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The Effect of Critical Factors on Team Performance of Human–Robot Collaboration in Construction Projects: A PLS-SEM Approach

Guodong Zhang [1,2], Xiaowei Luo [2], Wei Li [3], Lei Zhang [4] and Qiming Li [1,*]

[1] Department of Construction and Real Estate, School of Civil Engineering, Southeast University, Nanjing 211189, China; guodzhang3-c@my.cityu.edu.hk
[2] Department of Architecture and Civil Engineering, City University of Hong Kong, Tat Chee Ave., Kowloon Tong, Kowloon, Hong Kong; xiaowluo@cityu.edu.hk
[3] School of Civil Engineering, Nanjing Forestry University, Nanjing 210037, China; liwei0842@njfu.edu.cn
[4] Research Center of Smart City, Nanjing Tech University, Nanjing 211816, China; lz10@njtech.edu.cn
* Correspondence: 101001839@seu.edu.cn

Abstract

Human–Robot Collaboration (HRC) in construction projects promises enhanced productivity, safety, and quality, yet realizing these benefits requires understanding the multifaceted human and robotic factors that influence team performance. This study develops and validates a multidimensional framework that links key human abilities (operational skill, decision-making ability, and learning ability) and robot capacities (functionality and operability) to HRC team performance, with task complexity considered as contextual influence. A field survey of construction practitioners (n = 548) was analyzed using partial least squares structural equation modeling (PLS-SEM) to test direct effects and human–robot synergies. Results reveal that all five main effects are positive and significant, indicating that both human abilities and robot capacities have significant contribution. Moreover, every hypothesized two-way interaction is supported, evidencing strong interaction effects. Three-way moderation analyses further reveal that task complexity significantly strengthened the interactions of human abilities with robot functionality, whereas its interactions with robot operability were not significant. The study contributes an integrated and theory-driven model of HRC team performance that accounts for human abilities and robot capacities under varying task complexity, and validated constructs that can be used to diagnose and predict performance. The findings offer actionable guidance for project managers by recommending that they prioritize user-friendly robot operability to translate worker expertise into performance across a wide range of tasks, invest in training to strengthen operators' skills and decision-making, and, for complex tasks, pair highly skilled workers with high-functionality robots to maximize performance gains.

Keywords: human–robot collaboration; construction projects; team performance; influencing factors; PLS-SEM

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1. Introduction

The construction industry accounts for more than 13 percent of global GDP [1], while it has struggled for decades to shake off a reputation for low productivity, labor shortages, and high accident rates. Occupational diseases like musculoskeletal disorders [2] stemming from manual, repetitive, and strenuous tasks remain prevalent, directly influencing project profitability and bringing a heavy human cost. Most construction work is still performed by human workers now [3,4]. As a result, the quality in construction is rarely as stable as that in manufacturing with widely applied robots. Even skilled workers can complete only a limited number of components per shift, which restricts productivity [4]. Advanced technologies, especially construction robots, are critical for safe, efficient, and sustainable construction [5]. Human–robot collaboration (HRC) combines robots' speed, precision and repeatability with workers' intelligence, creativity, adaptability and reasoning [6]. Studies show that HRC can reduce worker workload by about 20%, improve efficiency by nearly 30%, and increase assembly accuracy by more than 80% compared with human-only teams [7]. Robots can take over rule-based, repetitive, hazardous or monotonous activities, completing them more safely and efficiently [8]. In site applications, such collaboration has been shown to reduce costs, shorten project schedules, and enhance construction quality by minimizing worker errors [9–11]. Therefore, HRC is not only another productivity tool, but also a pathway toward a safer and more sustainable construction sector.

Although the potential of HRC in construction is widely acknowledged, on-site adoption and effectiveness remain limited [12], partly because the mechanisms that shape HRC team performance are insufficiently understood. This limits our ability to predict and manage performance on site. First, prior studies have identified a range of factors that may influence HRC success [13–19]. Most of them, however, focus on human-centered variables such as trust, workload, and acceptance. Far less attention is given to robot attributes or to the technical and task dimensions that also matter. Consequently, the existing literature still lacks a holistic, empirically validated theoretical model capable of integrating these disparate strands into an explanatory framework. Second, the field rarely treats humans and robots as an integrated team unit, even though performance on construction sites emerges from socio-technical interactions among operators, robotic systems, and their task context [15,20]. Construction work is executed by heterogeneous and dynamically reconfigurable HRC teams (e.g., rebar tying, façade installation, site inspection) rather than by isolated humans or robots [21]. "Heterogeneous" refers to teams with a mix of workers with different skills and robots with varying functions. For example, in façade installation, skilled humans perform tasks like alignment, while robots handle heavy lifting. "Dynamic" emphasizes the teams' ability to adjust based on changing task needs, such as integrating new robots or reallocating human workers to optimize efficiency. Instead, explicit complementarities between human abilities and robot capacities are seldom modeled, interaction pathways (e.g., how operability enables operators to translate skill into performance) are under-theorized, and construct-valid measures remain scarce [22,23]. Third, boundary conditions are not well specified. The task complexity, a defining feature of construction that ranges from routine to highly uncertain work [24], is rarely modeled as a moderating factor, leaving unclear when HRC will succeed or fail.

Together, these limitations constitute a clear research gap. The related research field remains descriptive, cataloging factors rather than clarifying their interaction mechanisms, and cannot yet predict the HRC team performance. The motivation of this paper is to form a holistic, empirically grounded, and predictive team-level framework that integrates human, robot, and task dimensions, clarifies their interaction mechanisms, and understand and optimize HRC team performance. Therefore, this study aims to answer the following research questions:

RQ1: What are the key latent constructs that influence HRC team performance in construction?

RQ2: What are the specific, measurable indicators that constitute each latent construct?

RQ3: What are the causal relationships between these key factors and HRC team performance?

RQ4: How can a PLS-SEM model be developed and validated to provide practitioners with suggestions for predicting and improving HRC team performance?

To answer these questions, this study adopts a partial least squares structural equation modeling (PLS-SEM), a prediction-oriented approach that characterizes influencing mechanism research now widely used in construction management, because it can estimate complex causal networks and remain reliable with small samples [25].

The following are the study's main goals: (1) identifying a comprehensive set of HRC team-performance factors from different dimensions so that corresponsive enhancement can be tracked in the future, (2) testing whether these factors influence HRC team performance, (3) modeling the direct, indirect, and moderating pathways among constructs using PLS-SEM to enhance the team performance, and (4) interpreting the findings into actionable guidance for decision-makers and construction management practitioners.

By delivering the empirically validated and multidimensional model of HRC team performance in construction, the study makes a dual contribution. On the one hand, this paper provides a theoretical framework of factors influencing HRC team performance and addresses the knowledge gap in the literature through a narrative approach. On the other hand, the result will help practitioners in HRC practical applications through the identification of strategies to improve team performance, thereby improving construction project performance and success.

2. Literature Review

2.1. Development of HRC in Construction

HRC in the construction sector is best understood not as a single technology but as a spectrum of interaction modalities [26]. It is the cooperative work of robots and humans in a shared or adjacent workspace across tasks such as assembly, inspection, material handling, fabrication, and maintenance. To structure this field, scholars classify HRC by robot autonomy and the matching degree of human involvement [21]. These levels range from simple, pre-programmed robotic actions with high human oversight to fully autonomous systems requiring minimal human intervention. This classification is critical because the factors influencing team performance will differ across autonomy levels. For instance, a teleoperated robot handling a hazardous task is a different collaboration pattern than a semi-autonomous robot assisting a human in assembly. The evolution of HRC in construction has been gradually promoted by the goals of improving safety, boosting productivity, and enhancing quality [27]. Early single-task construction robots (STCRs)—for bricklaying, excavation, and curtain-wall installation—were built to reduce physical strain and safety risks and borrowed heavily from pre-programmed industrial methods [28]. These robots typically operate in highly structured environments and are designed for repetitive tasks. On construction sites, strict safety considerations confine STCRs to fixed zones, a practice that effectively keeps them physically separate from human workers [29]. As a result, the status of HRC can rarely be achieved under this situation. Instead, robots and humans merely coexist, with little direct interaction between the two parties.

Recent scholarship on construction robotics indicates a gradual shift from single-purpose automation to mobile and cyber-physically integrated systems that operate in shared workspaces with humans [30–32]. On the sensing and mobility side, quadruped and wheeled platforms are increasingly used for repeatable site inspection and progress verification, improving temporal consistency of observations and linking field data to project records. Studies report autonomous or supervised navigation and human–robot teaming benefits in on-site monitoring tasks [33,34]. Beyond inspection, field robots have advanced in repetitive and physically demanding operations. Rebar tying and cage fabrication systems now combine active perception, robust pose estimation, and coverage planning, showing reliable tying of intersections and automated assembly workflows [35–37]. Bricklaying research continues to refine force–position control and task-level planning, with BIM-informed strategies improving placement accuracy and cycle consistency [38]. Interior-finish robots have progressed from feasibility demonstrations to intelligent spraying systems with stable operation and safety features, while on-site thin-layer printing with cementitious plaster extends robotic finishing toward continuous, mobile fabrication [39–41]. At the equipment scale, autonomy modules for excavators integrate multi-sensor perception, trajectory generation, and hydraulic control, enabling operation on uneven, cluttered terrain; the literature spans autonomous walking excavators, hybrid data-driven motion planning, and database-driven model predictive control, alongside shared-control frameworks that blend operator input with autonomy [42–44]. These capabilities are increasingly coupled with integrated UAV–UGV mapping to accelerate site digitization and model-based management, providing higher-frequency updates for planning and exception handling [9]. In parallel, construction-specific human–robot interaction research proposes pre-task planning tools for risk identification and examines multidimensional impacts on efficiency, quality, workload, and worker perceptions, emphasizing operability, predictability, and calibrated autonomy when people and robots share tasks and space [7,45].

Similar trends have been reported in North America, Europe and Australia, where autonomous mobile robots have been tested for structural inspection and laser-based surveying in complex built environments [23,46–48]. Recent reviews and case studies document mobile manipulators and legged platforms performing repeatable site traversals, LiDAR-based mapping, and progress capture under obstacle conditions, laying the perception and navigation foundations for HRC [33,49,50]. Beyond North America, Europe, and Australia, similar technological momentum is evident across Asia where academic and industry are actively advancing robotic construction systems. In Singapore and Hong Kong, research into construction automation has culminated in the deployment of mobile robotic platforms for tasks such as facade installation, autonomous rebar tying, and progress tracking using vision and LiDAR systems [5,51–53]. Notably, the integration of mobile manipulators with digital twin frameworks and BIM-enabled environments to enable context-aware planning and semantic navigation in dynamic construction sites [54,55]. In recent years, quadruped robots have been trialed not only in infrastructure inspection but also in autonomous progress monitoring and real-time 3D reconstruction of construction environments under unstructured and dynamic conditions [34,56,57]. These trials have highlighted the growing emphasis on adaptive locomotion, terrain-aware path planning, and robust localization in partially known environments—factors critical to safe and effective HRC. Furthermore, initiatives like the SAM robotic bricklaying platforms (Semi-Automated Mason) illustrate how collaborative robots can augment skilled masons by improving productivity and ergonomics [21,57]. These initiatives also underscore a global convergence toward multi-robot coordination, heterogeneous sensor fusion, and resilience to occlusions and environmental changes [58].

Building on these advances, HRC teams combine human flexibility and problem-solving with robotic strength and precision to achieve higher overall productivity and safety performance [7,59]. For example, robots excel at handling heavy, repetitive, and precise tasks, which can raise output rates and relieve workers of strenuous labor. A modeling study showed that introducing proactive HRC could boost construction productivity by up to 22% [60]. Safety performance also tends to improve with well-designed HRC. Robots can be delegated to perform dangerous jobs such as demolition and reduce workers' exposure to harm [61]. In collaborative scenarios, separating human and robot working zones or using safety control measures has been shown to significantly mitigate collision risks. Experiments in virtual settings found that keeping a defined distance or barrier increases workers' safety perception and awareness, improving overall team safety [62]. In general, HRC can realize safety first better. In practice, robots handle hazardous work while humans focus on planning and problem-solving [63]. This lowers accident risk and reduces physical strain and fatigue. The result is a healthier, more sustainable workforce. The most important objective of HRC is to lower the human physical and cognitive workload while increasing productivity [64]. For example, the wearable assistant robots have lessened manual handling loads and injuries on sites [7].

Recent studies show that effective human–robot teams can improve efficiency, work quality, and safety in construction projects compared with all-human workflows [59]. However, realizing these gains consistently requires careful consideration of the factors that influence HRC team performance.

2.2. Factors of HRC Team Performance in Construction

The components of HRC teams, including workers, robots, and tasks, as well as the way workers and robots collaborate, determine the overall performance of the collaborative team [13,19,64–67]. The characteristics of these components and their interactions significantly impact team performance, including efficiency, safety, quality, flexibility, and creativity [63,64,68–71]. These elements rarely operate in isolation and instead they interact dynamically, with the strengths or weaknesses in one domain amplifying or mitigating the effects of another. Understanding these factors comprehensively is essential for designing HRC systems that optimize team performance across diverse construction scenarios. Therefore, it is fundamental to analyze the key influencing factors across various dimensions to predict and improve overall team performance.

2.2.1. Human-Level Factors

In HRC, understanding the human factors that contribute to team performance is crucial for effective collaboration between workers and robotic systems. A key distinction in human-level factors is between trainable skills and psychological attitudes, as these two categories influence team performance in fundamentally different ways [72–74]. This differentiation is essential because skills are external and observable, whereas psychological attitudes are internal and subjective [75,76]. Skills, such as the operational skill, are external, observable, and can be systematically improved through training, practice, and experience [77]. From a managerial perspective, these skills can be directly enhanced by structured training programs, knowledge transfer initiatives, and on-site practice, thereby enabling workers to more effectively operate robots, make sound decisions under uncertainty, and adapt to evolving technologies [7]. By contrast, psychological attitudes—including trust in robots, openness to innovation, and willingness to communicate—are internal and subjective [78,79]. They are shaped less by technical training and more by organizational culture, leadership style, and team climate [80,81]. For managers, this implies that while skills require targeted investment in capability building, attitudes must be nurtured through fostering trust, transparent communication, and supportive work environments.

The capabilities and characteristics of the human workers are pivotal in HRC team performance. The skill levels, decision-making abilities and learning abilities of operators determine how effectively they can work with robots. Humans can make high-level decisions from complex information, adjust to unexpected changes, and solve novel problems that robots cannot handle autonomously [82]. For instance, a well-trained construction worker can intuitively intervene if a robot encounters an unforeseen site condition, preventing errors and downtime. Studies highlight that adequate training and learning capacity are essential: workers must develop new technical skills and mental models to collaborate smoothly with robots [83]. Positive attitudes and psychological factors like trust in the robot, openness to innovation, and communication efficacy also critically affect HRC outcomes [84–86]. If workers distrust a robot or feel anxious about its actions, coordination suffers. By contrast, when humans perceive robots as a reliable partner, they engage more in collaboration. Empirical research in construction has found that operators' trust and comfort levels can influence team performance, which is that higher trust often correlates with more efficient task execution and information flow [13,87]. Thus, human factors such as technical proficiency, cognitive readiness, decision-making abilities and skills individually influence how well the team functions.

2.2.2. Robot-Level Factors

On the robotic side, the functionality, reliability, and usability of the robots are key performance drivers. A robot's capabilities set the upper bound of what the team can accomplish. Robust hardware and software ensure the robot can operate consistently without frequent breakdowns or errors, thereby avoiding work interruptions. The robot must be operable and responsive to human input. Factors like an intuitive user interface, effective communication, and appropriate autonomy greatly affect collaboration quality [88–90]. Research indicates that HRC success depends on robots that can adapt to changing site environments and integrate into existing workflows [26]. For example, a site-inspection robot with autonomous navigation and obstacle avoidance reduces oversight burden and lets the human focus on analysis [33]. The robot that moves in a predictable and human-like way tends to improve the operator's comfort and task performance, whereas erratic or opaque behavior can reduce team efficiency [91]. In sum, high HRC performance requires capable, user-friendly robots that meet task demands and collaborate smoothly with humans.

