Article

Human–Robot Collaboration as an Experiential Process Shaped by Trust, Cognitive Load, and Interaction Transparency

Yijie Xu[1], Jieyu Xu[2], Yixuan Zhou[1]*

1 Zhejiang Normal University, Jinhua, 321004, China
2 Zhejiang Cancer Hospital, Hangzhou, 310022, China
*Correspondence: chowyh@zjnu.edu.cn

Citation: Xu, Y. J., Xu, J, Y., & Zhou, Y, X. (2025). Human-Robot Collaboration as an Experiential Process Shaped by Trust, Cognitive Load, and Interaction Transparency. *Journal of Arts and Cultural Studies*, 4 (2), 1-19. https://doi.org/10.23112/acs25120501

Check for updates

Received: October 02, 2025
Revised: November 15, 2025
Accepted: November 25, 2025
Published: December 05, 2025

Publisher's Note: KIHSS stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Abstract: ***Background:*** As AI and robotics advances, human–robot collaboration (HRC) is becoming more common in manufacturing, healthcare and service settings. This shift pushes interactive systems to focus more on intelligence and user-centered design. However, most systems prioritize task efficiency and automation over important human factors such as cognitive load, trust and interaction transparency. This oversight limits adaptability and negatively affects user experience, posing challenges for human–computer interaction (HCI). ***Purpose:*** This paper examines how to integrate human factors engineering into "systems." It introduces an analytical framework focused on cognitive load, trust and interface transparency to enhance system adaptability and improve user satisfaction. ***Methods:*** This study combines a literature review and qualitative analysis to identify interaction strategies and design features from key collaboration scenarios. User feedback is then used to validate the impact of cognitive load, trust and transparency on these mechanisms. ***Results***: The results show that integrating these human-factor variables improves usability, interaction effectiveness, and perceived trustworthiness. Reduced cognitive load and clearer interaction transparency help users better understand how the system works, while enhanced trust leads to more stable and sustained collaborative interaction. ***Conclusions:*** The research builds on existing HRC models by adding a human-factor dimension and offers evidence-based guidance for designing user-centered intelligent interaction systems with interdisciplinary relevance and broad applicability.

Keywords: Human – robot collaboration(HRC); Human factors engineering; Human – computer interaction(HCI); Interactive system design; Cognitive load

1. Introduction

1.1 Research Background

Human–robot collaboration (HRC) is expanding beyond manufacturing into healthcare, social services, and education, thereby promoting intelligent systems that focus on human needs. Advances in artificial intelligence (AI) and robotics now support autonomous negotiation, intent prediction, and multimodal coordination, making interactions more natural and beneficial in domestic service, emergency response, and hazardous-environment exploration.

However, most collaborative systems still focus on task efficiency and action optimization without addressing users' cognitive load, trust formation, or sense of control. This gap adversely affects usability, satisfaction, and real-world adaptability. Future systems must incorporate real-time behavior analytics to detect effects, intentions, and cognitive state, thereby enabling personalized, adaptive interactions.

Incorporating human factors engineering into HRC interaction design complements traditional automation and creates a user-centered approach, with both theoretical and practical benefits. Applying these principles helps designers align robots with user needs, improve ergonomics, and boost productivity while ensuring health and safety.

1.2 Research Objectives

HRC research now recognizes the importance of user perceptions for system acceptance and outcomes, but three issues remain. First, trust, cognitive load, and interface transparency are modeled separately for each individual user rather than as an integrated system. Second, the feedback loop between user perceptions and system behavior remains unclear, which hinders dynamic design adjustments. Third, theoretical frameworks often do not translate well into practice, limiting their real-world effectiveness.

To address the gaps mentioned above, this study is guided by three research questions:

Q1. In HRC systems, is there an inherent connection among the three human-factor variables, trust, cognitive load, and interaction transparency? How can an analytical framework be developed that analyzes these variables together?

Q2. In real-world collaboration scenarios, through what mechanisms do these human-factor variables influence user perceptions, experiences, and system acceptance？

Q3. For design practice, how can human factors be systematically integrated into interactive systems to achieve dynamic adaptation and human-centered optimization?

Accordingly, this paper advances the following three research objectives:

1. Building on the existing literature, systematically map human-factor applications in HRC and identify key connections among trust, cognitive load, and interface transparency. It clarifies how these variables are operationalized in HRC and highlights their main relationships, providing a solid theoretical basis for future research.

2. Developing a human-factors analytical framework by analyzing user-experience data from typical HRC scenarios to understand the interconnections among trust, cognitive load, and transparency, offering fresh insights into their complex relationship.

3. Propose practical and transferable design recommendations as a systematic guide for integrating human factors into interactive systems, enabling dynamic adaptation, human-centered optimization, and enhanced user experience and collaborative performance.

