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ORIGINAL ARTICLE

Risk response capability assessment for the digital twin-based human–robot collaboration

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Abstract
Human–robot collaboration, which integrates human dexterity with robotic precision, demonstrates significant potential for enhancing productivity. The concept of a digital twin, as an advanced technology facilitating virtual-real interactions, offers a novel framework for an intelligent human–robot collaboration paradigm. The utilization of digital twin-based approaches in human–robot collaboration has been extensively advocated to simulate collaborative processes, validate collaboration strategies, and monitor operational status. The human–robot collaboration digital twin represents a sophisticated system that encompass both physical and virtual collaboration scenarios. The capability to respond to risks within this system is essential for sustaining stable operations and ensuring the effective execution of tasks. The objective of this paper is to refine the theoretical foundations of the application of digital twins in human–robot collaboration. It introduces an innovative assessment framework for comprehensively measuring the risk response capabilities of the human–robot collaboration digital twin. This framework encompasses 4 risk response capacity levels, 5 assessment dimensions, and 18 evaluation factors. Furthermore, the paper proposes the Analyze-Evaluate-Calculate-Recommend methodology for assessing risk response capacity. The implementation of this method is elucidated through a detailed case study focused on human–robot collaborative assembly. This study presents a comprehensive approach to evaluating the risk response capabilities of digital twins in human–robot collaboration. The proposed methodology offers practitioners in the domain of human–robot collaboration a framework and criteria for determining the stability of the established digital twin systems.

Keywords Human–robot collaboration · Digital twin · Risk response capability · Evaluation factors

1 Introduction

Industry 4.0 facilitates the intelligent execution of mass-customized production through the integration of advanced technologies, including robotics, artificial intelligence, blockchain, and the Internet of Things. As Industry 4.0 continues to evolve, certain researchers have observed that its primary emphasis lies in the optimization of production and manufacturing processes, as well as the enhancement of equipment automation levels during development [1]. This focus, however, has led to a relative neglect of human factors and the manifestation of social value within this paradigm. Industry 5.0 builds upon the foundations established by Industry 4.0, emphasizing the central role of human agency while prioritizing personalization, flexibility, and a high level of intelligence within the production process [2]. This paradigm advocates for human–robot collaboration (HRC) and the customization of production, with the objective of advancing and transforming manufacturing methodologies

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to incorporate more human-centric attributes. Within the framework of Industry 5.0, the development of an innovative intelligent HRC manufacturing model aimed at facilitating personalized and customized production has emerged as a prominent area of interest in the industrial production sector [3].

HRC refers to the cooperation between humans and robots, either in a practical contact mode or in a contactless mode, to jointly accomplish a complex task [4]. In HRC, both humans and robots are capable of exchanging operational intentions and behaviors via direct or indirect interactions. They can collaboratively manage resources and information within the system, as well as adaptively refine and enhance the task execution process [5]. Humans possess the capacity for rapid learning, comprehension of rules, and effective emergency response, whereas robots excel in executing precise operations without experiencing fatigue. Consequently, HRC integrates human dexterity with robotic precision, offering a proficient approach to customized production. However, traditional HRC models are deficient in digital, intelligent, and networked collaborative concepts and interaction methodologies, rendering them inadequate to meet the demands of Industry 5.0. In recent years, the emergence of digital twin (DT) technology has significantly advanced the digital, networked, and intelligent evolution of human production and daily life, thereby presenting a novel framework for the development of an intelligent HRC aligned with the principles of Industry 5.0 [6].

DTs are propelled by multidimensional models and integrated data, enabling the control and optimization of physical work processes through real-time interactions [7]. This advancement offers a novel technological approach to comprehending, managing, and transforming the physical environment. The remarkable capabilities of DTs in real-time interaction, visualization, and monitoring have garnered significant attention within the HRC domain. Numerous applications based on DTs have been proposed in this context, including real-time monitoring of collaborative processes [8], virtual assembly debugging [9], and strategy validation in virtual environments [10]. DT-driven HRC employs intelligent devices to gather diverse data from both humans and robots, which, when combined with sophisticated algorithms, facilitates the simulation, optimization, and prediction of collaborative processes within a virtual framework. Consequently, the incorporation of DT technology into HRC effectively enhances the sensing of human and robot states, decision-making, and validation processes, as well as the visualization and monitoring of workflows.

The integration of DT technology and HRC is commonly referred to as the Human–Robot Collaboration Digital Twin (HRCDT). This framework encompasses both physical and virtual HRC scenarios [11]. The virtual HRC scenario is characterized by DT models that represent physical entities within the corresponding physical HRC scenario, facilitating the simulation, analysis, and monitoring of these physical interactions. The HRCDT enhances conventional HRC paradigms by incorporating virtual-control-physical collaborative concepts and intelligent interaction methods characterized by one-to-one mapping. This advancement fosters the digitalization, networking, and intelligent evolution of HRC systems [12]. While there have been some initiatives exploring DT-based HRC applications, the predominant focus of existing research has been on utilizing DT models to facilitate the collaborative process. There remains a notable gap in the literature regarding a comprehensive examination of HRCDT from a holistic standpoint, particularly concerning its capacity to mitigate risks. The HRCDT operates as a dynamic and intricate system, wherein variations in human behavior, fluctuations in robot operational processes, inaccuracies in DT models, and changes in environmental conditions contribute to uncertainties within the collaborative manufacturing framework. These fluctuations introduce risks that can adversely impact the functionality of the HRCDT system. Consequently, the capability of HRCDT to respond to risks is essential for sustaining stable system operations and ensuring the effective completion of tasks. The critical aspects involved are as follows: first, how to assess the risk response capability of the constructed HRCDT and, second, how to improve the risk response capability of HRCDT if it does not meet the requirements. In these two aspects, due to the lack of systematic assessment indexes and evaluation processes, it is difficult to judge whether the constructed HRCDT can meet the demand for stable operation, and it is also difficult to quantitatively evaluate the robustness of the constructed HRCDT.

To address this gap, this study seeks to develop a methodology for assessing the risk response capability of HRCDT. Initially, the study defines the level of risk response capability pertinent to HRCDT. Subsequently, a comprehensive evaluation system is proposed, encompassing five dimensions and 18 evaluation factors. Following this, the assessment methodology is delineated. Ultimately, the validity of the proposed approach is substantiated through its application to an assembly of HRCDT.

The rest of this paper is organized as follows. Section 2 provides an overview of the related work. Section 3 defines the risk response capability levels of HRCDT. Section 4 investigates the risk response capability evaluation factors. Section 5 examines the assessment method. Section 6 validates the evaluation process of risk response capability through an HRC assembly case. Section 7 concludes the contributions of this work and future research directions.

2 Related works

The impressive capabilities of DT technology in digitization and intelligence have generated significant interest within the HRC domain. Despite the existence of certain applications utilizing DT in HRC, there remains a deficiency in research that examines the risk response capabilities of HRCDT from a comprehensive, global standpoint. To address this gap, the present study develops a systematic assessment framework, including criteria and methodologies, for evaluating the risk response capabilities of HRCDT. This section reviews pertinent literature across three critical areas and identifies the existing gaps that necessitate further investigation.

2.1 Digital twin

The notion of the DT originated from a 2002 report by the University of Michigan, which aimed to establish a center for product lifecycle management [13]. At that time, the early concepts introduced by Professor Michael Grieves did not garner significant attention, primarily due to the limitations posed by the nascent state of data acquisition technologies, computational capabilities, and algorithms. It was not until 2010 that the term "digital twin" was formally articulated in a written context by NASA, which subsequently advanced the concept [14]. In 2012, a collaborative effort between NASA and the Air Force Research Laboratory resulted in the proposal of DT applications for future aircraft, addressing the imperative for these vehicles to be highly loaded, lightweight, and capable of enduring prolonged operation in extreme environments [15]. DTs offer a novel approach to observing, comprehending, managing, and transforming the physical realm by creating virtual models that accurately reflect the structure, properties, functions, and behaviors of physical entities [16]. These models exhibit high fidelity, evolutionary characteristics, and interactive capabilities, utilizing data to facilitate interactions between the virtual and physical worlds.

DT technology is renowned for its exceptional capability to accurately represent the physical world and forecast future developments, thereby instigating significant transformations within various industries [17]. Central to the functionality of DT are virtual models and twin data. A virtual model serves as a replica of a physical entity, capable of characterizing and delineating the physical entity across multiple temporal and spatial dimensions [18]. Twin data, which are fundamental to the operation of DTs, typically encompass physical data, virtual data, knowledge data, and derived data [19]. By leveraging the synergistic interaction between the multidimensional DT model and twin data, DT technology can effectively articulate the multidimensional characteristics of physical entities, accurately depict their actual behaviors and states, and analyze prospective developmental trends. This capability facilitates the fulfillment of practical functional services and application requirements, including simulation, emulation, monitoring, optimization, and prediction of physical entities.

DT technology has increasingly emerged as a significant catalyst for digital transformation and advancement across multiple sectors, including smart manufacturing [20], smart cities [21], and smart healthcare [22]. However, the implementation of DT within HRC remains in its early stages. Despite some initial efforts, several challenges persist that require resolution.

2.2 Digital twin-based human–robot collaboration

Given that DT technology facilitates the simulation, analysis, and visual monitoring of physical entities, it has the potential to significantly enhance safety in collaborative environments, mitigate safety risks, and ensure worker safety. Li et al. [8] introduced a DT-based security control framework for HRC, along with a corresponding methodology for testing and analyzing potential security risks through the construction of virtual models representing various HRC scenarios. Choi et al. [23] developed a hybrid safety sensing system that integrates augmented reality and DT technologies, which accurately assesses the minimum safe distance between humans and machines in real-time, presenting this information to users via mixed reality glasses. Maruyama et al. [24] created a DT-based HRC system that simulates worker movements and evaluates physical loads, thereby promoting safe working conditions for individuals. Wang et al. [25] proposed an advanced DT framework that leverages deep learning techniques. This framework is capable of detecting both robots and humans, recognizing and classifying their behaviors, and mitigating hazardous situations by identifying and highlighting abnormal behaviors.