2.2.3. Task-Level Factors

The nature of the task being performed, such as its complexity, uncertainty, and structure, fundamentally shapes HRC team dynamics. Task complexity is a critical factor. The complex construction tasks, like involving many interdependent steps or real-time problem solving, tend to demand greater human oversight and decision-making, which can strain the team if not properly managed [7]. In such cases, the human must frequently intervene or guide the robot, potentially slowing down work if the interfaces or role allocations are not optimized. High complexity or novel tasks also increase cognitive workload on the human operator, as they must monitor the robot closely and handle unpredictable situations [92]. By contrast, for well-structured or repetitive tasks, robots can take on a larger share of the work with minimal human input. Effective HRC thus depends on matching the task to the appropriate level of automation [93]. Another task factor is whether the collaboration is physical at a distance. Physical collaboration demands careful safety measures, whereas remote collaboration places emphasis on communication bandwidth and interface design [94]. The hazard level of the task also matters because tasks in hazardous environments will benefit more from robotic involvement [95]. In summary, factors like task complexity, uncertainty, and structure influence how the human–robot team (HRT) should be organized and how performance will be affected. Simplifying task workflows and clearly defining roles can substantially improve HRC productivity and safety in construction.

2.2.4. Interactive Effects

Human, robot, and task factors do not operate in isolation and their interactions determine the team performance which should be considered jointly [96]. For example, a highly autonomous robot might improve efficiency, but if the operator is not adequately trained or mentally prepared, they may mistrust the robot or struggle to intervene when needed, undermining performance [97]. Conversely, if the autonomy of the robot is too low on a complex task, the human may become overburdened, leading to errors or slower progress [98]. Finding the optimal balance is crucial for HRC team performance. Empirical evidence shows that human factors directly affect performance. On the other hand, robots are designed to be cognitively compatible, such as moving in human-like ways and providing timely feedback, enhancing the team performance [99]. Studies have identified trust and communication as particularly important interactive factors. High mutual trust and clear communication correlate with better collaboration [100]. These findings highlight that optimizing HRC performance requires us to consider how human abilities, robot capabilities, and task characteristics dynamically influence each other. Successful HRC teams emerge when human strengths are effectively augmented by robot strengths in a way that fits the task. Achieving this collaboration involves tuning both human and robot factors to the specific task context.

2.3. PLS-SEM Modeling in Construction

In construction management research, Partial Least Squares Structural Equation Modeling (PLS-SEM) has become an increasingly popular analytic method for exploring complex and multi-factor relationships [25]. As a component-based variant of structural equation modeling, PLS-SEM is designed to estimate latent variables and the causal paths between them simultaneously. It is especially suited to exploratory studies with predictive aims, handling small to medium sample sizes and non-normal data distributions common in field research [101,102]. PLS-SEM has been widely used in construction to investigate a variety of topics of new technology adoption [103–105]. For instance, recent research has made extensive application of PLS-SEM in examining drivers of innovation in robotics, automation, and drone deployment on building projects, reflecting the method's capacity to accommodate diverse human, technical, and organizational variables in one analytical framework [106,107].

Within HRC research specifically, PLS-SEM enables rigorous analysis of how human factors, robot characteristics, and task characteristics influence team performance. You, Kim, Lee, Kamat and Robert [62] used the method to investigate safety perceptions in human–robot construction teams under different workspace configurations in a virtual environment. Their model linked constructs such as trust in the robot, team identification, perceived safety, and intention to collaborate, revealing that separating human and robot work zones improved perceived safety indirectly by increasing trust. Likewise, Parvez et al. [108] applied an extended Technology Acceptance Model (TAM) via SEM to demonstrate that perceived usefulness and ease of use were significant predictors of the intention to adopt robots on site. These studies illustrate how PLS-SEM can integrate human, technical, and contextual variables into a causal network, uncovering pathways of factors of HRC team performance.

PLS-SEM is well suited for building and validating HRC team performance models. Its flexibility enables integrated frameworks that capture the multidimensional nature of HRC and link human–robot–task interactions to outcomes such as productivity, safety, and quality.

2.4. Knowledge Gap in the Literature

Although the potential of HRC in construction has been widely acknowledged, its successful implementation continues to face significant challenges. A growing body of scholarship has identified a diverse set of factors that may influence the performance of HRC teams, ranging from human characteristics such as skill level, trust, and adaptability to robot-related attributes such as autonomy, reliability, and usability, as well as task and environmental conditions [24,109–111]. Despite this substantial descriptive groundwork, the current state of knowledge remains fragmented. Most studies have approached these factors in isolation, generating valuable catalogs of potential influences that provide a strong foundation for integration into a coherent theoretical structure [15,26,112,113]. Building on this groundwork, the opportunity now lies in advancing theory by clarifying how these variables interact, reinforce, or counteract one another in shaping HRC team performance—a domain that remains ripe for further exploration and theoretical development. This lack of integration has two important consequences. First, without a unifying framework, it is difficult to compare results across studies. The existing literature offers little guidance on the relative importance of different factors and on the pathways through which they influence performance. Second, the absence of validated predictive models constrains the ability of practitioners to design and manage HRC teams with confidence that specific interventions (like training, robot interface design, or task allocation) will reliably lead to improved outcomes.

The existing research remains descriptive or exploratory based on controlled laboratory experiments with small and homogeneous participant groups [62,114]. These studies help surface candidate variables but do not capture the complexity and variability of real projects. Interaction mechanisms among human, robot, and task factors are seldom modeled to enable empirical tests of causal relationships. As a result, the field struggles to move from qualitative observations to quantitative predictions—progress that is essential for advancing theory and guiding practice.

Addressing this gap requires a methodological shift from analyzing potential factors qualitatively toward developing and validating structural models that explicitly represent the relationships among factors. PLS-SEM offers a particularly suitable approach, as it enables the simultaneous estimation of measurement models for latent constructs and the evaluation of complex causal paths [25]. By employing such a method, it becomes possible to move beyond descriptive listings of influences toward constructing a scientifically grounded and predictive framework for understanding and optimizing HRC team performance in construction.

3. Research Methodology

A conceptual model is first rooted in a clear research strategy. Guided by the results of a literature survey, this strategy provides the basis for formulating hypotheses to be tested with empirical evidence [115]. In this study, the research methodology strictly follows the sequential hybrid approach of qualitative and quantitative data collection, interpretation, and modeling [116], which is a systematic methodology consisting of conceptual study, empirical study, and study output, as shown in Figure 1.

In the conceptual stage, the study reviewed the literature to identify gaps in HRC for construction. From this review, the main factors influencing HRC team performance were extracted and grouped into three dimensions: human abilities, robot capacities, and task characteristics. Guided by related theory, the study then developed hypotheses for both main effects and interactions.

In the empirical stage, the study collected data with a structured questionnaire targeted at construction professionals experienced in robotics and automation. A total of 548 valid responses were obtained. To ensure measurement robustness, reliability and validity were assessed using Cronbach's α, composite reliability, average variance extracted, and discriminant validity. The theoretical model was validated with PLS-SEM, model fit indices were examined, and hypothesized paths were tested. Both main and moderating effects were analyzed to capture HRC performance under varying task complexities.

Finally, the study produced a validated PLS-SEM model of HRC team performance and its implications. The model explained variance in team performance, demonstrated that human and robot factors contribute through both direct and interaction effects, and confirmed the moderating role of task complexity. These results advance HRC theory in construction and provide practical guidance for projects.

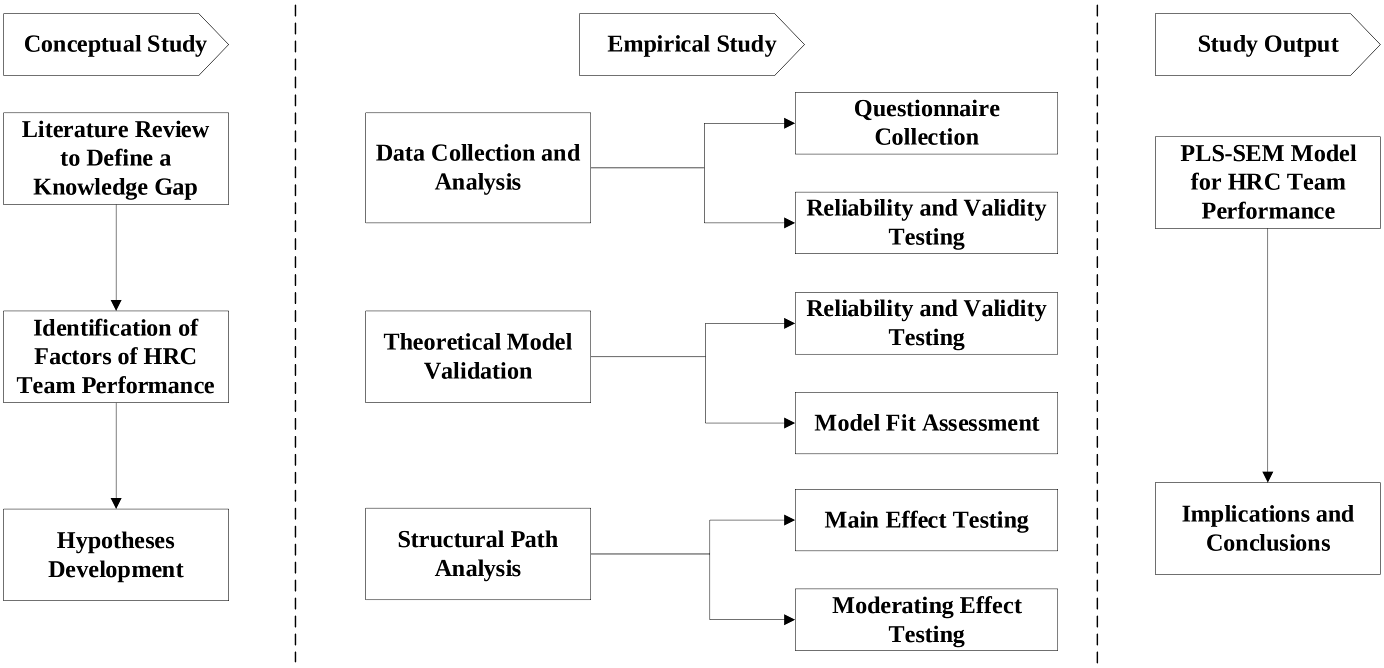

Figure 1. Research Methodology.

4. Conceptual Framework and Hypotheses Development

4.1. Related Theory Foundations

To deeply explore HRC team performance in construction, it is necessary to build a solid theoretical foundation [117]. The Technology-to-Performance Chain (TPC) model, proposed by Goodhue and Thompson [118], is a core theoretical framework for explaining how information technology affects performance. It is highly instructive for understanding the role of technology in collaborative teams. The TPC model believes that two prerequisites must be met simultaneously for information technology to be transformed into individual or team performance: (1) technology is effectively utilized; and (2) there is a good fit between technology and tasks (Task-Technology Fit, TTF) [118]. TTF is defined as the degree of fit between technical functions and task requirements, emphasizing whether technology can effectively support users in completing their work tasks. The TPC model structure aligns with HRC. The robotic systems, as a new technological medium, are introduced into the construction production process to assist humans in completing complex tasks such as handling, inspection, and execution. Their value must be demonstrated through collaboration with human workers and their alignment with specific construction tasks. Only when the capabilities of robots match on-site task requirements and workers are willing and able to effectively use the technology can the expected team performance be achieved [119]. This corresponds to the technology–task–human coupling mechanism in the TPC model.

Therefore, guided by the TPC and TTF logic, this study deliberately scopes the antecedents to HRC team performance to human abilities that determine whether the technology can be effectively utilized, and robot capacities that determine whether the technology fits the task demands [118]. Within this socio-technical coupling, the human side is represented by three ability constructs—operational skill, decision-making ability, and learning ability—that are repeatedly identified in human–robot interaction (HRI) and construction management literature as first-order drivers of effective technology use in dynamic construction environments [120–123].

The operational skill captures the worker's technical proficiency in operating and supervising robots [124]. In construction HRC, such proficiency reduces procedural errors, shortens intervention time, and improves handoffs between manual and automated steps [122]. Decision-making ability reflects the capability to make timely, context-appropriate judgments under uncertainty—allocating tasks between human and robot, overriding robot actions, and replanning when site conditions change [16,125]. Learning ability represents adaptive capacity to acquire new procedures as robot autonomy levels evolve; in practice, adaptive learners close the utilization gap and unlock more of the robot's capability over time [126]. Collectively, these three ability constructs map to the user capability and utilization of the TPC. On the robot side, the model includes functionality and operability as distinct capacity constructs [124,127]. Functionality denotes what the robot can do (e.g., reliability, responsiveness, and autonomy level) and therefore sets the technical ceiling of task–technology fit in construction settings [128,129]. Operability denotes how easily humans can direct and collaborate with the robot (e.g., interface clarity, predictability, controllability), aligning with the ease-of-use pathway highlighted by TAM and HRI usability research as a core determinant of effective use and performance [130–132]. Prior empirical and design work in collaborative manufacturing and construction shows that operability frequently amplifies human expertise and moderates breakdowns at the human–robot boundary [133,134]. This construct set can better explain HRC team performance that capable workers (skillful, decisive and adaptive) effectively utilize capable technologies (functional and operable) on tasks that those technologies fit.

Other frequently discussed constructs in HRC research, such as trust, communication, and safety, are not modeled as focal antecedents in this framework [82,110]. Trust and communication emerge only when humans and robots interact. They are relational mechanisms shaped by human abilities, robot capacities, and task context, rather than attributes of either party alone [135,136]. In line with TPC and TTF logic, these constructs are more appropriately conceptualized as interactional pathways whose influence is captured through the complementarities between human and robot factors and the moderating role of task complexity, rather than as exogenous inputs [96,137]. Safety, by contrast, is treated as a performance outcome rather than an antecedent [138]. Similarly to productivity and quality, safety is realized during task execution and not a pre-existing trait of the human or the robot. Positioning safety as an outcome preserves a clear causal chain from abilities and capacities, through interaction mechanisms, to team performance, and avoids conflating predictors with results.

In summary, although TPC originated in the field of information systems, its core logic, that technological value depends on the utilization and TTF, is highly consistent with the mechanisms of HRC. Therefore, introducing TPC theory into the HRC scenario not only has theoretical rationality, but also provides a clear theoretical basis for identification and analysis of the factors affecting HRC team performance. The TPC theory provides a clear theoretical perspective for identifying the key factors influencing the HRC team performance. By emphasizing the logic of technology, utilization, and performance, it indicates that efforts to advance the intelligent transformation of the construction sector must systematically consider the interactive mechanism among human factors, technology and tasks.

4.2. Identification of Related Factors

A structured literature investigation was conducted to discover the factors affecting HRC team performance with the three steps: journal selection, article screening, and paper analysis.

Firstly, to ensure the broadest coverage of construction engineering and automation research, this study selected Scopus as the literature source because Scopus has been adopted in numerous reviews related to construction robots compared with other platforms [21,27,109,139,140]. Moreover, Scopus provides wider reach across interdisciplinary domains [141], making it well suited to the cross-cutting nature of HRC studies.