1.3 Research Methods

This study uses a three-phase mixed-methods approach. Initially, a literature review on HRC, trust mechanisms, cognitive load, and interaction transparency identifies key variables and their relationships, forming a preliminary analytical framework. Next, case studies across service, education, and assistive manufacturing scenarios combine interface evaluation, interaction flow mapping, and semi-structured interviews to uncover human factors conflicts and perceptual gaps, thereby refining the framework. Finally, an interview-based study guided by the framework examines how users perceive trust, load, and transparency in real collaborative situations, providing experiential evidence for final model adjustments. Throughout the process, text analysis, thematic synthesis, and basic descriptive techniques ensure efficient and reliable results that connect theory with real-world practice.

1.4 Research Overview

To address complex, multi-level human factor challenges, the study follows three stages: theoretical development, mechanism validation, and application derivation. First, we define the problem and review literature on human factors engineering, HRC, and intelligent system interaction to establish a solid foundation. Second, we propose a three-dimensional framework: trust, cognitive load, and transparency, and validate its relevance through case studies in real-world collaboration. Finally, we refine the model by analyzing survey and interview data, uncovering key influence patterns, and generating practical design guidelines. Each phase builds on the previous one, transforming abstract concepts into empirically supported, implementable solutions. Based on these findings, we develop practical, transferable design guidelines for systematically integrating human factors into interactive systems, enabling dynamic adaptation, human-centered optimization, and enhanced user experience and collaboration(as shown in Figure 1).

