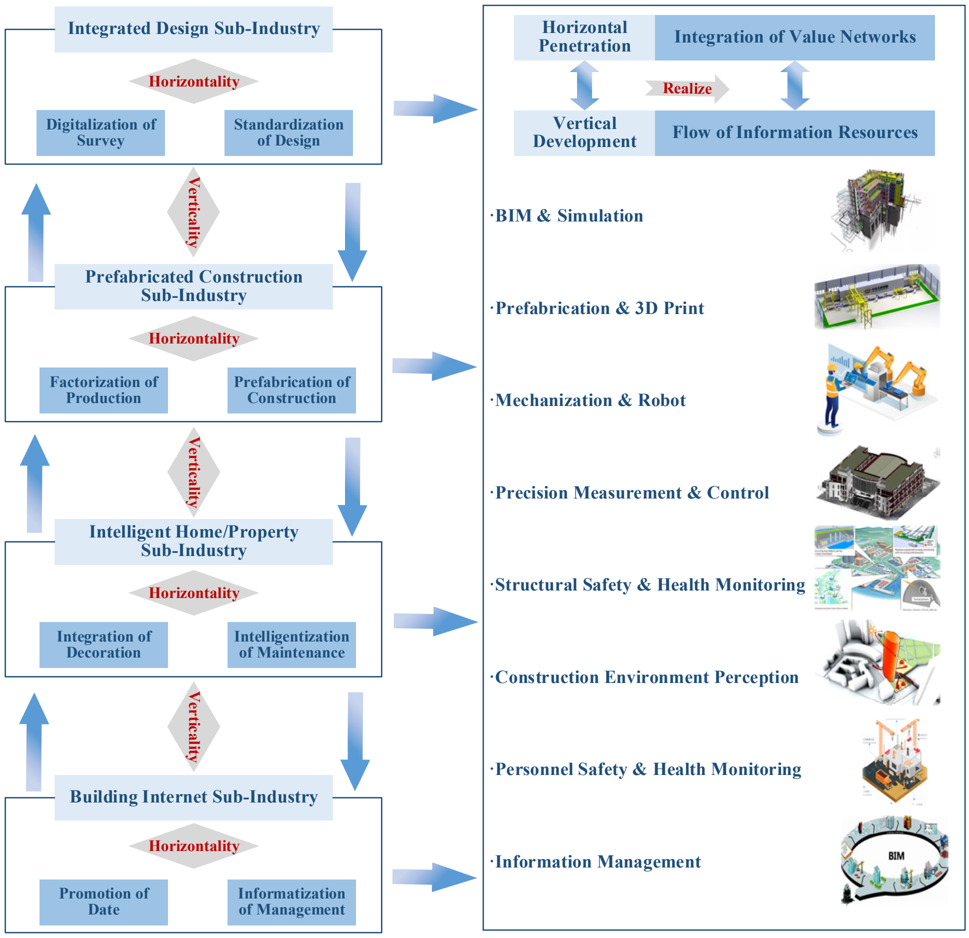


**Figure 1.** Characteristics, sub-industries, and key technologies of intelligent construction.

#### 2.2.1. The Direct Effect of HS on IICT

Companies involved in HS have relatively similar knowledge bases. Engaging in synergistic innovation with competitors facilitates the exchange of valuable knowledge, accelerates the understanding and assimilation of required knowledge, and helps alleviate the internal knowledge pressures related to exploring new research areas and technologies [63–66]. Unfortunately, factors such as cost benefits and cultural strategies have led to skepticism about HS, resulting in relatively low levels [67]. Additionally, scholars have asserted that knowledge embedded in the R&D process of individual companies is difficult to disseminate within HS networks [68], making HS even more challenging. In the field of ICT, the relationship between core stakeholders in each sub-industry can be likened to HS, wherein key module technologies are jointly focused. For instance, in the integrated design sub-industry, each design company collaborates to develop design integration software with BIM as the core, encompassing the integration of professional designs and stages of information. Overall, through synergy among the core interests in the sub-industry, each company can benefit from resource combination, risk reduction, and cost-sharing, thereby jointly promoting IICT. This leads to the following hypothesis:

**H1:** *HS has a positive effect on IICT*.

2.2.2. The Direct Effect of VS on IICT

In comparison to HS, VS exhibits a lower similarity in knowledge base, leading to reduced relative efficiency and speed of technological innovation. However, it also enhances the scope and connectivity of technological innovation. In the context of VS, companies in different industry chain segments have heterogeneous resource endowments. Synergistic innovation based on this diversity can assist companies in identifying potential technological frontiers and business needs, as well as integrating diverse expertise and strategic perspectives to enhance their solutions or develop new technological approaches. In the realm of ICT, the interconnected relationships among sub-industries represent VS, resulting in collaborative development, application, and promotion of key module technologies across upstream, midstream, and downstream sectors [66,69,70]. Ultimately, the interconnected relationships among sub-industries facilitate the utilization of resources and knowledge from other parties to reshape the production and delivery processes of products or services through VS, providing companies with increased resources and opportunities for learning and knowledge utilization, ultimately enhancing their capabilities in IICT. This leads to the following hypothesis:

**H2:** *VS has a positive effect on IICT*.

*2.3. The Mediating Role of AI between SR and IICT*

Social network theory explains the relationships and bonds formed by established social actors (including individuals, groups, and organizations in society) and examines social behavior within the context of the social network system. Granovetter, M. S. pioneered the concept of relationship strength [71] and categorized it into strong and weak relationships based on four dimensions: frequency of interactions, affective energy, degree of affinity, and reciprocal exchange. Furthermore, he argued that strong relationships sustain relationships within organizations, while weak relationships foster connections between organizations. Uzzi expanded on this theory by introducing the "paradox of relational embeddedness" in the realm of technological innovation networks. He emphasized that network relationships should strike a balance between being too rigid to dissolve and too loose to establish connections, instead aiming for an ideal strength [72].

The existing literature [26,73,74] has also demonstrated that the synergistic innovation network comprises technological innovation agents. The core intermediary element of this network lies in the interaction between these agents, specifically in the interactive relationships among technological synergistic innovation agents. This interaction facilitates the flow and aggregation of various types of innovation factors, thereby realizing the advantages of technological synergistic innovation for each agent and enabling highly efficient innovation output. Building upon this theory, the present study categorizes the AI of synergistic innovation into two types: SI, which has a direct impact on the outcomes of technological innovation, and WI, which has an indirect effect on the outcomes of technological innovation.