DT is extensively utilized in HRC assembly to enhance the physical assembly process through the simulation of assembly behaviors, validation of assembly strategies, and monitoring of the assembly process within a virtual environment. This approach not only conserves resources but also increases operational efficiency. Lv et al. [26] introduced a collaborative framework for human–robot assembly that integrates a physical assembly system, a virtual assembly system, and a data management center. This framework facilitates the analysis of data to refine assembly performance and behaviors. Sun et al. [9] developed a DT-driven debugging framework for HRC assembly, which leverages environmental data to synchronize the virtual and physical assembly debugging processes. Oyekan et al. [10]

established a DT-based simulation test environment aimed at assessing the efficacy of HRC strategies. Bilberg et al. [27] proposed a DT system designed for the flexible assembly of HRC, which extends the application of virtual simulation models created during the design phase to real-time operational control, dynamic skill-based task allocation between humans and robots, task sequencing, and the development of corresponding robotic programs. This methodology facilitates the implementation of flexible HRC systems. Malik et al. [28] presented a DT-based framework for the verification of HRC simulations, exploring the application of visual, immersive, and haptic simulations, as well as virtual reality, in the design and evaluation of HRC assembly systems. Their event-driven simulation framework aids in the formulation of assembly plans, optimization of layouts, and refinement of robot control procedures.

The aforementioned literature review underscores the substantial body of research concerning the application of DT technology in HRC, indicating a robust foundation in this domain. Nevertheless, there exists a deficiency in methodologies aimed at examining the risk response capabilities of HRCDT from a comprehensive viewpoint. Given the inherently unpredictable nature of collaborative processes, the integration of DT technology introduces additional risks. It is imperative to focus on the risk response capabilities of HRCDT systems to ensure their stable operation and the effective completion of tasks. Currently, the implementation of DT technology within HRC is hindered by the absence of evaluation standards and methodologies for assessing the risk response capabilities of HRCDT, complicating the assessment of whether the developed HRCDT possesses the requisite stability to fulfill operational demands.

2.3 Risk assessment in human–robot collaboration

Risk response capability pertains to the extent to which a system can effectively address risks, encompassing its ability to identify, predict, and mitigate such risks, as well as its susceptibility to disruptions resulting from these risks. The primary objective of risk assessment is to identify potential hazards and evaluate the associated risks, thereby establishing a foundation for risk reduction efforts [29]. Given the limited literature available on the risk response capacity of HRCDT, this section will focus on the existing literature concerning risk assessment in HRC. It is anticipated that an analysis of current risk assessment methodologies in HRC will serve as a valuable reference for the development of an assessment framework for the risk response capacity of HRCDT.

Conducting a risk assessment prior to HRC operation ensures worker safety. It also has important economic implications. The presence of risks can result in the remanufacturing of products, thereby leading to substantial resource wastage [30]. Within the context of HRC, the primary sources of risk are attributed to technological factors and human involvement [31]. Aspects of technology that pose risks include software (e.g., collaborative robot programming risks), control software (e.g., programming risks for controlling robot motion, speed, and force), hardware (e.g., risks to the physical components of the robot), and application-specific hazards (e.g., risks to the fumes from welding). Human risk aspects include psychosocial (e.g., risk of human error), cognitive ergonomics (e.g., risk of overload due to increased knowledge), and physical ergonomics (e.g., risk of musculoskeletal disorders). In current HRC practice, risk assessment is performed based on experience, expert knowledge, simple methods (e.g., brainstorming), and simple tools (e.g., checklists) [32]. Awad et al. [33] proposed an iterative design methodology that utilizes model-driven risk assessment and decision support based on rule and expert-systems approaches. The method automatically identifies potential risks in the design of HRC work scenarios. When detailed analysis is required, formal methods and expert knowledge may not provide the required fidelity, in which case simulation-based approaches are often employed. Bobka et al. [34] developed a software platform that can model and simulate HRC systems. This platform enables the simulation of the robot's movement speed and the calculation of the safe distance between the human and the robot. This allows some risks to be avoided before collaboration begins.

Some scholars have argued that current HRC risk assessment tools lack a human focus. Alenjareghi et al. [35] explored in detail how HRC risk assessment can be enhanced by artificial intelligence (AI). Through their study, it was found that AI-based risk assessment tools rely on the quality of the data they are trained on. If the data is biased or incomplete, the risk assessment may be inaccurate. Therefore, the advantages of AI in risk assessment can only be maximized by combining the risk assessment results of AI with human decision-making. Giallanza et al. [36] argued that workers' unsafe behaviors increase the likelihood of the occurrence of unpredictable risks in HRC. Therefore, they emphasized the necessity of integrating human factors in hazard analysis and risk assessment. Hanna et al. [37] argued that existing risk assessment guidelines are problematic and that current regulations only propose control measures and lack a focus on active safety. They consider that human safety needs to be combined with system flexibility and efficiency in risk assessment, rather than just implementing physical measures to reduce risk. Zhang et al. [38] suggest that robots need to perform a risk assessment of operational intent based on human motion characteristics before executing human intent commands. Risks can be avoided by implementing appropriate coping strategies based on the assessment results.

The integration of DT technology introduces corresponding DT models to the physical entities within HRC, thereby transforming HRCDT into a complex intelligent system characterized by numerous interacting factors. The existing literature on risk assessment in HRC indicates that both robots and humans are central subjects of this assessment, which offers valuable insights for investigating the risk response capabilities of HRCDT. Furthermore, the effectiveness of the HRCDT's risk response capabilities is contingent upon the accuracy of the DT model, the adequacy of twin data transmission quality, and the stability of the collaborative environment.

2.4 Research gaps

Despite the significant interest in DT technology among experts, scholars, and enterprises within the realm of HRC, there exists a paucity of research focused on the risk response capacity of HRCDT. The methodology for assessing risks in HRC offers valuable insights for evaluating the risk response capabilities of HRCDT. Firstly, it is essential to identify reasonable and comprehensive evaluation dimensions that align with the characteristics of HRCDT, as this is crucial for accurately measuring its risk response capability. Secondly, ensuring human safety constitutes a fundamental requirement for HRCDT; thus, it is imperative to design evaluation factors that pertain to human safety, thereby reflecting the capacity of HRCDT to safeguard human operators. Lastly, the selection of appropriate methods for quantifying the evaluation indicators remains a significant area of inquiry.

The objective of this research is to develop a comprehensive evaluation system and implementation methodology for assessing the risk response capacity of HRCDT, thereby addressing the deficiencies identified in the current literature. The proposed evaluation framework comprises 18 evaluation factors categorized into 5 dimensions, and it establishes a four-tier scale for measuring the risk response capacity of HRCDT. Furthermore, the study provides a detailed exposition of the implementation process for enhancing HRCDT's risk response capabilities, and the efficacy of the proposed methodology is substantiated through a case study involving an HRC assembly.

3 Risk response capability assessment system

This section provides a comprehensive overview of the methodology employed in the development of the HRCDT risk response capacity assessment system. It encompasses the identification of assessment dimensions, the delineation of risk response capability levels, and the specification of evaluation factors. Initially, the assessment dimensions pertinent to risk response capacity are established based on the unique characteristics of HRCDT. Subsequently, the various levels of risk response capability are articulated. Finally, the content of the evaluation factors corresponding to each dimension across the different levels of risk response capability is defined.

3.1 Assessment dimensions

In evaluating the risk response capacity of HRCDT, it is essential to first establish the focus of the assessment, specifically identifying the dimensions to be evaluated. The HRCDT framework encompasses both physical and virtual scenarios involving HRC. Risks may arise from these two contexts, with physical scenarios involving interactions between robots and humans, while virtual scenarios pertain to DT models of these entities. The interaction of information within these physical and virtual environments is contingent upon twin data. Furthermore, alterations in the network system can influence the efficiency of this data interaction, while modifications in the collaborative environment can impact task execution. Consequently, dynamic fluctuations in the elements of robots, humans, twin data, network systems, and collaborative environments may introduce potential risks. Thus, these five dimensions have been identified as critical components for assessing the risk response capability of HRCDT. A comprehensive description of each of these dimensions is provided below.

(1) Robot: the main performers of collaborative tasks. Within the framework of HRCDT, operational data is gathered in real-time via the robot's intrinsic sensors as well as external sensor systems. The DT model of the robot is responsible for analyzing and processing this operational data to facilitate the control, monitoring, and optimization of the robot's functions. The DT models of robots encompass geometric, physical, behavioral, and rule-based components [39]. The capabilities that can be realized through various configurations of these DT models vary accordingly.
(2) Human: the decision maker of the HRC task, responsible for giving instructions to the robot and assisting the robot to work. In HRCDT, the human DT model can realize the monitoring of a human's working status and physiological status. The human DT model contains physiological, behavioral, and rule models [39]. Different sub-models give different functions to the human DT model.
(3) Twin data: a bridge for information exchange between the HRC physical scene and the HRC virtual scene. The twin data encompasses the operational data of both robots and humans within physical environments, as

well as simulation data produced in virtual settings, along with other pertinent information [40]. The operational data includes parameters related to robot functionality, human physiological metrics, and data concerning unexpected environmental disturbances. Simulation data pertains to the simulation of DT model processes, behavioral simulations, and validation data for these processes. Additionally, other relevant data comprises algorithms, expert knowledge, and industry standards.

(4) Network system: plays a crucial role in assessing the quality of data transmission. The compatibility, accessibility, and overall quality of the network system have a direct impact on the efficacy of data transmission within the HRCDT, which in turn influences the operational effectiveness of HRCDT.

(5) Collaborative environment: serves as a fundamental component for the stable functioning of the HRCDT system. This environment encompasses both the physical workspace and the virtual simulation setting. Alterations within this environment may introduce uncertainties and pose risks that could impact the operational efficacy of the HRCDT.

The aforementioned five dimensions comprehensively encompass all facets of HRCDT. The risk response capability assessment system for HRCDT, developed based on these five dimensions, is adequately equipped to fulfill the necessary requirements.