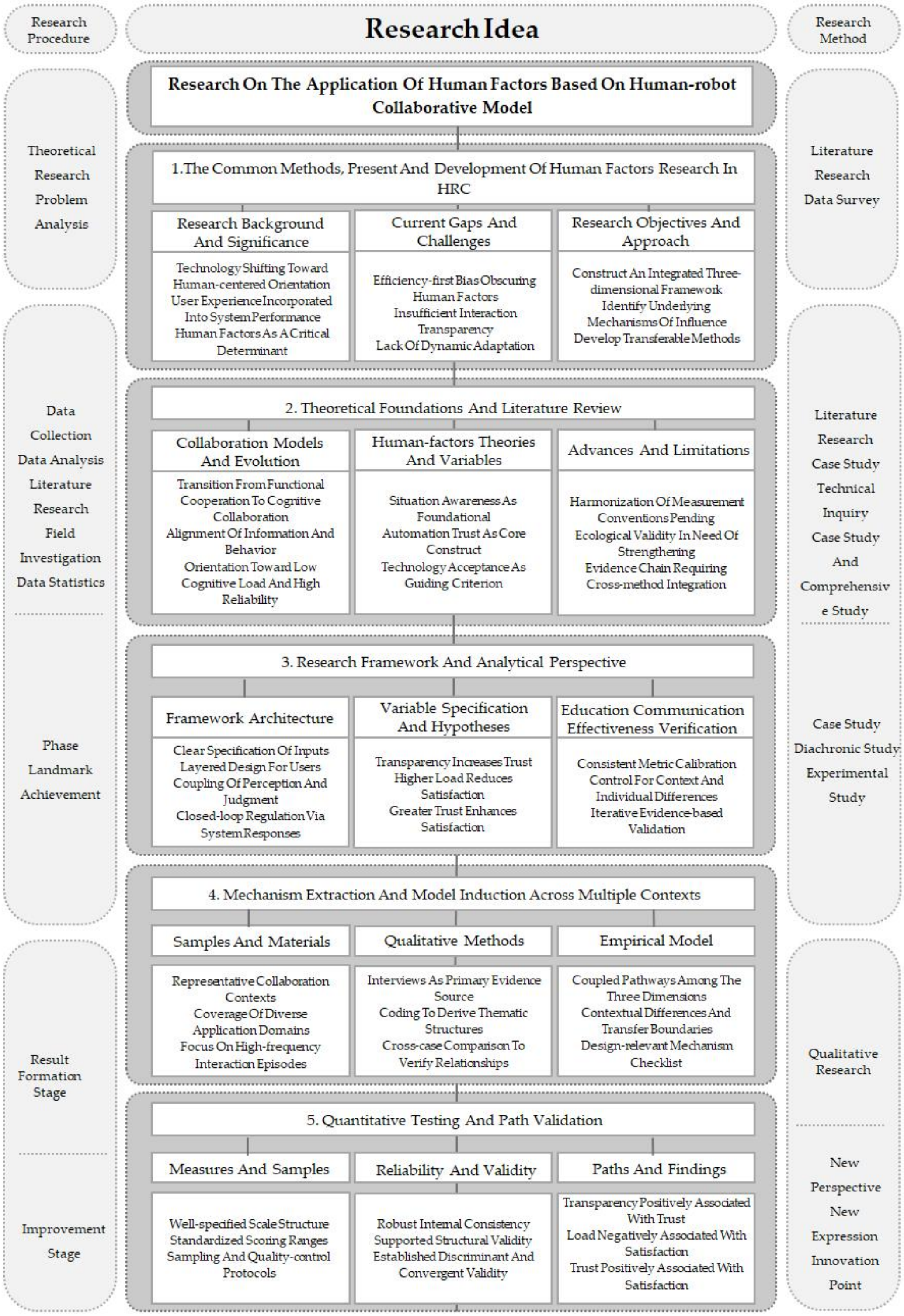

Figure 1. Frame diagram

2. Theoretical Foundations and Literature Review

2.1 Foundational Models and Evolution of HRC

As AI and autonomous systems advance, HRC has shifted from basic physical support to comprehensxive cognitive–behavioral partnerships. Researchers agree that effective HRC relies on information symmetry, complementary behavioral, and cognitive alignment between humans and robots to enable efficient, low-effort task performance (Zhang et al., 2024). Consequently, robots must understand and execute human instructions and autonomously adapt to changing environments and demands for truly seamless interaction.

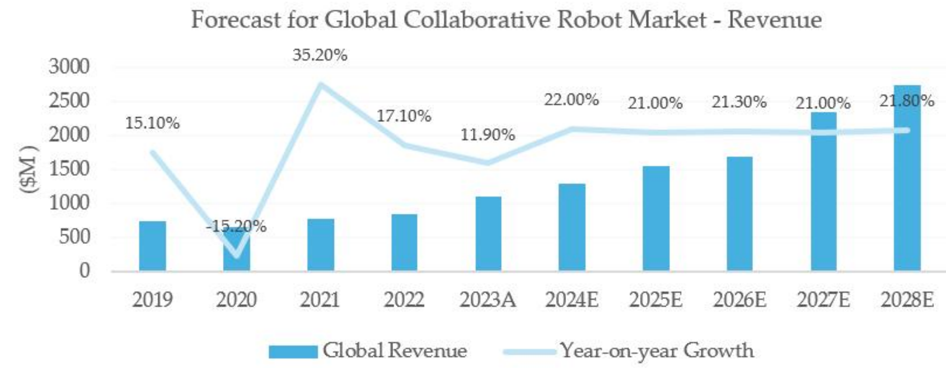

Figure 2. Forecast for Global Collaborative Robot Market – Revenue
Source: Interact Analysis

Two perspectives dominate the evolution of the HRC model. The first, from educational technology, outlines four stages—tool support, cooperation, augmentation, integration, and co-creation—emphasizing the evolving human–robot relationship and its role in knowledge generation. Zhu et al. (2023) applied this model to education, showing that human–machine co-creation reshapes instructional design, cognitive strategies, and learning ecosystems. This approach views HRC as a systemic overhaul of cognitive and social structures, with humans and robots sharing equal responsibility in knowledge creation and task execution.

Another perspective on HRC is through organizational management and intelligent decision-making, with a focus on task division and trust in complex environments. In digital enterprises, HRC now includes information trust, algorithm integration, and shared judgment. Zhang et al. (2024) identify cognitive labor division, collaboration transparency, and human–robot trust as key mechanisms and emphasize the need to design for user understanding and acceptance of algorithms. This perspective extends HRC's role in economic management and shows that mutual trust and comprehension are essential for efficient collaboration.

These perspectives indicate that HRC research is shifting from task-based structural connections to cognition-driven relationship interaction. This change reflects advances in AI's interactive intelligence and social capabilities and suggests that future models must integrate adaptive collaboration structures, embedded human-factor mechanisms, and multi-stakeholder value negotiations. Such models need to adapt to evolving tasks and environments while aligning human and machine factors to support effective decision-making and optimal collaboration(as shown in Figure 2).

2.2 The Application Evolution of Human Factors Engineering in Human-Computer Interaction

As human-robot collaboration systems develop, human factors engineering in interaction design has shifted from focusing solely on efficiency and safety to aligning user psychology with system behavior. Recent research highlights its role as the bridge between human cognition and intelligent system responses. Zheng (2024) notes that beyond improving efficiency and safety, this field also promotes harmonious and effective collaboration between humans and intelligent systems.

In HRC, the ability to monitor users' cognitive load, attention, and emotions has become essential for evaluating collaboration and adoption. Zheng (2024) notes this as a shift from humans adapting to machines toward machines adapting to humans. As a result, interfaces have moved from static layouts to dynamic sensing and adjustment, broadening the scope of human factors engineering and supporting human-centered collaboration. This flexibility better addresses individual needs and enhances user experience and satisfaction.

Integrating human factors engineering into HRC models is essential for enhancing system adaptability and user-centered interaction. This strategy provides a solid theoretical foundation and a clear framework for addressing key challenges. Applying human factors principles deepens our understanding of user needs and behaviors, which in turn guides the design of more intuitive, intelligent systems that support seamless, efficient collaboration between humans and robots(as shown in Figure 3).

