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Review

Artificial Intelligence in Human–Robot Collaboration in the Construction Industry: A Scoping Review

Bo Peng [1,2,*], Maxwell Fordjour Antwi-Afari [1], Bilal Manzoor [3], Evans Boateng [4], Emmanuel Nyamekye Antwi Afari [5] and Zezhou Wu [6]

1 Department of Civil Engineering, College of Engineering and Physical Sciences, Aston University, Birmingham B4 7ET, UK; m.antwiafari@aston.ac.uk
2 School of Management, Hefei University of Technology, Hefei 230009, China
3 Department of Building and Real Estate, Faculty of Construction and Environment, The Hong Kong Polytechnic University, Kowloon, Hong Kong SAR, China; bilal.manzoor@polyu.edu.hk
4 Department of Construction Technology and Management, Kwame Nkrumah University of Science and Technology, Kumasi AK-384-1973, Ghana; boatengproustevans@gmail.com
5 Directorate of Physical Development and Estate Management, University of Cape Coast, Cape Coast CC-123-1749, Ghana; emmanuel.afari@ucc.edu.gh
6 Department of Construction Management and Real Estate, College of Civil and Transportation Engineering, Shenzhen University, Shenzhen 518000, China; wuzezhou@szu.edu.cn
* Correspondence: 2024110969@mail.hfut.edu.cn

Abstract

With the gradual rise of automation and human–robot collaboration (HRC), artificial intelligence (AI) is expected to significantly change the construction industry by automating design and decision-making processes, thus improving both productivity and safety. Despite the growing research trends in AI and HRC, no study has synthesized the existing studies of AI in HRC in the construction industry. This paper aims to conduct a review of AI in HRC in construction and summarize the current mainstream topics, research gaps, and future research directions. A scoping review and science mapping analysis were used to explore extant literature in the studied domain and conduct keyword co-occurrence analysis, respectively. In this study, 210 relevant articles were retrieved from the Scopus database from 1993 to July 2025. The results revealed five main clusters regarding the co-occurrence of keywords. Four mainstream research topics were discussed, including (1) AI techniques and applications, (2) the use of extended reality (XR) in HRC, (3) the challenges of HRC, and (4) the application of HRC in the architecture, engineering, and construction (AEC) sector. Moreover, this study provided a detailed summary of research gaps and future research directions. These findings offer researchers and practitioners a deeper understanding of AI applications in HRC for construction case studies and serve as actionable directions to advance this field.

Keywords: artificial intelligence; human–robot collaboration; construction industry; scoping review; scientometric analysis

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1. Introduction

The concept of human–robot collaboration (HRC) in the construction industry has attracted increasing attention from researchers and practitioners worldwide for many years. It has been extensively studied due to its benefits of enabling generalized robots to quickly adapt to the complex and dynamic construction environment [1]. HRC refers to a coupled dynamical system that involves interaction between humans, robots, and the environment to accomplish a task [2]. The construction industry is traditionally characterized as being labor-intensive, involving multi-disciplinary stakeholders, with low productivity and frequent occurrences of injuries or accidents [3]. According to the data collected by Eurostat, in 2022, across the entire European Union, nearly a quarter of fatal workplace accidents occurred in the construction industry. For every 100,000 employed individuals, there were 1506 non-fatal accidents and 2.10 fatal accidents [4]. In the European Union, the two types of injuries that were particularly common in 2022 were wounds and superficial injuries (accounting for 27.6% of the total) and dislocations, sprains, and strains (25.5%) [4]. Unlike HRC in other fields, such as the manufacturing industry, which focuses on efficient optimization of automation, the construction industry focuses on the integration of human skills and machine intelligence to improve productivity and address safety issues [1]. Specifically, HRC aims to increase construction productivity through seamless team dynamics and effective collaboration to deal with unpredictable uncertainties in construction activities [5]. For example, HRC can improve productivity and safety by coordinating a robotic system with human skills, thereby reducing physically repetitive and dangerous construction activities. In addition, it can significantly mitigate the challenges posed by changes in robot dynamic planning and task execution [6].

Artificial intelligence (AI) can be defined as a technological system that simulates and extends human intelligent behavior through processes such as perception, learning, reasoning, and decision-making [7]. AI techniques have been studied in the existing literature in various aspects [8–13]. For instance, Voulodimos et al. [8] reviewed deep learning (DL) techniques such as convolutional neural networks, deep Boltzmann machines, and deep belief networks, and provided their history, advantages, and disadvantages. Mirzaei et al. [9] conducted a comprehensive review of machine learning (ML) 3D point cloud data processing in architecture and infrastructure applications. Ohri and Kumar [14] summarized the self-supervised learning schemes based on deep neural networks and computer vision tasks. They reported that these methods are more helpful than supervised learning techniques in performing downstream computer vision tasks such as image classification, object detection, and image segmentation because they allow the network to learn from deep visual features. Hamilton et al. [15] also explored neuro-symbolic AI (NeSy) in natural language processing (NLP), finding that systems that compile logic into neural networks can meet most NeSy goals with lower computational costs and higher performance.

Intelligent robots have been implemented in various construction activities such as site preparation, removing hazardous waste, coating structural elements, and others [16,17]. Despite the usefulness of intelligent robots, they rarely achieve significant productivity due to construction projects' uniqueness, complexity, and multidisciplinary stakeholders [18]. Moreover, the dynamic nature of the construction environment can affect the deployment of intelligent robots on sites [19]. Therefore, in contrast to traditional intelligent robots, the construction industry could implement HRC, where a task is collaboratively shared and completed between humans and robots within an environment [3]. For example, construction workers can participate in task decision-making and planning, while robots conduct repetitive, demanding activities. AI enabling HRC is not only useful for path planning, task assessment, and algorithm optimization, but also enhances robot intelligence and autonomous decision-making. For example, AI can enhance HRC to possess perceptual intelligence, enabling robots to navigate dynamic environments while human cognitive and action intelligence can be achieved through computer vision, process mining, and expert systems [20].

Existing research has also conducted detailed reviews and empirical analyses of the challenges of HRC application in construction. Zhang et al. [1] summarized the existing literature on HRC for on-site construction. They discussed cutting-edge technologies for potential HRC applications, including adaptive programming, communication methods, physical interaction interfaces, HRC management, and safety issues. Fu et al. [21] reviewed the application of HRC in modular construction manufacturing (MCM), highlighting how HRC can enhance productivity and flexibility in MCM processes. Rodrigues et al. [22] developed a multidimensional taxonomy to understand and categorize complex interactions between humans and robots in construction, focusing on three key dimensions: team, task, and environment. In the context of Construction 5.0, Marinelli [23] conducted a literature review and bibliometric analysis of HRC in construction, highlighting their challenges and future directions. Their study also summarized the digital development in the construction field during Industry 4.0 and proposed prospects for HRC in Construction 5.0. Other reviews of AI applications in construction have been conducted. Borboni et al. [24] conducted a systematic review of AI in collaborative robots for industrial applications, providing various difficulties and future directions for current robots. Pan and Zhang [25] conducted a scientometric and qualitative analysis of AI in construction engineering and management, identifying six key future directions. Regona et al. [26] reviewed the application of AI in the planning, design, and construction phases of the construction project life cycle, identifying the adoption challenges and opportunities of AI.

It is noteworthy that existing research has focused on the challenges of HRC application or the adoption of AI in construction. These studies have discussed the historical development, status, future directions, and challenges of HRC or AI in the era of Construction 5.0. While there has been a growing interest in either AI or HRC applications in construction, previous research has predominantly focused on individual challenges without reviewing HRC concepts in construction from the perspective of AI techniques. The unique contribution of this research is to conduct a review of AI in HRC in construction, offering insightful challenges of HRC, AI techniques, and other HRC applications (e.g., cognitive and physical knowledge) in construction. It adopted a scoping review and science mapping analysis to synthesize and identify mainstream topics, research gaps, and future research directions for AI in HRC applications in construction. The adopted method seeks to provide inclusive perspectives on emerging issues that address a key research question: "What are the mainstream topics, research gaps, and future research directions of AI in HRC in construction?".

Therefore, this paper aims to conduct a state-of-the-art review of AI in HRC in the construction industry. The specific research objectives include (1) examining annual research publication trends and conducting a keyword co-occurrence analysis; (2) identifying mainstream research topics on AI in HRC in construction; and (3) discussing research gaps and recommending future research directions on AI in HRC in construction.

2. Research Methods

To achieve the stated research objectives, this paper adopted a scoping review and science mapping analysis to identify relevant articles from the Scopus database and to generate scientific knowledge data, respectively. The adopted method—scoping review and science mapping analysis—consists of six steps. The scoping review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [27]. It consists of (1) search strategy; (2) literature screening; (3) selection process; and (4) inclusion, data extraction, and quality assessment. These processes provided detailed insights into identifying, selecting, and evaluating relevant articles in the studied domain. In addition, the science mapping analysis was mainly based on the VOSviewer version 1.6.20. It consisted of two additional steps, namely (5) a scientometric analysis and (6) a qualitative discussion. The science mapping analysis helped to reveal the keyword co-occurrence analysis and mainstream research topics. An overview of the research method is shown in Figure 1.

Step 1	**Step 2**	**Step 3**	**Step 4**
Scoping review			
Identification	**Screening**	**Eligiblility**	**Included, data extraction, quality assessment**
Total articles published identified in the Scopus database search. (n=758)	Total 758 articles entered into screening: ↓ Articles excluded based on the limitations (subject areas, source type, publication stage, language). (n=329)	Articles titles and abstracts assessed for eligibility. (n=210) ↓ Eligible articles. (n=210)	Articles included, further extracted, and through quality assessment. (n=210)
Step 5		**Step 6**	
Science mapping			
Science mapping analysis		**Qualitative discussion**	
Scientometric analysis via VOSviewer (1) Co-word analysis: Key words (2) Co-author analysis: Countries and Regions		(1)Summary of main research topics (2)Research gaps and future directions	

Figure 1. Overview of the research methods.

2.1. Search Strategy

The first step is to obtain a preliminary set of documents through a keyword search in the Scopus database. The Scopus database was chosen because it is widely regarded as a comprehensive and reliable database with reputable peer-reviewed journals published by several publishers [28]. Also, the indexing process within the Scopus database is faster and easier to understand than in other databases [29]. The search was conducted in July 2025. Without applying any "date range", the following keywords were used for the search: (AI OR artificial intelligence) AND (HRC OR human–robot collaboration OR man-machine interaction OR human-computer interaction). This initial search yielded 758 documents.

2.2. Literature Screening

In the second step, the documents were further screened according to specific criteria. These include subject area (engineering), document type (conference papers and articles), source type (conference proceedings and journals), publication stage (final), and language (English). Since this paper focuses on AI in HRC in construction, only articles from the "engineering" discipline were selected. Due to the recency of the studied topic, the number of journal articles currently published was not sufficient for a comprehensive review. Therefore, conference papers were also included. Finally, to ensure accuracy and authenticity, only articles in their final stage were considered. As such, the full search string for Scopus was: (TITLE-ABS-KEY (AI OR artificial intelligence) AND TITLE-ABS-KEY (HRC OR human–robot collaboration OR man-machine interaction OR human-computer interaction) AND (LIMIT-TO (SUBJAREA, “ENGI”)) AND (LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (SRCTYPE, “p”) OR LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (PUBSTAGE, “final”)) AND (LIMIT-TO (LANGUAGE, “English”)). After the screening process, a total of 329 articles were retained.