3.2 Risk response capability levels

Ensuring human safety and realizing safe production is the primary task of HRC. The main research objects of HRC are robots and humans, and the interaction behaviors between robots and humans can easily lead to the occurrence of risks, such as incorrect action programming of robots and unsafe worker behaviors [36]. HRCDT is a traditional HRC scenario with the addition of a virtual HRC scenario and the connecting interactions between the virtual and real scenarios. Consequently, the sources of risk within HRCDT have proliferated, necessitating a broader consideration of various factors. In the context of risk assessment for HRC, safety standards mandate the evaluation of potential risks prior to the operation of robots [41]. The ISO international standard that guides risk management defines the process of risk assessment to include risk identification, risk analysis, and risk evaluation [42].

Risk response capacity reflects the ability of HRCDT to resist risk. An increase in risk response capacity means that HRCDT is more effective in reducing the probability of risk occurrence. HRCDT risk response capacity is quantitatively calculated from the scores of the evaluation factors in each dimension. For easy understanding and analysis, risk response capacity is expressed as a one-dimensional interval number. Interval numbers can express the ambiguity and uncertainty in human cognition. According to the methods and steps of risk assessment in HRC, the risk response capability of HRCDT is defined to include four levels, which are threshold judgment, risk identification, risk feedback, and risk prediction, as shown in Fig. 1. Therefore, the HRCDT risk response capability level is set as $L=\{L_1, L_2, L_3, L_4\}$. The levels range from 0 to 4 and are divided into five subintervals $l_x=[a_x, b_x)$, $x=1, 2, 3, 4$, where a_x and b_x are the left and right limits of the interval.

3.2.1 Threshold judgment (L_1: [0,1))

Threshold judgment means that the HRC virtual scenario determines if each index parameter is within the required threshold to determine whether a risk has occurred, as shown in Fig. 2. The HRCDT system with this capability is in the first level (L_1) of the risk response capability degrees.

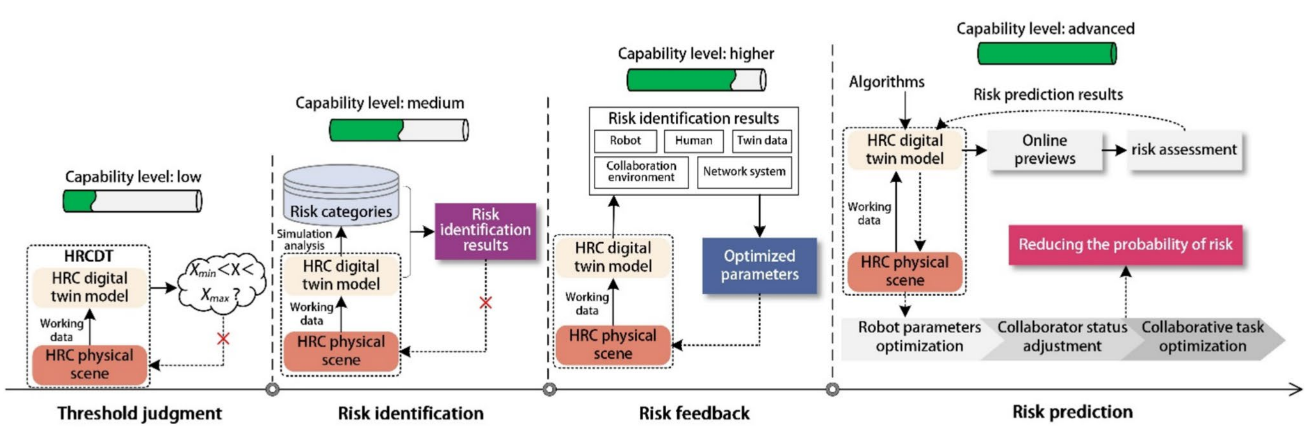


Fig. 1 HRCDT risk response capability levels

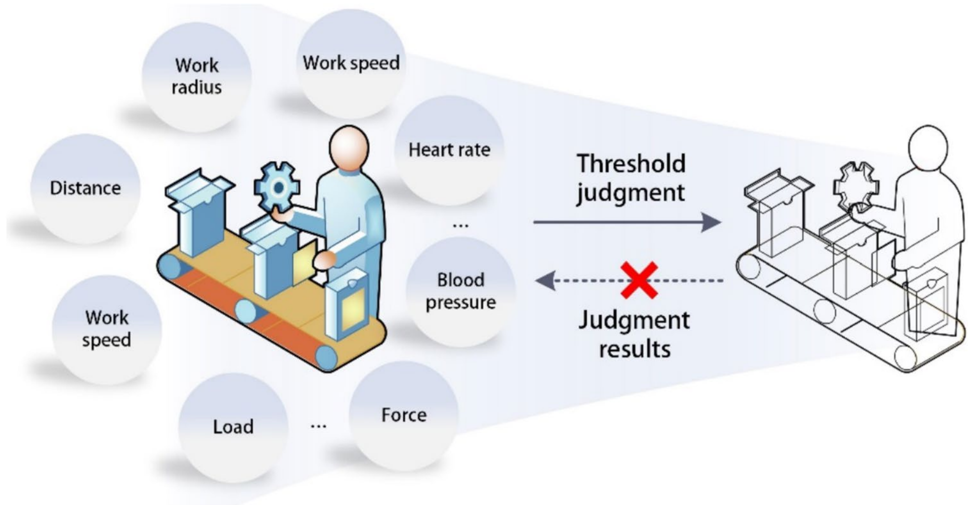


Fig. 2 HRCDT risk response capability level 1

At this level, the HRCDT models facilitate the monitoring of various indicators, including those related to robot operations, human physiological parameters, network conditions, and the collaborative environment. The assessment of the collected operational data is employed to ascertain whether these indicators fall within acceptable operational thresholds. Nonetheless, the current capabilities of the HRCDT models are limited to basic numerical evaluations; they are unable to address more intricate scenarios and do not provide feedback regarding risk assessments in HRC physical contexts. Consequently, the DT offers minimal assistance to the HRC physical processes, resulting in a lower risk response capability of the HRCDT at this level.

3.2.2 Risk identification (L_2: [1,2))

Risk identification refers to the HRC virtual scenario can directly make judgments about the risk categories in the collaboration process, as shown in Fig. 3. The HRCDT system with this capability is in the second level (L_2) of the risk response capability degrees.

At this stage, the HRCDT models are capable of identifying risks across multiple dimensions, including robotics, human factors, twin data, network systems, and collaborative environments. Through the simulation and analysis of operational data of each dimension, potential risk categories are discerned and utilized as a foundation for risk identification. However, it is important to note that these models are limited to categorizing risks and do not provide strategies for risk mitigation, nor do they integrate the results of risk identification into the HRC physical scenarios to preemptively address these risks. Consequently, while this level of DT technology offers enhanced support for the HRC process, the risk response capability of the HRCDT at this stage is considered to be moderate.

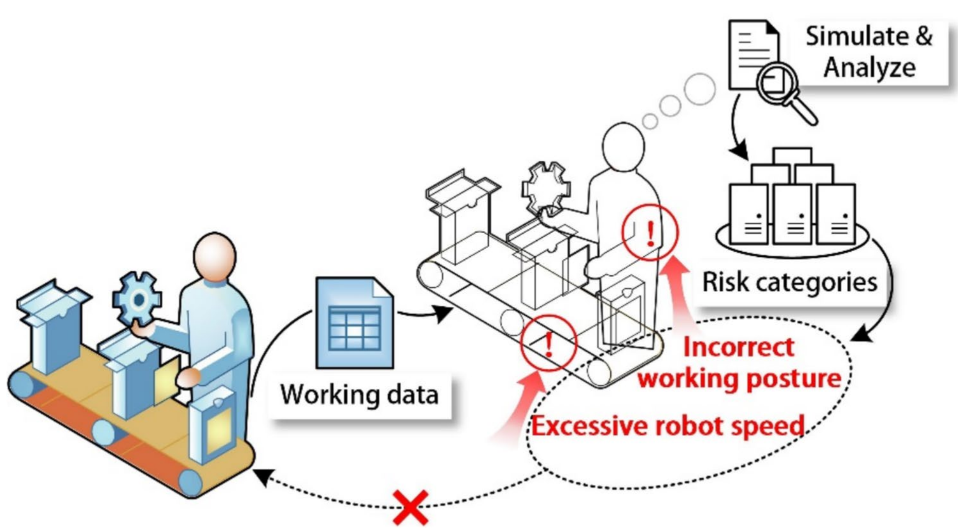
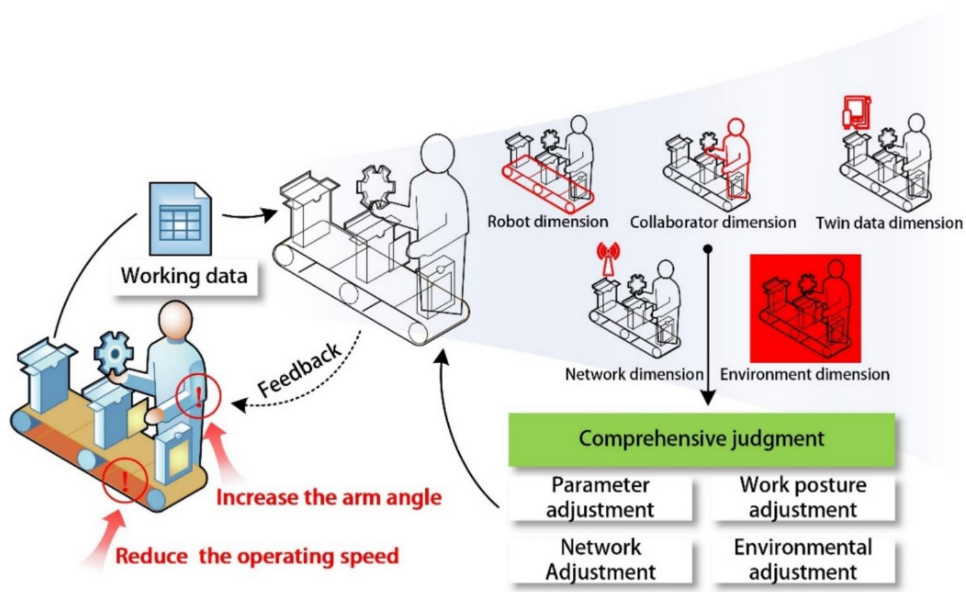


Fig. 3 HRCDT risk response capability level 2

Fig. 4 HRCDT risk response capability level 3



3.2.3 Risk feedback (L_3: [2,3))

Risk feedback represents the HRC virtual scenario can send back the identified risks to the HRC physical scenario, as shown in Fig. 4. The HRCDT system with this capability is in the third level (L_3) of the risk response capability degrees.