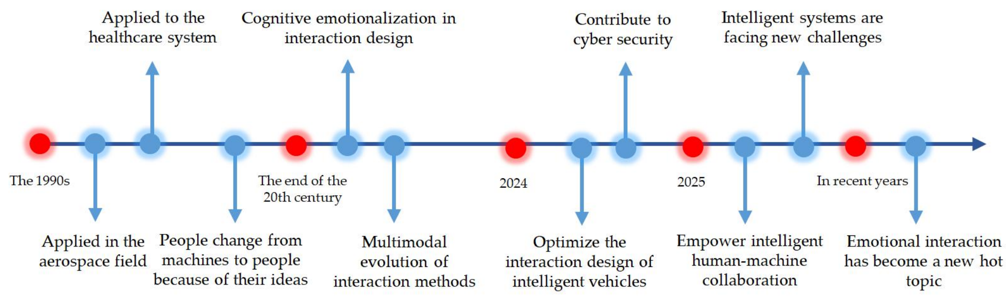

Figure 3. The application evolution of human factors engineering in human-computer interaction

2.3 Research on Trust, Sense of Control, and Cognitive Factors in Human-Robot Interaction

This study examines HRC models and finds that trust, perceived control, and cognitive load significantly affect interaction quality. These factors are critical to smooth collaboration. At the same time, system characteristics such as uncertainty, lack of explainability, and potentially misleading "hallucinations" continually diminish users' trust expectations (Yu et al., 2025). When trust decreases, engagement and perceived control also decrease. Likewise, opaque or rigid feedback diminishes control, increases cognitive load, and reduces performance and collaboration stability.

Therefore, establishing a human-factor mechanism based on trustworthiness, perceived control, and low cognitive load is key to adaptive, intelligent HRC. It preserves user trust and control while minimizing cognitive strain, boosting efficiency, and task stability. Clear communication reduces misunderstandings and ensures smooth coordination. This approach improves user experience and system performance, strengthening the foundation for future human-computer interaction (HCI).

2.4 Literature Review and Analysis

1) Current Research Topics and Trends

Recent research (Fu et al., 2023) shows that HRC's evolution from industrial automation to intelligent collaboration efficiency depends on both algorithmic optimization and human cognitive, affective, and social adaptability. Theoretical development is divided into three stages—Technology-Driven Era, the Human-Factors Exploration Era, and the Socio-Technical Integration Era (Wang et al., 2018; Garcia et al., 2023; Cao et al., 2024; Yan et al., 2024; Charalambous et al., 2017; Wang et al., 2025; Ren et al., 2023). Early research prioritized algorithmic task-allocation efficiency, followed by studies that modeled human intent recognition and response strategies, and the current challenge is creating models that balance long-term stability with collective adaptability (Wang et al., 2018; Yan et al., 2024).

Technology-driven optimization focuses on algorithmic enhancements to improve robot responsiveness and adaptability. Multimodal perception fusion achieves ±0.3 mm spatiotemporal accuracy (Garcia et al., 2023; Fan et al., 2023), and a lightweight interaction design reduces operator cognitive load by 40%. These advancements demonstrate that technical performance gains significantly increase short-term collaboration efficiency (Wang et al., 2018; Garcia et al., 2023; Cao et al., 2024).

Research on Human - factor feedback and collaboration stability shows that physiological measures and group social dynamics each uniquely impact HRC. Analysis of galvanic skin response and electroencephalogram (EEG) support a comfort - assessment framework with a validity coefficient of 0.85. Cross-cultural studies reveal significant differences in emotional contagion (Zhang et al., 2021; Charalambous et al., 2017). These findings highlight the complexity of HRC at the socio-technical level (Yan et al., 2024; Yan & Jia, 2022; Wang et al., 2025).

Table 1. Research Phases and Trends

Research Phase	Focus	Key Developments	Technologies & Methods	Significance
Technology-Driven Era	Emphasize robot autonomy and task efficiency	Optimization of task-allocation algorithms, faster responses	Response latency controlled at the millisecond level	Enabled initial gains in collaborative efficiency
Human-Factors Exploration Era	Address individual cognitive load and psychological adaptability	Modeling of physiological and psychological indicators, development of an assessment framework	Cognitive load reduced by 40 %, comfort validity coefficient of 0.85	Established foundational human-factors insights at the individual level
Socio-Technical Integration Era	Study dynamic interactions and adaptation between teams and robots	Social-behavior modeling, design of group-adaptation mechanisms	±0.3 mm spatiotemporal synchronization, multimodal perception fusion	Expanded HRC research into complex socio-technical systems

2) Contributions and Limitations of Existing Research

Recent HRC studies have delivered notable technical advances. Multimodal perception fusion has raised task recognition accuracy above 95 % (Wang et al., 2018; Cao et al., 2024), and lightweight interaction design has cut training time to one-third that of traditional methods (Na, 2024; Fan et al., 2023). However, over 200 hours of continuous use led to a 28 % drop in user satisfaction, highlighting the need to address trust dynamics in long-term collaboration (Yan et al., 2024).