2.3. Selection Process

Two independent reviewers, BP and MFAA, carefully read the title, abstract, and full text of 329 articles based on the eligibility criteria set in this study. Any disagreements were resolved through consensus. The eligibility criteria were designed to exclude articles (1) that were mistakenly identified and, therefore, not related to “engineering” or published in a journal or conference proceeding (e.g., Wu et al. [30] was mistakenly identified because it was not published in a peer-reviewed journal); (2) that had no accessible full text; (3) that were not related to AI, HRC, or construction—and, therefore, were completely out of scope [31]—and (4) whose content was partially related to the studied domain. For example, articles that mentioned AI or HRC but whose application domain was agriculture, healthcare, space engineering, etc. (e.g., Chu et al. [32] only discussed the applications in the medical field). Finally, a total of 211 articles were considered to be eligible for a detailed review.

2.4. Included, Data Extraction, and Quality Assessment

The included articles were further reviewed to extract relevant information (i.e., publication year, author, title, publication type, method, etc) after conducting a quality assessment. Like previous studies [33,34], a quality assessment checklist consisting of 10 questions was used to assess the objective, study design, method, and data collection of the 210 articles. Articles that passed 70 to 100% of the quality assessment checklist were considered for further evaluation in this study.

2.5. Scientometric Analysis

After the scoping review, 210 articles were used as input variables for the scientometric analysis. There are many commonly used bibliometric research software packages [35]. The VOSviewer software was selected because it can help reveal current trends, fundamentals, and research hotspots [34,36]. It indicates correlation by providing a distance-based bibliometric grid visualization. In this paper, the keyword co-occurrence analysis was the only scientometric analysis that was conducted.

2.6. Qualitative Discussion

The final step is the qualitative discussion, which aims to conduct a further and more detailed review of the 210 selected articles, involving discussion of concepts, themes, developments, and findings. In addition, this paper discusses the research gaps and future research directions for the application of AI in HRC in construction.

3. Results

3.1. Annual Publication Trend of Articles

The bibliographic data of the included articles were analyzed according to the year of publication. The annual publication trend of the 210 articles was analyzed from 1993 to July 2025, as shown in Figure 2. Before 2016, the number of related articles published was relatively stable, with a maximum of seven articles per year. This may be due to the lower levels of AI development and industrialization during those years. Since 2016, the number of published articles has sharply increased, a fact that may be due to the emergence of Industry 4.0, the significant development of AI, and the recent trend of digital transformation in construction. An increasing number of scholars are paying attention to AI and HRC, with construction emerging as an area urgently requiring transformation. The number of articles published from 2018 to 2023 has fluctuated, which may be influenced by factors such as economic stability and the COVID-19 pandemic. However, it still shows an upward trend. The number of publications in 2024 was the highest, with a total of 27 articles, representing an increase of 68.75% compared to the previous year. At this point, there were only 10 published papers on the application of AI and HRC in construction in July 2025, but it is predicted that this number will increase significantly in the second half of the year. In summary, research on AI and HRC in construction has been a popular topic in recent years, and it is expected that the number of related studies will continue to increase in the coming years.

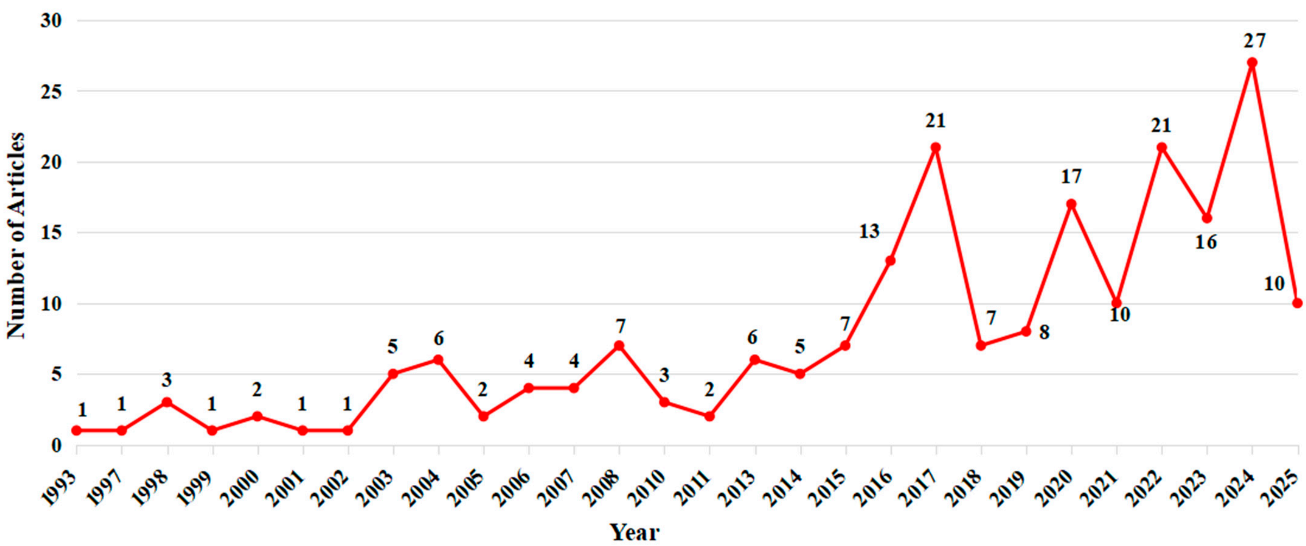

Figure 2. Annual publication trend of articles related to AI in HRC in construction.

3.2. Keyword Co-Occurrence Analysis

This analysis uses keywords as nodes in a network to illustrate the relationships between different keywords in the literature to show the composition and structure of knowledge in the studied field. In VOSviewer, "author keyword" is used as the analysis unit. From a total of 896 keywords, the minimum occurrence of keywords was set to five, resulting in 23 keywords. Keywords that have similar meanings were combined (e.g., human–robot interaction and human–robot collaboration). After eliminating keywords with repeated semantics, 16 keywords were finally obtained. Table 1 provides a quantitative summary of keyword co-occurrence analysis. It can be observed that the topic "human-computer interaction" has the highest occurrence frequency, with 55 instances, and also has the second-highest average citation count, 19.44. The "intelligent robot" ranks first, with an average citation count of 24.33. The terms "augmented reality" and "intelligent manufacturing" appear only seven and six times, respectively, but they both have the highest average normalized citation count, at 1.95. The average publication year of "robot learning" is nearly 2025, indicating that this keyword represents the most cutting-edge current research direction. The four clusters derived from Table 1 are explained as follows:

1. Cluster 1 (AI techniques in robotic systems)—The development of AI techniques (e.g., DL, ML, and NLP) is an important driver of robotic systems. The application of DL can effectively improve the performance of service robots [37]. The application of ML and other AI techniques is crucial for robot gesture recognition, which facilitates communication between humans and robots [38]. Natural communication and language understanding play a significant role in the development of robots and human–machine communication [39]. A typical scenario is that large language models (LLMs) are also being utilized for voice communication to perform general tasks [40].
2. Cluster 2 (Extended reality (XR) in HRC applications)—Augmented reality (AR) and mixed reality (MR) are often closely related technologies in the context of HRC. Employees can use glasses with MR and AR capabilities to respond appropriately to scanned components and perform necessary maintenance [41]. A classification visualization scheme based on MR and AR technology can reduce the cognitive burden on robots [42]. The integration of VR and AR systems in terms of perception-decision-making-control can achieve real-time process optimization [43].
3. Cluster 3 (HRC in construction safety)—Safety is a key research concern of HRC. Mohammadi Amin et al. [44] developed a visual perception system to help robots recognize human behavior and increase the safety of dynamic changes. Different HRI models also increase the safety of autonomous vehicles and have a positive impact on road safety [45].
4. Cluster 4 (Human perceptions in HRC applications)—Trust between humans and robots is the key to ensuring the safety of HRC. The summary of the trust factors and advanced trust models helps humans to enhance the level of trust with robots [46]. It was reported that participants have a significant decrease in trust in autonomous systems when dealing with real-world consequences [47]. Zhang and Yang [48] found that robots with physical human-like appearance were perceived as having lower levels of anthropomorphism and intelligence. Furthermore, the design of interaction functions on robots did not significantly increase these perceptions.

Table 1. Quantitative summary of the keyword analysis of AI in HRC in construction.

Keywords	Cluster	Occurrences	Average Publication Year	Links	Average Citations	Average Normalized Citations	Total Link Strength
Artificial intelligence	1	32	2020	13	17.25	1.41	51
Human–robot interaction	3	55	2018	15	19.44	1.08	45
Intelligent robots	4	15	2023	14	24.33	1.43	38
Collaborative robots	4	12	2024	9	2.83	0.58	23
Industrial robots	4	8	2024	11	0.38	0.15	23
Robot learning	1	5	2025	12	2	0.50	19
Machine learning	1	14	2020	10	5	0.41	19
Large language model	1	6	2024	12	6.33	1.40	17
Robotics	1	11	2019	8	8.73	1.37	17
Virtual reality	2	7	2023	8	11.43	1.15	15
Smart manufacturing	1	6	2024	11	9.83	1.95	14
Trust	3	7	2021	7	3.29	0.79	13
Social robots	1	6	2019	8	9.33	0.46	13
Augmented reality	2	7	2022	7	15.71	1.95	10
Computer vision	1	5	2024	7	3	0.56	7

3.3. Countries/Regions Co-Occurrence Analysis

After setting the minimum number of documents for each country to five and the minimum citation to five, 14 out of 41 countries met this threshold. Figure 3 shows a network of co-occurrence analysis for these 14 countries/regions. The countries/regions shown in Figure 3 are divided into several nodes. It was found that the United States, Japan, China, Germany, and the United Kingdom are among the top five countries/regions in the research field.

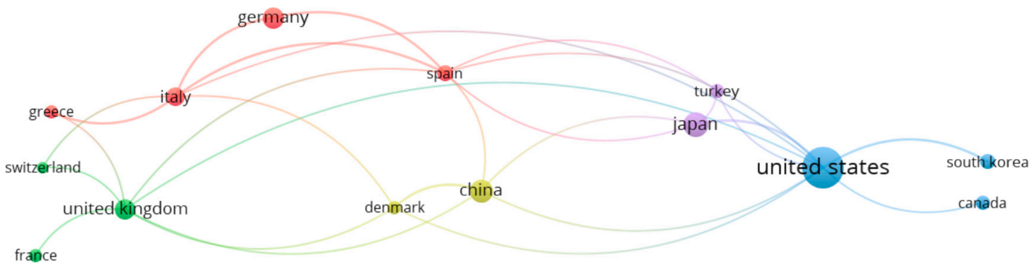

Figure 3. Network of countries/regions co-occurrence analysis.

Table 2 summarizes the contributions of various countries/regions to the application of AI and HRC in construction. Among them, the United States has the most relevant articles, with 66 publications and the highest citation count of 1397. It has close relationships with other countries and is at the forefront of theory or application in this field. Japan ranks second with 23 articles. Next, countries/regions such as China (20 articles), Germany (17 articles), and the United Kingdom (15 articles) have also made significant contributions to the number of published articles. From this, we can infer that economically developed countries/regions have more relevant articles than relatively developing countries/regions, indicating that developed countries/regions pay more attention to research on AI and HRC technologies in construction.

Table 2. Quantitative summary of countries/regions co-occurrence analysis.