2.3.1. The Mediating Role of SI between HS and IICT

SI is defined as the process of directly influencing the outcomes of technological innovation, which significantly contributes to the deep acquisition of knowledge. It is characterized by strong relevance, high constraint, and a high conflict rate, thereby exerting a substantial enhancing effect on the breakthrough of complex technologies [72]. In the context of HS, agents share strong similarities in core technology and possess a high degree of consistency in innovation goals. As a result, SI facilitates the development of in-depth exchanges between agents, enabling the sharing of information and resource integration for core technology. This leads to the generation of various alternative or complementary choices for the same technological innovation objective, ultimately driving breakthroughs and innovations in key technological modules [75,76]. Regarding ICT, the intelligentization of construction sites relies heavily on the continuous expansion of the database, necessitating extensive data sharing among construction companies. This enables the continuous iteration and updating of the platform, as well as facilitating intelligent management, optimization, early warning, and decision-making throughout the project site's life cycle. Based on these considerations, this study proposes the following hypothesis:

**H3:** *SI plays a more pronounced mediating role between HS and IICT compared to WI.*

2.3.2. The Mediating Role of WI between VS and IICT

Compared to SI, WI is defined as an indirect process that influences the outcomes of technological innovation with low information redundancy, strong independence, minimal backflow, and few external constraints [77]. In VS, the diversity of agents and the comprehensiveness of relationships enable companies to identify potential synergistic partners and innovation opportunities for each agent through WI. This allows companies to explore uncharted territories, uncover more knowledge spillovers, generate cutting-edge technological solutions, and form in-depth developmental strategies. WI also expands the scale advantage of technological innovation and increases the likelihood of forming technological innovation alliances [71]. In the context of ICT, the intelligent construction industry's collaboration alliance can continuously absorb upstream, midstream, and downstream industry companies to achieve the interactive synergy of ICT in scientific research, design, production, construction, testing, and operation activities within the construction engineering field. Based on these considerations, this study proposes the following hypothesis:

**H4:** *WI plays a more pronounced mediating role between VS and IICT compared to SI.*

*2.4. The Moderating Role of KC between AI and IICT*

The knowledge base view emphasizes that knowledge is a company's most strategic resource. Inter-company collaboration is an effective way to integrate knowledge across company boundaries [29]. The knowledge base of the company consists of the set of knowledge elements it owns and the relationship between the knowledge domains of these elements. Innovation involves reorganizing knowledge elements within the knowledge base [78]. Exploiting different links between knowledge elements can help companies achieve technological differentiation [79]. The concept of "coupling" originated from physics. In organizational management, coupling emphasizes the degree of interaction and interdependence between systems or elements [80]. Previous studies have defined KC as the degree of combination of knowledge elements from different domains, or as a dynamic complementary relationship with fit characteristics. Drawing on Yayavaram, S.'s viewpoint [81], this study defines KC as the process in which different knowledge elements owned by different knowledge agents obtain synergy and overflow diffusion through dynamic association, mutual fit, and effective complementarity. A high level of KC implies strong connections between knowledge elements of different agents, giving them great potential to integrate internal and external knowledge for technological innovation. Meanwhile, based on the findings of Huang, L. [37] and Jin, N. [82], there was an inverted U-shaped non-linear relationship between KC and green innovation in manufacturing companies. Changes in KC have an inverted U-shaped impact on a company's innovation performance, and changes in existing knowledge or coupling of existing knowledge with new knowledge within a company have a direct positive impact on a company's innovation performance. ICT is often built based on building industrialization (prefabricated building). Therefore, it requires the cross-border, deep integration of modern information technology with intelligent technology as the core and advanced construction technology led by industrialization, which is a typical KC process. This study proposes the following hypotheses:

**H5:** *KC plays a positive moderating role between SI and IICT.*

**H6:** *KC plays a positive moderating role between WI and IICT.*

In summary, the study developed a theoretical model, depicted in Figure 2.

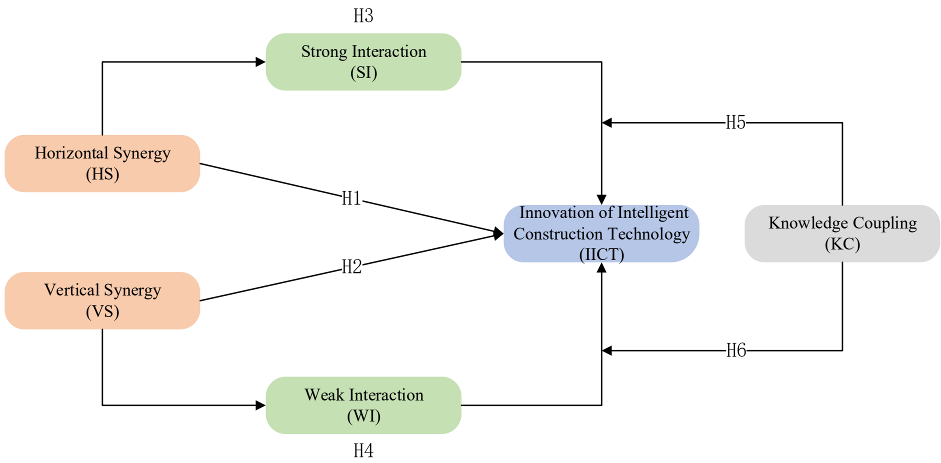


**Figure 2.** Theoretical model.

## 3. Methodology

### *3.1. Research Process*

This study aimed to explore the relationship between SR, AI, KC, and IICT. The overarching logical framework of the study is illustrated in Figure 3. Primary data were collected through a questionnaire, and correlation and regression analyses were conducted to verify the research process, which consisted of three stages.