At this level, the HRCDT models exhibit a relatively comprehensive framework for risk identification. These models are capable of concurrently executing a complex risk identification process across various dimensions, including robot, human, twin data, network system, and collaboration environment based on actual operational data. Furthermore, the outcomes of risk identification across these multiple dimensions can be subjected to a holistic evaluation, and optimization parameters for each indicator are provided. These optimized indicators are subsequently communicated back to the robotic systems or serve as reminders for human operators to adjust their work conditions. However, it is important to note that risks can only be identified post-occurrence and cannot be anticipated based on the operational data. This level of DT facilitates comprehensive risk identification and enables feedback mechanisms; thereby, the risk response capability of the HRCDT at this level is higher.

3.2.4 Risk prediction (L_4: [3,4))

Risk prediction stands for the real-time monitoring of the HRC physical process by the HRC virtual scenario to predict the risks that will occur in advance, as shown in Fig. 5. The HRCDT system with this capability is in the fourth level (L_4) of the risk response capability degrees.

At this level, the HRC virtual scenario is capable of engaging with the physical HRC scenario in a real-time, closed-loop fashion, thereby providing a dynamic representation of the current risk status associated with robots, humans, network systems, and other relevant factors. By employing models, data, and algorithms, it is possible to conduct online forecasts of future HRC physical processes, assess the likelihood of risk events across various dimensions, and facilitate timely and intelligent risk evaluations. Informed by the outcomes of risk predictions, HRC tasks can be optimized to mitigate the likelihood of risk occurrences. This level of DT technology enhances the ability to anticipate risks within the HRC framework, thereby safeguarding human participants. The risk response capability degree of the HRCDT is advanced.

3.3 Risk response capability evaluation factors

The assessment criteria for each dimension are established based on the levels of risk response capability, resulting in a comprehensive HRCDT risk assessment framework, as illustrated in Fig. 6. A detailed explanation of the evaluation factor of risk response capability for each dimension is provided below.

3.3.1 Evaluation factors for the robot dimension

In HRC, robots are responsible for executing the majority of tasks, and their safety mechanisms significantly mitigate the likelihood of risk occurrences [16]. Within the context of HRCDT, the DT model of a robot operating in a virtual HRC environment is capable of identifying and assessing potential risks by analyzing the robot's operational data. The various functionalities of the robot's DT model exhibit differing capacities for risk management. Furthermore, the

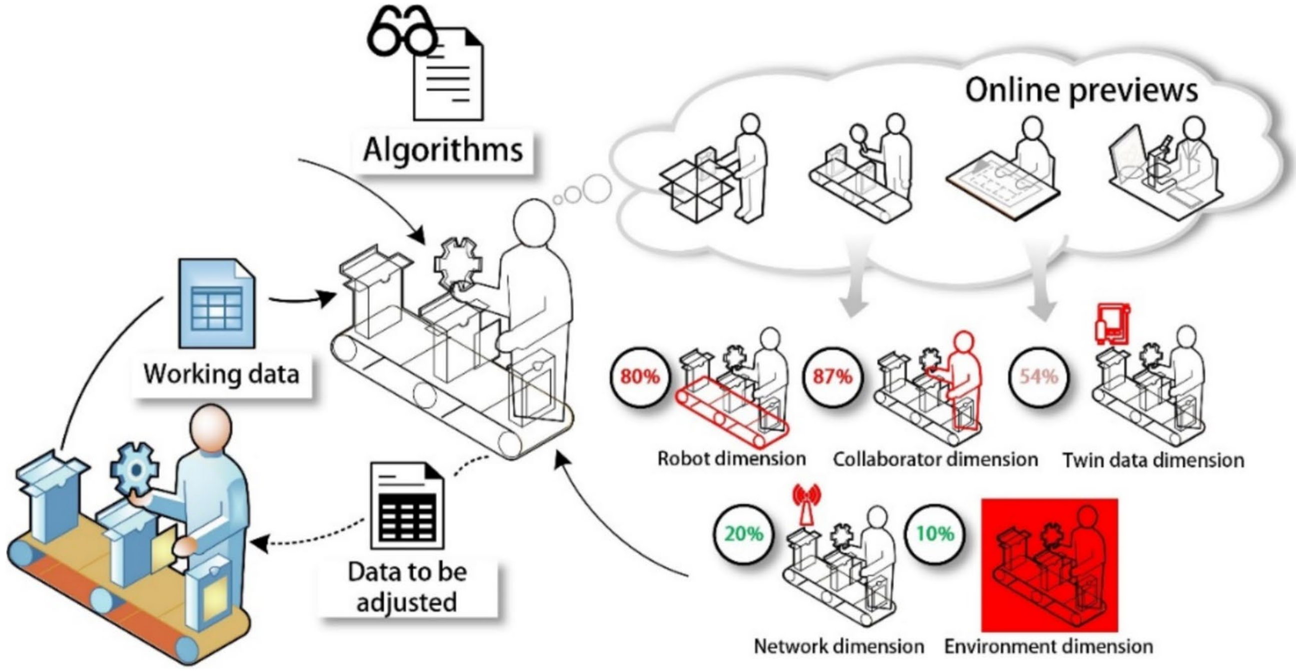
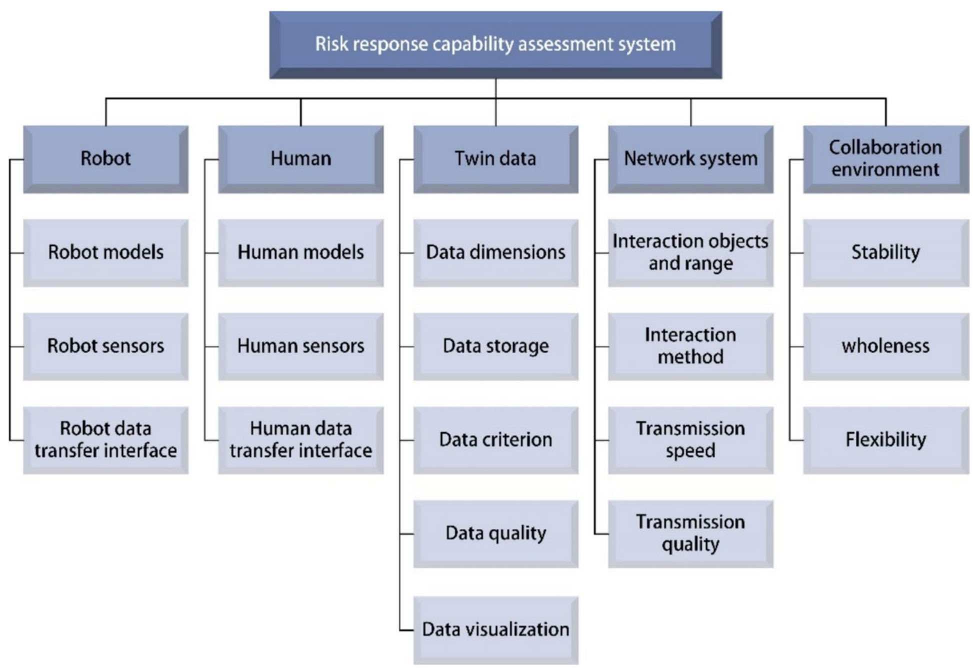


Fig. 5 HRCDT risk response capability level 4

Fig. 6 Risk response capability assessment system for HRCDT



type of data generated by the robot also influences risk assessment outcomes. Consequently, the evaluation of risk response capabilities in the robotic dimension is based on factors such as robot models, robot sensors, and the robot data transmission interface, with these factors being categorized into distinct levels, as illustrated in Table 1.

3.3.2 Evaluation factors for the human dimension

The foremost objective of HRC is to ensure human safety [32]. Human risks may arise from alterations in work status, as variations in physiological parameters, work-related fatigue, and improper postures can adversely impact

Table 1 Risk response capability evaluation factors for the robot dimension

Evaluation factors	Risk response capability level and content	Supportable risk response capability levels
Robot models (RM)	Level 1 (RM1): Behavioral models are available	L_1
	Level 2 (RM2): Behavioral models and geometric models are available	$L_1 \sim L_2$
	Level 3 (RM3): Behavioral, geometric, and physical models are available	$L_1 \sim L_3$
	Level 4 (RM4): Behavioral, geometric, physical, and rule models are available	$L_1 \sim L_4$
Robot sensors (RS)	Level 1 (RS1): The type and number of sensors do not meet the needs of monitoring the various indicators of the robot, and the sensor data needs to be read manually	L_1
	Level 2 (RS2): The type and number of sensors do not meet the need to monitor the robot's indicators, and some sensor data can be read automatically	$L_1 \sim L_2$
	Level 3 (RS3): The type and number of sensors can meet the needs of monitoring the various indicators of the robot, and partial sensor data can be read automatically	$L_1 \sim L_3$
	Level 4 (RS4): The type and number of sensors can meet the needs of monitoring the various indicators of the robot, and the sensor data can be read automatically	$L_1 \sim L_4$
Robot data transfer interface (RI)	Level 1 (RI1): No data interface	——————
	Level 2 (RI2): Data interfaces are available, but the type and number do not meet the needs	L_1
	Level 3 (RI3): Data interfaces are available, the type and number of which meet the requirements and can support partial data transfer	$L_1 \sim L_3$
	Level 4 (RI4): Data interfaces are available, the type and number of which meet the requirements and can support full data transfer	$L_1 \sim L_4$