Recent human-factors assessment research findings show clear divergence. Models based on individual physiological and psychological metrics now predict stress states with 85 % accuracy. Group-level studies find that emotional contagion accounts for 36% of the variance in collaboration efficiency (Yan & Jia, 2022; Zhang et al., 2021). A recent meta-analysis identifies a 17% gap in predictive validity mainly due to overlooked group interaction dynamics (Rani et al., 2024). Incident analyses reveal that 65 % of collaboration failures stem from unclear responsibility allocation, underscoring the need for a robust theoretical framework to prevent breakdowns (Yan et al., 2024; Wang et al., 2025).

3) Research Questions

In light of these gaps, this study focuses on three interrelated issues.

At the theoretical level, three critical issues demand attention. First, user trust may lag behind fluctuations in system performance (Wang et al., 2018; 2025). Second, the propagation of social pressure in group networks might follow small-world characteristics, as hypothesized by Charalambous et al. (2017). Third, the ethical boundaries for responsibility allocation during emergencies require clarification, as highlighted by Cao et al. (2024) and Yan et al. (2024).

Methodological challenges include developing composite trust metrics that integrate behavioral logs and physiological signals (prediction error still 32 %, Yan & Jia, 2022); validating the link between group physiological synchrony and task performance (Zhang et al., 2021); and devising algorithms capable of 10 ms response times (Garcia et al., 2023).

Practical challenges include creating fatigue-prevention measures for long-term use, developing adaptive strategies for cross - cultural teams and building dynamic responsibility - allocation frameworks. Meeting these needs demands combining recent system - implementation advances (Wang et al., 2018; Cao et al., 2024) with human - factors assessment insights (Charalambous et al., 2017; Zhang et al., 2021).

Table 2. Sorting out the core research questions

Level	Key Issue	Related Work	Theoretical and Methodological Significance
Theoretical	Lag effect of trust on system performance fluctuations	From human-machine collaboration to deviation: Understanding the catastrophe and resilience mechanisms of human-machine behaviors in intelligent environments	Reveals how trust dynamics influence task performance over time
	Propagation of social pressure in small-world collaboration networks	The development of a Human Factors Readiness Level tool for implementing industrial human-robot collaboration	Explores structural pathways of collective stress transmission
	Ethical boundaries of responsibility allocation in emergencies	Measuring Human Comfort in Human–Robot Collaboration via Wearable Sensing	Establishes normative foundations for responsibility in high-uncertainty environments
Method	Composite trust metrics from behavioral logs and physiological signals	A review on human comfort factors, measurements, and improvements in human–robot collaboration	Advances in quantitative multimodal data integration for trust modeling
	Correlation between group physiological synchrony and task performance	Intelligent extraction method of natural resource elements based on human-machine collaboration	Clarifies structural links between team physiological coupling and collaborative outcomes
	Algorithmic approaches for achieving a 10 ms response time	Deep learning framework for controlling work sequence in collaborative human–robot assembly processes	Enhances system responsiveness and agility in high-frequency interaction scenarios
Application	Long-term fatigue-prevention solutions	From human-machine collaboration to deviation: Understanding the catastrophe and resilience mechanisms of human-machine behaviors in intelligent environments	Improves resilience of physiological and psychological load management in sustained interactions
	Adaptive human-factors strategies for cross-cultural teams	The development of a Human Factors Readiness Level tool for implementing industrial human-robot collaboration	Establishes culturally aware, generalizable adaptation mechanisms for HRC

	Dynamic responsibility-allocation framework for emergent tasks	Designing an interaction interface for supportive human-robot collaboration: A co-creation study involving factory employees	Guides decision-support system design for flexible role switching and clear responsibility sharing

3. Research Framework and Analytical Perspectives

3.1 Adopted Human-Factors Theoretical Models

As HRC systems operate in areas requiring high cognitive load and complex decision-making, scholars consider uni-dimensional performance metrics insufficient for understanding adoption and adaptability (Sun et al., 2020). Accordingly, this study draws on three human-factors models.

First, the Situation Awareness (SA) model describes perception, comprehension, and projection, showing how task-state transparency, interface readability, and information accessibility influence cognitive load (Bütepage & Kragic, 2017). Widely applied in aviation, traffic control, and collaborative systems, SA frames user cognition under high task demands. Second, the Automation Trust model defines trust as evaluations of system ability, integrity, and compassion (Sun et al., 2020) demonstrated that trust mediates between transparency and user behavior, shaping decisions to intervene or rely on automation. Third, the Unified Theory of Acceptance and Use of Technology (UTAUT) identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as key factors driving technology adoption . In collaborative robotics, UTAUT explains system acceptance, trust formation, and the smoothness of user integration in complex intelligent environments (Jacob et al., 2023; Zhai et al., 2023).

In summary, the SA model targets cognitive perception; the Automation Trust model emphasizes users' evaluations of system ability, integrity, and compassion; and UTAUT maps behavioral adoption drivers. Combined, they furnish a robust theoretical basis for defining human–factor variables and their interactions.