The second step is searching for relevant research based on the selected database with a Boolean search between 2010 and 2025. The title/abstract/keywords fields were selected in Scopus to ensure that only papers explicitly addressing these terms were captured. The Boolean string adopted was as follows:

TITLE-ABS-KEY = ("human robot collaboration" OR "human robot interaction" OR "construction robot*") AND ("construction site*" OR "building project*" OR "civil engineering" OR "construction engineering" OR "construction management" OR "building engineering" OR "off-site construction" OR "industrialized construction") AND ("team performance" OR "productivity" OR "safety" OR "quality")

The initial sweep yielded 521 publications. Titles, abstracts, and keywords were then examined against three criteria: (1) the study must focus explicitly on HRC within a construction context; (2) the study must discuss factors, metrics, or determinants of team or task performance; (3) this study must provide either empirical data or a conceptual framework linking factors to performance. After this first pass, 118 papers met all criteria.

The third step is factor extraction based on grounded theory which is often used in construction management research [142–144]. Through iterative coding and categorization, this paper identified three overarching dimensions that recur across the literature, including human ability, robot capacity, and task characteristics. The first is human ability. Successful HRC depends critically on the abilities of the human worker, since humans are not only robot operators but also decision-makers and learners in dynamic construction environments [145]. Within human capacity, the operational skill, decision-making ability, and learning ability were identified as key competencies [146,147]. Operational skill reflects the technical proficiency of workers in operating and supervising robots, thereby reducing errors and improving coordination efficiency [148,149]. Decision-making ability captures the cognitive capability to make timely and effective judgments under uncertainty, which is crucial in construction's dynamic and variable conditions [16]. Learning ability represents the adaptability of workers to acquire new skills and adjust to novel robotic systems, enabling performance improvement [150]. Second is robot capacity. Within robot capacity, two determinants of functionality and operability were highlighted [151,152]. Functionality refers to the technical performance of the robot, including autonomy, reliability, precision, and responsiveness, which directly influence productivity and safety [153]. Operability reflects the usability and interface design of the robot, capturing how easily humans can control and interact with it, which affects the fluency of collaboration [154]. Finally, under task characteristics, task complexity was identified as a critical contextual determinant, as tasks that are novel, interdependent, or uncertain impose higher cognitive and coordination demands on both humans and robots, thereby amplifying or decreasing the influence of the aforementioned factors on team performance [155].

In summary, six specific factors, including operational skill, decision-making ability, learning ability, robot functionality, robot operability, and task complexity, emerged as the most significant determinants of HRC team performance, forming the foundation for the hypothesis development presented in the following section [112,156].

4.3. Hypotheses Development

Building on the conceptual framework, this paper develops specific hypotheses for how human abilities, robotic capacities, and their interactions influence HRC team performance, as well as how these relationships may depend on task complexity. Human operators' abilities are expected to be a fundamental driver of HRC team outcomes. First, a construction worker's operational skill defined as proficiency in operating and interacting with robots should enhance the team performance. Skilled operators can better utilize robotic functions and avoid errors, leading to more efficient and accurate task completion [13]. Research shows that adequate training and technical knowledge on how to use robots enable humans to intervene effectively to prevent downtime when robots face issues. For example, training improved HRC performance by increasing operators' confidence and coordination with robots [83]. Thus, a higher level of operational skill is good for collaboration to improve overall team productivity and quality. Therefore, this study hypothesizes:

H1: *Operational skill is positively related to HRC team performance.*

Second, the decision-making ability of human workers is considered as the factor to improve HRC team performance [109]. In complex construction tasks, human judgment is critical for handling uncertainty and making real-time adjustments that automated systems alone cannot [157]. An operator with strong decision-making skills can optimally allocate tasks between themselves and the robot, choose when to intervene or override robot actions, and adapt plans at any time, thereby enhancing team effectiveness [158]. Human decision-making capabilities are key factors affecting outcomes in HRC [16]. When faced with unexpected site conditions, human workers can instruct the robot or replan the task to avoid delays. Teams with workers who make sound decisions will achieve better performance than those with less decisive workers. Hence:

H2: *Decision-making ability is positively related to HRC team performance.*

Third, this paper considers the human operator's learning ability, which is the capacity to acquire new skills and adapt to new technologies or procedures. This factor should have a positive impact on HRC team performance, especially given the introduction of robots into construction [159]. A learning-oriented operator can more quickly master the robot's interfaces and functions, continually improve how they collaborate with the robot, and update their mental models for coordination. Operators who actively learn and adapt contribute to HRC work and can unlock more robot potential over time [160]. Workers who try to understand new HRC processes tend to find innovative ways to divide labor with robots and overcome workflow bottlenecks. In contrast, low learning ability may result in low utilization of robots [161]. This study therefore hypothesizes:

H3: *Learning ability is positively related to HRC team performance.*

In addition to human factors, the capabilities of the robot are hypothesized to significantly influence HRC team performance [60]. One critical dimension is robot functionality, which encompasses the robot's technical performance, like autonomy level, reliability, precision, and ability to handle complex tasks [42,162]. A highly capable robot can execute more tasks independently named high task-technology fit [118], and with fewer errors or breakdowns to improve team productivity and quality. Prior research in construction robotics has shown that advanced functionality enables robots to contribute meaningfully without constant human correction, which in turn raises overall team efficiency [33]. Hence:

H4: *Robot functionality is positively related to HRC team performance.*

Another key technical factor is robot operability, referring to the ease with which humans can operate and interact with robots. A functional robot may not contribute to team performance if it is difficult to control or communicate with. Intuitive operability with user-friendly interfaces, clear feedback and ergonomics could reduce the cognitive burden on workers and facilitate the collaboration. When robots are easy to operate, human workers can more quickly learn the controls, confidently adjust robot actions, and effectively supervise the collaboration process. This aligns with TAM showing that perceived ease of use is a strong predictor of technology effectiveness and adoption in teams [163]. Therefore, a robot designed for high operability will significantly enhance team performance. Thus:

H5: *Robot operability is positively related to HRC team performance.*

Beyond their individual impacts, human and robot factors also reinforce each other in shaping team performance [164]. According to the TPC theory, technology yields performance benefits only when users are both willing and able to utilize it effectively, and when the technology's capabilities suit the task at hand [165]. Thus, pairing high human ability with high robot capacity should yield synergistic gains, whereas weakness in either constrains the other. For example, a skilled operator cannot compensate for a low-capability robot, and a capable robot is underused by an untrained operator. Prior work likewise finds that HRC success depends on joint optimization, as changes in robot behavior influence outcomes differently depending on the operator's state [166]. Accordingly, this study hypothesizes positive interactions between each human ability and each robot capacity, and states the formal hypotheses as follows:

H6: *The interaction between operational skill and robot functionality is positively related to HRC team performance.*

H7: *The interaction between operational skill and robot operability is positively related to HRC team performance.*

H8: *The interaction between decision-making ability and robot functionality is positively related to HRC team performance.*

H9: *The interaction between decision-making ability and robot operability is positively related to HRC team performance.*

H10: *The interaction between learning ability and robot functionality is positively related to HRC team performance.*

H11: *The interaction between learning ability and robot operability is positively related to HRC team performance.*

Each of the above reflects the expectation that when humans and robots both contribute their strengths, the HRC team achieves more than the sum of its parts. For example, H6 posits that an operator's expert skill in using robots magnifies the performance gains from an advanced robot's functions. Similarly, H8 suggests that a worker's strong decision-making, combined with a versatile robot, leads to better strategy execution and problem-solving on site. These hypotheses echo prior findings that human–robot fit is crucial [167]. A good match of human competencies with robot capabilities leads to higher efficiency, better safety, and smoother teamwork [168,169].

As tasks grow more complex, these relationships are increasingly moderated by task complexity [92]. Task complexity in construction refers to the degree a task is novel, difficult, or involves many interdependent steps and uncertainties [170]. Complex tasks typically demand greater human abilities [171]. Under high complexity, the value of a skilled human and a capable robot should be even more pronounced, since each can compensate for the challenges the other faces [172]. Prior studies indicate that as task complexity rises, performance increasingly depends on effective HRC and shared decision-making [173,174]. Therefore, this paper hypothesizes that task complexity positively moderates the interaction effects between human and robot factors on performance. Specifically:

H12: *The more complex the task is, the stronger the positive effect of the interaction between human operational skill and robot functionality on HRC-team performance.*

H13: *The more complex the task is, the stronger the positive effect of the interaction between human operational skill and robot operability on HRC-team performance.*

H14: *The more complex the task is, the stronger the positive effect of the interaction between human decision-making ability and robot functionality on HRC-team performance.*

H15: *The more complex the task is, the stronger the positive effect of the interaction between human decision-making ability and robot operability on HRC-team performance.*

H16: *The more complex the task is, the stronger the positive effect of the interaction between human learning ability and robot functionality on HRC-team performance.*

H17: *The more complex the task is, the stronger the positive effect of the interaction between human learning ability and robot operability on HRC-team performance.*

In summary, H12–H17 propose that high task complexity will magnify the performance impact of having both high human and high robot factors. When tasks are straightforward, a moderate human–robot pairing may suffice, but as complexity grows, any weakness is exposed, and a well-matched and highly capable HRT becomes critical for productivity and safety. This set of hypotheses extends the theoretical framework by incorporating context that not only do human and robot factors matter, but when they matter most depends on task conditions. Figure 2 illustrates the conceptual model summarizing these hypotheses, including human ability, robot capacity, and their interactions affecting team performance, under the moderating influence of task complexity.

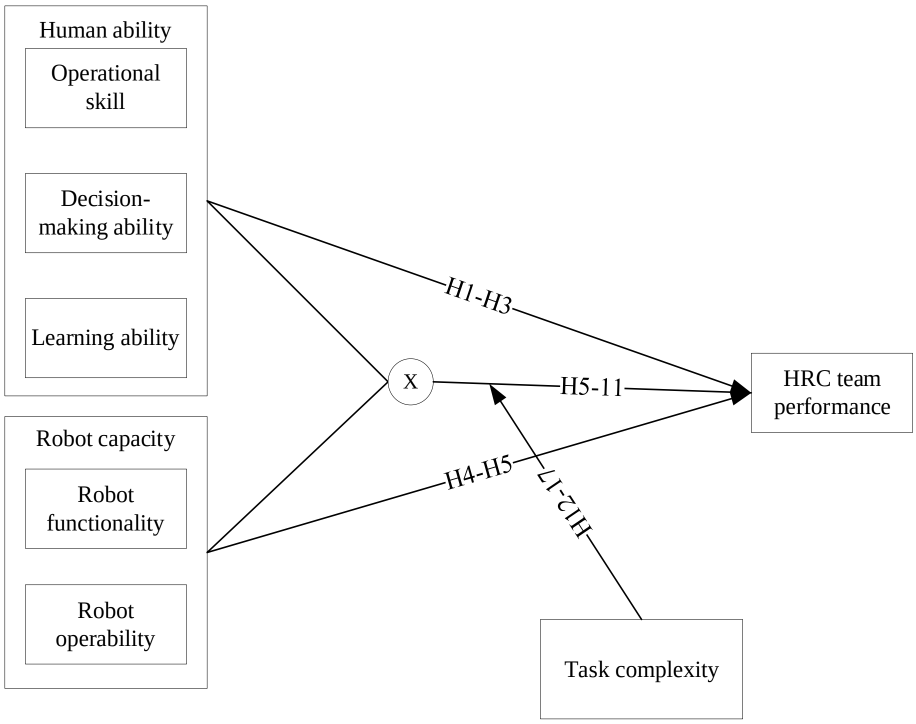

Figure 2. Conceptual Framework of HRC Team Performance.

4.4. Robot Technology Scope

Building on the design considerations in Section 4.3, the scope of robotic systems assessed is delineated to anchor subsequent measurement and analyses in authentic on-site collaboration contexts.

To ensure that construct measurement reflects real HRC on construction sites, the robot technology scope is defined as field-deployed systems used in shared or adjacent workspaces. The scope was specified a priori and applied consistently in participant screening and survey instructions for both the pilot and main studies. The included categories are:

(1) Interior wall finishing robots: systems for surface material application and preparation, including spraying/painting and plastering (mortar application, leveling, compacting, troweling), as well as automated putty sanding with force control and dust collection.

(2) Floor construction and finishing robots: systems for sub-base leveling and surface treatment, including concrete floor screeding/leveling (with elevation control), floor grinding/polishing (from rough to precision), and floor coating application (closed-loop delivery of primer/intermediate/top coats).

(3) Tiling and panel installation robots: systems that automate or assist placement tasks, including floor tile-laying (grabbing, adhesive application, placement, seam alignment) and wall/prefabricated panel positioning and installation.

(4) Inspection and surveying robots: systems for dimensional/quality inspection and site monitoring, including wheeled/quadruped platforms with integrated measurement modules and UAV-based progress/safety inspection with automated data capture and analysis.

The scope reflects two principles: (i) practice representativeness—prioritizing HRC system types widely used in current Chinese construction practice, thereby aligning measures of human capabilities (e.g., operational skill, decision-making, learning), robot characteristics (functionality, operability), and task complexity with actual site conditions; and (ii) policy alignment—mapping the scope to promotion lists of governments for robotics and intelligent construction [175–180], ensuring congruence with governmental priorities and facilitating interpretation.

5. Developing PLS-SEM Model

To empirically test the hypotheses, this paper designed a field study in the construction industry using a questionnaire-based survey and analyzed the data with PLS-SEM. This section describes the questionnaire sample, the survey procedure and instrument, and the data analysis approach.

5.1. Pilot Study and Pre-Survey Analysis

Prior to the main survey, a pilot study is conducted to verify item clarity and content validity, and to optimize items via item analysis and exploratory factor analysis (EFA). The pilot also examines potential common method bias and data-quality issues, thereby supporting robust measurement and structural modeling.

Pilot participants are frontline personnel recruited from 2 to 3 active construction projects. The sample size is 80. Data is collected through paper and online channels. Table 1 presents the demographic characteristics of the respondents. Respondents were predominantly male (88.75%). Age was concentrated in the 45–54 (36.25%) and 35–44 (31.25%) groups, indicating a middle-aged workforce. Educational attainment clustered around middle school (28.75%) and high school (27.50%), with 11.25% at primary or below and 15.00% at junior college and above. Occupationally, concrete workers (28.75%), interior decorators (25.00%), and rebar workers (22.50%) comprised the largest shares. Site experience focused on 2–5 years (38.75%) and 5–10 years (28.75%). Most participants worked on residential building sites (58.75%). Regionally, respondents were drawn primarily from West China (38.75%), followed by East China (32.50%) and Central China (28.75%).

Table 1. Demographic information of the respondents in the pilot study.

Variable	Category	Frequency	Percentage
Gender	Male	71	88.75%
	Female	9	11.25%
Age	18–24	2	2.50%
	25–34	21	26.25%
	35–44	25	31.25%
	45–54	29	36.25%
	≥55	3	3.75%
Education	Primary school or below	9	11.25%
	Middle school	23	28.75%
	Technical secondary school	14	17.50%
	High school	22	27.50%
	Junior college and above	12	15.00%
Role	Equipment operator	2	2.50%
	Concrete worker	23	28.75%
	Rebar worker	18	22.50%
	Form worker	4	5.00%
	Interior decorator	20	25.00%
	Other	13	16.25%
Years of experience on construction site	≤2	7	8.75%
	2–5	31	38.75%
	5–10	23	28.75%
	10–15	17	21.25%
	≥15	2	2.50%
Type of construction sites	Residential building	47	58.75%
	Public building	22	27.50%
	Office building	11	13.75%
Region	East China	26	32.50%
	Central China	23	28.75%
	West China	31	38.75%

Table 2 delineates the latent constructs, providing operational definitions aligned with the study's HRC context and explicit boundaries to safeguard discriminant validity. Each construct is defined by what it captures in practice and what it excludes to avoid conceptual spillover. Operational skill is defined as workers' procedural proficiency in setting up, operating, and supervising robots to minimize procedural errors and intervention time; it is restricted to routine technical handling and standardized procedures, explicitly excluding higher-order judgment and adaptive learning. Decision-making ability denotes timely, context-appropriate judgments under uncertainty and emphasizes appraisal and choice quality, while excluding routine operational fluency and longitudinal adaptation. Learning ability captures the rate and effectiveness of acquiring, updating, and transferring HRC-relevant knowledge and skills, focusing on adaptation speed rather than one-off execution or moment-to-moment judgment. Robot functionality reflects the robot's intrinsic performance envelope—accuracy, reliability, and sensing/actuation—distinct from robot operability, which concerns the ease, intuitiveness, and stability of human control, interface clarity, mode switching, and feedback. Task complexity indexes cognitive and coordination demands arising from task interdependence, uncertainty, time pressure, and required precision, independent of human capabilities or robotic specifications. Finally, HRC team performance is confined to joint outcomes—productivity, safety, coordination quality, and rework—rather than antecedent capacities or technological features. Consistent with these boundaries, items exhibiting salient cross-loadings that blurred construct demarcations were removed during the pilot, and the surviving indicators were renumbered accordingly.