Table 2 Risk response capability evaluation factors for the human dimension

Evaluation factors	Risk response capability level and content	Supportable risk response capability levels
Human models (HM)	Level 1 (HM1): No models are available	——————
	Level 2 (HM2): Physiological models are available	L_1
	Level 3 (HM3): Physiological models and behavioral models are available	$L_1 \sim L_3$
	Level 4 (HM4): Physiological, behavioral, and rule models are available	$L_1 \sim L_4$
Human sensors (HS)	Level 1 (HS1): The variety and number of sensors do not meet the need to monitor the physiological indicators of humans. Sensor data need to be read manually	L_1
	Level 2 (HS2): The variety and number of sensors do not meet the need to monitor the physiological indicators of humans. Partial sensor data can be read automatically	$L_1 \sim L_2$
	Level 3 (HS3): The variety and number of sensors can meet the needs of monitoring the physiological indicators of humans. Partial sensor data can be read automatically	$L_1 \sim L_3$
	Level 4 (HS4): The variety and number of sensors can meet the needs of monitoring the physiological indicators of humans. All sensor data can be read automatically	$L_1 \sim L_4$
Human data transfer interface (HI)	Level 1 (HI1): The human model has partial input interfaces for static parameters and no output interfaces. Physiological parameters can be received	L_1
	Level 2 (HI2): The human model has input interfaces for some static and some dynamic parameters, but no output interfaces. Physiological and human work parameters can be received	$L_1 \sim L_2$
	Level 3 (HI3): The human model has input and output interfaces for partial static and dynamic parameters. Physiological and work parameters can be received and optimized work parameters can be fed back	$L_1 \sim L_3$
	Level 4 (HI4): The human model has all the input and output interfaces needed to satisfy the interaction requirements	$L_1 \sim L_4$

human performance [31]. Similar to the robotic dimension, DT models of humans can analyze work-related data to detect potential risks. Consequently, human models, sensors, and data transfer interfaces are employed as evaluative factors for assessing risk response capabilities within the human dimension, with the levels of these factors categorized as presented in Table 2.

3.3.3 Evaluation factors for the twin data dimension

Twin data, encompassing both physical and virtual information, serves as a fundamental component for facilitating virtual-real interactions [43]. The HRCDT models leverage physical scenario data from HRC for analytical and optimization purposes, subsequently relaying the optimized simulation data back to both robots and humans. A diverse range of data dimensions can yield more comprehensive insights into the HRC physical scenarios, while robust data storage capabilities mitigate the risk of data breaches. Standardized data enhances interaction efficiency, and high-quality data contributes to the precision of risk assessments. Furthermore, data visualization aids individuals in intuitively and effectively understanding the dynamics of the collaborative process. Consequently, data dimensions, data storage, data standards, data quality, and data visualization are identified as evaluative factors for assessing the risk response capabilities associated with twin data dimensions, with the degree of these factors categorized as illustrated in Table 3.

3.3.4 Evaluation factors for the network system dimension

The network system serves as the conduit for data transmission. In the context of HRCDT, the interplay between virtual and real elements is inherently linked to the network infrastructure. The speed and quality of data transmission are critical for effective data interaction [44]. Furthermore, the characteristics of the interaction objects and the modes of interaction within the HRCDT framework significantly influence the system's ability to deliver timely data for risk identification and forecasting. Consequently, the interaction objects and their scope and the methods of interaction, as well as the speed and quality of transmission, are identified as key evaluative factors for assessing the risk response capabilities of the network system

Table 3 Risk response capability evaluation factors for the twin data dimension

Evaluation factors	Risk response capability level and content	Supportable risk response capability levels
Data dimensions (DD)	Level 1 (DD1): Robot operational data, human physiological metrics data	L_1
	Level 2 (DD2): Robot operational data, human physiological data, and work data. Operational data for HRCDT models	$L_1 \sim L_2$
	Level 3 (DD3): Robot operational data, human physiological and work data, operational data of HRCDT models, and connectivity interaction data	$L_1 \sim L_3$
	Level 4 (DD4): Robot operational data, human physiological and work data, operational data of HRCDT models, connectivity interaction data, and predictive service data	$L_1 \sim L_4$
Data storage (DS)	Level 1 (DS1): Data cannot be stored and the risk of leakage is high	——
	Level 2 (DS2): Partial physical data can be stored, virtual data cannot be stored, and leakage risk is medium	L_1
	Level 3 (DS3): Physical data can be stored. Partial virtual data can be stored. Leakage risk is low	$L_1 \sim L_3$
	Level 4 (DS4): Both physical and virtual data can be stored without risk of leakage	$L_1 \sim L_4$
Data criterion (DC)	Level 1 (DC1): Data non-standardization	——
	Level 2 (DC2): Partial data normalization. Data in different dimensions are not compatible	$L_1 \sim L_2$
	Level 3 (DC3): Partial data standardization. Single-dimension data is compatible	$L_1 \sim L_3$
	Level 4 (DC4): All data is standardized. Data in all dimensions are compatible	$L_1 \sim L_4$
Data quality (DQ)	Level 1 (DQ1): Physical data may be subject to quality risks such as errors, duplications, and omissions	L_1
	Level 2 (DQ2): Partial physical data are free of quality risks. Virtual data may have quality risks such as errors, duplicates, and omissions	$L_1 \sim L_2$
	Level 3 (DQ3): Physical data has no quality risk. Partial virtual data may have quality risks such as errors, duplications, and omissions	$L_1 \sim L_3$
	Level 4 (DQ4): All dimension data are complete and correct with no quality risk	$L_1 \sim L_4$
Data visualization (DV)	Level 1 (DV1): Model file data can be visualized	L_1
	Level 2 (DV2): Model file data and physical entity operational environment data can be visualized	$L_1 \sim L_2$
	Level 3 (DV3): Model file data, physical entity operational environment data, and data in the DT model operational environment can be visualized	$L_1 \sim L_3$
	Level 4 (DV4): All data can be visualized	$L_1 \sim L_4$

Table 4 Risk response capability evaluation factors for the network system dimension

Evaluation factors	Risk response capability level and content	Supportable risk response capability levels
Interaction object and range (NR)	Level 1 (NR1): No interactive objects	————
	Level 2 (NR2): Including humans and robots, and DT models of humans and robots	$L_1 \sim L_2$
	Level 3 (NR3): Includes humans and robots, DT models of humans and robots, twin data, and functional services	$L_1 \sim L_3$
	Level 4 (NR4): Includes humans and robots, DT models of humans and robots, twin data, functional services, and other physical entities in collaborative environments	$L_1 \sim L_4$
Interaction method (NM)	Level 1 (NM1): Interactive configuration is performed manually	L_1
	Level 2 (NM2): Manually assisted connection, single-direction interaction. Manual assistance is required when automatic interaction is not possible	$L_1 \sim L_2$
	Level 3 (NM3): Adaptive connectivity with two-way automatic interaction	$L_1 \sim L_3$
	Level 4 (NM4): Adaptive connectivity. Bidirectional automatic interaction. Interaction is reconfigurable	$L_1 \sim L_4$
Transmission speed (NS)	Level 1 (NS1): Data transmission delay is more than 1 min	L_1
	Level 2 (NS2): Data transmission delay is less than 1 min	$L_1 \sim L_2$
	Level 3 (NS3): Data transmission delay is less than 1 s	$L_1 \sim L_3$
	Level 4 (NS4): Data transmission delay is less than 200 ms	$L_1 \sim L_4$
Transmission quality (NQ)	Level 1 (NQ1): False transmissions, missed transmissions, data unavailability, and blocking delays exist	L_1
	Level 2 (NQ2): False transmissions, missed transmissions, and data unavailability are essentially non-existent, and blocking delays exist	$L_1 \sim L_2$
	Level 3 (NQ3): False transmissions, missed transmissions, data unavailability, and blocking delays do not exist. Data monitoring capability is available	$L_1 \sim L_3$
	Level 4 (NQ4): False transmissions, missed transmissions, data unavailability, and blocking delays do not exist. Data monitoring and early warning mechanisms are complete	$L_1 \sim L_4$

dimension. The levels of these factors are categorized as presented in Table 4.

3.3.5 Evaluation factors for the collaboration environment dimension

The stability of the HRC environment is essential for facilitating an effective collaborative process. A stable collaborative environment mitigates various potential risks [45]. Concurrently, the ability to integrate, as well as to automatically configure and reconfigure the components of the environment, is critical for the optimal utilization of the risk prediction service provided by the HRCDT. Consequently, the stability, integrity, and adaptability of the environment are employed as evaluative criteria for assessing the risk response capabilities within the context of the collaborative environment. The degree of these factors is presented in Table 5.

4 Risk response capability assessment method

Section 3 presents the elevation factors associated with the risk response capability of the HRCDT and delineates the various levels corresponding to each factor. To assess the risk response capacity of the HRCDT system utilizing these evaluation factors, this section introduces a proposed assessment methodology, illustrated in Fig. 7.