Country	Documents	Citations	Norm. Citations	Total Link Strength
United States	66	1397	73.59	11
Italy	13	65	12.57	9
Spain	9	124	8.66	9
United Kingdom	15	160	10.15	7
China	20	80	20.39	6
Japan	23	273	14.26	5
Denmark	6	41	6.17	5
Germany	17	170	10.07	4
Greece	6	55	7.76	3
Turkey	7	68	3.90	3
Switzerland	5	204	11.15	2
South Korea	8	92	9.06	2
France	6	79	3.27	1
Canada	7	50	5.11	1

4. Discussion

4.1. Mainstream Topics of Articles

Figure 4 presents the mainstream topics of the included articles. As shown in Figure 4, the articles were categorized into four main aspects: 49 articles focused on AI techniques and applications (23%), 14 articles focused on the use of extended reality (XR) in HRC (7%), 27 articles were related to the challenges of HRC (13%), and 120 articles focused on the application of HRC in architecture, engineering, and construction (AEC) (57%). Of the articles on AI, only four articles are reviews, and the remaining articles all provide AI-based solutions to specific problems. Approximately half of the XR articles present reviews of existing work or visions of future potential, and the other half were about related technologies. Regarding the challenge section, only seven articles address specific technologies, and the rest are technical issues facing HRC applications. Lastly, in the HRC articles, different HRC models and schemes are introduced, while also emphasizing the importance of using HRC technology and integrating AI into AEC research problems.

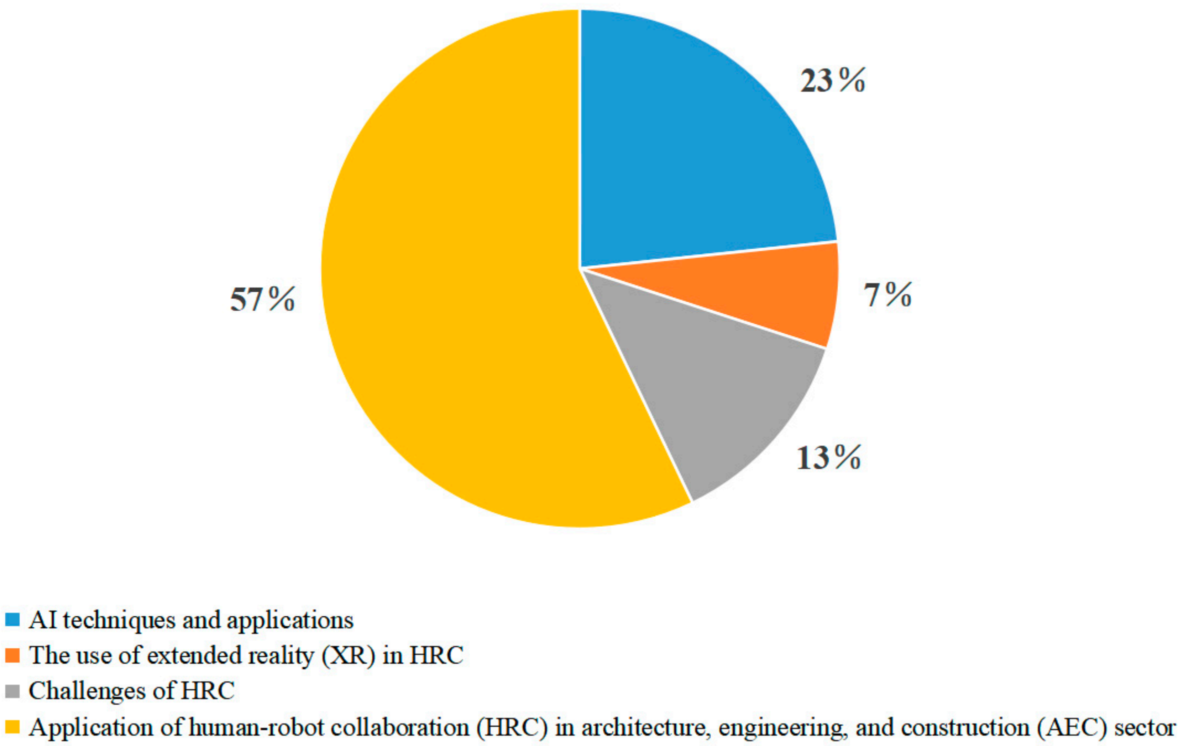

Figure 4. Mainstream topics of AI in HRC in construction.

4.1.1. AI Techniques and Applications

A total of 49 articles focused on AI techniques such as ML, DL, NLP, and others. Only two articles reviewed existing literature, and the other articles introduced how AI techniques could be applied in HRC.

1. Machine learning (ML)
   ML is a major branch of AI techniques. It enables computers to make predictions or decisions about new data by learning patterns and features from data using algorithms. The most popular type of ML algorithm discussed in the articles is neural networks (NN). This computational technique, inspired by biological nervous systems, mimics how the human brain processes information. Of the 16 articles discussing ML, seven dealt with the use of different types of NN, including traditional NN and artificial neural networks (ANN). For example, Zhang et al. [49] collected facial motions through a facial motion unit analyser to provide data input to the feedforward NN. Supervised ML algorithms (e.g., random forest (RF), support vector machine (SVM), K-nearest neighbor (KNN), etc), reinforcement learning, and transfer learning were applied in previous HRC studies to develop HRI models or frameworks. For example, Sugiyama et al. [50] used a model based on RF to estimate the response obligation in human-computer multi-party dialogue. The experiment shows that, compared with the traditional methods, this model reduces the false response rate to 17.3%, a decrease of 21% from the baseline, and increases the F1 score by 9.2%. Wang et al. [51] used KNN to build a real-time framework for human intention estimation and cooperative motion planning of robotic manipulators. Liu et al. [16] proposed a physiological HRC framework to enhance safety during construction tasks based on ML algorithms.
2. Deep learning (DL)
   DL is a subfield of ML that relies primarily on the structure of NNs. DL models

can automatically learn complex representations from large datasets without the need to manually extract features. The most frequently discussed DL model in the included articles was convolutional neural networks (CNNs). Other topics such as image semantic analysis, agent model, and active learning were also discussed. CNN has strong learning and data processing abilities; therefore, it is mostly used to solve problems in complex situations or to improve the interaction and enhance the ability of HRC. For example, CNNs were used to improve the accuracy and real-time performance of gesture recognition in complex environments [52]. Their research employed stacked convolutional layers and an improved bottleneck block for feature extraction. Compared to traditional models, its efficiency increased by 54%, and in the 3D space capture experiment, the success rate reached 98.5%. CNN was also used to support HRI frameworks and improve the perception level of HRC [44]. Garcia et al. [53] developed an HRC framework based on CNN to sense and predict collaborative workspace and human behavior captured from RGB camera data for decision-making on an assembly process. For other DL models, Toda and Kubota [54] used spiking neural networks (SNNs) with high energy consumption properties combined with time series location data of people and objects to estimate human behavior. Guinot et al. [55] used a variable long short-term memory (LSTM) of the recurrent neural network (RNN) model to analyze and learn subtle cues in human movement. The experiment showed that the success rate for the wiping task was 93%, for the grasping and placing task it was 90%, and for the combined task it was 79%. In industrial settings, on assembly lines, it is possible to reduce worker distraction by 40%. Image semantic analysis enriched with knowledge-level spatial information was used to assist robots in making navigation choices [56] or verbal and gesture interactions [57].

3. Natural language processing (NLP)
NLP aims to enable computers to understand, interpret, and generate human language, covering several techniques from basic string processing to complex semantic understanding and generation. In the included articles, NLP is mainly used as a foundational method to form a system or environment. Examples include natural, humanized conversation environments driven by NLP that embed dialogue strategies into the generation of human–machine dialogue strategies [58], and agile integrated approaches to HMI and knowledge management [59]. In addition, the Transformer architecture is also widely applied in NLP. Schirmer et al. [60] integrated a transformer-based NLP model for safety hazard identification during assembly steps through a decision-making process by human safety experts. In recent years, LLMs have developed rapidly. Ranasinghe et al. [40] developed a voice interaction framework based on LLMs, which helps robots collaborate. Research based on GPT-4o has proposed a dual-agent LLM framework. Compared with the traditional single-agent framework, the error detection rate has increased by 93.5%, and the task completion rate has increased by 141.7%.

4. Fuzzy techniques
Fuzzy logic is a type of logic system that deals with uncertainty and fuzzy concepts. It is widely used in natural language description, uncertainty in human decision-making process, and modeling of complex systems. For example, fuzzy logic was combined with robotics to propose a damping controller that improves the safety of HRC [61]. For instance, by combining fuzzy logic with robotics technology, a damping controller was proposed, which enhanced the safety of HRC [61]. Under the condition of a sudden load increase, the speed overshoot decreased by 42%, and the power fluctuation range was reduced to ± 2.3W. However, there is still a delay in the

high-speed task. Jiang and Wang [62] proposed a fuzzy logic controller to design a human decision-making model that encompasses psychological risk effects involving tasks between humans and robots.

4.1.2. The Use of Extended Reality (XR) in HRC

There were 14 articles on XR, mainly covering AR, Virtual Reality (VR), MR, and other aspects. The level of interest in these topics was relatively evenly distributed across the articles. Symmetric reality (SR) was less studied and could be a new direction for further studies.

1. Augmented reality (AR)
   By superimposing virtual information into the visual presentation of the real world, AR creates a rich and deep interactive environment for users. In the included articles, AR was combined with AI and other technologies for HRC applications [63] and to enhance the flexibility and adaptability of operating systems [64].
2. Virtual reality (VR)
   VR creates a completely virtual environment where users are fully immersed in this computer-generated world via a head-mounted display (HMD). In the included articles, VR was mainly used to assist in the recognition of realistic robots [65] and to improve the working ability (operational capacity) and efficiency of robots [66].
3. Mixed reality (MR)
   MR technology is a combination of VR and AR which not only superimposes virtual images on the user's real environment, but which can also interact with the real world. In the included papers, MR is mainly applied to assisted robot interaction [67] and the construction and verification of hybrid map frameworks [42]. This MR environment that integrates virtual and real elements can achieve bidirectional interactive control between physical robots and virtual avatars, ensuring the safety and traceability of multimodal interaction [43].
4. Symmetric reality (SR)
   SR is a relatively new concept in the field of XR, which explores a more balanced way of HRC, which is neither completely dominated by the real world nor the virtual world. Instead, it emphasizes balance and symmetry between the two realms. Among the included articles, there is only one study on SR, focusing on the analysis of task definition. In the SR application, the robot is seen as a virtual agent with the same status in the physical environment. As such, HRC in SR is a process of equivalent interaction between two virtual and physical environments [68].

4.1.3. Challenges of HRC

Based on the included articles, this paper identified four key challenges of HRC applications, namely, trust, safety, ethics, and fairness.

1. Trust
   The issue of trust is a key challenge affecting technology acceptance and the effectiveness of cooperation. Research on trust issues accounts for more than half of the 27 articles on the challenges of HRC. Trust between HRC is multifaceted, covering everything from design and emotion to generational differences and methodological considerations. The degree of trust generated by users based on perception may affect the shape design of humanoid robots [48]. St-Onge et al. [69] designed a reverse interface for robots to act as real controllers in HRC through experiments. For emotions, Guo et al. [70] explored how human trust in robots can be improved by designing robots to actively reason and respond to human emotions and trust levels in shared tasks. Robb et al. [71] reported on different generations' perceptions of robotics and

AI, pointing out the subtle nature of trust between different age groups. Research has shown that trust is a key component to the acceptance and effective use of AI and HRC systems, and future studies are needed. Parron et al. [72] developed a database to calculate and analyze the relationship between robot performance factors and human trust levels.