3.2 Construction of the Analytical Framework

In complex interactive systems, user behavior arises not from a simple linear response but from the dynamic interaction of environmental perception, cognitive evaluation, and system feedback. To capture this process, we integrate the aforementioned theoretical models into a four-stage human-factors framework: input, perception, judgment, and response. This framework details how human-factor variables progressively influence user interactions throughout task execution.

During the input stage, external cues such as interface elements, environmental context, and user states, including physiological and emotional shape task readiness, mirror SA's information-acquisition phase (Gervasi et al., 2022). In perception, users interpret goals, feedback, and system predictability; transparency and consistency are key to initial trust evaluations (Bütepage & Kragic, 2017; Yu et al., 2025). During judgment, dynamic trust assessment, perceived control, and strategy adjustments occur, reflecting SA's comprehension/projection and cognitive processing in collaborative tasks (Sun et al., 2020). In the response stage, behavioral outputs such as performance, intervention tolerance, and emotional feedback (satisfaction) emerge, while adoption decisions are shaped by organizational policies and social norms per UTAUT (Jacob et al., 2023; Zhai et al., 2023).

The framework highlights stage-wise transmission paths and feedback mechanisms of human variables, providing a robust theoretical basis for measuring variables and conducting empirical path analysis in future studies.

3.3 Definition of Key Concepts and Variable Specification

In developing a human-factors analysis framework for HRC, a precise definition of core variables is essential for ensuring logical rigor. Prior studies show that impacts depend on both model structure and detailed descriptions of user cognition, psychology, and behavior (Jacob et al., 2023). We therefore identify three dimensions: collaboration efficiency, interaction satisfaction, and perceived cognitive load.

Collaboration efficiency gauges the smoothness and coordination of human–robot task execution. It uses objective metrics such as task duration, error rate, and interruption count, reflecting basic human-factor adaptation (Jacob et al., 2023). Moreover, interaction satisfaction captures users' subjective experience and value judgments, depending on task outcomes, trust levels, perceived control, and feedback consistency; it predicts continued system adoption (Sun et al., 2020; Yu et al., 2025). Besides, perceived cognitive load measures strain on users' mental resources during collaboration, including attention allocation, information processing, and emotion regulation; it is assessed via NASA-TLX scores, eye-tracking metrics, and heart-rate variability (Gervasi et al., 2022; Zheng, 2024).

This study combines the SA, trust-building, and UTAUT models into a three-dimensional human-factor framework that connects cognitive, emotional, and behavioral processes with clear measurement pathways. Limitations include missing moderator variables such as gender and culture, insufficient real-time multimodal adaptation, and a sole focus on user-side metrics; future work should incorporate bidirectional modeling of system factors to improve generalizability and predictive accuracy.

3.4 Explanation of the Scope of Application and Limitations of the Framework

This framework applies to three types of HRC scenarios. First, it supports personalized response systems in service robots, which adapt interactions to individual user needs and preferences. Second, it is relevant to warehouse coordination and task-allocation platforms in smart manufacturing, enabling efficient collaboration between robots and human workers to optimize production flow and resource use. Third, it extends to semi-autonomous interaction systems in education and healthcare, where robots can engage and collaborate with humans while maintaining necessary human oversight. All these domains involve frequent interactions, require trust-building, and carry the risk of diminished perceived control. Consequently, applying human-factors models to adapt and optimize interaction is essential for efficiency and safety (Zhu et al., 2023; Zhang et al., 2024). However, this framework has limitations: it relies mainly on qualitative configurational analysis and lacks dynamic simulation to manage high-frequency feedback or system disturbances, limiting accurate robot behavior prediction; the strength of inter-variable pathways and the precision of moderating effects require validation through cross-sample empirical studies; and its focus on single-user scenarios leaves its applicability in multi-agent, multi-user environments untested.