The implementation of the method is structured into four distinct phases: analysis, evaluation, calculation, and recommendation. Initially, the HRCDT system undergoes a comprehensive analysis across five dimensions, robot, human, twin data, network system, and collaborative environment, to assess the current state of the HRCDT system. Subsequently, the risk response capability levels

Table 5 Risk response capability evaluation factors for the collaboration environment dimension

Evaluation factors	Risk response capability level and content	Supportable risk response capability levels
Environment stability (ES)	Level 1 (ES1): Frequent changes in equipment and personnel in the environment. High risk of environmental uncertainty	L_1
	Level 2 (ES2): Partial equipment and personnel in the environment are stable. The risk of environmental uncertainty is moderate	$L_1 \sim L_2$
	Level 3 (ES3): Equipment and personnel in the environment are stable. Less risk of environmental uncertainty	$L_1 \sim L_3$
	Level 4 (ES4): Equipment and personnel are stabilized in the environment. Additional equipment or personnel can be automatically linked. No uncertainty risks	$L_1 \sim L_4$
Environment wholeness (EW)	Level 1 (EW1): The parts of the environment are independent of each other	L_1
	Level 2 (EW2): The components of the environment are fused at the data level	$L_1 \sim L_2$
	Level 3 (EW3): The components of the environment are integrated at the level of data and functional services	$L_1 \sim L_3$
	Level 4 (EW4): The components of the environment are integrated at the level of data, functional services, and model-based decision-making	$L_1 \sim L_4$
Environment flexibility (EF)	Level 1 (EF1): Not configurable, not reconfigurable	L_1
	Level 2 (EF2): Manually assisted configuration, not reconfigurable	L_1
	Level 3 (EF3): Automatic configuration. Manually assisted reconfiguration	$L_1 \sim L_3$
	Level 4 (EF4): Automatic configuration and reconfiguration	$L_1 \sim L_4$

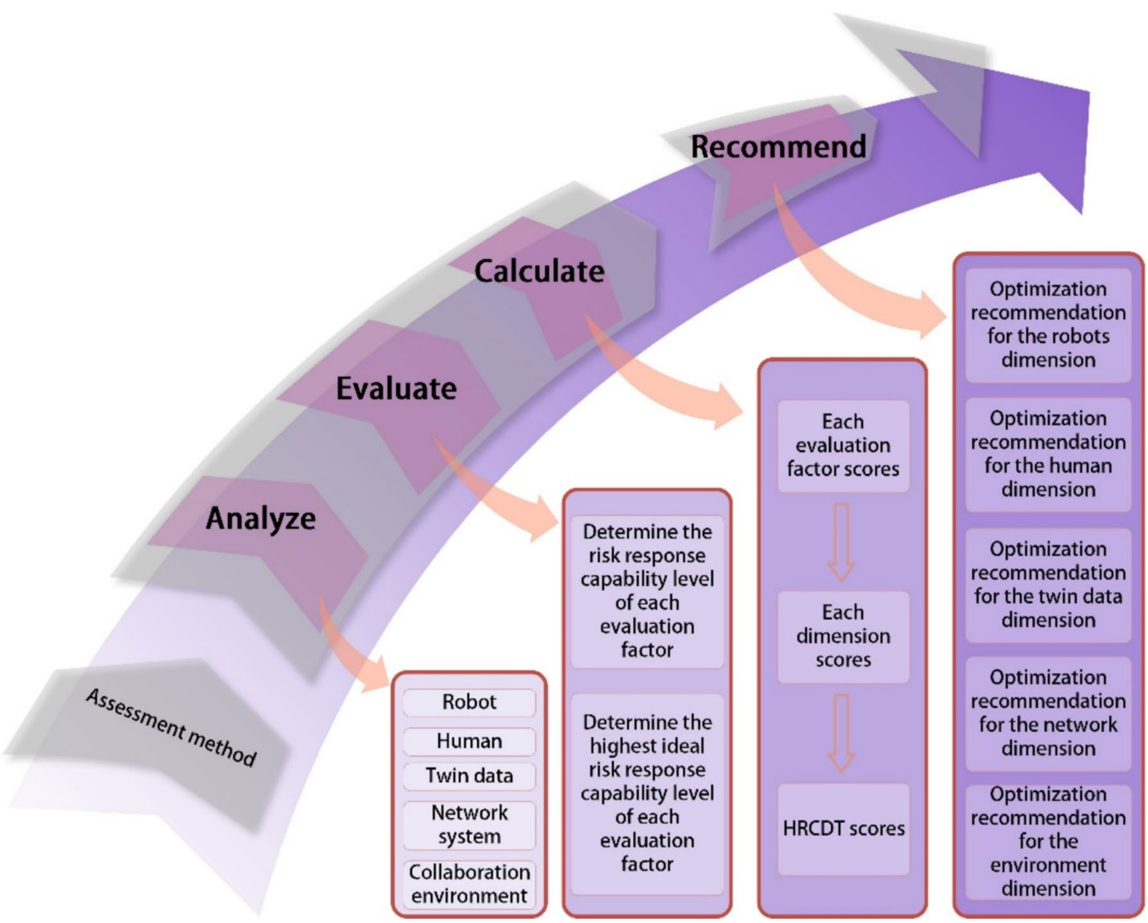


Fig. 7 Risk response capability assessment method

of the evaluation factors pertinent to each dimension are evaluated, utilizing Tables 1, 2, 3, 4, and 5 to identify the highest level that can be supported by these factors. Following this evaluation, a calculation of the risk response capability score is conducted, which ultimately determines the risk response capability level of the HRCDT system based on the derived score. In conclusion, recommendations for enhancement are formulated for those dimensions exhibiting lower risk response capability ratings, informed by the outcomes of the preceding calculations.

The methodology for determining the HRCDT risk response capacity score involves a three-step process. Initially, the risk response capability score for each evaluation factor is computed. Subsequently, the risk response capability score for each dimension is derived by integrating the weights assigned to the evaluation factors based on the first step. Finally, the overall risk response capability score for HRCDT is established by aggregating the weights of each dimension based on the second step. The weights assigned to the evaluation factors within the dimensions, as well as the weights of the dimensions within the HRCDT framework, are established based on the specific context of the application.

4.1 Step 1: calculation of risk response capacity scores for evaluation factors in each dimension

Determine the risk response capability level of the evaluation factor as f_{XX} based on the risk response capability level and the basic information of the assembly HRCDT system. After optimization, the highest ideal risk response capability level that can be achieved for an evaluation factor is denoted as $f_{\max}^{XX}$. For example, an HRCDT's data storage (DD) evaluation factor has a risk response capability level of 2, i.e., $f_{DD}=2$. Considering that an upgrade of its data storage equipment can be expected to achieve a risk response capability of level 3, in this case, $f_{\max}^{DD}=3$. Define the risk response capability score calculation formula for each evaluation factor as shown in Eq. (1).

$$
\begin{aligned}
&s_{XX}=f_{XX}+\gamma\omega_{XX}\left(f_{\max}^{XX}-f_{XX}\right)\\
&\gamma=\begin{cases}1 & ,\ f_{\max}^{XX}-f_{XX}\le 1\\ -1 & ,\ f_{\max}^{XX}-f_{XX}>1\end{cases}\\
&XX\in(RM,RS,\cdots,EF)
\end{aligned}
\tag{1}
$$

where s_{XX} denotes the risk response capability score of each evaluation factor. γ is the judgment coefficient. ω_{XX} is the weight of the evaluation factor in the dimension.

When the difference between the risk response capability level of an evaluation factor and its highest supportable risk response capability level is not more than one level, we consider that the possibility of increasing the risk response capability level of the evaluation factor by adjustment is higher, and take $\gamma=1$. In this case, Eq. (1) indicates that the risk response capability scores represented by this part of the possibilities are increased based on the current risk response capability level. Conversely, the risk response capability score represented by this part of the likelihood is subtracted from the current risk response capability rating.

4.2 Step 2: calculation of risk response capacity scores for each dimension

The risk response capability scores of the five dimensions are calculated using the scores of each evaluation factor as shown in Eq. (2).

$$
\begin{aligned}
&s_X=\sum\omega_{XX}s_{XX}\\
&X\in(Robot,Human,\cdots,Collaboration\ environment)
\end{aligned}
\tag{2}
$$

where s_X denotes the risk response capability score of each dimension.

The risk response capability level d_X for each dimension is determined based on s_X. For example, if $s_X=2.3$, the risk response capability level of this dimension is considered to be 2. If $s_X=2.8$, the risk response capability level of this dimension is considered to be 3.

4.3 Step 3: calculation of risk response capacity scores for the HRCDT system

Based on the risk response capability scores of the five dimensions, the risk response capability score of the HRCDT is calculated using Eq. (3), and the risk response capability level of HRCDT is determined based on s.

$$
\begin{aligned}
&s=\sum\omega_X\left[s_X+\gamma\omega_{XX}\left(d_{\max}^X-d_X\right)\right]\\
&\gamma=\begin{cases}1 & ,\ d_{\max}^X-d_X\le 1\\ -1 & ,\ d_{\max}^X-d_X>1\end{cases}
\end{aligned}
\tag{3}
$$

where s denotes the risk response capability score of HRCDT. γ is the judgment coefficient. ω_X is the weight of the dimension. $d_{\max}^X$ is the highest ideal risk response capability level for the dimension, indicating the highest risk response capability level that can be achieved by optimization of the dimension. $d_{\max}^X$ is represented by the highest ideal risk response capability level of the evaluation factors in the dimension.

Here, we provide Algorithm 1 as below to demonstrate the process of calculating the HRCDT risk response capacity score.

Algorithm 1 HRCDT risk response capability score calculation

Require: The risk response capability level of the evaluation factor f_{XX}, where $XX \in (RM, RS, \cdots, EF)$; The highest ideal risk response capability level of the evaluation factor $f_{\max}^{XX}$; The highest ideal risk response capability level of the dimension $d_{\max}^{X}$.

1: Calculate the weight of evaluation factors ω_{XX}:

2: Construct the judgment matrix $A_X = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$, where n means the number of evaluation factors in that dimension, $X \in (Robot, Human, \cdots, Collaboration\ environment)$.

3: **for** $XX \in (RM, RS, \cdots, EF)$ **do**

4: $\omega_{XX} = \frac{1}{n}\sum_{j=1}^{n}\frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}}, i = 1, 2, \cdots, n$

5: **end for**

6: Calculate the weight of evaluation factors ω_X:

7: Construct the judgment matrix $B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{15} \\ b_{21} & b_{22} & \cdots & b_{25} \\ \vdots & \vdots & \cdots & \vdots \\ b_{51} & b_{52} & \cdots & b_{55} \end{bmatrix}$.