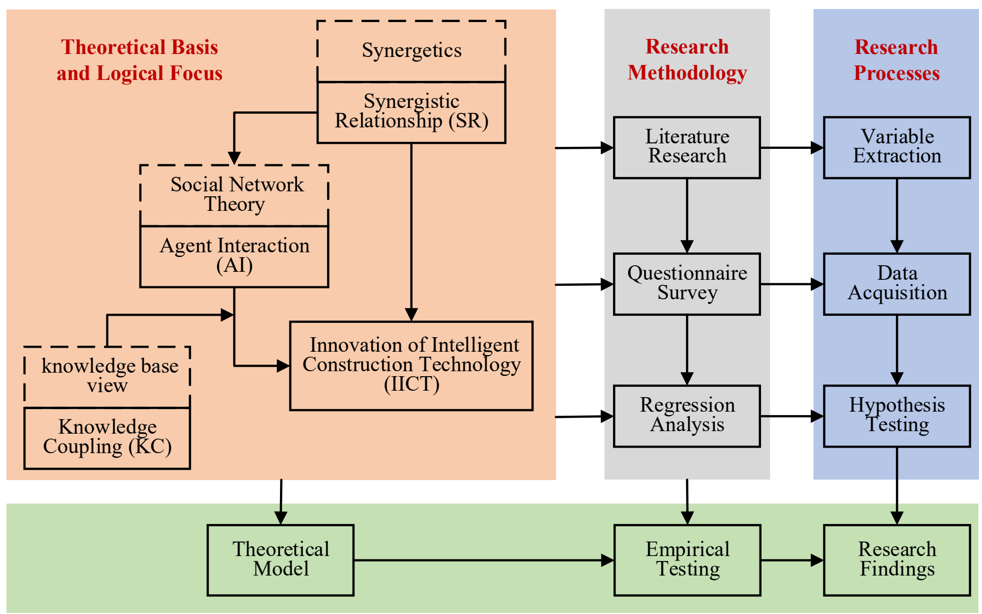


**Figure 3.** Research logics.

Stage 1: Based on previous studies and the related literature, the research hypotheses were formulated using the logical framework of "characteristics-behaviors-results" in organizational behavior. The measurement and control variables were designed by combining synergetics, social network theory, and knowledge base view. The original data were obtained through a questionnaire survey of relevant personnel.

Stage 2: Correlation and regression analyses were employed to examine the relationship between the variables of interest. First, a direct effect test was conducted to verify the relationship between SR and IICT. Secondly, a mediation effect test was performed to explore the mediating role of AI. Lastly, a moderation effect test was conducted to assess the moderating effect of KC.

Stage 3: The findings are first discussed individually, followed by the presentation of the theoretical contributions and managerial implications of the study. Finally, the study limitations and future outlook are summarized.

### *3.2. Measuring Instrument*

The variables in this study were measured using a 5-point Likert scale ranging from 1 ("don't agree at all/never") to 5 ("completely agree/frequently"). To prevent common method bias and ensure multi-source data collection, this study rigorously adhered to the guidelines recommended by Podsakoff, P. M. [83]. The questionnaire was designed with separate sections, and the scale items were randomly ordered. Quality control questions were included, and certain items were reverse-coded. Additionally, a fully anonymous survey was conducted multiple times to collect the data. Following the separation of the questionnaires, Questionnaire A contained HS, SI, KC, and several control variables, while Questionnaire B consisted of VS, WI, IICT, and other control variables. The questionnaires were distributed withing a 4-week interval.

Questionnaires A and B were distributed at different times within the same company. Questionnaire A was distributed in the first week, followed by the distribution of Questionnaire B four weeks later. These questionnaires were completed by different managers or key employees. To ensure matching, Questionnaires A and B were linked using code names assigned to each company. The questionnaires were primarily distributed through graduated alumni in their respective companies, supplemented by the snowball sampling method to expand the sample size. Given the complex and highly synergistic nature of ICT, this study aimed to comprehensively cover the upstream, midstream, and downstream sectors of the intelligent construction industry chain. The sample included various stakeholders such as EPC general contractors, consulting firms, design companies, prefabricated component manufacturers, construction companies, property management firms, engineering technology organizations, and equipment manufacturers.

The scales used in this study were adapted from established scales found in the existing literature. They underwent a thorough review process by industry experts and professors specializing in the field of intelligent construction. This ensured the rigor and completeness of the scale items. Finally, the scale items for this study were obtained, as presented in Table 1.

SR: The scale items for SR were primarily derived from the main dimensions of technological innovation, based on the research findings of Wang, C. [84]. Additionally, recognizing the significance of information and resource sharing in SR, this study incorporated the scale items for "information sharing" and "resource sharing" as proposed by Saleem, H. [85] and Chierici, R. [86]. Subsequently, SR was further divided into two measurement aspects: HS and VS. Ultimately, a total of eight scale items were determined.

AI: This study synthesized and developed the scale items for AI, drawing on the research of Hershberg, E. [87], Robinson, D. T. [88], and Prahalad, C. K. [89], with necessary adjustments to address the specific research context of technological innovation. AI is categorized into two main aspects: SI and WI. The scale for WI in this study was adapted from Fan, M.'s research scale [28] on inter-company interactions. In summary, this study resulted in the development of four scale items for SI and four scale items for WI.

**Table 1.** Scale items.

| Variable | | No. | Content | Reference |
|---|---|---|---|---|
| SR | HS | HS 1 | Companies in the same industrial chain provide us with information sharing and resource sharing. | Wang, C. [84]<br>Saleem, H. [85]<br>Chierici, R. [86] |
| | | HS 2 | Companies in the same industrial chain communicate with us on R&D matters of intelligent construction technology. | |
| | | HS 3 | Companies in the same industrial chain join us to participate in the R&D process of intelligent construction technology. | |
| | | HS 4 | Companies in the same industrial chain promote the application and popularization of intelligent construction technology together with us. | |
| | VS | VS 1 | Companies in the different industrial chains provide us with information sharing and resource sharing. | |
| | | VS 2 | Companies in the different industrial chains communicate with us on R&D matters of intelligent construction technology. | |
| | | VS 3 | Companies in the different industrial chains join us to participate in the R&D process of intelligent construction technology. | |
| | | VS 4 | Companies in the different industrial chains promote the application and popularization of intelligent construction technology together with us. | |
| AI | SI | SI 1 | Our company responds and promotes the development of technology innovation. | Hershberg, E. [87]<br>Robinson, D. T. [88]<br>Prahalad, C. K. [89]<br>Fan, M. [28] |
| | | SI 2 | Our company transfers employees according to the needs of technological innovation. | |
| | | SI 3 | Our company participates in and promotes the deepening of industry–university–research cooperation. | |
| | | SI 4 | Our company promotes the outsourcing of businesses that do not have core competitive advantages. | |
| | WI | WI 1 | Our company organizes or participates in the negotiation and exchange. | |
| | | WI 2 | Our company organizes or participates in the observation and study. | |
| | | WI 3 | Our company organizes or participates in publicity and promotion. | |
| | | WI 4 | Our company is very willing to make strategic synergies. | |
| KC | | KC 1 | New knowledge can flow quickly between interacting agents. | Chen, H. [90] |
| | | KC 2 | Compatibility or substitution between existing and new knowledge can be realized. | |
| | | KC 3 | New knowledge acquired by our company can be continuously matched to complete the knowledge system. | |
| | | KC 4 | Our company can acquire new knowledge through agent interaction to support technological innovation. | |
| IICT | | IICT 1 | Our company breaks new ground in the field of intelligent construction. | Guo, Z. [49]<br>Yan, X. [91]<br>Li, T. [10]<br>Fan, M. [28] |
| | | IICT 2 | Our company introduces advanced technologies from other fields into our field. | |
| | | IICT 3 | Our company integrates technological innovation into marketing strategy and strategic planning. | |
| | | IICT 4 | Our company puts intelligent construction technology into use in the market. | |
| | | IICT 5 | Our company gains good benefits and creates high value from the application of intelligent construction technology. | |
| Control Variables | | CV 1 | Company nature | Li, Y. [92]<br>Zhou, K. [93] |
| | | CV 2 | Company scale | |
| | | CV 3 | Company age | |
| | | CV 4 | The company's R&D investment proportion | |