2. Safety
Safety issues ensure the welfare of workers' lives, the implementation of technology, and the progress of projects. Technological advances are important in ensuring the safety of modern production systems, with a focus on control safety measures and physical robotic assistance to protect human workers in complex manufacturing environments. Islam and Lughmani [73] investigated the strategies to improve the safety of cyber-physical production systems (CPPS), highlighting the potential risks involved. Cen et al. [74] proposed a framework for mobile robotic arms designed to assist human workers, addressing a range of safety concerns by providing robotic support that can adapt to dynamic industrial environments. Beyond that, attempts to give robots human-like senses are effective. Perception modules based on vision and touch can largely measure the distance between humans and robots and adjust the speed of robots. Mohammadi Amin et al. [44] developed a vision-based system to detect intentional and accidental interactions between humans and robots, which can improve safety and the robot's perception of human intentions. Islam et al. [75] have developed a flexible connection decision-making framework for Cyber-Physical systems, which is capable of responding promptly to dynamic changes and resisting sudden dangers.
3. Ethics
Ethical issues are not only about the application of technology but also about social norms, principles, and values. Morality and ethics can affect the public's trust and acceptance of HRC. Consequently, several articles have explored various dimensions of ethics. For example, Komatsu [76] revealed the moral responsibility of AI developers and the public's expectations of AI for ethical decision-making by comparing how people with different responsibilities in a task judge moral error. Lewis and Minior [77] discussed multiple forms of ethical deliberation based on ontology, which have played a role in studying the ethical and social implications of HRC. Metzler and Lewis [78] highlighted the role of personal morality and religious beliefs in shaping the social integration of robots. However, at the same time, there are still many ethical challenges associated with AI. For instance, Dajani, et al. [79] pointed out that in the HRC, machines might obtain supervisory rights, leading to excessive collection of personal data and threatening privacy rights and autonomy. Algorithmic bias may be embedded in robot learning systems, leading to discriminatory decisions, and the existing legal framework is difficult to clearly define liability [80].
4. Fairness
The decisions, behaviors, and interactions of AI systems need to ensure that they are fair to all users and free from bias and discrimination. Claure et al. [81] encouraged researchers to use existing theories, practices, and formalized equity indicators to promote fairness in HRC and transparency in AI. Londono et al. [80] proposed a framework for classifying the sources of bias and the resulting types of discrimination. They also studied scenarios of unfair outcomes and strategies for mitigating these situations.

4.1.4. Application of Human–Robot Collaboration (HRC) in Architecture, Engineering, and Construction (AEC) Sector

In this study, 120 articles were reported on HRC applications within AEC. Figure 5 illustrates the distribution of research articles into six HRC applications in the AEC sector. They include system, framework, platform, screen, index, and solution.

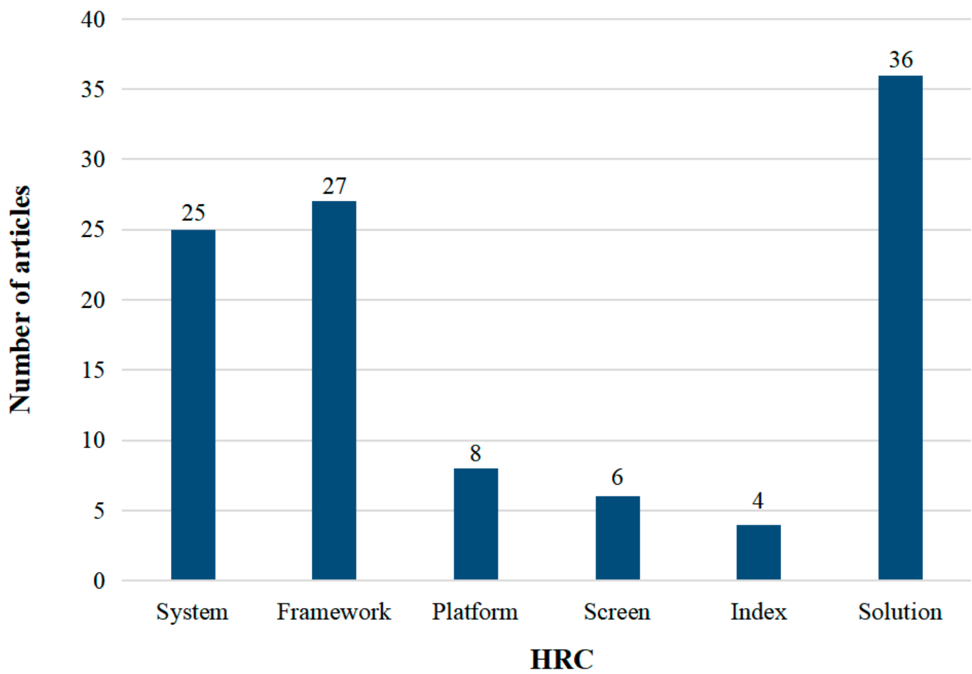

Figure 5. Number of articles on HRC applications in AEC.

1. System
   In HRC, the system refers to the overall computing environment where users interact, which can include hardware, software, user interfaces, and underlying supporting technologies. In this paper, HRC-related systems have a high diversity and depth, reflecting the characteristics of interdisciplinary integration in this field. For example, Podpora et al. [82] designed a custom Internet of Things (IoT) subsystem to obtain information before the actual interaction occurs. Othman and Yang [83] outlined the HRC system to solve the collaborative interaction requirements of humans and robots in intelligent manufacturing. Jaroonsorn et al. [84] proposed a robot control system for collaborative object-handling tasks. Liang et al. [85] proposed a digital twin (DT) framework that can simulate and optimize human–machine collaboration on building construction sites in real time. The digital binary-based system proposed by Lee et al. [86] enabled dynamic robots to rapidly perform adaptive task assignments in construction environments. Ryu et al. [87] combined bionics and dynamics to develop a humanoid robot system that enables robots to carry out more accurate path planning in complex built environments.
2. Framework
   Frameworks typically guide the collection of theories, methods, and tools that are used to design, implement, and evaluate interactions between users and computer systems. The articles can be categorized based on the following types of frameworks. (1) Operation and control framework. Wang and Zhu [88] proposed a visual-based framework to capture and interpret the gestures of construction workers. (2) Cognitive and learning frameworks. Shukla et al. [89] developed a robot framework that uses graph data to encapsulate knowledge structure and realizes new task learning

through knowledge transfer. (3) Theory and application development framework. Breazeal et al. [90] proposed a theoretical framework based on joint intention theory and cooperative discourse theory that allows humans to use speech, gesture, and expression cues to cooperate with humanoid robots to complete joint tasks. Peltason and Wrede [91] combined insights from dialogue modeling with software engineering requirements for robotic systems to propose a generalized framework that can be applied to new scenarios. Scibilia et al. [92] developed an ANN framework that helps robots predict human intentions during collaborative operations.

3. Platform
A Platform usually refers to the hardware and/or software environment that supports the running of software applications. Platforms typically provide a set of tools, services, and standards that enable developers and users to build, run, and interact with the environment. In the included articles, platforms can be divided into the following types. (1) Robot platform: robotic solutions for assisting HRC and personal care [93]. (2) Digital cloud platform: it communicates through a 5G network, transmits mechanical parameters and construction instructions of unmanned bulldozers, and achieves ultra-low-delay earth-moving monitoring [94]. (3) HRI platform: a platform that enables HRC in industrial tasks [58] (4) Database: constructing a conversational corpus [95].

4. Interface
An HRC interface is a medium between a user and a computer or machine to facilitate effective communication and interaction. Some of the included articles focused on new HRC operating interfaces, such as user interfaces for autonomous vehicles [96], and intelligent human–machine interfaces that recognize human gestures and hand/arm movements [97]. Construction workers can use a manual interface to control the force to guide the robot to install the glass [98]. Other studies focus on technical aspects, such as fusing information on and around video windows [99].

5. Index
In the field of HRC, it is very important to evaluate the quality of robotic systems and interactions. These metrics help researchers and developers quantify and evaluate robot performance, the effectiveness of interactions, and user experience and satisfaction. The articles include research related to metric development [100,101], collation [102], and overview [103]. Park et al. [104] expanded the TAM-IDT model, improved the understanding of architects on the intention to use HRC, and found the tendency of perceived usefulness and perceived ease of use.

6. Solution
Some of the included articles focused on technologies, methods, systems, or procedures designed to solve specific problems or needs, which are collectively referred to as solutions. These solutions include but are not limited to (1) HRC technologies and methods [41]; (2) robot control and intent expression (e.g., knowledge transfer and robot control [105]); (3) interactive perception and cognition (e.g., joint attention and non-verbal cues [106]); and (4) communication and comprehension (e.g., Communication-based Discourse understanding model [107]). In the construction sector, collaborative robots are widely used to replace workers performing dangerous tasks. Xu et al. [108] used semi-autonomous robots for high-altitude drilling and ceiling drywall installation in project management.

4.2. Research Gaps of AI in HRC in Construction

With the gradual application of AI techniques in HRC in construction, the problems caused by different technologies and the integration of several advanced technologies can be revealed. For example, the robustness of AI systems is often insufficient. The planning and execution of AI techniques are not always compatible with industrial paradigms. Hidden ethical issues need to be considered when using AI, and the initiative of robots under the auspices of AI still needs improvement. Figure 6 summarizes the main research gaps of AI in HRC in construction.

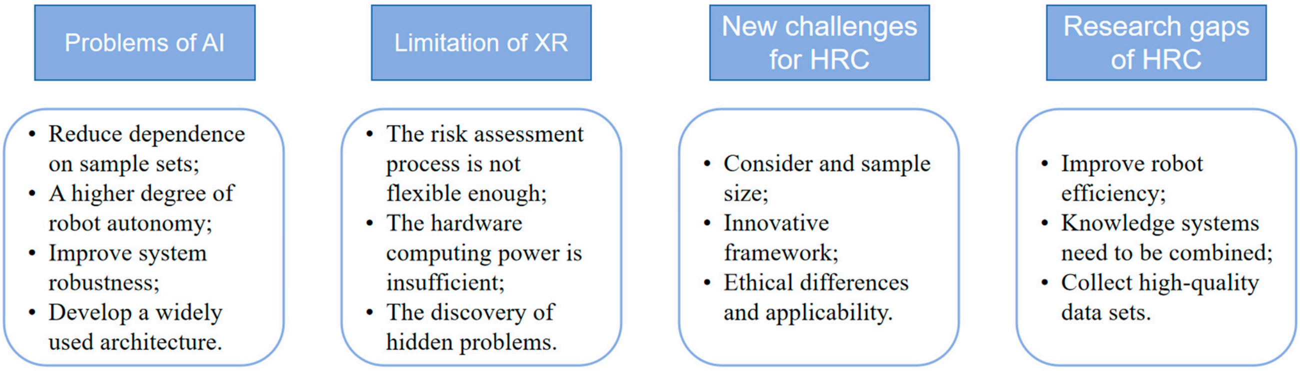

Figure 6. Research gaps of AI in HRC in construction. Note: AI = Artificial Intelligence; HRC = Human–Robot Collaboration; XR = Extended Reality.

4.2.1. Problems Related to AI Applications

AI provides several key advantages and innovations to enhance the performance of HRC, which greatly improves the user experience and interaction efficiency. However, several challenges remain in the application of AI. The application of AI requires innovative approaches to address current limitations. The current research methods mainly rely on large datasets but lack the integration of domain knowledge and human expertise with deep learning models, and the generalization ability remains questionable [109]. For instance, when an operator suddenly requests the robot to grasp a tool that is not included in the training data, the system can detect it, but with limited accuracy [110]. This indicates that AI performs inconsistently when facing unforeseen objects in HRC. AI has limited autonomy enhancement for robots. Solutions to applicable problems have been extensively studied, but the implementation of a truly autonomous robot remains an issue that opens exciting possibilities for future research [111]. Future studies should also explore how the robustness of the system could be addressed. For example, meta-reinforcement learning and improving learning strategies through data can reduce the need for interaction and cognitive load training [112]. It is necessary to consider the integration of cognition to adapt the capabilities of HRC, and solutions for different scenarios [63]. Several crucial research questions require further investigation:

1. How can domain knowledge and human expertise be systematically integrated into AI models to compensate for limited training data?
2. How can AI-driven robots achieve context-aware decision-making without constant human intervention?
3. How can meta-learning strategies generalize robustness across diverse HRC scenarios without task-specific retraining?
4. What standardized frameworks or modular designs would enable scalable, interoperable AI systems for HRC across industries?