Table 2. Preliminary measurement of constructs: operational definitions, item pool, and reliability.

Construct	Operational Definition	Boundaries	Label	Item	Cronbach's Alpha
Operational skill (OS)	Operators' procedural proficiency in setting up, operating, and supervising construction robots, minimizing procedural errors and intervention time during HRC.	Focuses on technical handling and standardized procedures; excludes broader decision judgment (DA) and learning pace (LA).	OS1	I understand how to operate and interact with robots in my work.	0.862
			OS2	I have the technical knowledge required to collaborate with robots.	
			OS3	I am capable of understanding the robot's instructions, signals, or outputs.	
			OS4	I make few or no mistakes when following standard procedures in using robots.	
			OS5	I usually need detailed step-by-step instructions to carry out robot operations.	
			OS6	I can complete tasks efficiently within the given time.	
Decision-making ability (DA)	Capability to make timely, context-appropriate judgments under uncertainty (e.g., override, re-plan, allocate work between human/robot).	Focuses on judgment under constraints; excludes procedural operation (OS) and learning adaptivity (LA).	DA1	I can make quick decisions within limited time.	
			DA2	I consider multiple possibilities before making a decision.	
			DA3	I can weigh pros and cons and make reasonable choices when facing complex problems.	
			DA4	I can make sound decisions even when information is incomplete.	
			DA5	I take responsibility for my decisions and adjust them when necessary.	
Learning ability (LA)	Adaptivity and learning pace in acquiring new HRC procedures and features, and updating mental models through experience.	Focuses on rate and depth of learning; distinct from robot ease-of-use (RO) and one-off skill snapshot (OS).	LA1	I improve my work practices based on my experiences collaborating with robots.	
			LA2	I think using the robot requires little mental effort.	
			LA3	I can quickly learn how to operate new robotic or automated systems introduced in construction projects.	
			LA4	I quickly learn new robot operations by observing coworkers' demonstrations.	
			LA5	I actively seek to understand the latest technologies and human–robot collaboration processes in construction.	
			LA6	Even without formal training, I can teach myself to use new robot features correctly.	
Robot functionality (RF)	Robot's technical performance envelope (autonomy, reliability, responsiveness, accuracy, consistency) to execute construction tasks and adapt sequences.	Focuses on what the robot can do; excludes UI/interaction usability (RO).	RF1	The robot can operate autonomously for complex tasks and adjust its task sequence without human intervention.	
			RF2	The robot's actions are predictable and transparent.	
			RF3	The robot responds quickly to commands or changes.	
			RF4	The robot maintains consistent performance across different tasks and conditions.	
			RF5	The robot accurately responds to my inputs or instructions in real-time.	
Robot Operability (RO)	Human-centered usability during collaboration: intuitive interface, controllability, smooth manual/auto switching, low effort to learn.	Focuses on how easily humans can direct the robot; distinct from capability breadth (RF).	RO1	The construction robot is easy for me to operate, even without specialized training.	
			RO2	The robot's interface is user-friendly and intuitive for construction tasks.	
			RO3	I can control and adjust the robot's behavior smoothly during collaboration.	
			RO4	It does not take much effort to learn how to work with the construction robot effectively.	
			RO5	I can switch between manual and automatic modes smoothly and confidently.	

Table 2. *Cont.*

Construct	Operational Definition	Boundaries	Label	Item	Cronbach's Alpha
Task complexity (TC)	TC captures the task's contextual difficulty and structure along cognitive demand, responsibility clarity, and critical impact. The higher TC means more challenging, less structured tasks that place greater demands on HRC.	Task difficulty; not an attitude or capability.	TC1	My tasks are complex and require high levels of analysis and decision-making.	
			TC2	My tasks involve high technical complexity (e.g., specialized tools, calibration, parameter tuning) that requires advanced expertise.	
			TC3	Task responsibilities are clearly allocated between human and robot.	
			TC4	My tasks require intensive coordination with other trades/teams and are highly interdependent across steps.	
			TC5	The tasks have a major impact on construction progress.	
			TC6	Site conditions (e.g., congestion, noise, dust, weather) frequently increase task difficulty or require on-the-fly adjustments.	
HRC Team Performance (HTP)	Multidimensional outcomes attributable to HRC on the task/project: productivity, safety, quality, flexibility, creativity.	Performance construct; not an antecedent.	HTP1	Our team achieves high productivity with the robot.	
			HTP2	Robot use contributes to a safe work environment.	
			HTP3	The quality of our outcomes has improved with the robot.	
			HTP4	The team is flexible when facing changes during tasks.	
			HTP5	The HRC brings creativity climate in the task completion.	

Additionally, the pilot reliability analysis indicated satisfactory internal consistency. In particular, operational skill achieved a Cronbach's α of 0.862 (Table 2), which exceeds conventional thresholds (0.70) [181] and evidences high internal consistency among its retained indicators. This supports the construct's measurement stability following the removal of cross-loading items.

Following the pilot reliability checks, a cross-loading analysis was conducted to assess item-level discriminant clarity (Table 3). Exploratory factor analysis with Varimax rotation yielded a largely simple structure. Items were retained when their primary loading was at least 0.60 and when the gap between the primary loading and the largest secondary loading was 0.20 or more. Consistent with these rules, several indicators displayed salient loadings on two or more factors and could not be cleanly assigned: OS5 within operational skill, DA4 within decision-making ability, LA4 and LA6 within learning ability, RO5 within robot operability, and TC2, TC4 and TC6 within task complexity. These cross-loading items were removed to safeguard convergent and discriminant validity. After their deletion, the remaining indicators showed clear primary loadings with materially reduced secondary loadings, producing an improved simple structure. Labels for the retained indicators were then renumbered for continuity (OS1–OS5; DA1–DA4; LA1–LA4; RO1–RO4; TC1–TC4), while constructs without deletions kept their original numbering.

5.2. Questionnaire Sampling

This paper employed a questionnaire survey to collect data for testing the theoretical model. The survey approach was chosen because it allows gathering perceptual and attitudinal data from a large sample of industry practitioners, which is suitable for the exploratory nature of this research and the use of PLS-SEM.

To ensure representativeness, a multi-stage sampling approach was adopted. At the first stage, the sampling was organized at the project level, with each active construction site treated as a separate unit. These projects were located in several provinces across China and involved contractors and subcontractors of different sizes, ensuring that the sample was not biased toward a single locality or firm. At the second stage, workers within each site were stratified by trade (e.g., equipment operators, rebar workers, concrete workers, form workers, interior decorators, and general labor). The number of respondents from each trade was kept in proportion to their actual presence on the site, so that the occupational structure of the sample reflected the real composition of the workforce. This stratification was specifically designed to reduce potential sampling bias by avoiding overrepresentation of any single trade. Eligibility criteria required respondents to be at least 18 years old, currently employed on-site, and to have had direct exposure to robots or robotic-assisted work. The final survey was conducted over a period of five months.

Table 3. Rotating component matrix.

Construct	Label	Component														
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Operational skill (OS)	OS1							0.803								
	OS2							0.856								
	OS3							0.749								
	OS4							0.762								
	OS5				0.852											
	OS6							0.835								
Decision-making ability (DA)	DA1			0.803												
	DA2			0.725												
	DA3			0.722												
	DA4											0.866				
	DA5			0.876												
Learning ability (LA)	LA1						0.766									
	LA2						0.839									
	LA3						0.841									
	LA4										0.849					
	LA5						0.863									
	LA6													0.819		
Robot functionality (RF)	RF1	0.900														
	RF2	0.773														
	RF3	0.861														
	RF4	0.870														
	RF5	0.795														
Robot Operability (RO)	RO1		0.857													
	RO2		0.791													
	RO3		0.786													
	RO4		0.876													
	RO5															0.753
Task complexity (TC)	TC1								0.843							
	TC2									0.869						
	TC3								0.770							
	TC4														0.879	
	TC5								0.777							
	TC6												0.739			
HRC Team Performance (HTP)	TP1					0.785										
	TP2					0.772										
	TP3					0.793										
	TP4					0.812										
	TP5					0.850										

Several measures were taken to minimize sampling bias. First, respondents were recruited from multiple sites operated by different contractors and located in different regions, reducing the likelihood of site-specific bias. Second, the stratified sampling ensured proportional representation of each trade relative to their actual distribution on site. Third, the combination of online and on-site distribution channels increased accessibility and reduced non-response bias. Finally, strict data cleaning procedures were applied: responses with missing values, straight-lining patterns, or duplication were carefully screened out.

To verify the clarity and contextual suitability of the instrument, a pilot test involving 80 frontline workers from three projects was conducted [182], because it was essential to ensure that construction workers could fully understand the questionnaire items and any issues arising during completion could provide useful input for refinement. Feedback from site stewards and workers was then incorporated to adjust phrasing, remove ambiguity, and align examples with site-specific terminology. To further reduce potential bias, the questionnaire was distributed through both online and on-site channels, enabling wider participation and minimizing non-response bias [183]. After data collection, rigorous quality checks were carried out: responses with missing data, straight-lining patterns, or duplication were carefully removed. The final survey was subsequently conducted over a five-month period across multiple active construction sites. After screening for missing responses, straight-lining, and duplication, a total of 548 valid questionnaires were retained for analysis, forming the basis of the dataset used in this study. The demographic profile of the respondents is presented in Table 4. The 548 valid respondents were exclusively frontline construction personnel. They represented a wide range of site roles, including equipment operators, concrete workers, rebar workers, form workers, interior decorators, and other supporting trades, with work experience ranging from less than two years to more than fifteen years. The demographic breakdown in Table 4 shows that the sample covers different age groups and education levels, thereby capturing the heterogeneity of China's construction workforce [184]. This profile indicates that the survey reflects the perspectives of the actual site workforce, rather than a narrow occupational or demographic segment.

Table 4. Demographic information of the respondents.

Variable	Category	Frequency	Percentage
Gender	Male	472	86.13%
	Female	76	13.87%
Age	18–24	24	4.38%
	25–34	119	21.72%
	35–44	145	26.46%
	45–54	217	39.60%
	≥55	43	7.85%
Education	Primary school or below	42	7.66%
	Middle school	209	38.14%
	Technical secondary school	73	13.32%
	High school	126	22.99%
	Junior college and above	98	17.88%
Role	Equipment operator	45	8.21%
	Concrete worker	108	19.71%
	Rebar worker	139	25.36%
	Form worker	73	13.32%
	Interior decorator	87	15.88%
	Other	96	17.52%
Years of experience on construction site	≤2	47	8.58%
	2–5	153	27.92%
	5–10	207	37.77%
	10–15	82	14.96%
	≥15	59	10.77%
Type of construction sites	Residential building	239	43.61%
	Public building	173	31.56%
	Office building	136	24.82%
Region	East China	178	32.48%
	Central China	203	37.04%
	West China	167	30.47%

5.3. Sample Demographics

Table 4 presents the demographic characteristics of the respondents. The sample is overwhelmingly male (86.13%), which is consistent with the gendered nature of the construction industry where men represent the dominant labor force. The sample's demographics mirror the construction industry's workforce, which is heavily male dominated in China, women constitute a low proportion of construction workers, typically at a level below 14% [185]. In terms of age, the majority of respondents are concentrated in the 35–44 age group (26.46%), followed by those aged 25–34 (21.72%), together comprising nearly half of the sample. This indicates that young and middle-aged adults remain the backbone of the construction workforce. Nevertheless, a considerable proportion of workers fall within the 45–54 age group (39.60%), suggesting a heavy trend of aging within the labor force.

Regarding educational attainment, the largest group of respondents hold a middle school education (38.14%), followed by high school (22.99%) and technical secondary school qualifications (13.32%), reflecting the generally modest educational background of construction workers and pointing to opportunities for improvement in workforce training and development.

Occupationally, rebar workers constitute the largest category (25.36%), followed by concrete workers (19.71%), form workers (13.32%), and interior decorators (15.88%). Equipment operators account for 8.21%, while other trades make up 17.52%, indicating that the survey encompasses a wide range of construction roles and thereby enhances the representativeness and generalizability of the findings. Moreover, the types of robots encountered in practice are closely aligned with the occupational roles of the respondents. For example, concrete and flooring workers typically engage with screeding, grinding, and coating robots; interior decorators and masonry workers often collaborate with spraying, plastering, and tile-laying robots; form and assembly workers mainly operate wall-panel installation robots; while surveyors and quality inspectors are more likely to interact with measurement robots, quality-inspection devices, and drones for safety and progress monitoring. This correspondence between roles and robot types reflects actual deployment patterns on Chinese construction sites and provides further contextual richness to the dataset.

In terms of years of experience, workers with 5–10 years of experience (37.77%) and those with 2–5 years (27.92%) together account for more than 60% of the sample, highlighting the relatively high mobility and turnover in the construction labor market. At the same time, the presence of a substantial minority with more than 15 years of experience (10.77%) reflects a core group of long-term skilled workers who contribute to the stability of the labor force.

For the type of construction sites, the largest share of respondents reported working on residential building projects (43.61%), followed by public building projects (31.56%) and office buildings (24.82%). This distribution mirrors the overall project landscape in China, where residential developments dominate but are complemented by substantial investment in public infrastructure and office construction. Regionally, the respondents were relatively evenly distributed, with 32.48% from East China, 37.04% from Central China, and 30.47% from West China, ensuring coverage of different parts of the country and further enhancing the representativeness of the dataset.

5.4. Survey Instrument

The study used a structured questionnaire with multi-item scales for each latent construct in the research model. All items were measured on five-point Likert scales (1 = "strongly disagree," 5 = "strongly agree"). Respondents indicated how much each statement described their HRC team or project. The scales drew on prior literature where possible and were supplemented with items tailored to HRC in construction. Table 1 summarizes the constructs and their items.

The first construct set concerns human workers. Operational skill was measured by five items that assess team members' ability to operate and interact with construction robots. These items capture technical knowledge and procedural proficiency; higher scores indicate greater skill in handling the robotic system. Decision-making ability was measured by four items that assess the capacity to make quick and sound choices under time pressure and complexity, reflecting evidence from human-factors research on managing HRI. Learning ability was measured by four items that capture how well workers acquire new skills, adapt to robot use, and seek HRC-related knowledge through experience. It is worth noting that LA2 ("I think using the robot requires little mental effort") may appear conceptually close to perceived ease of use [186]. However, in this study it was included under learning ability because it reflects the cognitive resources required for workers to acquire and internalize new robotic knowledge and skills. Whereas perceived ease of use captures the usability of the system itself, LA2 addresses the extent to which workers can adapt with minimal mental strain during the learning process. This distinction allows LA2 to complement LA1, LA3, and LA4 by capturing the cognitive dimension of learning ability.