KC: Scale items for KC were constructed by Chen, H. [90], and they were also based on a synthesis of previous studies. This study reviewed and adapted Chen's scale items for KC, resulting in the development of four scale items for KC.

IICT: Technological innovation is typically evaluated based on input and output indicators. This study reviewed the research conducted by Guo, Z. [49], Yan, X. [91], and Li, T. [10] on intelligent construction. Drawing on Fan, M.'s scale [28] on technological innovation, five scale items were employed to measure the level of IICT.

Control variables: Previous research has highlighted that ownership structure influences a company's access to innovation resources [92,93], subsequently impacting its technological innovation performance. Similarly, company size and age are known to influence resource accumulation and capacity reserves, thereby affecting the impact of technological innovation. Additionally, R&D investment plays a crucial role in driving technological innovation, with higher investments generally leading to improved innovation activities and outcomes. Consequently, this study identified and incorporated four scale items at the company level as control variables.

### *3.3. Data Collection*

This study examined the role of SR, AI, KC, and IICT, and it employed a questionnaire survey for data collection. The survey was conducted using two methods: firstly, through field research by distributing paper questionnaires to respondents on-site and collecting them afterward; secondly, through online research by sending the questionnaire link to respondents via email and conducting the survey online.

From February to June 2023, the research group contacted 52 companies related to intelligent construction to gauge their interest in participating in the study. Of these, 37 companies responded positively, resulting in a company-level response rate of 71.15%. The formal questionnaire survey then collected two types of questionnaires, A and B, from each respondent, resulting in the recovery of 212 questionnaires. After excluding incomplete and inconsistent responses, 186 valid questionnaires remained, yielding a recovery rate of 87.74%.

### *3.4. Test Methods*

(1) Regression analysis

Regression analysis is a statistical method used to study the relationship between quantitative data, specifically, the relationship between an independent variable (X) and a dependent variable (Y) [94]. Typically, regression analysis is conducted following a correlation analysis. However, it is important to note that while correlation does indicate a relationship between variables, it does not necessarily imply a causal relationship.

To determine the significance of a regression analysis, the first step is to conduct an F-test. If the F-value in the upper right corner of the output indicates a significant result, then the regression analysis is deemed meaningful to pursue. Next, to analyze the relationship between a specific X and Y, it is necessary to determine whether there is a statistically significant relationship—i.e., whether the $p$-value is less than 0.05. A $p$-value less than 0.05 indicates a relationship between the variables, while a $p$-value greater than 0.05 suggests no relationship. Finally, once a relationship has been established, it is important to determine whether it is positive or negative. This can be carried out by examining either the "unstandardized coefficient" or the "standardized coefficient". If the coefficient is greater than 0, then it indicates a positive influence. Conversely, if the coefficient is less than 0, then it suggests a negative influence [95,96].

(2) Mediation effect

The mediation effect is a statistical concept used to elucidate the impact of a variable on the relationship between independent and dependent variables. It aids in comprehending the mechanism through which the influence of one variable is conveyed through another [97]. When testing the significance of the mediation effect, the bootstrap sampling method emerges as a dependable approach [98].

To initiate the mediation effect test, data encompassing the independent, mediating, and dependent variables must be gathered. Subsequently, the mediating effect value is computed using methods such as regression analysis, with the size of the indirect effect typically serving as the indicator. Following this, multiple bootstrap samples are generated by employing the bootstrap sampling method to extract samples from the original data in a flexible manner. For each bootstrap sample, the mediating effect value is recalculated, enabling the construction of confidence intervals based on the recalculated values. Ultimately, the significance of the mediating effect is determined by assessing the range of the confidence intervals. Leveraging the bootstrap sampling method enables a more precise estimation of the confidence interval for the mediating effect, thereby enhancing the reliability of the mediation effect test. This method is especially well-suited for small sample sizes and non-normal distributions, as it circumvents the need to rely on assumptions regarding an underlying distribution [99–101].

(3) Moderating effect

The moderating effect refers to the examination of whether the impact of the independent variable (X) on the dependent variable (Y) is influenced by a moderating variable (Z) [102,103]. Specifically, it investigates whether there is a significant difference in the strength of the X–Y relationship at different levels of Z. Additionally, control variables are incorporated into the model.

Model 1: the independent variable is X and the dependent variable is Y, and its significance is relatively small. Model 2: the independent variables are X and Z, and the dependent variable is Y. Model 2 only adds the moderator variable Z on the basis of Model 1; the significance of this model is also relatively small. Model 3: the independent variables are X, Z, and X*Z, and the dependent variable is Y. Model 3 adds the interaction term on the basis of Model 2; this is the core model. If the interaction term (X*Z) shows significance, then it indicates a moderating effect. Simple slope plots illustrate the variation in the strength of the X–Y relationship across different levels of the moderating variable. The moderator variable is categorized into three levels: average (mean), high (mean + standard deviation), and low (mean—standard deviation). By comparing the slope of the straight line, we can assess the impact of the independent variable (X) on the dependent variable (Y) at each level of the moderating variable (Z) [104,105].