4.2.2. Limitations of Extended Reality (XR)

The XR field is experiencing significant growth and development and is often cross-applied with AI and HRC fields [63,66]. However, there are still some limitations in the application of XR, which hinder its wide application. For example, flexibility in the planning and execution of most applications should be combined with industrial safety, and the assessment of risks should be updated and improved promptly. However, the risk assessment procedures currently used in the industry struggle to keep up with the flexibility of the new paradigm [64]. Real-time optimization and reverse control are challenging to implement. In the actual assembly environment, if the index scores are not satisfactory, the module needs to be re-planned and analyzed. This iterative optimization requires frequent switching between the virtual and physical systems, which may cause the assembly process to be interrupted and affect the overall efficiency [43]. Limited hardware computing, particularly GPUs in AR devices, restricts the ability to render high-quality, large-volume data for calculations and simulations. Although performance can be improved by optimising the model and reducing the capacity data [65], computing power still affects the quality and speed of data processing. With the advancement of AI and HRC, some new areas, such as SR, are proposed. Because the absolute independence of the virtual agent has never been created, its hidden problems, such as ethical issues, should be anticipated and addressed proactively [68]. As a new field, SR has many technical challenges, but its concept has bright prospects. Several crucial research questions require further investigation:

1. How can real-time risk-monitoring systems be designed to align with the flexibility of industrial XR applications?
2. What hardware innovations (e.g., edge computing, neuromorphic chips) could overcome GPU bottlenecks in AR/VR devices?
3. How should interdisciplinary guidelines (e.g., ethics-by-design for virtual agents) be structured to preempt emergent risks?

4.2.3. New Challenges for HRC

In Section 4.1.3, we categorized the challenges into four perspectives: trust, safety, ethics, and fairness. They solve different problems and promote the development of different fields, but at the same time, there are still some shortcomings. For trust, researchers have developed different models or used new AI techniques such as the online application of extreme learning machine (ELM) models to process facial expressions [70], or the use of a ChatGPT 3.5 robot assistant to judge negative comments [113]. Gualtieri et al. [114] developed a preliminary design guideline for cognitive ergonomics using a seven-step approach. The number of participants in the expert survey was relatively small (N = 108), which might have an impact on the generalizability of the results in terms of statistics. More considerations and samples are needed for future research. To address these problems, future research should include a wide range of settings and actors [47], improve the accuracy of communication [113], and increase datasets [48]. In the included articles, AI technologies such as ML are often used as frameworks to solve safety problems [73]. However, there is a need for more innovative frameworks to provide comprehensive solutions. Researchers should use new technologies such as cloud-based systems and semantic systems to enhance system functionality and customization [73], or systems that can integrate multiple functional modules [74]. In ethical philosophy, religious belief is often regarded as an important factor affecting moral behavior and values. As a new technology, users' acceptance of HRC would be affected by the differences in religious beliefs [78]. Therefore, the development and application of related services should still consider the issue of ethical differences and applicability. In addition to the AI framework, interdisciplinary norms are also necessary. For instance, the collaborative formulation of norms from disciplines such as law and medicine can establish implementable fairness standards and ethical guidelines [79,80]. Several crucial research questions require further investigation:

1. What methodologies (e.g., synthetic data augmentation, active learning) can optimize sample efficiency while ensuring model generalizability across diverse HRC scenarios?

2. How can modular design principles enable frameworks to evolve with emerging technologies (e.g., quantum computing, embodied AI)?
3. What cross-cultural ethical benchmarks (e.g., region-specific value hierarchies) should guide HRC design to mitigate religious or ideological biases?

4.2.4. Research Gaps in HRC

With the increasing maturity of different technologies, HRC has been gradually applied to different scenarios, but some studies have also identified the limitations of its current development. The commonly used facial recognition technology requires a large amount of work, and the efficiency of the robot is not guaranteed at present. Val-Calvo et al. [115] suggested that improving the robot's autonomy requires a fundamental restructuring of the approach to this problem. In addition, the knowledge modules of robots are still relatively segmented, and one of the future directions of HRC is combining different kinds of knowledge to make it skilled and qualified to help humans complete collaborative tasks. This could involve combining cognitive and physical knowledge [116] or integrating physical knowledge with a mathematical background [87]. With the increasingly close interaction between AI and HRC, high-quality data integration is the core of this field. This allows ML algorithms to learn from many user interactions and explore new areas [117]. However, in the research from waste to creative robot design, Gkournelos et al. [118] found that under the influence of economic assessment and various interference factors such as dust and vibration in the industrial environment, there are multiple obstacles from the laboratory prototype to actual application. Furthermore, fusion technology may become an important way to solve problems in this field [119]. At present, most robots based on NLP still have difficulty understanding the logic and human intention of complex tasks, and robots are weak in integrating different types of knowledge [116]. SR technology has broad prospects but still faces many challenges, such as technical complexity and data processing [68]. For the construction scene with high personnel density and complex work, safety is also the focus of attention. For example, the occurrence of accidents caused by high-frequency interaction between workers and robots is a persistent problem [120]. It is difficult for agents to interpret and act with the currently designed programs. With the development of new technologies, ethics has also become a mainstream issue that needs to be addressed. Several crucial research questions require further investigation:

1. How can adaptive control algorithms be designed to dynamically balance speed and precision in human–robot collaborative environments?
2. How should knowledge representation frameworks (e.g., ontologies, graph databases) be standardized to enable interoperability across diverse robotic systems?
3. Where can domain-specific, ethically sourced datasets (e.g., construction sites, healthcare) be systematically curated to reflect real-world HRC complexities?

4.3. Future Research Directions for AI in HRC in Construction

Through keyword co-occurrence analysis, qualitative discussion of mainstream topics, and research gaps, Figure 7 proposes a research framework for future research directions of AI in HRC in construction. Notably, these research trends have some intersections rather than independence. For example, a data library of interaction patterns and components, as well as multi-modal interactions, can improve the user experience of seamless integration of real and virtual environments. The future of AI in HRC in construction can be foreseen in several directions, including:

1. Improve future robots' understanding of human intentions and needs through AI technologies (e.g., NLP and improved perception systems).

2. Equip robots with more advanced learning algorithms to enable them to learn from experience and optimize their performance by allowing automatic adjustment of behavioral strategies in response to changing tasks and new operating environments.
3. Integrate advanced security protocols and ethical decision-making frameworks for supervising robot behavior.
4. Develop an interdisciplinary development framework for HRC systems to help develop humane, safer, and ethical cooperative robots to adapt to the rapidly changing construction environment.
5. Implement strict ethical standards and review mechanisms to establish and improve the transparency, reliability, and consistency of HRC systems.
6. Use of XR technologies to simulate construction tasks for planning and training, problem identification, and optimizing HRC strategies.
7. Use of SR to promote the integration of physical space and virtual space, and develop intelligent building systems that allow users to perceive and operate virtual elements in physical space, such as viewing building models through AR to facilitate planning and layout.
8. Wearable devices can be used to monitor the user's physiological state and robot systems in real time, where the operation of the robot is to adapt to the user's current health state and stress level.
9. Integrate different types of technologies such as IoT, big data, and cloud computing to enable functions such as task management, data analytics, and resource optimization.

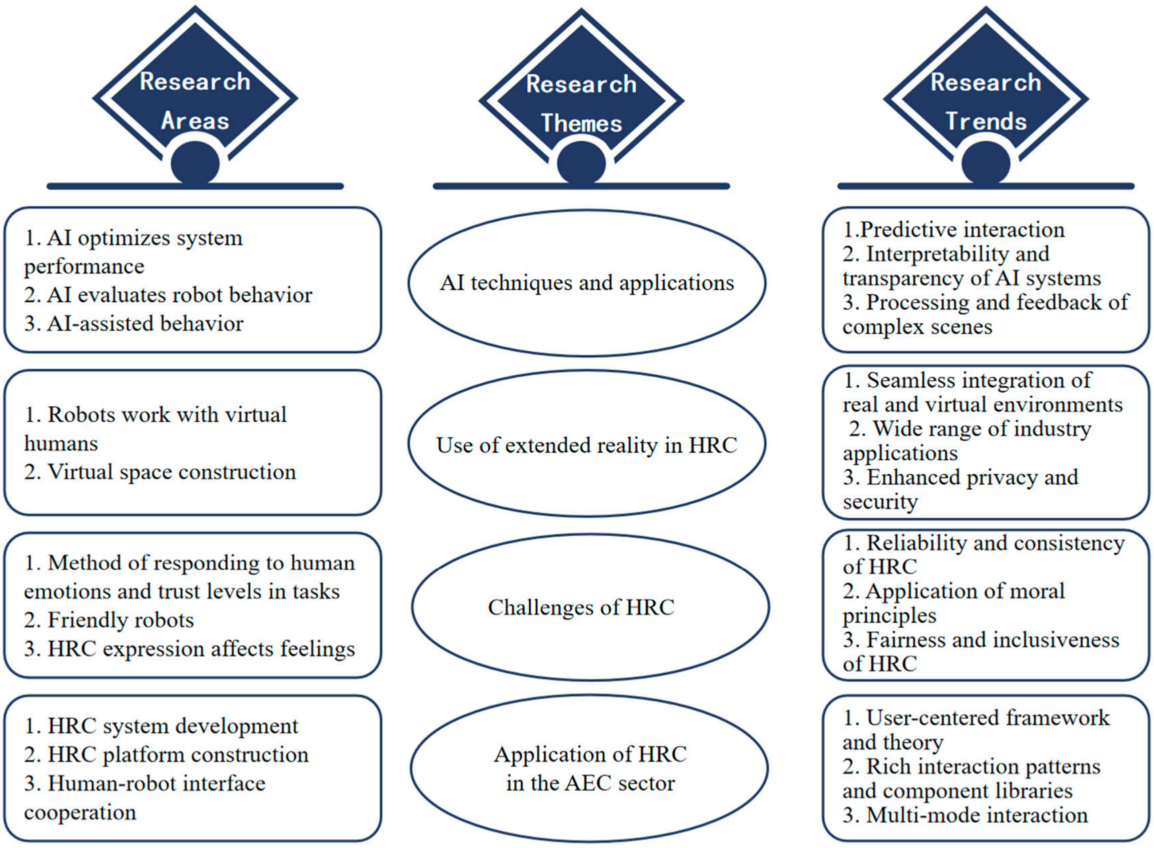

Figure 7. Future research trends of AI in HRC in construction. Note: AI = Artificial Intelligence; HRC = Human–Robot Collaboration; AEC = Architecture, Engineering, and Construction.

5. Conclusions

This paper presents a review of AI in HRC in construction and identifies the mainstream topics, research gaps, and future research trends. By searching articles from 1993 to

July 2025, 210 articles were retrieved from the Scopus database. The adopted method combined a scoping review and science mapping analysis. The results found four mainstream topics including AI techniques and applications, the use of XR in HRC, the challenges of HRC, and the application of HRC in the AEC. Moreover, four main research gaps were summarized. They include (1) problems related to AI applications, (2) limitations of XR, (3) new challenges for HRC, and (4) research gaps of HRC. Based on the research gaps, this paper summarizes the future research directions related to AI in HRC in construction. The findings of this would help researchers and construction practitioners understand how AI and HRC would impact construction resources and processes. The following section discusses the theoretical and practical contributions of the research as well as its limitations.