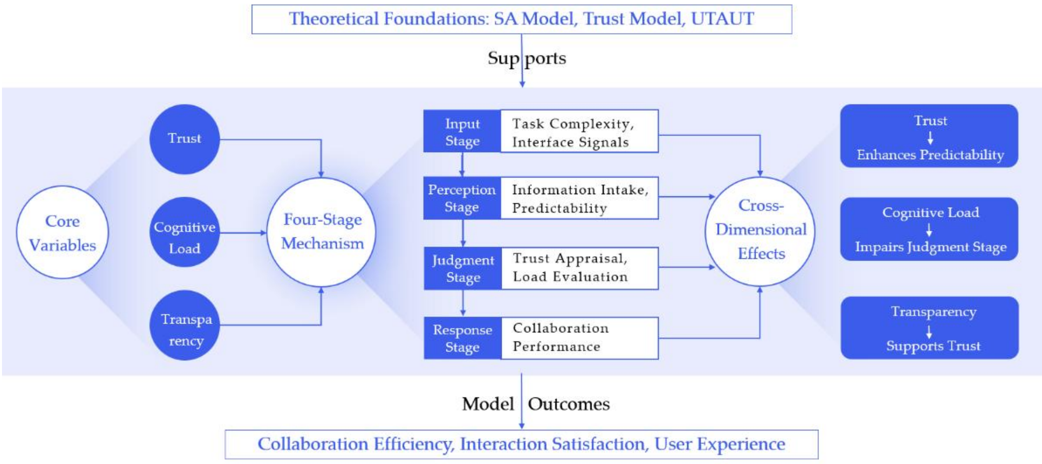

Figure 4. Human–Robot Collaboration Human-Factors Model

Future research should investigate cultural adaptation, mechanisms of multimodal perception, and real-time feedback adjustments to enhance the framework's generalizability and practical value. This will help better address diverse user needs, integrate multimodal data more accurately, and extend its applicability across varied scenarios(as shown in Figure 4).

4. Case Analysis and User Opinion Mining

4.1 Explanation of Case Selection

As HRC becomes common in service, manufacturing, and healthcare, user perceptions and behaviors critically determine system adaptability. Research shows that human-factor variables affect robot acceptance, interaction patterns, and performance during dynamic cooperation (Broadbent et al., 2009; Wu & Zhang, 2024; Huck et al., 2021). Case analysis provides a qualitative approach to uncover underlying psychological mechanisms and behavioral patterns in collaboration. Examining interactions in specific scenarios reveals how users perceive and respond to robot behaviors and how these responses influence workflow and efficiency.

This study selected three representative cases based on their typicality, diversity, and interview ability: hotel service robots, industrial collaborative arms, and eldercare medical robots. These contexts, service, manufacturing, and healthcare, involve frequent interaction, high perceptual load, and a strong human-factor sensitivity. In-depth analysis of users' collaborative behaviors and assistance strategies provides valuable insights to guide the design of more human-centered, efficient robotic systems.

Figure 5. Hotel service robots, industrial collaborative arms, and eldercare medical robots

During the study, we examined users' perceptual experiences when interacting with robots, focusing on their understanding of robot behaviors, emotional responses, and satisfaction with the collaboration, as well as specific adaptations, such as aligning actions with the robot's workflows and utilizing its support to improve efficiency. These observations illuminate the dynamic evolution of HRC and its effects on task outcomes.

To capture interaction nuances, we combined observation, interviews, and surveys, and analyzed demographic differences in age, gender, and professional background to assess their influence on experience and efficiency(as shown in Figure 5).

4.2 Case Analysis Dimension

This study examines multi-stage processes of human factor variables in collaborative interaction through an analytical framework comprising four dimensions: task system characteristics, cognitive processing, behavioral adaptation, and perceived feedback efficacy. The framework combines users' subjective experiences and emphasizes perception, judgment, and response pathways in HRC research (Chen et al., 2023; Huck et al., 2021).

Task and system characteristics shape collaboration complexity and cognitive engagement. Robot autonomy, feedback methods, and task structure influence risk assessment and role assignment. In industrial contexts, operators monitor highly automated systems, while in service settings, users act as collaborators or requesters (Huck et al., 2021). Users' cognitive processes include trust formation, perceived control, and cognitive load regulation. Trust arises from consistent robot actions and clear explanations; unpredictable behavior or opaque logic reduces control and undermines efficiency (Broadbent et al., 2009). Behavioral adaptation reflects the shift from passive response to proactive strategy during sustained collaboration. For instance, hotel staff initially experience technology anxiety and job replacement fears; familiarity and transparent feedback then increase their engagement and initiative, demonstrating human factor plasticity (Wu & Zhang, 2024). Perceived feedback efficacy drives continued use and value judgments. Effective feedback enhances efficiency and strengthens cognitive trust and psychological safety. In medical caregiving, users prefer robots that convey emotion and clarify intentions (Broadbent et al., 2009) (as shown in Figure 6).