## 4. Results

### *4.1. Sample Description and Reliability Test*

In this study, we obtained 186 valid samples through statistical analysis and gathered the basic information of 37 sample companies, as presented in Table 2. Among the valid samples, most companies are state-owned, with the majority being large and medium-sized. The establishment years of these companies are primarily concentrated in the 10–20 years range. Additionally, over seventy percent of the companies' R&D investment exceeds 3%, indicating a stronger emphasis on technology, a greater need for synergy, and a relatively robust innovation capability.

The scale items used in this study were derived from previous research, which ensured the reliability and validity of the scales used. In addition, this study employed two methods to further validate the reliability and validity of the scales.

In this study, the reliability of the questionnaire was assessed using SPSS 25.0, and the corresponding results are presented in Table 3. All scale items had Cronbach's α values above 0.8, which exceeds the accepted threshold of 0.7 and indicates ideal internal consistency.

**Table 2.** Descriptive Statistics of Sample Companies' Information.

| Variable | Classification | Quantity | Percentage |
|---|---|---|---|
| Company nature | Private | 13 | 35.14% |
| | State-owned | 24 | 64.86% |
| Company scale | Small and Micro company | 7 | 18.92% |
| | Medium-sized company | 12 | 32.43% |
| | Large company | 18 | 48.65% |
| Company age | 1–10 years | 8 | 21.62% |
| | 10–20 years | 22 | 59.46% |
| | More than 20 years | 7 | 18.92% |
| The company's R&D investment proportion | Below 3% | 8 | 21.62% |
| | 3–5% | 23 | 62.16% |
| | Above 5% | 6 | 16.22% |

**Table 3.** Reliability and validity.

| Variable | Scale Item | Factor Load (>0.6) | Cronbach's $\alpha$ (>0.7) | AVE (>0.5) | CR (>0.7) |
|---|---|---|---|---|---|
| HS | HS 1 | 0.802 | 0.830 | 0.5757 | 0.844 |
| | HS 2 | 0.724 | | | |
| | HS 3 | 0.798 | | | |
| | HS 4 | 0.706 | | | |
| VS | VS 1 | 0.747 | 0.892 | 0.6284 | 0.8702 |
| | VS 2 | 0.868 | | | |
| | VS 3 | 0.853 | | | |
| | VS 4 | 0.689 | | | |
| SI | SI 1 | 0.858 | 0.930 | 0.7401 | 0.9192 |
| | SI 2 | 0.883 | | | |
| | SI 3 | 0.875 | | | |
| | SI 4 | 0.824 | | | |
| WI | WI 1 | 0.796 | 0.876 | 0.6661 | 0.8886 |
| | WI 2 | 0.805 | | | |
| | WI 3 | 0.840 | | | |
| | WI 4 | 0.823 | | | |
| KC | KC 1 | 0.782 | 0.885 | 0.6251 | 0.8695 |
| | KC 2 | 0.831 | | | |
| | KC 3 | 0.787 | | | |
| | KC 4 | 0.761 | | | |
| IICT | IICT 1 | 0.822 | 0.870 | 0.5504 | 0.8586 |
| | IICT 2 | 0.726 | | | |
| | IICT 3 | 0.776 | | | |
| | IICT 4 | 0.745 | | | |
| | IICT 5 | 0.626 | | | |

Note: The values listed in parentheses serve as criteria for evaluation.

To further evaluate convergent validity, exploratory factor analysis (EFA) was conducted. The factor loadings for all observed variables were found to be higher than 0.6, indicating a strong relationship between the variables and their respective latent factors. The average variance extracted (AVE) values were greater than 0.5, demonstrating that more than 50% of the variance in each construct was captured by its indicators. The composite reliability (CR) values were above 0.8, indicating satisfactory internal consistency reliability.

Collectively, these findings provide evidence that the questionnaire used in this study has robustness and reliability. The high Cronbach's $\alpha$ values and factor loadings, along with the satisfactory AVE and CR values, indicate an ideal internal consistency and a good convergent validity of the measurement instrument.

In addition to evaluating the reliability and convergent validity of the questionnaire, it is equally crucial to assess the model fit when conducting confirmatory factor analysis (CFA) using AMOS 26.0, adhering to widely accepted academic standards. This step allows us to determine whether the proposed theoretical model adequately represents the observed data.

To gauge the model fit, various fit coefficients were examined, including absolute fit, incremental fit, and parsimonious fit. These coefficients provide valuable insights into how well the theoretical model aligns with the empirical data. After performing the CFA analysis, the results were obtained, as presented in Table 4. Taken together, these findings suggest that the proposed theoretical model fits the observed data well. The favorable fit coefficients obtained from the CFA analysis support the validity and reliability of the measurement instrument and provide confidence in the accuracy of the research findings.

**Table 4.** Model fit coefficients.

| Type of Indicator | Fitted Coefficient | Standard | Actual Value | Judgment |
|---|---|---|---|---|
| Absolute Fit Measures | $\chi^2$/df | <3.00 | 1.66 | Yes |
| | GFI | >0.90 | 0.93 | Yes |
| | AGFI | >0.90 | 0.91 | Yes |
| | RMSEA | <0.05 | 0.04 | Yes |
| Incremental Fit Measures | NFI | >0.90 | 0.93 | Yes |
| | RFI | >0.90 | 0.96 | Yes |
| | IFI | >0.90 | 0.90 | Yes |
| | TLI | >0.90 | 0.94 | Yes |
| Parsimonious Fit Measures | CFI | >0.90 | 0.93 | Yes |
| | PGFI | >0.50 | 0.91 | Yes |
| | PNFI | >0.50 | 0.84 | Yes |
| | PCFI | >0.50 | 0.88 | Yes |

### *4.2. Common Method Bias Test and Correlation Analysis*

To test for common method bias, this study employed two methods. Firstly, EFA was used to conduct the Harman one-factor test [83], as shown in Table 5. The results indicated that a total of six factors with an eigenvalue greater than 1 were extracted, of which the first factor explained 34.81% of the total variation, which is less than the commonly accepted threshold of 40%. Additionally, the cumulative variance explained by the factors with eigenroots greater than 1 was 73.754%. This implies that the six extracted factors can account for 73.754% of the total information, which signifies the favorable outcomes of this factor analysis. Secondly, one-factor CFA was used to test for common method bias for all scale items. The results showed that the one-factor analysis model fit was significantly lower, indicating that there was no serious common method bias problem in this study.