5.1. Contribution to Theory

This study conducts a review on the application of AI in HRC in the construction industry, aiming to discuss current research topics, identify research gaps, and recommend future research directions. Although existing literature has extensively explored the technical realization of HRC and the independent application of AI, there is a lack of in-depth analysis of the collaborative mechanisms of AI-enabled HRC in construction scenarios, especially on how to balance human decision-making and machine autonomy in dynamic construction environments. Through keyword co-occurrence analysis, country/region co-occurrence analysis, and qualitative discussion, this study identified four mainstream research topics and constructed a framework for future research directions. This study depicts the evolution of the research focus and reveals how different AI technologies, such as ML, DL, NLP, and fuzzy logic, are integrated into the HRC system. This comprehensive methodological approach not only highlights the transparency and reliability of the included articles but also captures the interdisciplinary connections, thereby providing support for the panoramic presentation of AI-driven HRC research. With the support of advanced technologies, it will promote the paradigm shift of construction HRC from instrumental assistance to cognitive collaboration, solving more related problems.

5.2. Contribution to Practice

The study adopted a combined approach of scoping review and science mapping analysis on the application of AI in HRC in the construction industry. The results of this review provide in-depth insights for construction stakeholders to understand the most advanced AI technologies used in human–robot collaborative construction tasks, laying a reference for the development of the next generation of intelligent construction systems. For example, the analysis of keywords and countries provides a reference guide for other scholars to conduct similar literature searches in this research field. The main research themes identified offer valuable insights for practitioners and scholars to discover more practical applications of using AI in human–machine interaction tasks. Additionally, the proposed future research directions enable researchers to address current research gaps, expand research development, and contribute to the existing body of knowledge. Finally, since AI technology can be widely applied in various scenarios, this review provides an opportunity to explore the proposed research directions.

5.3. Limitations of the Study

As with other reviews, this paper has some limitations. First, it excludes the most recent studies from July 2025 and beyond, and most of the included articles were published in conference and journal sources; thus, it may impact the reported results in this study. Therefore, future reviews should consider other sources (e.g., book chapters, trade journals) and recently published articles. Secondly, since the sample articles were limited to the engineering field, the results may not be generalized to other fields. Future reviews should consider expanding the scope to various fields and databases, thus providing a more comprehensive study. Lastly, this paper only considered relevant journal and conference articles retrieved from the Scopus database. As such, there may be limited sources that could affect the number of included articles. Consequently, future studies could consider other databases such as Web of Science, IEEE Xplore, and others.

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References

1. Zhang, M.; Xu, R.; Wu, H.; Pan, J.; Luo, X. Human–robot collaboration for on-site construction. *Autom. Constr.* **2023**, *150*, 104812. [CrossRef]
2. Bauer, A.; Wollherr, D.; Buss, M. Human–robot collaboration: A survey. *Int. J. Humanoid Robot.* **2008**, *5*, 47–66. [CrossRef]
3. Wei, H.H.; Zhang, Y.; Sun, X.; Chen, J.; Li, S. Intelligent robots and human-robot collaboration in the construction industry: A review. *J. Intell. Constr.* **2023**, *1*, 1–12. [CrossRef]
4. ec.europa.eu. (n.d.) Accidents at Work Statistics. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Accidents_at_work_statistics#Incidence_rates (accessed on 1 January 2020).
5. Tomori, M.; Ogunseiju, O.; Nnaji, C. A Review of Human-robotics interactions in the construction industry. In Proceedings of the Construction Research Congress, Des Moines, IA, USA, 20–23 March 2024; pp. 903–912. [CrossRef]
6. Ahsan, S.; El-Hamalawi, A.; Bouchlaghem, D.; Ahmad, S. Mobile technologies for improved collaboration on construction sites. *Archit. Eng. Des. Manag.* **2007**, *3*, 257–272. [CrossRef]
7. Simmons, A.B.; Chappell, S.G. Artificial intelligence-definition and practice. *IEEE J. Ocean. Eng.* **1988**, *13*, 14–42. [CrossRef]
8. Voulodimos, A.; Doulamis, N.; Doulamis, A.; Protopapadakis, E. Deep learning for computer vision: A brief review. *Comput. Intell. Neurosci.* **2018**, *2018*, 7068349. [CrossRef]
9. Mirzaei, K.; Arashpour, M.; Asadi, E.; Masoumi, H.; Bai, Y.; Behnood, A. 3D point cloud data processing with machine learning for construction and infrastructure applications: A comprehensive review. *Adv. Eng. Inform.* **2022**, *51*, 101501. [CrossRef]
10. Fernandes, L.L.D.A.; Costa, D.B. A conceptual model for measuring the maturity of an Intelligent Construction Environment. *Archit. Eng. Des. Manag.* **2024**, *20*, 1403–1426. [CrossRef]
11. Li, Y.; Antwi-Afari, M.F.; Anwer, S.; Mehmood, I.; Umer, W.; Mohandes, S.R.; Wuni, I.Y.; Abdul-Rahman, M.; Li, H. Artificial intelligence in net-zero carbon emissions for sustainable building projects: A systematic literature and science mapping review. *Buildings* **2024**, *14*, 2752. [CrossRef]
12. Wang, J.; Antwi-Afari, M.F.; Tezel, A.; Antwi-Afari, P.; Kasim, T. Artificial Intelligence in Cloud Computing technology in the Construction industry: A bibliometric and systematic review. *J. Inf. Technol. Constr.* **2024**, *29*, 480–502. [CrossRef]
13. Zhang, X.; Antwi-Afari, M.F.; Zhang, Y.; Xing, X. The impact of artificial intelligence on organizational justice and project performance: A systematic literature and science mapping review. *Buildings* **2024**, *14*, 259. [CrossRef]
14. Ohri, K.; Kumar, M. Review on self-supervised image recognition using deep neural networks. *Knowl.-Based Syst.* **2021**, *224*, 107090. [CrossRef]

15. Hamilton, K.; Nayak, A.; Božić, B.; Longo, L. Is neuro-symbolic AI meeting its promises in natural language processing? A structured review. *Semantic Web* **2024**, *15*, 1265–1306. [CrossRef]
16. Liu, Y.; Habibnezhad, M.; Jebelli, H. Brainwave-driven human-robot collaboration in construction. *Autom. Constr.* **2021**, *124*, 103556. [CrossRef]
17. Attalla, A.; Attalla, O.; Moussa, A.; Shafique, D.; Raean, S.B.; Hegazy, T. Construction robotics: Review of intelligent features. *Int. J. Intell. Robot. Appl.* **2023**, *7*, 535–555. [CrossRef]
18. Ma, X.; Mao, C.; Liu, G. Can robots replace human beings?—Assessment on the developmental potential of construction robot. *J. Build. Eng.* **2022**, *56*, 104727. [CrossRef]
19. Feng, C.; Xiao, Y.; Willette, A.; McGee, W.; Kamat, V.R. Vision guided autonomous robotic assembly and as-built scanning on unstructured construction sites. *Autom. Constr.* **2015**, *59*, 128–138. [CrossRef]
20. Zhang, R.; Lv, Q.; Li, J.; Bao, J.; Liu, T.; Liu, S. A reinforcement learning method for human-robot collaboration in assembly tasks. *Robot. Comput.-Integr. Manuf.* **2022**, *73*, 102227. [CrossRef]
21. Fu, Y.; Chen, J.; Lu, W. Human-robot collaboration for modular construction manufacturing: Review of academic research. *Autom. Constr.* **2024**, *158*, 105196. [CrossRef]
22. Rodrigues, P.B.; Singh, R.; Oytun, M.; Adami, P.; Woods, P.J.; Becerik-Gerber, B.; Soibelman, L.; Copur-Gencturk, Y.; Lucas, G.M. A multidimensional taxonomy for human-robot interaction in construction. *Autom. Constr.* **2023**, *150*, 104845. [CrossRef]
23. Marinelli, M. From industry 4.0 to construction 5.0: Exploring the path towards human–robot collaboration in construction. *Systems* **2023**, *11*, 152. [CrossRef]
24. Borboni, A.; Reddy, K.V.V.; Elamvazuthi, I.; AL-Quraishi, M.S.; Natarajan, E.; Azhar Ali, S.S. The expanding role of artificial intelligence in collaborative robots for industrial applications: A systematic review of recent works. *Machines* **2023**, *11*, 111. [CrossRef]
25. Pan, Y.; Zhang, L. Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Autom. Constr.* **2021**, *122*, 103517. [CrossRef]
26. Regona, M.; Yigitcanlar, T.; Xia, B.; Li, R.Y.M. Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 45. [CrossRef]
27. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *BMJ* **2009**, *339*, b2535. [CrossRef]
28. Katoch, R. IoT research in supply chain management and logistics: A bibliometric analysis using vosviewer software. *Mater. Today Proc.* **2022**, *56*, 2505–2515. [CrossRef]
29. Chadegani, A.A.; Salehi, H.; Yunus, M.M.; Farhadi, H.; Fooladi, M.; Farhadi, M.; Ebrahim, N.A. A comparison between two main academic literature collections: Web of Science and Scopus databases. *arXiv* **2013**, arXiv:1305.0377. [CrossRef]
30. Zhang, F.; Xu, B.; Zeng, X.; Ding, K. Gesture-driven interaction service system for complex operations in digital twin manufacturing cells. *J. Eng. Des.* **2024**. [CrossRef]
31. Lee, S.; Lee, S.; Park, H. Integration of Tracking, Re-Identification, and Gesture Recognition for Facilitating Human–Robot Interaction. *Sensors* **2024**, *24*, 4850. [CrossRef]
32. Schewior, J.; Grefen, R.; Verde, R.; Ergardt, A.; Zhao, Y.; Kullmann, W.H. Speech-Controlled Robot Enabling Cognitive Training and Stimulation in Dementia Prevention for Severely Disabled People. *Curr. Dir. Biomed. Eng.* **2024**, *10*, 543–546. [CrossRef]
33. Harrison, R.; Jones, B.; Gardner, P.; Lawton, R. Quality assessment with diverse studies (QuADS): An appraisal tool for methodological and reporting quality in systematic reviews of mixed-or multi-method studies. *BMC Health Serv. Res.* **2021**, *21*, 1–20. [CrossRef]
34. Jiang, Q.; Antwi-Afari, M.F.; Fadaie, S.; Mi, H.Y.; Anwer, S.; Liu, J. Self-powered wearable Internet of Things sensors for human-machine interfaces: A systematic literature review and science mapping analysis. *Nano Energy* **2024**, *131*, 110252. [CrossRef]
35. Van Eck, N.J.; Waltman, L. Visualizing bibliometric networks. In *Measuring Scholarly Impact: Methods and Practice*; Springer International Publishing: Cham, Switzerland, 2014; pp. 285–320. [CrossRef]
36. Lu, M.; Antwi-Afari, M.F. A scientometric analysis and critical review of digital twin applications in project operation and maintenance. *Eng. Constr. Archit. Manag.* **2024**. [CrossRef]
37. Ma, Q.; Ma, T.; Lu, C.; Cheng, B.; Xie, S.; Gong, L.; Fu, Z.; Liu, C. A cloud-based quadruped service robot with multi-scene adaptability and various forms of human-robot interaction. *IFAC-PapersOnLine* **2020**, *53*, 134–139. [CrossRef]
38. Chang, J.Y.; Tejero-de-Pablos, A.; Harada, T. Improved optical flow for gesture-based human-robot interaction. In Proceedings of the 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 20–24 May 2019; pp. 7983–7989. [CrossRef]
39. Bamdale, R.; Sahay, S.; Khandekar, V. Natural human robot interaction using artificial intelligence: A survey. In Proceedings of the 2019 9th annual Information Technology, Electromechanical Engineering and Microelectronics Conference (IEMECON), Jaipur, India, 13–15 March 2019; pp. 297–302. [CrossRef]