8: **for** $X \in (Robot, Human, \cdots, Collaboration\ environment)$ **do**

9: $\omega_X = \frac{1}{5}\sum_{j=1}^{5}\frac{b_{ij}}{\sum_{k=1}^{5} b_{kj}}, i = 1, 2, \cdots, 5$

10: **end for**

11: Calculate the evaluation factor risk response capacity score s_{XX}:

12: **if** $f_{\max}^{XX} - f_{XX} \le 1$ **then**

13: $s_{XX} = f_{XX} + \omega_{XX}\left(f_{\max}^{XX} - f_{XX}\right)$

14: **else**

15: $s_{XX} = f_{XX} - \omega_{XX}\left(f_{\max}^{XX} - f_{XX}\right)$

16: **end if**

17: Calculate the dimension risk response capacity score s_X:

18: **for** $XX \in (RM, RS, \cdots, EF)$ **do**

19: $s_X = \sum \omega_{XX} s_{XX}$

20: **end for**

21: Calculate the HRCDT risk response capacity score s:

22: **if** $d_{\max}^{X} - d_X \le 1$ **then**

23: $s = \sum \omega_X \left[s_X + \omega_X\left(d_{\max}^{X} - d_X\right)\right]$, where d_X is the risk response capacity level obtained based on s_X.

24: **else**

25: $s = \sum \omega_X \left[s_X - \omega_X\left(d_{\max}^{X} - d_X\right)\right]$

26: **end if**

27: **Ensure:** HRCDT risk response capacity score s.

5 Case study

To validate and implement the proposed assessment method for evaluating the risk response capability of the HRCDT, an evaluation of the HRCDT system within the context of an assembly case is conducted. The assembly case is illustrated in Fig. 8. This system involves the collaborative efforts of robots and humans to assemble the clamping mechanism of a handling robot. Figure 8 presents both the physical and virtual assembly scenarios of

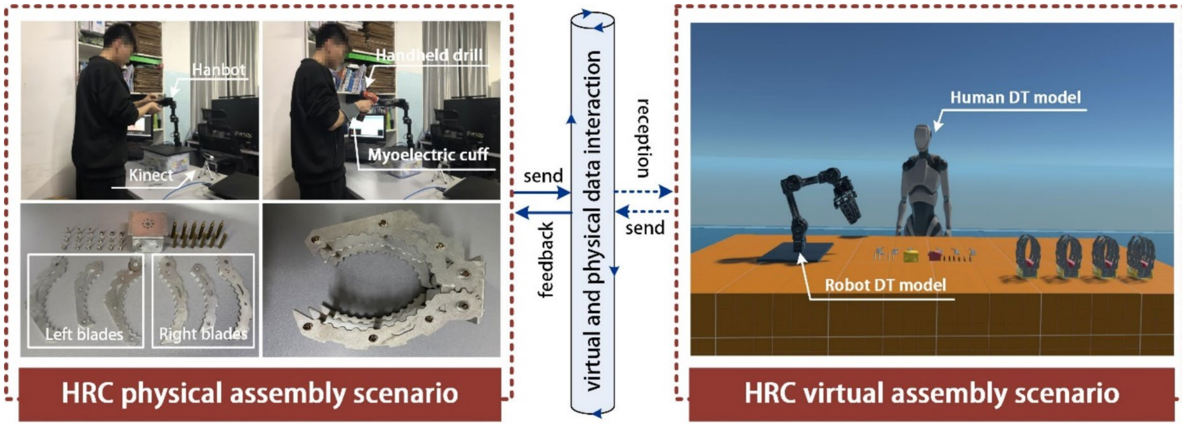


Fig. 8 Assembly HRCDT system

HRC, which collectively constitute the assembly HRCDT system.

5.1 Scenario analysis

The main information of the assembly HRCDT system is as follows. The robot is a desktop robot with five degrees of freedom, which supports software manipulation but cannot work completely without human assistance. The human is an adult male with normal physical parameters. The DT model of the robot consists of geometrical, physical, and behavioral models, which can accurately describe the robot's working behavior. The DT model of the human consists of the physiological model, behavioral model, and rule model, which can accurately describe the physiological state and working state of the human. The robot itself does not have enough sensors to meet the requirements of monitoring the robot's indicators, so it needs to be connected to external sensors artificially. Human wears sensor devices to monitor heart rate, blood pressure, and other indicators, while the myoelectric cuff can collect the human's electromyographic signals for analysis to determine fatigue status. All the work data collected by the sensors can be read directly by the DT models through the network system. The data that can be obtained include basic parameter data and operational data of the robot, the physiological data and work data of the human, the simulation data of the DT models, and the configuration data of the connected interactions. All data is standardized, complete, and accurate, all dimensions are compatible, and every data can be stored. Both the working data in the physical assembly scenario and the simulation data of the DT model can be visualized in the virtual scenario. Network connections between physical scenarios, virtual scenarios, sensors, and control software are manually assisted. The connections are configured so that there are no data miscommunication, leakage, data unavailability, or blocking delays. The type and number of devices and the number of personnel in the collaborative environment are stable. The various parts are compatible and integrated at the data level, but manual assistance is required for configuration, and autonomous iterative optimization cannot be achieved.

5.2 Evaluate and calculate

According to the above information on the assembly HRCDT system, the risk response capability of the assembly HRCDT system is evaluated based on the HRCDT risk response capability evaluation method proposed in this paper.

First, the weights assigned to the five assessment dimensions and the 18 evaluation factors within the assembly HRCDT are established utilizing the analytic hierarchy process (AHP), with the findings presented in Table 6. Among the various assessment dimensions, the robot is assigned the highest weight, while the collaborative environment is attributed the lowest weight. The relatively low weight assigned to the human dimension can be attributed to the fact that, within this assembly HRCDT framework, the human primarily fulfills roles related to decision-making and task supervision. Consequently, fluctuations in the human state exert minimal influence on the execution of tasks, thereby having a negligible effect on the risk response capabilities of the assembly HRCDT system. As a result, the weight of the human dimension within the assembly HRCDT system is comparatively low.

Table 6 The weights of the evaluation factors and dimensions for assembly HRCDT

Safety evaluation factors		Weights of evaluation factors ω_{XX}	Weights of dimensions ω_X
Robot	RM	0.5714	0.4185
	RS	0.2857	
	RI	0.1429	
Human	HM	0.1634	0.0973
	HS	0.5396	
	HI	0.2970	
Twin data	DD	0.0624	0.2625
	DS	0.2659	
	DC	0.0926	
	DQ	0.3864	
	DV	0.1928	
Network system	NR	0.0705	0.1599
	NM	0.1395	
	NS	0.3031	
	NQ	0.4869	
Collaboration environment	ES	0.1220	0.0618
	EW	0.3196	
	EF	0.5584	

Second, the levels of risk response capability, as well as the highest ideal risk response capability levels for the 18 evaluation factors within the assembly HRCDT system, have been established, as illustrated in Table 7.

Table 7 f_{XX} and $f_{\max}^{XX}$ for assembly HRCDT

Dimensions	Evaluation factors	f_{XX}	$f_{\max}^{XX}$
Robot	RM	3	4
	RS	2	3
	RI	2	2
Human	HM	3	4
	HS	3	4
	HI	2	3
Twin data	DD	3	4
	DS	4	4
	DC	4	4
	DQ	4	4
	DV	3	4
Network system	NR	3	4
	NM	2	2
	NS	3	4
	NQ	3	4
Collaboration environment	ES	3	3
	EW	2	4
	EF	2	3

Third, the risk response capability score for the assembly HRCDT is determined using Eqs. (1)–(3), with the outcomes of the calculation process presented in Table 8.

As indicated in Table 8, the calculated value of s is 3.3944. This suggests that the risk response capability of the assembly HRCDT falls between levels 3 and 4, with a tendency towards level 3, which is characterized by risk feedback. This finding implies that the assembly HRCDT possesses a more comprehensive risk identification framework, enabling the DT model to effectively identify risks and provide feedback for optimization outcomes.

5.3 Discussion

The risk response capability of the assembly HRCDT has been assessed and determined to be at level 3, incorporating risk feedback mechanisms. To facilitate a clearer comprehension of the risk response capability rating for the assembly HRCDT system, the data presented in Table 8 has been graphically represented in Fig. 9.

As illustrated in Fig. 9, the dimension of twin data exhibits the highest level of risk response capability, whereas the dimension related to the collaborative environment demonstrates the lowest level of risk response capability. The overall risk response capability level of the assembly HRCDT is rated at 3. In contrast, the dimensions of RS, RI, HI, NM, EF, and EW all fall below the threshold of 3 across all evaluation criteria, indicating a failure to meet the overall standard. To enhance the aforementioned evaluation factors, the following recommendations are proposed: (1) Select collaborative robots equipped with an appropriate type and number of sensors that fulfill operational requirements, along with comprehensive data interfaces. (2) Incorporate an interface for the transfer of human work parameters. (3) Employ suitable algorithms and strategies to promote the effective integration of models at the decision-making level. (4) Investigate methods for the automatic configuration and reconfiguration of DT models to ensure their continued advancement.