**Table 5.** Explanation of variance.

| Factor Number | Eigenroot | Explanation of Variance % | Cumulative % |
|---|---|---|---|
| 1 | 8.703 | 34.81 | 34.81 |
| 2 | 3.114 | 12.457 | 47.267 |
| 3 | 2.143 | 8.571 | 55.839 |
| 4 | 2 | 7.999 | 63.838 |
| 5 | 1.326 | 5.303 | 69.141 |
| 6 | 1.153 | 4.613 | 73.754 |
| 7 | 0.616 | 2.464 | 76.219 |
| … | … | … | … |
| 25 | 0.116 | 0.465 | 100 |

Note: "…" denotes factors 8 to 24, which were excluded as they were irrelevant to the study findings.

The correlation coefficients of the variables are presented in Table 6, indicating that both independent variables (HS and VS) are significantly correlated with the dependent variable (IICT), as well as the mediator variable (SI and WI) and the moderator variable (KC). Therefore, further regression relationship studies are appropriate [106]. Specifically, the correlation coefficient between HS and IICT is 0.209 ($p$ < 0.01), indicating a positive and significant relationship. This suggests that higher levels of HS are associated with increased IICT. Similarly, the correlation coefficient between VS and IICT is 0.343 ($p$ < 0.01), highlighting a positive association. These findings lend support to the proposed hypotheses and provide a strong statistical foundation for subsequent hypothesis testing.

**Table 6.** Correlation coefficients.

| Variable | HS | VS | SI | WI | KC | IICT |
|---|---|---|---|---|---|---|
| HS | 1 | — | — | — | — | — |
| VS | 0.573 ** | 1 | — | — | — | — |
| SI | −0.397 ** | −0.412 ** | 1 | — | — | — |
| WI | 0.244 ** | 0.318 ** | −0.321 ** | 1 | — | — |
| KC | 0.313 ** | 0.371 ** | −0.337 ** | 0.346 ** | 1 | — |
| IICT | 0.209 ** | 0.343 ** | −0.331 ** | 0.401 ** | 0.617 ** | 1 |

Significance of correlations: ** $p < 0.01$.

### 4.3. Direct Effect Test

To explore the relationships between independent variables and the dependent variable while accounting for the potential effects of control variables, this study employed the multiple regression model of SPSS 25.0.

Table 7 presents the results. In using Model 1, the focus was on examining the influence of control variables (CV1, CV2, CV3, and CV4) on IICT. The results revealed that CV3 had a significant positive effect on IICT, with a β coefficient of 0.307. Furthermore, the *p*-value of less than 0.01 suggests a high level of statistical significance, indicating that the relationship between CV3 and IICT is unlikely to have occurred by chance. Moving on to Model 2, the emphasis was on examining the effect of the independent variable (HS) on IICT. HS demonstrates a significant positive effect on IICT (β = 0.209, $p < 0.01$). Therefore, hypothesis H1 is supported. Finally, in Model 3, the objective was to assess the effect of the independent variable (VS) on IICT. VS shows a significant positive effect on IICT (β = 0.343, $p < 0.01$). Thus, hypothesis H2 is supported.

**Table 7.** Effect of CV, HS, and VS on IICT.

| | IICT | | | | | |
|---|---|---|---|---|---|---|
| | Model 1 | | Model 2 | | Model 3 | |
| | β | *p* | β | *p* | β | *p* |
| CV 1 | 0.003 | 0.953 | 0.009 | 0.88 | 0.002 | 0.977 |
| CV 2 | 0.018 | 0.86 | 0.04 | 0.697 | 0.046 | 0.642 |
| CV 3 | 0.307 | 0.000 ** | 0.309 | 0.000 ** | 0.294 | 0.000 ** |
| CV 4 | 0.063 | 0.543 | 0.043 | 0.667 | 0.077 | 0.428 |
| HS | — | | 0.209 | 0.000 ** | — | |
| VS | | | — | | 0.343 | 0.000 ** |
| F | 6.908 ** | | 8.420 ** | | 13.796 ** | |
| $R^2$ | 0.096 | | 0.139 | | 0.21 | |
| Adjusted $R^2$ | 0.082 | | 0.123 | | 0.194 | |

Significance of correlations: ** $p < 0.01$.

### 4.4. Mediation Test

In this study, our goal was to investigate the mediating effect of AI. To achieve this, we utilized the Proces plug-in developed by Bolin, J. H. in SPSS 25.0, which is a widely recognized method for testing mediation [107]. To ensure the accuracy and reliability of our results, we employed the bootstrap self-sampling method. This approach involves generating numerous random samples from the original data set and calculating the mediation effect for each sample. By doing so, we obtain a distribution of possible outcomes, which we can then use to estimate the upper and lower bounds of the mediation effect intervals.

To determine whether the mediating effect was statistically significant, we set a confidence level of 95%. We generated 5000 random samples and used the Bias-Corrected approach to estimate the upper and lower bounds of the mediation effect intervals. The widely accepted criterion for determining statistical significance is if the 95% confidence interval does not include 0. Overall, by utilizing these rigorous statistical methods, we were able to thoroughly investigate the mediating effect of AI.

As shown in Table 8, the analysis results of the mediation effect of SI and WI on the relationship between HS and IICT reveal that both mediating factors have a significant impact. The 95% confidence interval for both does not include 0, indicating their significance. Moreover, the mediation effect of SI (0.079) is greater than that of WI (0.062), providing support for hypothesis H3. Additionally, in the relationship between VS and IICT, the analysis of the mediation effect of SI and WI also demonstrates significant results. The 95% confidence interval for both mediating factors excludes 0, indicating their significance. Furthermore, the mediation effect of WI (0.072) surpasses that of SI (0.063), lending support to hypothesis H4.

**Table 8.** Mediation test results.

| Path | Effect | LLCI | ULCI | Conclude |
|---|---|---|---|---|
| HS→SI→IICT | 0.079 | 0.053 | 0.167 | significant |
| HS→WI→IICT | 0.062 | 0.037 | 0.139 | significant |
| VS→SI→IICT | 0.063 | 0.034 | 0.140 | significant |
| VS→WI→IICT | 0.072 | 0.048 | 0.152 | significant |

### *4.5. Moderation Test*

For the examination of KC's moderating effect, this study utilized SI and WI as independent variables, IICT as the dependent variable, and KC as the moderating variable. Hierarchical regression analysis was employed to test these relationships, and the findings are presented in Table 9. Model 1 shows a significant positive moderating effect of KC between SI and IICT ($\beta = 0.133$, $p < 0.01$), supporting hypothesis H5. However, model 2 suggests that there is a significant negative moderating effect of KC between WI and IICT ($\beta = -0.098$, $p < 0.05$), contradicting hypothesis H6.