40. Ranasinghe, N.; Mohammed, W.M.; Stefanidis, K.; Martinez Lastra, J.L. Large Language Models in Human-Robot Collaboration With Cognitive Validation Against Context-Induced Hallucinations. *IEEE Access* **2025**, *13*, 77418–77430. [CrossRef]
41. Mueller, R.; Vette, M.; Masiak, T.; Duppe, B.; Schulz, A. Intelligent real time inspection of rivet quality supported by human-robot-collaboration. *SAE Int. J. Adv. Curr. Pract. Mobil.* **2019**, *2*, 811–817. [CrossRef]
42. Das, A.; Kol, P.; Lundberg, C.; Doelling, K.; Sevil, H.E.; Lewis, F. A rapid situational awareness development framework for heterogeneous manned-unmanned teams. In Proceedings of the NAECON 2018-IEEE National Aerospace and Electronics Conference, Dayton, OH, USA, 23–26 July 2018; pp. 417–424. [CrossRef]
43. Xie, J.; Liu, Y.; Wang, X.; Fang, S.; Liu, S. A new XR-based human-robot collaboration assembly system based on industrial metaverse. *J. Manuf. Syst.* **2024**, *74*, 949–964. [CrossRef]
44. Mohammadi Amin, F.; Rezayati, M.; van de Venn, H.W.; Karimpour, H. A mixed-perception approach for safe human–robot collaboration in industrial automation. *Sensors* **2020**, *20*, 6347. [CrossRef]
45. Mokhtarzadeh, A.A.; Yangqing, Z.J. Human-robot interaction and self-driving cars safety integration of dispositif networks. In Proceedings of the 2018 IEEE International Conference on Intelligence and Safety for Robotics (ISR), Shenyang, China, 24–27 August 2018; pp. 494–499. [CrossRef]
46. Li, J.; Zhu, E.; Lin, W.; Yang, S.X.; Yang, S. A novel digital twins-driven mutual trust framework for human–robot collaborations. *J. Manuf. Syst.* **2025**, *80*, 948–962. [CrossRef]
47. Pedersen, B.K.M.K.; Andersen, K.E.; Köslich, S.; Weigelin, B.C.; Kuusinen, K. Simulations and self-driving cars: A study of trust and consequences. In Proceedings of the Companion of the 2018 ACM/IEEE international conference on human-robot interaction, New York, NY, USA, 5–8 March 2018; pp. 205–206. [CrossRef]
48. Zhang, A.; Yang, Q. To be human-like or machine-like? An empirical research on user trust in AI applications in service industry. In Proceedings of the 2022 8th International Conference on Automation, Robotics and Applications (ICARA), Prague, Czech Republic, 18–20 February 2022; pp. 9–15. [CrossRef]
49. Zhang, L.; Jiang, M.; Farid, D.; Hossain, M.A. Intelligent facial emotion recognition and semantic-based topic detection for a humanoid robot. *Expert Syst. Appl.* **2013**, *40*, 5160–5168. [CrossRef]
50. Sugiyama, T.; Funakoshi, K.; Nakano, M.; Komatani, K. Estimating response obligation in multi-party human-robot dialogues. In Proceedings of the 2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids), Seoul, Republic of Korea, 3–5 November 2015; pp. 166–172. [CrossRef]
51. Wang, Y.; Sheng, Y.; Wang, J.; Zhang, W. Human intention estimation with tactile sensors in human-robot collaboration. In Proceedings of the Dynamic Systems and Control Conference, Tysons, VA, USA, 11–13 October 2017; Volume 58288, p. V002T04A007. [CrossRef]
52. Bose, S.R.; Kumar, V.S.; Sreekar, C. In-situ enhanced anchor-free deep CNN framework for a high-speed human-machine interaction. *Eng. Appl. Artif. Intell.* **2023**, *126*, 106980. [CrossRef]
53. Garcia, P.P.; Santos, T.G.; Machado, M.A.; Mendes, N. Deep learning framework for controlling work sequence in collaborative human–robot assembly processes. *Sensors* **2023**, *23*, 553. [CrossRef]
54. Toda, Y.; Kubota, N. Attention Allocation for Multi-modal Perception of Human-friendly Robot Partners. *IFAC Proc. Vol.* **2013**, *46*, 324–329. [CrossRef]
55. Guinot, L.; Ando, K.; Takahashi, S.; Iwata, H. Analysis of implicit robot control methods for joint task execution. *ROBOMECH J.* **2023**, *10*, 12. [CrossRef]
56. Halilovic, A.; Lindner, F. Visuo-textual explanations of a robot's navigational choices. In Proceedings of the 2023 ACM/IEEE International Conference on Human-Robot Interaction, Stockholm, Sweden, 13–16 March 2023; pp. 531–535. [CrossRef]
57. Matuszek, C.; Pronobis, A.; Zettlemoyer, L.; Fox, D. Combining world and interaction models for human-robot collaborations. In Proceedings of the Workshops at the 27th AAAI Conference on Artificial Intelligence (AAAI 2013), Bellevue, WA, USA, 14–18 July 2013; Volume 1415. [CrossRef]
58. Li, C.; Park, J.; Kim, H.; Chrysostomou, D. How can i help you? an intelligent virtual assistant for industrial robots. In Proceedings of the 2021 ACM/IEEE International Conference on Human-Robot Interaction, Boulder, CO, USA, 8–11 March 2021; pp. 220–224. [CrossRef]
59. Preece, A.; Braines, D. Conversational services for multi-agency situational understanding. In Proceedings of the 2017 AAAI Fall Symposium, Arlington, VA, USA, 9–11 November 2017; Volume FS-17-01, pp. 179–186, ISBN 978-157735794-0.
60. Schirmer, F.; Kranz, P.; Manjunath, M.; Raja, J.J.; Rose, C.G.; Kaupp, T.; Daun, M. Towards a conceptual safety planning framework for human-robot collaboration. In Proceedings of the 42nd International Conference on Conceptual Modeling: ER Forum, 7th Symposium on Conceptual Modeling Education, SCME 2023, Lisbon, Portugal, 17 November 2023; Volume 3618.
61. Van Toan, N.; Kim, J.J.; Kim, K.G.; Lee, W.; Kang, S. Application of fuzzy logic to damping controller for safe human-robot interaction. In Proceedings of the 2017 14th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Jeju, Republic of Korea, 28 June–1 July 2017; pp. 109–113. [CrossRef]

62. Jiang, L.; Wang, Y. A personalized computational model for human-like automated decision-making. *IEEE Trans. Autom. Sci. Eng.* **2021**, *19*, 850–863. [CrossRef]
63. Chu, C.H.; Liu, Y.L. Augmented reality user interface design and experimental evaluation for human-robot collaborative assembly. *J. Manuf. Syst.* **2023**, *68*, 313–324. [CrossRef]
64. Umbrico, A.; Orlandini, A.; Cesta, A.; Faroni, M.; Beschi, M.; Pedrocchi, N.; Scala, A.; Tavormina, P.; Koukas, S.; Zalonis, A.; et al. Design of advanced human–robot collaborative cells for personalized human–robot collaborations. *Appl. Sci.* **2022**, *12*, 6839. [CrossRef]
65. Aschenbrenner, D.; Van Tol, D.; Rusak, Z.; Werker, C. Using virtual reality for scenario-based responsible research and innovation approach for human robot co-production. In Proceedings of the 2020 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR), Utrecht, The Netherlands, 14–18 December 2020; pp. 146–150. [CrossRef]
66. Rahman, S.M. An IoT-based common platform integrating robots and virtual characters for high performance and cybersecurity. In Proceedings of the 2019 SoutheastCon, Huntsville, AL, USA, 11–14 April 2019; pp. 1–6. [CrossRef]
67. Park, K.B.; Choi, S.H.; Moon, H.; Lee, J.Y.; Ghasemi, Y.; Jeong, H. Indirect robot manipulation using eye gazing and head movement for future of work in mixed reality. In Proceedings of the 2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW), Christchurch, New Zealand, 12–16 March 2022; pp. 483–484. [CrossRef]
68. Zhang, Z.; Wang, X. Machine intelligence matters: Rethink human-robot collaboration based on symmetrical reality. In Proceedings of the 2020 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Recife, Brazil, 9–13 November 2020; pp. 225–228. [CrossRef]
69. St-Onge, D.; Reeves, N.; Petkova, N. Robot-human interaction: A human speaker experiment. In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction, Vienna, Austria, 6–9 March 2017; pp. 30–38. [CrossRef]
70. Guo, T.; Obidat, O.; Rodriguez, L.; Parron, J.; Wang, W. Reasoning the trust of humans in robots through physiological biometrics in human-robot collaborative contexts. In Proceedings of the 2022 IEEE MIT Undergraduate Research Technology Conference (URTC), Cambridge, MA, USA, 30 September–2 October 2022; pp. 1–6. [CrossRef]
71. Robb, D.A.; Ahmad, M.I.; Tiseo, C.; Aracri, S.; McConnell, A.C.; Page, V.; Dondrup, C.; Chiyah Garcia, F.J.; Nguyen, H.N.; Pairet, È.; et al. Robots in the danger zone: Exploring public perception through engagement. In Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction, Cambridge, UK, 23–26 March 2020; pp. 93–102. [CrossRef]
72. Parron, J.; Li, R.; Wang, W.; Zhou, M. Characterization of Human Trust in Robot through Multimodal Physical and Physiological Biometrics in Human-Robot Partnerships. In Proceedings of the 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE), Bari, Italy, 28 August–1 September 2024; pp. 2901–2906. [CrossRef]
73. Islam, S.O.B.; Lughmani, W.A. A connective framework for social collaborative robotic system. *Machines* **2022**, *10*, 1086. [CrossRef]
74. Cen, D.; Sibona, F.; Indri, M. A framework for safe and intuitive human-robot interaction for assistant robotics. In Proceedings of the 2022 IEEE 27th International Conference on Emerging Technologies and Factory Automation (ETFA), Stuttgart, Germany, 6–9 September 2022. [CrossRef]
75. Islam, S.O.B.; Lughmani, W.A.; Qureshi, W.S.; Khalid, A. A connective framework to minimize the anxiety of collaborative Cyber-Physical System. *Int. J. Comput. Integr. Manuf.* **2024**, *37*, 454–472. [CrossRef]
76. Komatsu, T. Owners of artificial intelligence systems are more easily blamed compared with system designers in moral dilemma tasks. In Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction, Vienna, Austria, 6–9 March 2017; pp. 169–170. [CrossRef]
77. Lewis, L.; Minor, D. Considerations of moral ontology and reasoning in human-robot interaction. In Proceedings of the 2008 AAAI Workshop, Radnor, PA, USA, 23–26 October 2008; Volume WS-08-05, pp. 11–14.
78. Metzler, T.; Lewis, L. Ethical views, religious views, and acceptance of robotic applications: A pilot study. In Proceedings of the 2008 AAAI Workshop, Chicago, IL, USA, 13–14 July 2008; Volume WS-08-05, pp. 15–22.
79. Dajani, L.; Ferraro, A.; Maruyama, F.; Cheng, Y. Human Rights and Ethics Guiding Human-Machine Teaming. In Proceedings of the 2024 IEEE Global Humanitarian Technology Conference (GHTC), Radnor, PA, USA, 23–26 October 2024; pp. 254–261. [CrossRef]
80. Londoño, L.; Hurtado, J.V.; Hertz, N.; Kellmeyer, P.; Voeneky, S.; Valada, A. Fairness and Bias in Robot Learning. *Proc. IEEE* **2024**, *112*, 305–330. [CrossRef]
81. Claure, H.; Chang, M.L.; Kim, S.; Omeiza, D.; Brandao, M.; Lee, M.K.; Jung, M. Fairness and transparency in human-robot interaction. In Proceedings of the 2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Sapporo, Japan, 7–10 March 2022; pp. 1244–1246. [CrossRef]
82. Podpora, M.; Gardecki, A.; Beniak, R.; Klin, B.; Vicario, J.L.; Kawala-Sterniuk, A. Human interaction smart subsystem—Extending speech-based human-robot interaction systems with an implementation of external smart sensors. *Sensors* **2020**, *20*, 2376. [CrossRef]
83. Othman, U.; Yang, E. An overview of human-robot collaboration in smart manufacturing. In Proceedings of the 2022 27th International Conference on Automation and Computing (ICAC), Bristol, UK, 1–3 September 2022; pp. 1–6. [CrossRef]