The second set of constructs is about robots. The construct of robot functionality measured the robot's capabilities with five items. They address aspects such as the robot's autonomy, reliability, responsiveness, and accuracy in performing construction tasks. The robot operability was measured by four items to reflect the ease of use and interface quality of the robot. These items were derived from technology usability and tailored to collaborative robots. To further clarify the distinction between robot functionality and operability, their operationalization in this study was grounded in specific measurement items, supplemented by examples from construction practice. Robot functionality (RF) was assessed through five indicators (RF1–RF5) that capture the technical and performance-related capacities of robotic systems. These include the ability of robots to perform complex tasks autonomously and adapt task sequences without human intervention (RF1), the predictability and transparency of their actions (RF2), responsiveness to operator commands or environmental changes (RF3), consistent performance across diverse tasks and conditions (RF4), and the accuracy with which they respond to real-time inputs (RF5). For example, a concrete screeding robot that maintains uniform thickness across large floor areas while automatically adjusting to uneven surfaces would be considered high in functionality, as would a wall-panel installation robot that achieves precise alignment with minimal deviation under varying site conditions. Robot operability (RO), by contrast, emphasizes the human-centered aspects of robot use and was measured through four items (RO1–RO4). These items address whether robots can be operated without extensive specialized training (RO1), the user-friendliness and intuitiveness of their interfaces in construction tasks (RO2), the degree to which operators can smoothly control and adjust robot behavior during collaboration (RO3), and the overall effort required to learn and master robot operation (RO4). For instance, a spraying robot with a simple touch-screen interface that allows operators to easily adjust spray intensity and pattern would score highly on operability, even if its functional scope is limited. Conversely, a highly capable inspection robot may be rated lower on operability if its interface requires complex steps and extensive training before workers can effectively use it.

The third is task complexity. The task complexity used three items capturing the difficulty and structure of the tasks that HRT undertakes. Given the multi-faceted nature of construction tasks, this study measured complexity in terms of cognitive demand, clarity of task responsibilities, and the critical impact of the task. Higher task complexity indicates tasks are challenging and unstructured, which will intensify the need for strong HRC.

The last is HRC team performance. The construct of HRC team performance as the dependent variable, was operationalized through five items representing key performance dimensions in HRC identified from the literature [59]. The items covered productivity, safety, quality, flexibility, and team creativity. Respondents were asked to overall rate their agreement that the introduction of HRC had improved these aspects of performance on their task or project. All survey scale items are given in Table 5.

Table 5. Measurement scales and their evaluation.

Construct	Label	Item	Loading	Parameter
Operational skill (OS)	OS1	I understand how to operate and interact with robots in my work.	0.868 ***	Cronbach's α = 0.901 CR = 0.927 AVE = 0.717
	OS2	I have the technical knowledge required to collaborate with robots.	0.850 ***	
	OS3	I am capable of understanding the robot's instructions, signals, or outputs.	0.821 ***	
	OS4	I make few or no mistakes when following standard procedures in using robots.	0.870 ***	
	OS5	I can complete tasks efficiently within the given time.	0.823 ***	
Decision-making ability (DA)	DA1	I can make quick decisions within limited time.	0.895 ***	Cronbach's α = 0.888 CR = 0.922 AVE = 0.748
	DA2	I consider multiple possibilities before making a decision.	0.862 ***	
	DA3	I can weigh pros and cons and make reasonable choices when facing complex problems.	0.842 ***	
	DA4	I take responsibility for my decisions and adjust them when necessary.	0.858 ***	
Learning ability (LA)	LA1	I improve my work practices based on my experiences collaborating with robots.	0.873 ***	Cronbach's α = 0.870 CR = 0.911 AVE = 0.720
	LA2	I think using the robot requires little mental effort.	0.874 ***	
	LA3	I can quickly learn how to operate new robotic or automated systems introduced in construction projects.	0.815 ***	
	LA4	I actively seek to understand the latest technologies and human–robot collaboration processes in construction.	0.829 ***	
Robot functionality (RF)	RF1	The robot can operate autonomously for complex tasks and adjust its task sequence without human intervention.	0.874 ***	Cronbach's α = 0.905 CR = 0.929 AVE = 0.725
	RF2	The robot's actions are predictable and transparent.	0.872 ***	
	RF3	The robot responds quickly to commands or changes.	0.841 ***	
	RF4	The robot maintains consistent performance across different tasks and conditions.	0.844 ***	
	RF5	The robot accurately responds to my inputs or instructions in real-time.	0.823 ***	
Robot Operability (RO)	RO1	The construction robot is easy for me to operate, even without specialized training.	0.886 ***	Cronbach's α = 0.885 CR = 0.920 AVE = 0.743
	RO2	The robot's interface is user-friendly and intuitive for construction tasks.	0.870 ***	
	RO3	I can control and adjust the robot's behavior smoothly during collaboration.	0.850 ***	
	RO4	It does not take much effort to learn how to work with the construction robot effectively.	0.840 ***	
Task complexity (TC)	TC1	My tasks are complex and require high levels of analysis and decision-making.	0.874 ***	Cronbach's α = 0.816 CR = 0.889 AVE = 0.728
	TC2	Task responsibilities are clearly allocated between human and robot.	0.872 ***	
	TC3	The tasks have a major impact on construction progress.	0.841 ***	
HRC Team Performance (HTP)	HTP1	Our team achieves high productivity with the robot.	0.844 ***	Cronbach's α = 0.856 CR = 0.897 AVE = 0.634
	HTP2	Robot use contributes to a safe work environment.	0.823 ***	
	HTP3	The quality of our outcomes has improved with the robot.	0.886 ***	
	HTP4	The team is flexible when facing changes during tasks.	0.870 ***	
	HTP5	The HRC brings creativity climate in the task completion.	0.850 ***	

Note: *** $p < 0.01$; AVE = average variance extracted; and CR = composite reliability.

5.5. Data Analysis Techniques

The data analysis was conducted using PLS-SEM, which is particularly suitable for exploratory analysis in construction management because it can simultaneously estimate complex causal relationships among latent constructs while remaining robust with relatively small sample sizes and non-normal data distributions. The analysis followed the two-step approach of first assessing the measurement model and then evaluating the structural model.

For the measurement model, reliability was examined through factor loadings, Cronbach's α, and composite reliability (CR), while validity was assessed by the average variance extracted (AVE) and discriminant validity criteria. Indicator loadings above 0.70, Cronbach's α greater than 0.70, CR values greater than 0.70, and AVE values above 0.50 were considered satisfactory thresholds [101,181]. Discriminant validity was tested using the Heterotrait–Monotrait ratio of correlations (HTMT).

For the structural model, bootstrapping with 5000 resamples was applied to test the significance of the hypothesized paths. The model's explanatory power was assessed using R^2 and adjusted R^2, while multicollinearity was checked through variance inflation factors (VIFs). Interaction and moderation effects were tested by creating product indicators of human abilities and robot capacities, with task complexity specified as a moderator. The overall procedure was implemented using SmartPLS 4, which enables robust estimation and graphical visualization of path relationships.

This methodological approach ensured a rigorous evaluation of both the reliability and validity of the constructs, as well as a robust test of the hypothesized relationships, thereby providing a solid basis for interpreting the determinants of HRC team performance. Figure 3 presents the research model used for the analysis. In this model, operational skill, decision-making ability, and learning ability capture the human dimension of workers' capabilities, whereas robot functionality and robot operability represent the technical dimension of robotic systems. Task complexity is modeled as a factor that moderates the interaction between human and robot factors. Together, these constructs are hypothesized to influence HRC team performance, which is measured through five reflective indicators.

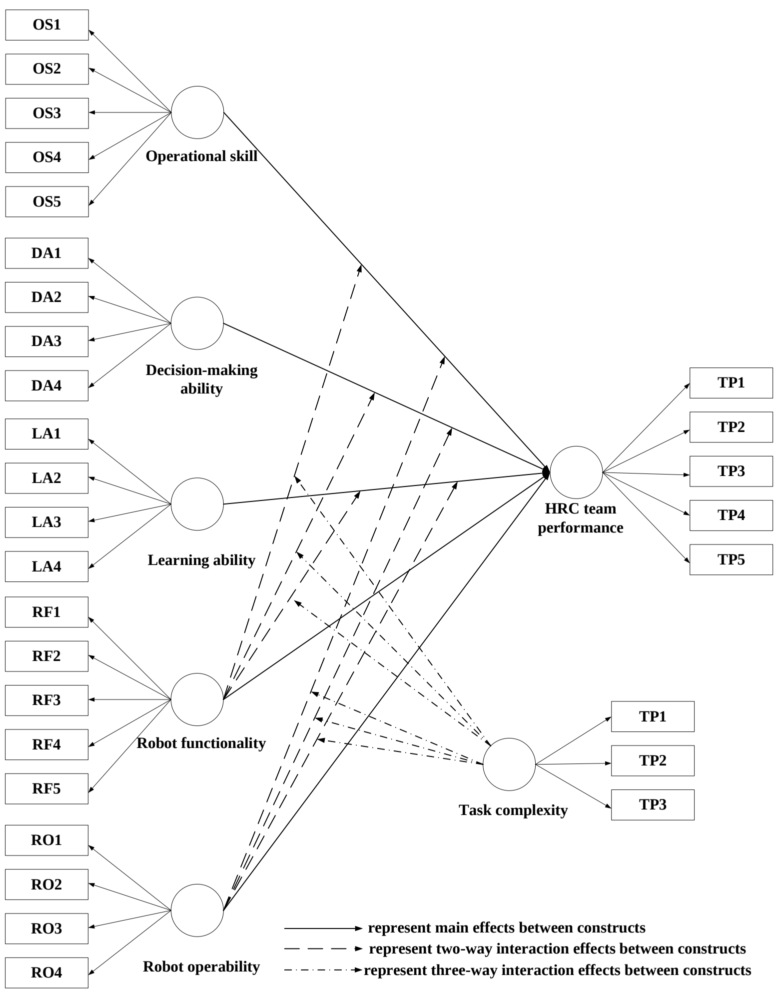

Figure 3. The PLS-SEM Model of HRC Team Performance.

6. Results

6.1. Reliability and Validity of Measures

Prior to testing the structural model, this paper assessed the reliability and validity of all measurement scales. Table 5 presents the indicator loadings and internal consistency metrics for each construct. All item loadings are well above the recommended 0.7 threshold and are highly significant ($p < 0.01$), demonstrating strong indicator reliability [187]. The CR values for all constructs range from 0.889 to 0.929 which are greater than 0.8, and the Cronbach's alpha is from 0.816 to 0.905, indicating the greater internal consistency for the constructs [181]. The AVE for each construct is well above 0.50 (0.634–0.743), confirming convergent validity [188]. Finally, to evaluate discriminant validity, the model computed the HTMT ratios between constructs [189]. All HTMT values fell below 0.85 (Table 6), confirming that each construct is empirically distinct from the others [189,190]. This provides strong evidence of discriminant validity.

Table 6. Heterotrait–Monotrait criterion of discriminant validity evaluation.

Variable	OS	DA	LA	RF	RO	TS	HTP
OS	1						
DA	0.337	1					
LA	0.344	0.348	1				
RF	0.311	0.237	0.28	1			
RO	0.234	0.28	0.219	0.396	1		
TS	0.209	0.151	0.149	0.195	0.177	1	
HTP	0.407	0.387	0.382	0.465	0.45	0.203	1

To address the potential for Common Method Bias (CMB) arising from the single-source data collection method, Harman's single-factor test was conducted [191,192]. All measurement items in the survey were subjected to an unrotated principal component analysis. The results showed that the first single factor accounted for 27.552% of the total variance (Table 7). As this value is well below the common threshold of 50%, it suggests that CMB is not a significant concern and is unlikely to have confounded the results of this study [191].

To check for potential multicollinearity, this study inspected both outer-model and inner-model VIFs [193]. Outer VIFs ranged from 1.000 to 2.794 across 47 observed indicators, and inner VIFs ranged from 1.307 to 1.824 across 23 structural relations. These values are well below conservative heuristics (VIF < 5.0, VIF < 3 as a stricter rule) [193], indicating that redundancy among predictors is limited and that variance inflation is unlikely to bias the estimates. Low inner VIFs suggest that the higher-order products do not introduce problematic dependencies with their constituent main effects.

For explanatory power, the endogenous construct HRC Team Performance attained $R^2 = 0.598$ (adjusted 0.582), which is commonly interpreted as moderate to substantial explanatory power for team-level performance in construction HRC settings. As Chin (1998) suggested, R^2 values of 0.67, 0.33, and 0.19 may be considered as substantial, moderate, and weak benchmarks, respectively [194]. The small difference between R^2 and Adjusted R^2 ($\Delta = 0.016$) shows that the model remains stable, and the included predictors provide substantial explanatory power rather than reflecting overfitting. The R^2 implies that the proposed model captures a sizeable share of real-world performance variability.

Together, these results indicate that the measurement model is both reliable and valid. The constructs capture unique aspects of HRC team dynamics with minimal overlap, justifying their use in subsequent structural analysis.

Table 7. Total Variance Explained for Harman's Single-Factor Test.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.265	27.552	27.552	8.265	27.552	27.552
2	2.967	9.891	37.443	2.967	9.891	37.443
3	2.428	8.095	45.537	2.428	8.095	45.537
4	2.171	7.235	52.773	2.171	7.235	52.773
5	2.025	6.752	59.524	2.025	6.752	59.524
6	1.948	6.493	66.018	1.948	6.493	66.018
7	1.740	5.798	71.816	1.740	5.798	71.816
8	0.570	1.899	73.715			
9	0.529	1.762	75.477			
10	0.518	1.728	77.205			
11	0.481	1.603	78.808			
12	0.474	1.579	80.387			
13	0.446	1.485	81.872			
14	0.414	1.381	83.253			
15	0.403	1.344	84.598			
16	0.398	1.325	85.923			
17	0.386	1.288	87.211			
18	0.364	1.212	88.423			
19	0.350	1.168	89.591			
20	0.346	1.152	90.743			
21	0.331	1.104	91.847			
22	0.322	1.073	92.921			
23	0.301	1.002	93.922			
24	0.297	0.991	94.913			
25	0.282	0.942	95.855			
26	0.269	0.897	96.752			
27	0.264	0.879	97.631			
28	0.247	0.824	98.455			
29	0.235	0.785	99.240			
30	0.228	0.760	100.000			

6.2. Structural Model and Hypothesis Testing

Having established measurement validity, the next step is to examine the structural model using PLS-SEM bootstrapping (5000 resamples). The model explains a substantial portion of variance in HRC team performance. The R square is 0.598, meaning about 59.8% of the variability in HRC team performance is accounted for by the five factors and their interactions. This indicates strong explanatory power for a behavioral model in a complex field setting. The standardized path coefficients and hypothesis testing results are summarized in Table 8.

The f^2 statistics were further examined to assess the relative influence of each construct on HRC team performance. According to Cohen's benchmarks (0.02 = small, 0.15 = medium, 0.35 = large), most of the predictors in this study produced small-to-medium effect sizes, with several reaching the medium range [195]. Among the human ability constructs, operational skill (f^2 = 0.161), decision-making ability (f^2 = 0.165), and learning ability (f^2 = 0.175) all achieved medium-level effects. Regarding robot-related factors, both robot functionality (f^2 = 0.155) and robot operability (f^2 = 0.181) also demonstrated medium effects, with robot operability emerging as the strongest contributor. For the interaction terms, the combinations of operational skill with robot functionality (f^2 = 0.111), operational skill with robot operability (f^2 = 0.126), and decision-making ability with robot functionality (f^2 = 0.107) yielded small-to-medium effects, while the interaction of decision-making ability with robot operability reached a medium effect (f^2 = 0.186). Similarly, learning ability interacting with robot functionality (f^2 = 0.129) and robot operability (f^2 = 0.148) were situated near the medium threshold. Regarding task complexity as a moderator, three interaction terms produced small-to-medium effect sizes: (OS × RF) × TC (f^2 = 0.110), (DA × RF) × TC (f^2 = 0.114), and (LA × RF) × TC (f^2 = 0.114). However, the interactions

(OS × RO) × TC (f^2 = 0.001), (DA × RO) × TC (f^2 = 0.001), and (LA × RO) × TC (f^2 = 0.008) were negligible, suggesting no meaningful effect.