**Table 9.** Moderating effect test results.

| | IICT | | | |
|---|---|---|---|---|
| | Model 1 | | Model 2 | |
| | β | *p* | β | *p* |
| CV 1 | 0.018 | 0.7 | 0.028 | 0.539 |
| CV 2 | 0.023 | 0.783 | 0.035 | 0.668 |
| CV 3 | 0.171 | 0.001 ** | 0.175 | 0.000 ** |
| CV 4 | 0.014 | 0.861 | 0.003 | 0.969 |
| SI | 0.136 | 0.006 ** | — | |
| WI | — | | 0.195 | 0.000 ** |
| KC | 0.489 | 0.000 ** | 0.483 | 0.000 ** |
| SI × KC | **0.133** | **0.007 **** | — | |
| WI × KC | — | | **−0.098** | **0.048 *** |
| F | 29.428 ** | | 27.604 ** | |
| $R^2$ | 0.444 | | 0.428 | |
| Adjusted $R^2$ | 0.429 | | 0.413 | |

Significance of correlations: (* $p < 0.05$), (** $p < 0.01$).

To offer a comprehensive illustration of the moderating effect of KC, this study employed a nuanced approach to examine the variations in SI on IICT at different levels of KC. Specifically, the analysis was conducted by considering KC levels that were one standard deviation above and below the mean, respectively. This method allowed for a detailed exploration of the moderating effect through simple slope analysis and visualization, providing a clearer understanding of how KC influences the relationship between SI and IICT. The results, illustrated in Figure 4 present a compelling demonstration of the moderating effect of KC. Specifically, at a high level of KC, the positive impact of IICT is significantly magnified compared to a low level of KC. This visual representation captures the distinct influence that KC has on the relationship between SI and IICT, underscoring the pivotal role it plays in enhancing the adoption and impact of ICT.

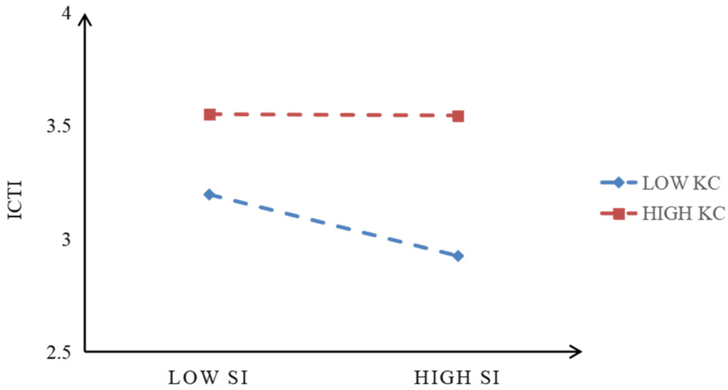


**Figure 4.** Moderating effect diagram.

## 5. Discussion

### *5.1. Research Findings*

Previous research has established a connection between SR and IICT; however, an important unresolved question remains: how does SR influence IICT, and what other critical components play a role? This aspect is vital for IICT. The present study examined the influence of SR on IICT, taking into account the mediating effect of AI and the moderating effect of KC. Multiple regression models, bootstrap self-sampling methods, and simple slope analysis were employed to elucidate these relationships and effects. As a result, the study offered partial support for the hypotheses, with further discussion of the six hypotheses provided below.

(1) Regarding the SR, both HS and VS significantly positively impact IICT

Drawing on synergetics, the synergy resulting from resource integration and complementary advantages can drive technological innovation activities. The empirical results of this study corroborate that SR serves as a key driver of IICT [108]. On the one hand, while engaging in horizontal collaborative technological innovation with "rival companies" may seem counterintuitive, companies within the same link of the industrial chain often share common goals and precise needs, facilitating resource and risk sharing. This approach helps reduce technology costs, accelerate R&D, and enhance innovation performance, aligning with the findings of Ramjaun, T. I. [109] and Wu, Q. [110]. On the other hand, companies across different links of the same industrial chain can establish SR among upstream, midstream, and downstream entities, fostering trust to devise development strategies and dynamic alliances, leveraging complementary resources and effective information to explore markets, optimize benefits, and, ultimately, achieve mutual success, consistent with the conclusions of Ozdemir, S. [111]. This study advanced beyond single SR research, analyzing and validating the impact of HS and VS on IICT, thereby enriching the understanding of SR's role in technological innovation.

(2) Concerning AI, SI serves as a mediator between HS and IICT, while WI serves as a mediator between VS and IICT

The social network theory suggests that both strong and weak relationships are the key elements that characterize technological innovation networks, which will affect the extent and depth of technological innovation in companies. The study's empirical results support the view that "the influence of SI and WI is crucial in forming and optimizing complex technological innovation networks", which echoes studies by Jiang, C. [112] and Hansen, M. T. [77]. Specifically, SI has a stronger mediating effect than WI between HS and IICT, and WI has a stronger mediating effect than SI between VS and IICT. Therefore, it is important to clarify the level of interaction that promotes IICT in different SRs. The analysis of the theoretical model of "SR-AI-IICT" involves the process of "introduction-absorption-innovation". It is expected to achieve the ideal state of obtaining resources from the interaction relationship without being constrained by the inappropriate interaction intensity. This study provides new theoretical perspectives for construction companies to pursue the path of IICT and deepened the research on the role of AI in SR.