84. Jaroonsorn, P.; Neranon, P.; Dechwayukul, C.; Smithmaitrie, P. Performance comparison of compliance control based on pi and FLC for safe human-robot cooperative object carrying. In Proceedings of the 2019 First International Symposium on Instrumentation, Control, Artificial Intelligence, and Robotics (ICA-SYMP), Bangkok, Thailand, 16–18 January 2019; pp. 13–16. [CrossRef]
85. Liang, C.J.; McGee, W.; Menassa, C.C.; Kamat, V.R. Real-time state synchronization between physical construction robots and process-level digital twins. *Constr. Robot.* **2022**, *6*, 57–73. [CrossRef]
86. Lee, D.; Lee, S.; Masoud, N.; Krishnan, M.S.; Li, V.C. Digital twin-driven deep reinforcement learning for adaptive task allocation in robotic construction. *Adv. Eng. Inform.* **2022**, *53*, 101710. [CrossRef]
87. Ryu, S.H.; Kang, Y.; Kim, S.J.; Lee, K.; You, B.J.; Doh, N.L. Humanoid path planning from hri perspective: A scalable approach via waypoints with a time index. *IEEE Trans. Cybern.* **2012**, *43*, 217–229. [CrossRef] [PubMed]
88. Wang, X.; Zhu, Z. Vision–based framework for automatic interpretation of construction workers' hand gestures. *Autom. Constr.* **2021**, *130*, 103872. [CrossRef]
89. Shukla, N.; Xiong, C.; Zhu, S.-C. A unified framework for human-robot knowledge transfer. In Proceedings of the 2015 AAAI Fall Symposium, Arlington, VA, USA, 12–14 November 2015; Volume FS-15.
90. Breazeal, C.; Brooks, A.; Chilongo, D.; Gray, J.; Hoffman, G.; Kidd, C.; Lee, H.; Lieberman, J.; Lockerd, A. Working collaboratively with humanoid robots. In Proceedings of the 4th IEEE/RAS International Conference on Humanoid Robots, Santa Monica, CA, USA, 10–12 November 2004; Volume 1, pp. 253–272. [CrossRef]
91. Peltason, J.; Wrede, B. Modeling human-robot interaction based on generic interaction patterns. In Proceedings of the 2010 AAAI Fall Symposium, Arlington, VA, USA, 11–13 November 2010; Volume FS-10-05, pp. 80–85.
92. Scibilia, A.; Pedrocchi, N.; Fortuna, L. A Nonlinear Modeling Framework for Force Estimation in Human-Robot Interaction. *IEEE Access* **2024**, *12*, 97257–97268. [CrossRef]
93. Mišeikis, J.; Caroni, P.; Duchamp, P.; Gasser, A.; Marko, R.; Mišeikienė, N.; Zwilling, F.; De Castelbajac, C.; Eicher, L.; Früh, M.; et al. Lio-a personal robot assistant for human-robot interaction and care applications. *IEEE Robot. Autom. Lett.* **2020**, *5*, 5339–5346. [CrossRef]
94. You, K.; Ding, L.; Zhou, C.; Dou, Q.; Wang, X.; Hu, B. 5G-based earthwork monitoring system for an unmanned bulldozer. *Autom. Constr.* **2021**, *131*, 103891. [CrossRef]
95. Cruz-Sandoval, D.; Eyssel, F.; Favela, J.; Sandoval, E.B. Towards a conversational corpus for human-robot conversations. In Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction, Vienna, Austria, 6–9 March 2017; pp. 99–100. [CrossRef]
96. Eom, H.; Lee, S.H. Mode confusion of human–machine interfaces for automated vehicles. *J. Comput. Des. Eng.* **2022**, *9*, 1995–2009. [CrossRef]
97. Alsayegh, O.A.; Brzakovic, D.P. Guidance of video data acquisition by myoelectric signals for smart human-robot interfaces. In Proceedings of the 1998 IEEE International Conference on Robotics and Automation (Cat. No. 98CH36146), Leuven, Belgium, 20 May 1998; Volume 4, pp. 3179–3185. [CrossRef]
98. Gil, M.S.; Kang, M.S.; Lee, S.; Lee, H.D.; Shin, K.S.; Lee, J.Y.; Han, C.S. Installation of heavy duty glass using an intuitive manipulation device. *Autom. Constr.* **2013**, *35*, 579–586. [CrossRef]
99. Baker, M.; Casey, R.; Keyes, B.; Yanco, H.A. Improved interfaces for human-robot interaction in urban search and rescue. In Proceedings of the 2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No. 04CH37583), The Hague, The Netherlands, 10–13 October 2004; Volume 3, pp. 2960–2965. [CrossRef]
100. Marathe, A.R.; Lance, B.J.; McDowell, K.; Nothwang, W.D.; Metcalfe, J.S. Confidence metrics improve human-autonomy integration. In Proceedings of the 2014 ACM/IEEE International Conference on Human-Robot Interaction, Bielefeld, Germany, 3–6 March 2014; pp. 240–241. [CrossRef]
101. Bensch, S.; Jevtic, A.; Hellström, T. On interaction quality in human-robot interaction. In Proceedings of the ICAART 2017, Proceedings of the 9th International Conference on Agents and Artificial Intelligence, Porto, Portugal, 24–26 February 2017; Volume 1, pp. 182–189. [CrossRef]
102. Hoffman, G. Evaluating fluency in human–robot collaboration. *IEEE Trans. Hum.-Mach. Syst.* **2019**, *49*, 209–218. [CrossRef]
103. Burghart, C.; Mikut, R.; Holzapfel, H. Cognition-oriented building blocks of future benchmark scenarios for humanoid home robots. In Proceedings of the IEEE International Conference on Humanoid Robots, Vancouver, BC, Canada, 22–23 July 2007; pp. 1–10.
104. Park, S.; Yu, H.; Menassa, C.C.; Kamat, V.R. A comprehensive evaluation of factors influencing acceptance of robotic assistants in field construction work. *J. Manag. Eng.* **2023**, *39*, 04023010. [CrossRef]
105. Roveda, L.; Veerappan, P.; Maccarini, M.; Bucca, G.; Ajoudani, A.; Piga, D. A human-centric framework for robotic task learning and optimization. *J. Manuf. Syst.* **2023**, *67*, 68–79. [CrossRef]
106. Yucel, Z.; Salah, A.A.; Mericli, C.; Mericli, T.; Valenti, R.; Gevers, T. Joint Attention by Gaze Interpolation and Saliency. *IEEE Trans. Cybern.* **2013**, *43*, 829–842. [CrossRef]

107. Ono, T.; Imai, M.; Nakatsu, R. Reading a robot's mind: A model of utterance understanding based on the theory of mind mechanism. *Adv. Robot.* **2000**, *14*, 311–326. [CrossRef]
108. Xu, X.; Holgate, T.; Coban, P.; García de Soto, B. Implementation of a robotic system for overhead drilling operations: A case study of the Jaibot in the UAE. *Int. J. Autom. Digit. Transform.* **2022**, *1*, 37–58. [CrossRef]
109. Peng, H.; Shi, N.; Wang, G. Remote sensing traffic scene retrieval based on learning control algorithm for robot multimodal sensing information fusion and human-machine interaction and collaboration. *Front. Neurorobot.* **2023**, *17*, 1267231. [CrossRef] [PubMed]
110. Ding, Q.; Zhang, E.; Liu, Z.; Yao, X.; Pan, G. Text-Guided Object Detection Accuracy Enhancement Method Based on Improved YOLO-World. *Electronics* **2024**, *14*, 133. [CrossRef]
111. Uğuzlar, U.; Cansu, E.; Contarlı, E.C.; Sezer, V. Autonomous human following robot based on follow the gap method. In Proceedings of the 2023 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Tomar, Portugal, 26–27 April 2023; pp. 139–144. [CrossRef]
112. Li, X.; Koren, Y.; Epureanu, B.I. Complementary learning-team machines to enlighten and exploit human expertise. *CIRP Ann.* **2022**, *71*, 417–420. [CrossRef]
113. Ye, Y.; You, H.; Du, J. Improved trust in human-robot collaboration with ChatGPT. *IEEE Access* **2023**, *11*, 55748–55754. [CrossRef]
114. Gualtieri, L.; Fraboni, F.; Brendel, H.; Pietrantoni, L.; Vidoni, R.; Dallasega, P. Updating design guidelines for cognitive ergonomics in human-centred collaborative robotics applications: An expert survey. *Appl. Ergon./Appl. Ergon.* **2024**, *117*, 104246. [CrossRef] [PubMed]
115. Val-Calvo, M.; Álvarez-Sánchez, J.R.; Ferrández-Vicente, J.M.; Fernández, E. Affective robot story-telling human-robot interaction: Exploratory real-time emotion estimation analysis using facial expressions and physiological signals. *IEEE Access* **2020**, *8*, 134051–134066. [CrossRef]
116. Castro, A.; Silva, F.; Santos, V. Trends of human-robot collaboration in industry contexts: Handover, learning, and metrics. *Sensors* **2021**, *21*, 4113. [CrossRef]
117. Li, C.; Chrysostomou, D.; Zhang, X.; Yang, H. IRWoZ: Constructing an industrial robot wizard-of-OZ dialoguing dataset. *IEEE Access* **2023**, *11*, 28236–28251. [CrossRef]
118. Gkournelos, C.; Konstantinou, C.; Angelakis, P.; Tzavara, E.; Makris, S. Praxis: A framework for AI-driven human action recognition in assembly. *J. Intell. Manuf.* **2023**, *35*, 3697–3711. [CrossRef]
119. Sidner, C.L.; Lee, C. Engagement rules for human-robot collaborative interactions. In Proceedings of the SMC'03 Conference Proceedings. 2003 IEEE International Conference on Systems, Man and Cybernetics. Conference Theme-System Security and Assurance (Cat. No. 03CH37483), Washington, DC, USA, 8 October 2003; Volume 4, pp. 3957–3962. [CrossRef]
120. A-lHamouz, S.O.; El-Omari, N.K.T.; Al-Naimat, A.M. An ISO compliant safety system for human workers in human-robot interaction work environment. In Proceedings of the 2019 12th International Conference on Developments in eSystems Engineering (DeSE), Kazan, Russia, 7–10 October 2019. [CrossRef]