Table 8. Model hypothesis verification results and path coefficients.

Hypothesis	Path (Effect)	β (Beta)	95% CI [LLCI, ULCI]	S.E.	f^2	T-Value	*p*-Value	Support or Not
H1	OS → HTP	0.147	[0.096, 0.208]	0.041	0.161	4.824	0.000	Yes
H2	DA → HTP	0.152	[0.101, 0.218]	0.029	0.165	5.285	0.000	Yes
H3	LA → HTP	0.182	[0.121, 0.240]	0.031	0.175	5.895	0.000	Yes
H4	RF → HTP	0.158	[0.095, 0.225]	0.033	0.155	4.785	0.000	Yes
H5	RO → HTP	0.199	[0.138, 0.262]	0.032	0.181	6.195	0.000	Yes
H6	OS × RF → HTP	0.081	[0.022, 0.142]	0.034	0.111	2.412	0.016	Yes
H7	OS × RO → HTP	0.122	[0.064, 0.183]	0.032	0.126	3.869	0.000	Yes
H8	DA × RF → HTP	0.06	[0.011, 0.122]	0.028	0.107	2.139	0.032	Yes
H9	DA × RO → HTP	0.203	[0.143, 0.265]	0.031	0.186	6.58	0.000	Yes
H10	LA × RF → HTP	0.134	[0.075, 0.194]	0.033	0.129	4.08	0.000	Yes
H11	LA × RO → HTP	0.163	[0.101, 0.229]	0.033	0.148	4.966	0.000	Yes
H12	(OS × RF) × TC → HTP	0.089	[0.028, 0.153]	0.035	0.110	2.563	0.010	Yes
H13	(OS × RO) × TC → HTP	0.059	[−0.008, 0.128]	0.034	0.001	1.751	0.080	No
H14	(DA × RF) × TC → HTP	0.071	[0.012, 0.138]	0.027	0.114	2.36	0.018	Yes
H15	(DA × RO) × TC → HTP	−0.010	[−0.070, 0.053]	0.033	0.001	0.304	0.761	No
H16	(LA × RF) × TC → HTP	0.094	[0.031, 0.158]	0.036	0.114	2.628	0.009	Yes
H17	(LA × RO) × TC → HTP	−0.069	[−0.145, 0.010]	0.037	0.008	1.849	0.064	No

Note: Path coefficients (β), 95% confidence intervals (CI), *p*-values, and effect sizes (f^2) are reported for all hypothesized relationships. The 95% CI was derived from 5000 bootstrap resamples and is presented as the lower limit (LLCI) and upper limit (ULCI). According to Cohen's (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively [195].

The 95% confidence intervals (CIs) for all hypothesized relationships are obtained through a non-parametric bootstrapping procedure with 5000 resamples and are reported in Table 8. Each interval is reported with its lower limit (LL) and upper limit (UL), offering a range within which the true parameter value is expected to fall with 95% confidence.

6.2.1. Main Effects

All five critical factors have significant positive effects on HRC team performance, supporting H1–H5. RO exhibits the strongest direct influence (β = 0.199, T = 6.195, $p < 0.001$), underscoring that an easy-to-operate and user-friendly robot substantially elevates team performance. LA is the next strongest predictor (β = 0.182, T = 5.895, $p < 0.001$); teams with members who quickly learn and adapt to new robotic systems see markedly better performance. RF (β = 0.158, $p < 0.001$), DA (β = 0.152, $p < 0.001$), and OS (β = 0.147, $p < 0.001$) also all positively influence performance at the 0.1% significance level. These results confirm that both human-related and robot-related capabilities contribute significantly and roughly comparably to HRC team success.

6.2.2. Two-Way Interaction Effects

All six hypothesized two-way interactions between human and robot factors are positive and statistically significant, providing strong support for H6–H11. This confirms the presence of collaboration effects in HRC teams. The performance impact of any human factor is magnified when paired with a high level of a complementary robot factor, and vice versa. Table 8 shows that the interaction of DA and RO (H9) is particularly large (β = 0.203, T = 6.580, $p < 0.001$), which is the highest of all interaction terms. This indicates that teams with strong decision-making skills performed disproportionately better when robots were highly operable, suggesting that intuitive design and ease of use magnify the value of human cognitive capabilities. Similarly, the interaction between LA and RO (H11) was also large and significant (β = 0.163, T = 4.966, $p < 0.001$), showing that adaptive learners capitalized more effectively on user-friendly robotic systems. OS interacted positively with

RO as well (H7: $\beta = 0.122$, $T = 3.869$, $p < 0.001$), confirming that skilled operators could better leverage robots when interfaces were straightforward and transparent.

The interactions with RF were also significant, though slightly weaker in magnitude. The interaction of OS and RF (H6), DA and RF (H8), and LA and RF (H10) yields a positive and significant coefficient, respectively (H6: $\beta = 0.081$, $T = 2.412$, $p = 0.016$; H8: $\beta = 0.060$, $T = 2.139$, $p = 0.032$; H10: $\beta = 0.134$, $T = 4.080$, $p < 0.001$). These findings indicate that advanced robot functionalities amplify the benefits of human abilities, but the moderating effect of robot operability appears stronger than that of robot functionality. Taken together, the two-way interaction results demonstrate that the effectiveness of human factors is conditional upon the quality of robot design. High levels of both human and robot capabilities jointly produce superior performance outcomes, validating the principle of socio-technical synergy in HRC.

6.2.3. Three-Way Interaction Effects

Task complexity (TC) was hypothesized to further moderate the two-way interactions between human abilities and robot capacities (H12–H17). Results show that three hypotheses were supported: H12, H14, and H16, all involving robot functionality.

For the interaction of OS and RF, the three-way interaction with TC (H12) was significant ($\beta = 0.089$, $T = 2.563$, $p = 0.010$). This indicates that under complex tasks, the joint influence of operator skill and robot functionality on performance became markedly stronger. In simple tasks, either high skill or strong functionality alone might be sufficient, but under high complexity, superior outcomes depended on both factors being simultaneously high. Similarly, DA and RF interacted positively with TC (H14: $\beta = 0.071$, $T = 2.360$, $p = 0.018$), suggesting that in demanding environments, advanced robot functions amplified the benefits of human cognitive skills, enabling teams to make more effective decisions under uncertainty. LA and RF also showed significant moderation by TC (H16: $\beta = 0.094$, $T = 2.628$, $p = 0.009$), confirming that adaptive learners working with advanced robots achieved the greatest performance improvements in highly complex scenarios.

By contrast, the three-way interactions involving RO—H13 (OS $\times$ RO $\times$ TC), H15 (DA $\times$ RO $\times$ TC), and H17 (LA $\times$ RO $\times$ TC)—were not statistically significant. Although RO consistently enhanced performance, its effects did not vary meaningfully across levels of task complexity. This suggests that user-friendly design benefits HRC teams across both simple and complex contexts, without being conditional upon the difficulty of the task.

Although the three-way interactions involving RO (H13, H15, and H17) were not statistically significant, this result can be explained by both theoretical and practical considerations. On the one hand, from the perspective of HRI theory, operability functions as a universal enabler that consistently reduces cognitive load and facilitates ease of use [196]. Its positive effect is therefore relatively independent of task difficulty, offering performance advantages under both simple and complex tasks [197]. Unlike robot functionality, which provides additional technical support that becomes particularly valuable in highly demanding contexts, operability delivers a stable benefit that does not rely on the level of complexity to manifest [198]. On the other hand, in practical construction scenarios, robot interfaces are typically designed to comply with standardized usability principles, ensuring that a baseline of user-friendliness is present across tasks of varying difficulty [159]. As a result, workers perceive the advantages of operability as constant, rather than conditional upon task complexity. Under high-complexity tasks, attention shifts to whether the robot can provide advanced functions—such as precise sensing, autonomous adjustment, or decision support—rather than whether it is easy to operate [117]. Consequently, robot operability maintains its positive role across contexts but does not exhibit an amplified interaction effect under complex tasks, which explains why its three-way moderation was not supported by the data.

The three-way interaction results therefore demonstrate that task complexity selectively intensifies the performance benefits of HRC, particularly when advanced robot functionalities are combined with strong human abilities. These findings highlight that the challenge of the task determines the extent to which combined human and technological strengths become indispensable.

6.2.4. Summary of Hypothesis Testing

All direct effects (H1–H5) and all two-way interaction effects (H6–H11)—11 hypotheses in total—are supported at $p < 0.05$, confirming that both human and robot factors exert significant influences on HRC team performance. Among the three-way interactions (H12–H17), three hypotheses (H12, H14, H16) are significant, while three (H13, H15, H17) are not supported. In total, 14 hypotheses are supported and 3 are rejected.

The structural model result demonstrates that both human and robot factors exert significant and complementary influences on HRC team performance. All main effects were strongly supported, confirming that operational skill, decision-making ability, learning ability, robot functionality, and robot operability are indispensable performance drivers. Moreover, the significant two-way interactions highlight the principle of socio-technical synergy, whereby human abilities and robot capacities reinforce each other. The moderating role of task complexity further reveals that advanced robot functionalities amplify human strengths particularly under demanding conditions, whereas operability provides a stable advantage across all contexts which is not statistically significant.

6.3. Interpretation of Interaction Effects

Based on the TPC and TTF, the reported interactions are not only statistical implications but expressions of the socio-technical coupling that governs HRC performance. Human abilities (OS, DA, and LA) determine utilization capacity (can people harness the technology), whereas robot capacities bifurcate into what the system can do (RF) and how easily humans can do it (RO). Performance emerges when utilization capacity meets a sufficient technical ceiling and when the task affords a good fit. The significance of all two-way interactions and their selective strengthening by task complexity (TC) directly reflect the logic of TPC and TTF. In both frameworks, higher capability on one side increases the marginal value of capability on the other. Across models of main effects, operational skill (OS), decision-making ability (DA), and learning ability (LA) display significant positive associations with team performance, as do robot functionality (RF) and robot operability (RO). Conceptually, human abilities determine utilization capacity—skilled execution, sound judgment under uncertainty, and rapid learning. RF sets the technical ceiling for what the system can sense, plan, and execute. RO governs translation efficiency at the human–robot interface. The positive main effects therefore indicate that both capacity and translation are binding elements of performance in HRC.

Given that task complexity (TC) operates as a contextual moderator throughout, the interpretations below explicitly articulate both the two-way interaction mechanisms and their TC-dependent amplification patterns.

(1) Interactions among OS, RF and TC

The positive interaction between OS and RF indicates technological complementarity rather than simple additivity. OS reduces intervention time and stabilizes exception handling. RF expands the feasible action set by providing reliable perception, adequate planning, and autonomy. When both dimensions are strong, skilled adjustments and timely overrides yield real performance gains because the robot can accurately execute the refinements detected by the operator. When functionality is limited or unstable, a substantial portion of operational skill is diverted to recovery activities for robots, and the marginal return to additional skill diminishes.

TC primarily amplifies the interaction through RF. As interdependence, uncertainty, and tolerance sensitivity increase, a larger share of the performance frontier is gated by what the robot can reliably perceive and execute. High OS then unlocks this frontier by selecting and timing functional features, for example, adaptive elevation control in floor screeding, and micro-pose correction during façade alignment.

From a managerial standpoint, high-skill workers should be matched with platforms that offer dependable autonomy and precise actuation to realize additive benefits. Training should expose skilled operators to advanced functional modules, such as position control in installation. Monitoring should include indicators such as override accuracy and stability under disturbance, which together reveal whether operational skill is being translated into realized output rather than dissipated by functional limitations.

(2) Interactions among DA, RF and TC

DA increases the value of RF by converting richer state information and autonomy affordances into superior action sequences. When sensing and autonomy are reliable, DA-strong operators can reprioritize tasks, re-sequence workflows, and time human–robot handovers to reduce blocking and rework. In such settings, DA does not merely select among fixed options; it leverages a broader and more informative state space to coordinate exception handling and align RF with upstream and downstream interdependencies.

The marginal return to DA is limited when RF is weak or unstable. Perception latency, false positives, and restricted planning depth constrain feasible branches so that even correct judgments have limited leverage. TC operates as a moderator. In high-TC environments with variable tolerances, frequent exceptions, and interdependent trades, stronger RF creates an expanded and more informative state space in which DA can operate, making the complementary salient. In low-TC routines with narrow variability, the incremental value of DA beyond standardized procedures diminishes once RF satisfies basic requirements.

(3) Interactions among LA, RF and TC

LA and RF interact through the progressive development of dynamic capability. As HRC teams internalize calibration routines, advanced modes, and failure signatures, they gain access to deeper portions of the capability envelope. For example, during floor screeding and surface finishing, the controller adapts force, speed, and tool height to local variations in concrete levelness and stiffness. High RF provides learnable affordances that justify cognitive investment, and the richer and more stable these affordances, the steeper the learning curve.

When RF is low, LA is underutilized. TC strengthens this interaction because complex tasks present more distinct situations from which to generalize, allowing workers with strong LA to extract reusable patterns from RF and to shorten the progression from basic proficiency to advanced exploitation. In highly standardized low-TC tasks, the returns to LA decline once essential routines have been mastered, regardless of RF depth.

For implementation, training should be sequenced to mirror the capability gradient. Stable core functions should be mastered first, followed by staged exposure to advanced RF modules with explicit maps from practice to feature and from feature to measurable benefit. Leading indicators include time to proficiency and the share of advanced-mode usage. Workers with strong LA should be redeployed to stations where RF depth is underexploited.

(4) Interactions among OS, RO and TC

OS converts RO into throughput and conformance by reducing losses in the translation from human intent to robot action. High RO, characterized by predictable state transitions and informative feedback, can compress cognitive overhead and lower error incidence. OS-strong operators consequently execute more cycles with fewer deviations.

The interaction exhibits recognizable boundaries. When RO is already very high, the additional benefit of incremental OS on routine tasks is smaller because the interface standardizes execution and limits variance. When RO is poor, OS must be diverted to state interpretation and recovery, which dilutes productive expression. The amplifying role of TC is generally weaker than in the interactions between human abilities and RF. Once RO crosses a basic usability threshold, the gains from reducing friction tend to be robust across TC levels.

In practice, the interface and workflow should make it easy for operators to express OS when time is tight. For example, RO ought to signal the current mode in a way that is immediately legible at a glance and at a distance, and the transition into a new mode should show a short preview of the expected tool motion so that the operator can cancel before actuation if it is not what was intended. Control mappings should remain stable across software updates so that the same hand motion or button sequence always produces the same robot response during screeding and façade alignment; if a change is unavoidable, the system should provide an on-screen reminder and a brief guided rehearsal before the shift starts.

(5) Interactions among DA, RO and TC

DA translates into action only if RO enables decisions to be enacted quickly and correctly. High RO provides clear feedback, responsive controls, and intuitive interruptibility, allowing operators to implement contingency plans in real time. When RO is poor, however, even accurate decisions may be delayed or executed incorrectly, leading to cumulative errors in high-TC environments. The moderating role of TC is threshold-like. In complex settings, the penalty for inadequate RO rises sharply, but once a basic level of usability is achieved, further refinements in RO add less value than comparable improvements in RF or human abilities. This aligns with empirical evidence that TC amplifies interactions between human and RF more strongly than human and RO.

From an implementation standpoint, the focus should be on decision throughput. Three intervals matter: the time from a system signal to comprehension by the operator, the time from a decision to the issuing of a command, and the time from command to confirmation of execution. If these intervals become consistently long under high-TC conditions, the priority should be redesigning the interface before adding more complex decision-support functions.

(6) Interactions among LA, RO and TC

LA benefits from RO because usable systems reduce the cognitive cost of learning and stabilize the mapping between action and feedback. When RO is consistent, operators can more easily form mental models, transfer knowledge within teams, and institutionalize best practices. In this sense, RO acts as a catalyst: it accelerates learning and knowledge diffusion rather than directly increasing capability.