(3) KC has a positive moderating effect on IICT under SI and a negative moderating effect on IICT under WI

The knowledge base view emphasizes that knowledge is the most strategic resource for companies. The core of interaction between companies is the exchange and collision of knowledge. A high level of KC implies that companies have a great potential to integrate internal and external knowledge and can well synergize the knowledge elements between the interacting agents [81]. This means that KC can achieve technological leapfrogging and, thus, improve the performance of innovation, resulting in a positive impact on technological innovation [93,113,114]. This study started from the perspective of KC and explored its moderating effect between the two types of AI and IICT, offering new insights into the field. On the one hand, this study verified the positive moderating effect of KC on IICT under SI. KC under SI can provide usable or substitutable resources that are closely related to their core competitiveness and extend beyond their knowledge base. It facilitates the identification and absorption of similar knowledge in the knowledge base and generates synergistic combinations that contribute to the generation of technological innovations, preventing companies' technological innovation activities from being caught in the "familiarity trap". It also corroborates the research of Sivadas, E. [115] and Dyer, J. H. [116]. On the other hand, this study also found an interesting conclusion that KC negatively moderates IICT under WI, which is contrary to Makri, M.'s study [117]. Under WI, upstream, midstream, and downstream companies with significantly different knowledge resource endowments, relying on their significant technological advantages, take on the tasks of different links in the innovation chain. Due to the existence of organizational inertia, companies will not easily give up their existing business areas and prefer to maintain the uniqueness of their core knowledge base. Therefore, WI will focus its limited attention on strategic synergies and cooperation as a way to serve the industry chain and the market, which weakens the impact of KC on IICT; moreover, investing too much attention in cross-domain technological innovation will increase the cost and reduce the efficiency. This is consistent with the principle of attention theory [118,119] and supports the results of this study. This study delved into the moderating effect of KC between the two types of AI and IICT, offering a fresh perspective that will contribute new insights to the field and extend the findings of previous research.

Overall, the academic significance and innovation of this study are as follows. Firstly, this study enriches the theoretical knowledge about IICT. The introduction and validation of these concepts and ideas provide new theoretical support and guidance for IICT. Secondly, this study expands the scope of research in related fields. By analyzing the interactions of these relationships in-depth, researchers can gain a better understanding of the dynamic processes and elements of IICT. Finally, this study provides new research directions and ideas for IICT. Future research can further explore the influence of other factors on IICT and expand the research methodology and theoretical framework.

### *5.2. Management Insights*

Previous studies have also confirmed the significant role of SR in technological innovation [58,62]. These studies have emphasized enhancing technological innovation performance through collaborative innovation networks [57,59]. This study investigated the interconnected relationships between SR, AI, KC, and IICT. The empirical findings demonstrated that appropriate SR, effective AI, and proficient KC positively influence IICT. These results will aid construction companies in understanding the impact of various SRs on technological innovation. Moreover, the study also examined the mediating role of

AI between SR and IICT, providing insights for construction companies to determine the optimal level of AI adoption to enhance IICT under different SRs. Additionally, the findings can guide decision-makers in construction companies to develop effective strategies for leveraging KC to enhance IICT.

This study has significant implications for the construction industry. Firstly, as a crucial component of economic and social development, the innovation ability of the construction industry directly affects the quality and efficiency of urbanization and infrastructure construction. This study provides the construction industry with an effective development path and strategic direction to lead future development. Secondly, with the rapid advancements in emerging information technology, ICT has become a critical development direction for the construction industry. This study offers scientific guidance for the construction industry to promote and apply ICT, and to push the industry towards a more intelligent and sustainable future. Furthermore, the research findings provide practical guidance for companies and practitioners in the construction industry. By understanding the positive impact of SR, AI, and KC on IICT, construction companies can optimize their internal management and external cooperation mechanisms, improve their innovation capability and competitiveness, and promote the healthy development of the industry. Simultaneously, practitioners can enhance their learning and training based on the research results, improve their professionalism and innovation awareness, and better adapt to the new requirements and challenges of the construction industry's development.

Building on this foundation, our study offers two crucial insights and managerial implications for construction company managers to enhance their organizational management practices and deepen their technological development strategies within the context of SR. Firstly, construction company managers should strategically develop and oversee various types of SR to enhance the potential and benefits of technological innovation. This study recommends considering SI in HS, which involves collaboration among different departments or units within the company, and WI in VS, which involves collaboration with external partners such as suppliers or research institutions. By fostering these SRs, construction companies can leverage diverse expertise and resources, leading to more effective and efficient technological innovation. Secondly, construction company managers need to recognize that different levels of AI have distinct impacts on KC and its role in driving innovation performance in ICT. To maximize the benefits of KC, construction companies should focus on improving the design and utilization of knowledge-sharing mechanisms, particularly emphasizing SI. This will ensure the effectiveness and relevance of KC, stimulate a strong motivation for learning and KC within the company, and ultimately facilitate innovation. By implementing these recommendations, construction company managers can enhance their organizational capabilities in technological innovation, foster a culture of collaboration and knowledge sharing, and ultimately achieve greater success in the development and implementation of ICT.

## 6. Conclusions

Based on the above empirical findings, this study draws the overall conclusion that SR, AI, and KC each exert varying degrees of influence on IICT. Drawing from theoretical perspectives such as synergetics, social network theory, and knowledge base view, six hypotheses were tested through correlation analysis and regression analysis, yielding the following results: (1) regarding the SR, both HS and VS significantly positively impact IICT; (2) concerning AI, SI serves as a mediator between HS and IICT, while WI serves as a mediator between VS and IICT; (3) KC has a positive moderating effect on IICT under SI and a negative moderating effect on IICT under WI.

While this study provides valuable implications, it is important to acknowledge certain limitations. Firstly, the focus of this study was solely on the influence of SR, AI, and KC on the cross-effect of IICT. To enhance future research, it is suggested that researchers categorize KC into complementary KC and alternative KC to further explore the moderating effects of different types of KC. This will enable a more nuanced understanding of how different forms of knowledge creation impact the cross-effect of IICT. Furthermore, investigating the impact of other relevant factors on both breakthrough IICT and incremental IICT could provide additional insights into the dynamic nature of technological innovation. By considering a broader range of variables, researchers can uncover more comprehensive explanations for the outcomes observed in this study. Secondly, it is worth noting that the sample size for this study was limited to 186 questionnaires. While efforts were made to ensure the representativeness of the sample, the small sample size may limit the generalizability of the research findings. Future studies should consider expanding the sampling range to include a larger and more diverse participant pool. This will help validate the findings across different contexts and enhance the external validity of the research. Lastly, while this study employed traditional hierarchical regression analysis to examine the moderating effect, it is recommended that future researchers employ the relational path model of structural equation modeling (SEM) to revalidate the theoretical model. SEM offers a more comprehensive and robust analysis framework, which can provide a deeper understanding of the complex relationships between variables and verify the proposed theoretical model.

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## Abbreviations

| | |
|---|---|
| ICT | Intelligent construction technology |
| IICT | Innovation of intelligent construction technology |
| SR | Synergy relationship |
| HS | Horizontal synergy |
| VS | Vertical synergy |
| AI | Agent interaction |
| SI | Strong interaction |
| WI | Weak interaction |
| KC | Knowledge coupling |

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