The evaluation factors RM and HM exhibit the highest scores concerning the risk response capabilities associated with robot and human dimensions, respectively. This observation aligns with the current state of DT applications in HRC. As indicated in Sect. 2.2, the majority of DT-based HRC applications prioritize the development of DT models. This trend suggests that there exists a significant level of consensus regarding model construction within DT-based HRC applications. The four evaluation factors of the twin data dimension meet the requisite demands, likely due to the extensive research on data across various disciplines, which has established a robust foundation and broad applicability. Consequently, despite the inclusion of virtual simulation data within twin data, the requirements for research in this area can be adequately addressed through existing data management methodologies

Table 8 Calculation results of the risk response capability score

Evaluation factors		s_{XX}	s_X	d_X	$d^X_{\max}$	s
Robot	RM	3.5714	2.9795	3	4	3.3944
	RS	2.2857				
	RI	2				
Human	HM	3.1634	3.1091	3	4	
	HS	3.5396				
	HI	2.2970				
Twin data	DD	3.0624	3.7863	4	4	
	DS	4				
	DC	4				
	DQ	4				
	DV	3.1928				
Network system	NR	3.0705	3.1944	3	4	
	NM	2				
	NS	3.3031				
	NQ	3.4869				
Collaboration environment	ES	3	2.2295	2	4	
	EW	1.3608				
	EF	2.5584				

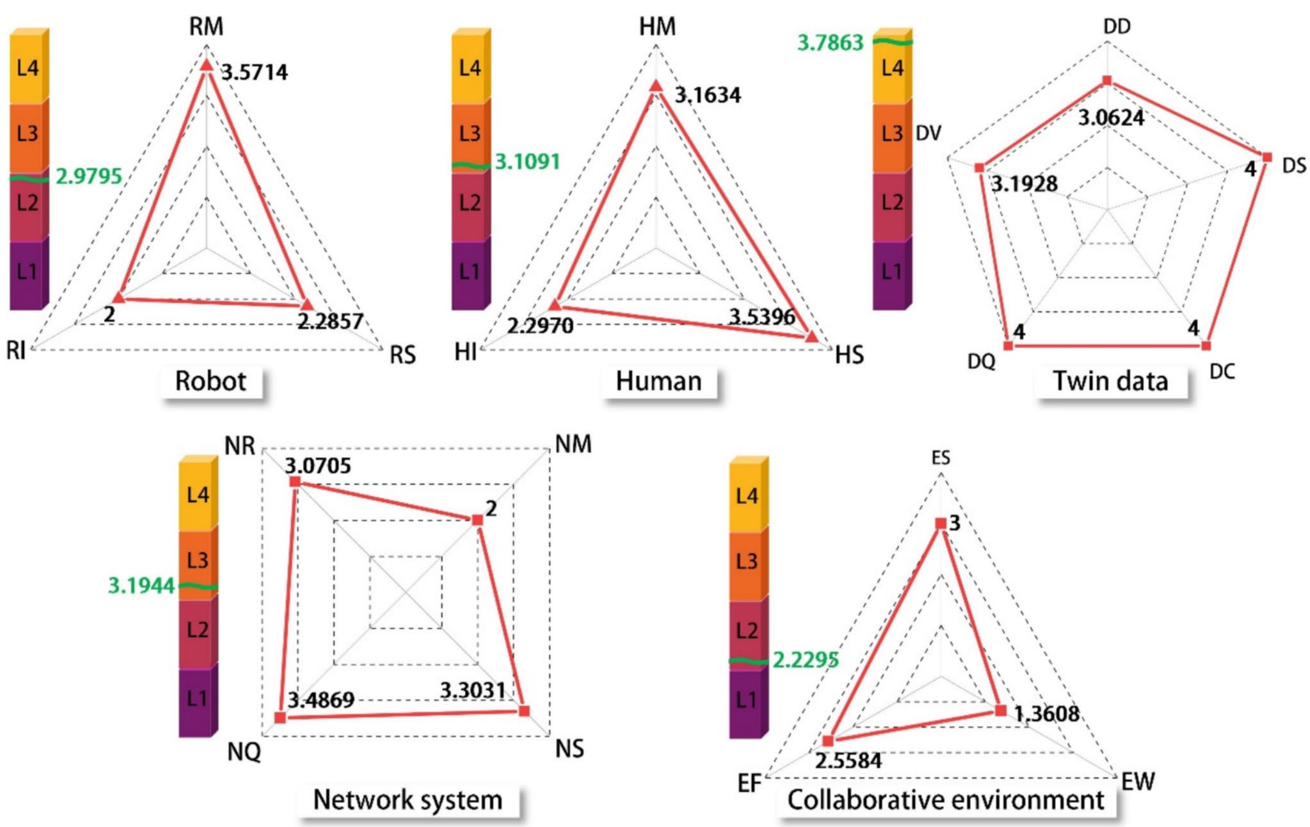


Fig. 9 Detailed calculation results

and experiences. Conversely, the EW score for the environment dimension is the lowest, indicating a deficiency in the research foundation necessary to cultivate a unified understanding of the comprehensive study of HRCDT environments.

The assessment framework and methodology delineated in this paper aim to establish a theoretical foundation and a practical approach for evaluating the risk resistance of HRCDT. The primary focus is on applications of DT technology within HRC. This assessment framework is applicable across various contexts, including assembly, handling, and welding, provided that DT technology is integrated into the HRC system. Nonetheless, several practical challenges may arise in the evaluation of HRCDT's risk response capacity. Firstly, ambiguous research objectives can hinder the assessment process. The proposed risk response capability evaluation specifically targets DT-based HRC applications, thereby excluding traditional HRC from the scope of this research. Secondly, a limited understanding of the application of DT in HRC may result in an incomplete comprehension of the components that constitute the HRCDT system. The implementation of DT extends beyond the mere creation of a virtual model; it necessitates consideration of various factors, including data management across virtual and real HRC scenarios and network transmission rates. A thorough understanding of the fundamental characteristics of the target HRCDT is essential for an accurate evaluation using the proposed assessment framework. Lastly, misconceptions regarding the levels of risk response capability and the optimal ideal risk response capability of the evaluation factors may lead to inaccuracies in calculating the risk response capability score for HRCDT. In the assessment method proposed herein, the sequence for calculating the risk response capability score follows the order of evaluation factor, assessment dimension, and HRCDT system. Consequently, the score assigned to the evaluation factor is critical for the accuracy of subsequent calculations.

The research conducted by Mitra et al. [46], Murino et al. [47], Xu et al. [48], and Kang et al. [49] has been selected for comparison with the methodology proposed in this paper, with the results presented in Table 9. The methodology outlined herein offers three distinct advantages over existing risk assessment approaches. Firstly, the evaluation framework is more holistic, encompassing various assessment dimensions, evaluation factors, and levels of risk response capability. Secondly, the methodology incorporates a differentiated weighting system for both assessment dimensions and evaluation factors. This differentiation acknowledges the varying significance of each dimension within the overall system, as well as the differing importance of evaluation factors within those dimensions. By assigning weights accordingly, the assessment results are rendered more reflective of actual conditions. Lastly, the assessment method is characterized by its comprehensiveness, as it includes not only a quantitative calculation process but also steps for optimizing the resultant calculations. Consequently, the proposed assessment system and methodology serve as reliable instruments for conducting a thorough and nuanced evaluation of HRCDT risk response capabilities.

Table 9 Comparison of risk assessment methods

Authors	Domain	Assessment dimensions	Evaluation factors	Risk level (risk response capability level)	Assessment method	Dimensions weights	Evaluation factors weights	Verification
Mitra et al. [46]	Seaport ecosystem	5	20	✗	Systemic Risk Capability Assessment (SRCA)	✗	✗	✗
Murino et al. [47]	HRC	8	✗	✗	Failure Mode and Effects Analysis (FMEA) and Proportional Risk Assessment technique (PRAT)	✗	✗	✓
Xu et al. [48]	Urban emergency shelters	6	47	✗	AHP	✓	✓	✓
Kang et al. [49]	Hybrid hydrogen-gasoline fueling stations	3	10	✗	Temporal Weighted Average (TOWA) and Temporal Weighted Geometric Average (TOWGA)	✗	✗	✓
Ours	HRCDT	5	18	4	Analyze-Evaluate-Calculate-Recommend	✓	✓	✓

6 Conclusion

This study examines the lack of a theoretical framework for evaluating the risk response capacity of HRCDT by analyzing existing literature on DT-based HRC and HRC risk assessment in this context. The proposed assessment system and methodology for evaluating risk response capabilities offer a standardized approach for determining the effectiveness of the developed HRCDT in identifying and mitigating risks to ensure system stability. The specific contributions of this research are outlined as follows.

A framework has been developed to evaluate the risk response capacity of HRCDT through the application of DT methodologies in HRC. This assessment framework encompasses various levels of risk response capability, assessment dimensions, and evaluation factors. Specifically, the risk response capability is categorized into four distinct stages, threshold judgment, risk identification, risk feedback, and risk prediction, with a comprehensive description of the risk response capabilities associated with each stage. The assessment dimensions consist of five key aspects: robot, human, twin data, network systems, and collaborative environments. In alignment with the characteristics of DT and HRC, these five dimensions are further refined into 18 specific evaluation factors. This evaluation framework serves as a valuable reference standard and provides guidance for enhancing the risk response capabilities of HRCDT.

A method for assessing risk response capability is proposed, consisting of four stages: Analyze, Evaluate, Calculate, and Recommend. Initially, the fundamental information regarding HRCDT is analyzed to ascertain the current situation across five evaluative dimensions. Subsequently, an initial assessment is conducted to determine the risk response capability level for each evaluation factor, as well as the optimal risk response capability level, based on the basic situation and the content related to risk response capability. The calculation of the HRCDT's risk response capability score is executed in three distinct steps. The first step involves calculating the risk response capability score for each evaluative factor. The second step integrates the results from the first step with the respective weights of the evaluative factors to derive the risk response capability score for each evaluation dimension. In the third step, the overall HRCDT risk response score is computed by amalgamating the results from the second step with the weights assigned to the assessment dimensions. The final score is then utilized to ascertain the risk response capability level. Ultimately, recommendations for optimization and enhancement are provided for those dimensions and evaluation factors that exhibit lower levels of risk response capability.

This research examines the risk response capacity of HRCDT and enhances the theoretical framework for the implementation of DT technology within the HRC. Nevertheless, the proposed methodology presents opportunities for further optimization. As the utilization of DT-based HRC continues to expand, it is imperative to augment the evaluation criteria for assessing risk response capacity. Future investigations should focus on the dynamic optimization and enhancement of these evaluation factors, which includes the integration of new indicators and the removal of outdated ones. Furthermore, this study addresses only a singular assessment of risk response capability for HRCDT. Given that the configuration of the HRCDT system may evolve in response to operational or demand fluctuations, ensuring that the risk response capacity of the dynamically adjusted HRCDT system remains adequate is an additional area warranting future research.

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Code availability Not applicable.

Declarations

Ethics approval The author confirms that the submitted work is original, has not been published elsewhere in any form or language, and that the manuscript has not been submitted to multiple journals for simultaneous consideration.

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