The interaction is strongest when RO remains stable across software versions and hardware models, so that learned procedures can be generalized. If RO changes frequently or inconsistently, LA is forced to be reinvested in re-learning interfaces, which slows overall mastery and reduces the spread of expertise. The influence of TC is indirect. Higher complexity provides more contexts in which learned routines can be applied, but without stable RO these benefits are fragile.

Managerially, standardizing RO patterns is a priority. Consistency across systems allows LA to scale, while in-interface support such as guided modes and contextual tips accelerates individual learning. Peer-to-peer knowledge sharing can then consolidate lessons into team routines. Success can be assessed through reduced recovery times without supervision, and faster convergence of teams on revised procedures.

The interpretation analysis shows that all hypothesized interactions between human abilities (OS, DA, LA) and robot capacities (RF, RO) are significant, and their strength is contingent on TC. OS, DA, and LA consistently improve performance, but their returns depend on whether RF provides a sufficient technical ceiling and whether RO offers a reliable execution channel. Interactions with RF are strongly amplified under high TC, because complex tasks increase the need for sensing, planning, and precise actuation; interactions with RO exhibit a threshold pattern, where benefits rise sharply once a usability baseline is reached but diminish thereafter.

In practice, this means that high-OS, DA, and LA workers deliver the greatest gains when paired with robots that have strong RF, especially in high-TC contexts such as precise screeding, façade alignment, and exception handling. RO plays a critical role in ensuring that human potential is not lost in translation, but its value is realized mainly through crossing a usability threshold that enables consistent, rapid, and error-free interaction. Together, these findings confirm the TPC and TTF perspective that performance emerges not from isolated human or robot capacities, but from their complementarity under contextual constraints.

7. Discussion

This study sets out to clarify the interaction of human abilities, robot characteristics, and task context in shaping HRC team performance. This discussion first situates the findings within existing research on HRC and socio-technical systems to identify where they confirm, extend, or challenge prior studies; it then elaborates on their theoretical implications for understanding HRC team performance, and finally addresses their practical significance for managers and project teams in construction.

7.1. Positioning the Findings Within HRC and Socio-Technical Literature

The present results can be situated within and across prior research on HRC and socio-technical systems. First, the simultaneous positive effects of human abilities (operational skill, decision-making, learning) and robot capacities (functionality, operability) corroborate the socio-technical premise that performance emerges from the joint optimization of humans and technology rather than from either in isolation [199]. This pattern also aligns with TPC and TTF logics, which posit that realized performance depends on both effective utilization by users and sufficient technological capability to meet task demands [118,120]. The coefficients observed for the five main effects thus empirically reinforce arguments in HRC and construction management that call for balanced investment in skills and technology.

Second, the study extends HRC team performance in construction by quantifying human and robot complementarities (H6–H11). Prior work has conceptually asserted that usability and interface quality enable human expertise to manifest, or that advanced robot capabilities strengthen human abilities [12,200,201]. The results generalize these notions with collected data that operability consistently amplifies the effects of decision-making, learning, and operational skill (with the decision-making and operability being the largest interaction), while functionality likewise strengthens all three human abilities. This provides multi-construct and team-level support for the proposition that the whole is greater than the sum of its parts in HRC.

Third, moderation by task complexity offers a differentiated picture that both confirms and refines prior theory on complexity, cognitive load, and automation support. Consistent with complexity and workload research [24,92,171], the three significant three-way interactions (H12, H14, H16) show that complex tasks selectively intensify the need for advanced robot functionality to complement strong human abilities. This extends existing HRC literature in construction, where complexity is often acknowledged but rarely modeled as a conditional amplifier of human–robot synergies [60]. At the same time, the non-significant three-way terms involving operability (H13, H15, H17) nuance common HRI expectations that usability matters more as cognitive demands rise [196,197]. The results suggest that operability functions as a universal enabler whose benefits are relatively stable across complexity levels, whereas functionality operates as a selective amplifier whose marginal value increases with complexity. This apparent contradiction with some laboratory findings may reflect domain and setting differences: (i) baseline compliance with usability guidelines in construction robots can make operability effects saturate across contexts, meaning that once a robot meets basic usability standards, further improvements in operability may not lead to substantial increases in performance [130,131,133]; and (ii) in complex field tasks, teams prioritize whether the robot can do more (like autonomy) over how easy it is to operate, shifting the binding constraint from usability to capability [128,129].

Collectively, these confirmations, extensions, and qualified contradictions advance the socio-technical account of HRC in construction. The field evidence specifies when robot functionality becomes decisive under high complexity, how robot operability universally enables human strengths, and why balanced investment in humans and technology is necessary to unlock performance.

7.2. Theoretical Implications

Taken together, the findings advance theory by highlighting three major implications regarding how human abilities, robot characteristics, and task complexity jointly shape HRC team performance.

First, the results empirically demonstrate that multi-dimensional human and robot factors simultaneously drive HRC team performance. Previous research on construction robotics often focused on either human factors (e.g., trust or workload) or technological features in isolation [100,110,114,202]. By integrating three core human abilities with two key robot attributes in one model, this study provides a holistic framework that explains about 60% of performance variance. The coefficients of direct effects of human abilities and robot capacities are from 0.15 to 0.2, suggesting that human factors and robot factors are of roughly equal importance in HRC. This provides empirical weight to conceptual arguments that successful HRT require both advanced technology and skilled workers.

Second, the strong support for all hypothesized two-way interactions contributes evidence of synergy in HRC. The quantitative validation that human and robot capabilities can jointly optimize the whole performance has been scarce in construction contexts [7,122]. The combined effect exceeds the sum of parts: a capable robot yields limited benefit without skilled operators, and skilled operators cannot fully offset a deficient robot. This extends the TPC logic to HRC teams: technology delivers maximum performance only when users can and will use it, and when its capabilities fit the task [118]. In the results, robot operability emerged as an especially effective moderator–a finding that aligns with human–computer interaction theory, which stresses that usability and interface design critically shape team performance [101,203,204]. In practice, easy-to-learn and controllable robots allow human expertise to surface; poor interfaces can bottleneck performance regardless of talent.

Third, the study examines three-way interactions with task complexity, a project attribute often overlooked in robotics research. Task complexity acts as a conditional amplifier for certain human–robot synergies. Under complex and unpredictable tasks (high TC), performance depends more on the joint presence of strong human abilities and high robot functionality. In other words, the payoff of any single factor is highest when complemented by strength in the other. This aligns with research on cognitive load and adaptive performance: in complex work, humans benefit more from decision support, automation, and advanced robot functions than in simpler tasks [196,205]. In high-complexity tasks, when robots provide advanced functionalities, they help reduce this cognitive load, allowing humans to focus on higher-level aspects of the task and robots can enhance the team's overall performance through adaptive strategies. In contrast, task complexity did not similarly amplify interactions involving robot operability, possibly because a baseline of good operability is required regardless of task complexity, and its effect tends to saturate. This suggests that, beyond a certain complexity threshold, functional capabilities (what the robot can do) are more important than operability (how easy the robot is to use), as even intuitive robots possess sufficient capabilities to handle the task's inherent difficulty.

7.3. Practical Implications for Construction Management and Robotics Implementation

The findings from this study provide several important insights for both construction management and the implementation of robotics in the industry.

7.3.1. Implications of Significant Interactions for Managers and Project Teams

The results provide several important implications for managers and project teams in construction.

First, the positive effects of operational skill, decision-making ability, learning ability, robot functionality, and robot operability confirm that both human competence and robot design independently enhance collaboration outcomes. For managers, this highlights the dual responsibility of investing in both workers and robotic technology. Training that enhances workers' technical, cognitive, and adaptive skills directly improves collaboration outcomes, while selecting robots with reliable functions and intuitive operability creates conditions for these abilities to translate into higher productivity and safety. For project teams, this means that continuous upskilling and familiarization with robotic systems is not optional but essential, as both human competence and robot design independently drive performance.

Second, the analysis shows that human abilities and robot capacities interact with each other when combined, underscoring the importance of aligning workforce skills with appropriate robotic features. For managers, this finding emphasizes that the benefits of workforce training are magnified only when paired with well-designed robots, and vice versa. Specifically:

Operational skill × robot functionality (H6): Skilled operators achieve disproportionate performance gains when robots are equipped with advanced technical functions. Managers should allocate their most experienced workers to tasks that involve technically demanding robots, while teams should recognize that skill–technology alignment is key to extracting value from high-end machines.

Operational skill × robot operability (H7): Even skilled operators perform better when interfaces are intuitive. This underscores the importance of user-friendly controls as a prerequisite for realizing human expertise.

Decision-making ability × robot functionality (H8): Strong decision-makers make more effective use of advanced robot functions, particularly when real-time adjustments are needed. Managers should therefore deploy cognitively strong workers alongside high-functionality robots in dynamic tasks.

Decision-making ability × robot operability (H9): The largest interaction effect observed indicates that intuitive interfaces substantially amplify the value of human judgment. Managers should prioritize operability in procurement, as poor usability can waste even the best human cognitive resources.

Learning ability × robot functionality (H10): Workers with high adaptive learning ability are better positioned to unlock the advanced functions of robots, suggesting that pairing adaptive learners with functional robots accelerates technology assimilation.

Learning ability × robot operability (H11): Adaptive learners benefit disproportionately from user-friendly robots, allowing teams to shorten learning curves and diffuse knowledge quickly across members.

Third, the moderating role of task complexity reveals that complex and uncertain tasks amplify the importance of combining strong human abilities with advanced robot functionality. Specifically:

Operational skill × functionality × task complexity (H12): Under complex tasks, superior outcomes occur only when skilled operators work with highly functional robots. Managers should reserve such pairings for high-risk or technically challenging activities, while project teams should align skill allocation with task criticality.

Decision-making ability × functionality × task complexity (H14): Decision-making capacity becomes more valuable when robots offer advanced functions in complex contexts. Managers can improve project outcomes by matching cognitively strong workers with advanced robots in uncertain or rapidly changing tasks.

Learning ability × functionality × task complexity (H16): Adaptive learners achieve the highest gains from advanced robots in complex tasks, highlighting that continuous training and exposure to functional systems prepare teams for demanding project environments.

By contrast, interactions involving robot operability (H13, H15, H17) were not moderated by task complexity, meaning that usability provides consistent benefits across both simple and complex tasks. For managers, this suggests that ensuring baseline operability is a universal requirement, independent of task difficulty. For project teams, it implies that ease of use reduces cognitive load and facilitates adoption in all contexts, but its value does not grow further in more complex situations.

Taken together, these results demonstrate that managers should view human abilities and robot capacities as interdependent levers. Project teams can use the interaction patterns as a roadmap for task allocation: pairs of high skill and high functionality for complex and critical work, adaptive learners with user-friendly robots for rapid diffusion, and consistent emphasis on operability as a universal enabler.

7.3.2. Investment in Both Human Abilities and Robot Capabilities

Maximizing HRC performance requires investment in both human capital and robotic technology. Training that builds operational skill, decision-making, and learning capacity has a direct positive effect on team outcomes. Paired with advanced robots, these human improvements produce multiplicative gains. Robotics adoption should not be treated as an equipment purchase. It must be accompanied by workforce development to ensure effective integration and use. Investments in highly functional robots—autonomy, sensing, and other advanced capabilities—are justified only when users are trained to operate them well, often requiring higher skill levels. The study finds that introducing a highly operable robot raises performance by about 0.4 units for high-skill teams but only 0.1 units for low-skill teams, a threefold difference. This indicates that returns on robotic technology depend on the readiness and competence of human workers. Consequently, firms should assess team skill levels before and during robot integration and align technology choices with worker capabilities.

In practice, construction companies can implement these training programs through the following steps:

(1) Develop Customized Training Programs

Design customized training courses based on specific tasks and the robots being used. For example, on construction sites, different levels of training should be designed according to the type of tasks the operators are collaborating with robots on. Basic training should focus on improving operational skills to ensure workers can efficiently operate robots for tasks like material handling or repetitive tasks. More advanced training should emphasize improving decision-making abilities and problem-solving, especially in complex environments where operators need to make rapid decisions to adjust the robots' working modes.

(2) Combine Simulation Training with On-Site Practice

Enhance workers' abilities to handle actual tasks by combining simulation environments and on-site operations. Simulation training can be performed using Virtual Reality (VR) or Augmented Reality (AR) technologies, where workers can practice complex construction tasks and interact with robots in a virtual environment to familiarize themselves with the operations and task allocation. These skills can then be transferred to on-site practical training, ensuring workers can effectively use robots in real-world conditions.

(3) Regular Assessment and Continuous Learning

Training should not be a one-time investment. With the rapid advancement of robot technologies, construction companies should establish an ongoing assessment and feedback mechanism. For example, the operators' abilities can be periodically tested to assess their performance in collaboration with robots, and training content should be adjusted based on these assessments. This approach ensures that workers are always prepared to handle the evolving technological landscape and can improve their work efficiency and decision-making capabilities.

By implementing these steps, companies can not only improve workers' operational efficiency when working with robots but also ensure that highly skilled workers can fully exploit the advanced functionalities of robots, thereby maximizing the return on investment in robotic technology.

7.3.3. Prioritization of Robot Operability

Among the robot-related factors, operability has proven to be the most critical. The study's findings emphasize that while robots with high functionality are essential, their ability to enhance team performance is greatly dependent on how easily human operators can control and interact with them. Robots that are highly functional but difficult to operate often fail to deliver the expected results. This is because the complexity of using such robots increases the cognitive load on operators, making collaboration less efficient and more errors. In contrast, robots that are user-friendly, even if their functionalities are somewhat limited, tend to produce better outcomes because they reduce the burden on human operators and facilitate smoother interaction.

The importance of operability goes beyond simple ease of use. It is a key factor in enabling high levels of collaboration between human workers and robots. The design of robots should prioritize intuitive interfaces, clear communication, and easily adjustable controls, all of which contribute to reducing the learning curve and fostering trust between humans and robots. In practice, companies should focus on selecting robots that are easy to operate, particularly during the initial stages of deployment. This approach ensures that workers can quickly adapt to the technology and incorporate it into their daily tasks. Over time, as operators become more familiar with the system and build greater confidence, the robot's functionality can be gradually expanded.

Another important implication of the findings is that the positive impact of robot operability remains stable regardless of task complexity. Unlike robot functionality, which becomes particularly valuable under highly complex tasks, operability functions as a universal enabler that consistently reduces cognitive load in both simple and demanding scenarios. This means that investments in operability—such as standardized, user-friendly interfaces and predictable control responses—are never wasted, because they deliver performance benefits across the full range of construction tasks. From a design perspective, this suggests that operability should be treated as a baseline requirement for any collaborative robot, while functionality enhancements can be tailored to specific high-complexity contexts.

For training and workforce development, the results imply that programs should place strong emphasis on helping operators quickly master robot interfaces and interaction routines rather than differentiating training intensity by task difficulty. Short, scenario-based training modules that focus on interface fluency and error recovery can accelerate adaptation and build operator confidence. Once a high level of comfort with robot operability is achieved, further training can then concentrate on exploiting advanced functionalities in complex projects.

This strategy is critical because focusing solely on advanced robot features, without considering ease of use, risks undermining the overall success of robot integration. High operability makes it easier for workers to adapt to and collaborate with robots, ultimately leading to more effective team performance. Therefore, it is essential for designers to prioritize user-friendly interfaces and simple controls in the early stages, with the understanding that robot functionality can be progressively enhanced as both operators' skills and their trust in the system grow.

7.3.4. Context-Specific Guidance for HRC Deployment

When planning HRC for specific tasks, the study treats task complexity as critical. For simple, routine work (low TC), moderate human skill or robot capability is often sufficient, and top-tier pairings face diminishing returns. For complex tasks (high TC), managers should pair the most skilled operators with the most advanced robots. Significant HRC means that, under complex conditions, weakness on either side sharply reduces performance. This has direct implications for resource allocation. For example, complex tasks such as robotic installation of curtain wall panels at height, which involve large component lifting and high-altitude operations with significant safety risks and uncertainties, should be assigned to a high-performing operator–robot pair. Pairing a highly skilled operator with a suboptimal robot (or the reverse) can depress outcomes and raise risk. Therefore, task assignments should focus on achieving a high human–robot fit, especially for critical and complex tasks.

The interaction between human and robot capabilities is significantly amplified in complex environments. When task complexity is high, any gap in either human ability or robot functionality can result in a sharp decline in performance. This is because complex tasks often require greater adaptability, problem-solving, and decision-making from both humans and robots. In these situations, workers need to have the skills to handle unexpected challenges, while robots must be capable of performing tasks autonomously or adjusting to changing conditions without constant human intervention. If either the human operator or the robot is not sufficiently skilled or capable, the performance of the entire team will be compromised.

For high-complexity tasks, it is essential to allocate the most skilled human operators to work with the most advanced robots. Such tasks, which often involve high risks or critical operations, require a strong synergy between human expertise and robot functionality. A mismatch between the complexity of the task and the capabilities of the human or robot components can lead to inefficiencies, delays, and increased safety risks. As a result, it is vital for managers to carefully assess the complexity of each task and assign the appropriate team composition. For complex tasks that require significant problem-solving, innovation, or adaptation, pairing skilled operators with advanced robots ensures that both human and robot strengths complement each other, maximizing overall team performance.

In practice, this means that project managers must be strategic about human–robot team composition. Assigning advanced robots to high-skill teams for complex tasks, while reserving simpler robots for less complex tasks or teams with lower skill levels, will optimize the overall performance of HRC teams. This approach helps to ensure that the right balance is struck between human capabilities and robotic functionalities, leading to greater productivity, efficiency, and safety in construction projects.

7.3.5. Cost–Benefit Considerations for HRC Deployment

Beyond technical and managerial issues, the study emphasizes the costs and benefits of adopting HRC. The economic implications are best read through the validated team-performance model. Empirically, (i) robot operability delivers consistent gains across contexts, (ii) robot functionality is especially valuable under high task complexity, and (iii) human capabilities are essential complements. Translating these insights into practice implies that the economic payoffs of HRC are conditional on the alignment between capability type and task context. It means that the benefits of HRC are maximized when high human abilities are paired with advanced robotic functions, and when robot operability is consistently prioritized. However, such deployments often entail higher upfront costs, including investment in advanced robotic systems, operator training, and integration infrastructure. Therefore, a framework is necessary for context-sensitive economic evaluation grounded in the study's capability–interaction model.

First, for routine or low-complexity tasks, investment in high-functionality robots may not be cost-effective. Since operability is the universal enabler, managers should prioritize robots that minimize training time and integration costs (high RO), while maintaining moderate functionality. The expected economic benefit arises from reduced supervision, faster learning curves, and lower maintenance overhead. Thus, ROI calculations in such contexts should emphasize savings in training and error correction rather than advanced automation features.

Second, for high-complexity or precision-critical tasks, the study shows that human–robot complementarities are strongest when highly skilled workers (high OS, DA and LA) are paired with high-functionality robots (high RF). In these cases, although the initial capital expenditure is higher, the economic return is realized through reduced rework, higher productivity, and avoidance of costly schedule delays. For example, the model's finding that task complexity amplifies the OS and RF interaction indicating that the relative economic gains of high RF increase disproportionately when tasks are complex and cognitively demanding. In practice, this means that cost–benefit assessments in such contexts can justify longer payback periods since the reduction in rework and delay penalties translates into substantial financial value, even if the benefits are less visible in simpler tasks.

Third, the study's findings justify a phased investment strategy. While the structural model itself examined performance effects, these insights can be translated into economic appraisal using tools such as ROI, payback, or NPV, allowing managers to align investment decisions with the capability–context interactions identified in the data.

The following four-step procedure provides a repeatable appraisal:

The first step is to diagnose task complexity and establish the baseline. Using the task-complexity (TC) instrument introduced in Section 5.4, project teams classify the target activity into low, medium, or high complexity on the basis of observable attributes. This classification anchors all subsequent economic assumptions. In parallel, a pre-deployment baseline is recorded for core operational metrics—crew composition and hours, takt time or output per day, rework incidence and unit rework costs, safety incident frequency and loss severity, and schedule-related penalties or time-value of early completion—over a sufficiently long window to average out short-term fluctuations. Where feasible, a matched "control" area is identified to support difference-in-differences comparisons in later stages, thereby improving internal validity when external factors (e.g., batch variability, weather) might confound before–after contrasts.

The second step is to match robot capabilities to task contexts. RO operates as a context-general factor that reduces procedure and learning errors. RF yields disproportionate value where TC is high. And the complementarities between human and robot capabilities are strongest when skilled operators (high OS, DA, and LA) are paired with advanced RF. Therefore, in low or medium TC, the configuration of high RO and RF fit for purpose is typically justified, because the dominant gains arise from faster learning, fewer interventions, and reduced supervisory burden. In contrast, in high TC, the configuration should deliberately combine skilled operators (high OS, DA, and LA) with higher RF, accepting higher capital intensity in exchange for stability under variability, tighter quality control, and mitigation of schedule risk. The phase can be split into two parts. In the first phase, deploy HRC in routine tasks with a focus on RO to develop learning and process templates. In later phases, add advanced RF to high-TC tasks once OS, DA, and LA can support it, and then scale by standardizing training and maintenance to increase utilization.

The third step is to quantify costs and benefits and establish a link between costs, benefits, and the model's mechanisms. Costs are divided into two categories. Capital expenditures (CapEx) cover equipment, integration, and initial training. Operating expenditures (OpEx) include maintenance, consumables, and software upgrades. Benefits are annualized and derived from baseline data. Four main dimensions are considered, including labor, quality, safety and schedule. The ANB can be used to evaluate the benefit and operationalized in two steps. First, improvements in each benefit channel are measured in their natural units: labor savings in crew-hours, quality gains in the number of defects avoided, safety gains in reduced incident frequency or severity, and schedule gains in days of acceleration. Second, these physical quantities are translated into comparable values by multiplying them with appropriate unit prices—such as the fully loaded wage rate per hour, the average rework cost per defect, the expected loss per incident, or the time-value per day of project delay or early delivery.

Let the improvement vector collect the four channels in their natural units:

$$\Delta = \left[\Delta\text{Labor}_{(\text{hours})},\ \Delta\text{Quality}_{(\text{units})},\ \Delta\text{Safety}_{(\text{incidents})},\ \Delta\text{Schedule}_{(\text{days})}\right]^{\top}$$

Define a unit-price vector (p) that maps each channel into currency:

$$\mathbf{p} = \left[p_L\ (\text{per hour}),\ p_Q\ (\text{per defect}),\ p_S\ (\text{per incident}),\ p_T\ (\text{per day})\right]^{\top}$$

Then, the annual net benefit in monetary terms is a simple inner product minus any OpEx change:

$$ANB = \mathbf{p}^{\top}\Delta - \Delta\text{OpEx}$$

where each component is computed as:

ΔLabor $=$ hours saved per year; $p_L =$ hourly wage.

ΔQuality $=$ (baseline defect rate − post rate) × applicable volume; $p_Q =$ unit rework cost.

ΔSafety $=$ reduction in incidents; $p_S =$ expected loss per incident.

ΔSchedule $=$ days of schedule gain or penalties avoided; $p_T =$ time value per day.

The final stage uses ANB as the central decision criterion. A simple rule is that ANB should be positive: if the aggregated benefits outweigh the added operating costs, the deployment passes the minimum viability threshold. Beyond this baseline, the required level of ANB depends on task complexity. For low or medium complex tasks, managers should expect relatively high ANB values before committing to wider adoption since gains are mainly derived from ease of use and faster learning. In these contexts, only deployments showing clear and rapid benefits should proceed. For high complex tasks, complementarities between human skills and robot functionality are stronger. Because these projects involve higher risks, even a moderate ANB may be acceptable if accompanied by evidence of reduced rework, fewer delays, or improved safety. In other words, the threshold is more flexible, as long as the benefits address high-impact risks.

The decisions should follow a phased path. The first is the pilot gate. This stage requires ANB > 0, based mainly on reduced errors and shorter onboarding. The second is the expansion gate. In more complex tasks, evidence is required that ANB reflects improvements in quality and schedule stability. The final is the scale-up gate. It requires ANB to remain consistently positive across multiple teams or projects.

Taken together, this procedure maintains theoretical continuity with the study's findings while providing practicable economic guidance. It enables project managers to evaluate adoption choices with financial discipline.

7.4. Limitations and Future Research Directions

While this study provides valuable insights into the interaction of human abilities, robot capacities, and task complexity in shaping HRC team performance, it is not without its limitations.

First, methodological constraints are worth noting. The study employs a cross-sectional design, which limits the ability to draw conclusions about causality over time. Future studies should use longitudinal data to track HRC performance over time. This would clarify how collaboration changes and how robots affect construction teams in the long term. Furthermore, the reliance on self-reported perceptions introduces the possibility of response bias, as participants may overstate or understate their experiences with robots. Future studies could address this limitation by incorporating devices to measure human and robot attributes in real-time. For instance, wearable sensors or brainwave monitoring devices could be used to capture cognitive and behavioral responses objectively, providing more precise data on human performance during HRC [114,206]. Additionally, robot status could be monitored in real-time using sensors or diagnostics tools to track robot functionality, operability, and performance metrics during task execution [207]. This would help reduce reliance on self-reports and provide a more accurate measurement of human performance in the context of HRC.

Second, a primary limitation of this study is its reliance on single-source, self-reported data collected at a single point in time, which introduces the potential for CMB. The observed relationships between human abilities, robot capacities, and performance may be partly inflated because some shared variance reflects the measurement method rather than the true constructs. The study applied statistical tests, such as full collinearity assessment and Harman's single-factor test, which suggested that common method bias was not a serious concern. Nevertheless, some potential for bias may still remain. Future research should therefore aim to validate these findings using a multi-source data collection strategy. For instance, team performance could be assessed through objective project metrics, providing a more robust test of the model's predictive validity.

In addition to the cross-sectional design, the study could benefit from experimental studies to observe HRC in a controlled laboratory environment. For example, wearable devices such as smart gloves, eye-tracking systems, and biosensors could be used to measure the real-time performance of human operators during specific tasks in HRC. These devices could monitor cognitive load, attention levels, and operational skill in a variety of task contexts, providing real-time data on human performance and enabling the isolation of specific human attributes [208]. Similarly, robot sensors can track accuracy, execution time, and error rates, yielding objective measures of functionality and operability across scenarios [121]. This setup would allow researchers to test specific hypotheses about HRI in a controlled environment, free from external confounding factors.

Furthermore, future studies could integrate longitudinal research designs, tracking teams over time to observe the evolution of HRC in real-world construction settings [209]. This could involve collecting data from wearable sensors or robot diagnostic systems over an extended period to analyze how human and robot performance change as workers gain experience and robots undergo updates [210]. Longitudinal studies would help uncover temporal patterns, such as how human skills develop and how robot performance improves over time, leading to a more comprehensive understanding of HRC team performance dynamics.

Another limitation concerns the demographic composition of the sample. Most respondents were male (86%), which reflects the reality of the construction industry workforce in China. Nevertheless, this gender imbalance may limit the generalizability of our findings to more gender-diverse contexts. Future studies should therefore aim to include a more balanced sample to test the robustness of the results.

Finally, the findings of this study are generalizable only to the construction industry, and several constraints should be noted when considering external validity. First, all respondents were drawn from construction projects in China. Although the dataset covers residential, public, and office projects across East, Central, and West China, it may not reflect conditions in other countries. Construction technologies, regulatory environments, and workforce demographics can differ, limiting external validity. Second, the types of robots reported by respondents reflect those most deployed in China, such as concrete screeding, plastering, tile-laying, panel installation, measurement, and inspection robots. Other regions may use different robotic solutions or integration practices. Third, the sample is overwhelmingly male (86%), which mirrors the demographic reality of the Chinese construction industry but may limit the applicability of the results to more gender-diverse contexts.

Beyond these geographical and demographic limitations, the generalizability of the findings is further constrained by the exclusive focus on the construction industry, where task complexity and HRI dynamics may differ substantially from other sectors. While the focus on construction is crucial given the industry's complexities, future research could enhance external validity by applying the framework to other industries. For instance, manufacturing and logistics may have different levels of task complexity, robot capabilities, and team dynamics, providing a broader context for understanding HRC performance [211,212]. Extending this framework to manufacturing environments could help investigate the impact of robotics in assembly lines, where robots and humans work in a highly structured environment, contrasting with the more flexible and dynamic nature of construction. Similarly, logistics environments with robots working in warehouse settings may have differing HRC dynamics, especially concerning tasks such as material handling and inventory management.

8. Conclusions

The study set out to explain how performance emerges in HRC teams in construction. It proposed and tested a multidimensional model centered on human and robot capabilities, with task complexity as a contextual moderator. Using PLS-SEM on frontline practitioner data, the analysis shows that three categories of human capability and two categories of robot capability each exert significant positive effects on team performance; all hypothesized human–

robot interaction effects are supported. Task complexity amplifies the interaction between human capabilities and robot functionality, but not the interaction with robot operability.

To integrate these findings with the study's guiding questions, the answers to the four research questions are consolidated as follows. First, for RQ1, the study validates six latent constructs—three human capabilities (operational skill, decision-making, learning), two robot capabilities (functionality, operability), and task complexity—as the foundation of HRC team performance. Second, for RQ2, these constructs are operationalized with actionable scales: functionality spans autonomy, reliability, responsiveness, precision, and consistency, while operability captures ease of use, interface intuitiveness, controllability, and learning burden; reliability and validity analyses support convergent and discriminant validity. Third, for RQ3, the structural results reveal five positive and significant main effects and significant human $\times$ robot interactions, evidencing complementary strengths; task complexity selectively strengthens the functionality pathway but not the operability pathway. Finally, for RQ4, joint assessment of the measurement and structural models yields a validated predictive framework with concrete managerial levers—prioritize operability to stabilize outputs, invest in training to enhance operational and decision skills, and, for high-complexity tasks, pair highly skilled workers with high-functionality robots to maximize performance gains.

For the theoretical and practical contributions, the research integrates the human–robot–task coupling into a testable team-performance model, addressing gaps regarding robot-side attributes and interaction mechanisms. The constructs and scales are reusable, giving project managers concrete tools for team diagnosis, resource allocation, capability building, and robot selection.

There are limitations of this study. The sample is drawn from Chinese construction projects, robot types skew toward local applications, and gender balance is uneven. External validity should therefore be tested across industries and regions. Future studies can combine experiments with longitudinal designs and leverage wearable and robot sensors to capture process-level indicators and track the co-evolution of human and robot capabilities.

In sum, the findings indicate that successful HRC in construction depends not only on the advancement of robotic technologies but also on the cultivation of human capabilities and the careful consideration of task characteristics. By clarifying the interaction among these factors, this study provides a predictive framework that can be used in enhancing productivity, safety, and quality in the evolving landscape of construction robotics.

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Abbreviations

The following abbreviations are used in this manuscript:

HRC	Human–Robot Collaboration
STCR	Single-Task Construction Robot
HRT	Human–Robot Team
TTF	Task–Technology Fit
TAM	Technology Acceptance Model
TPC	Technology-to-Performance Chain
HRI	Human–Robot Interaction
PLS-SEM	Partial Least Squares Structural Equation Modeling
OS	Operational skill
DA	Decision-making ability
LA	Learning ability
RF	Robot functionality
RO	Robot Operability
TC	Task complexity
HTP	HRC Team Performance
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait–Monotrait
R^2	Coefficient of Determination
β	Standardized Path Coefficient
Δ	Difference

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