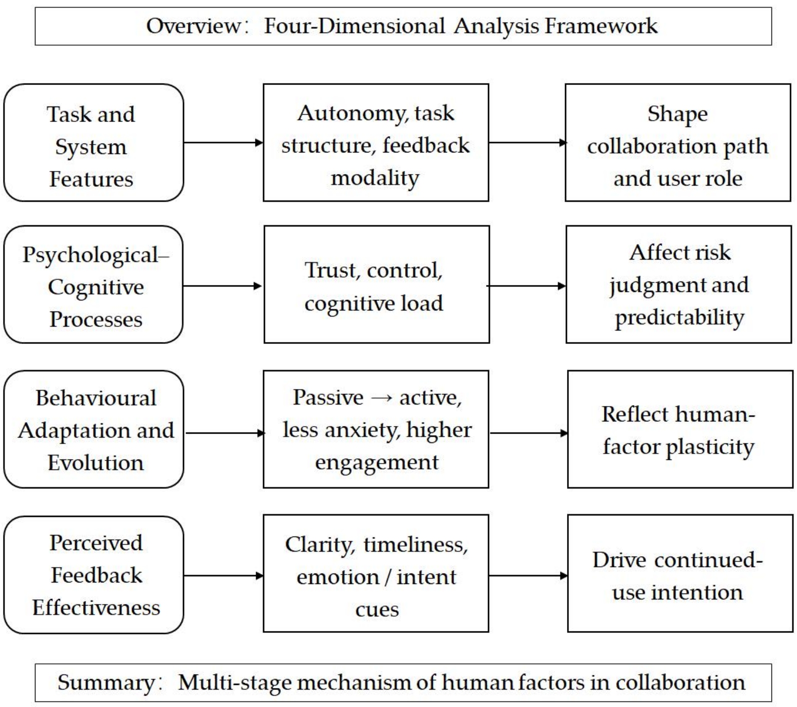

Figure 6. Four-Dimensional Human-Factors Analysis Framework for Human–Robot Collaboration

4.3 Semi-structured User Interviews

This study employed semi-structured interviews to investigate users' psychological constructs and interaction experiences in real-world HRC. This approach aimed to understand users' perceptions of robot behavior from a multidimensional human-factors perspective. The interview protocol comprised open-ended questions focused on three core themes: trust formation, sources of cognitive load, and interaction transparency. These themes allowed the study to systematically examine how users evaluate robot actions, the pressures they experience during interaction, and their acceptance of feedback mechanisms.

Participants were selected from hotel service robot systems, industrial collaborative arms, and eldercare medical robots. Four users per setting (twelve total) represented frontline staff, technical operators, and elderly users, ensuring a diverse range of experience. Interviews began with concrete scenario descriptions before probing users' psychological reactions. In the hotel service setting, participants were asked what their immediate reaction was when the robot greeted them for the first time and whether they tried to interact further. In the industrial scenario, they were asked if they understood system alerts or malfunctions and how this influenced their operational decisions. In the medical caregiving setting, they were asked whether the robot responded promptly to their requests and whether its behavior helped reduce feelings of loneliness or anxiety.

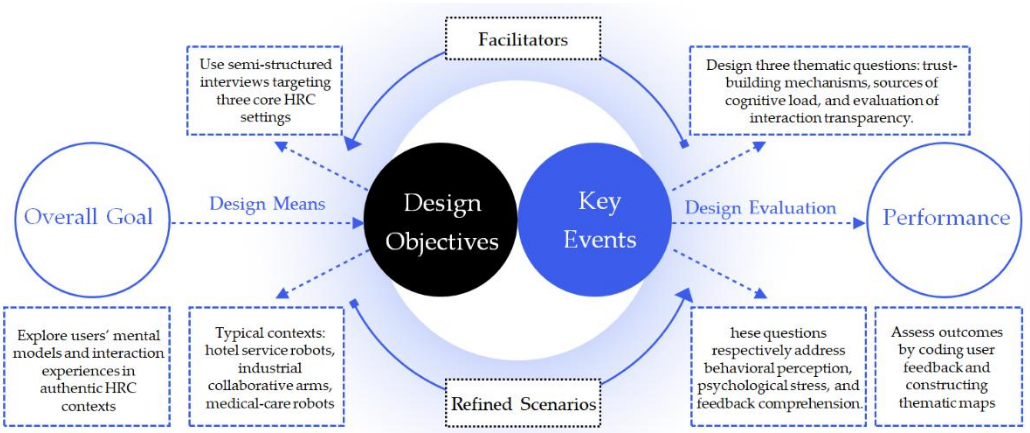

Figure 7. Logical framework diagram

All interviews were transcribed and verified for accuracy. The transcripts were imported into NVivo for open coding, axial clustering, and thematic analysis to ensure consistency and reliability. Detailed results are presented in the next section(as shown in Figure 7).

4.4 Summary and Coding Analysis of the Interview Content Themes

This study used axial coding to analyze interview data and reveal the psychological pathways and interaction mechanisms of key human factor variables in HRC. The analysis targeted three dimensions: trust formation, sources of cognitive load, and interaction transparency. NVivo open coding, combined with clustering, identified seven themes, and exemplar quotations reconstructed actual interaction contexts.

The first axial code, trust formation, explores how users build trust in robots. Initial trust often comes from humanlike appearance and friendly communication. For example, one hotel staff member said, "It calls me by name and even winks; I feel it understands me." When robots malfunction, timely verbal alerts and self-corrections foster compensatory trust. As another user noted, "When it makes an error, it tells me 'correcting now,' so I feel there is still hope." These findings show that both visual design and fault-recovery feedback influence trust perception.

The second axial code, sources of cognitive load, identifies three main contributors to user processing demands: multimodal input such as simultaneous speech and graphics; task ambiguity from unclear interface information; and delayed feedback. In an industrial setting, one participant said that overlapping speech and icons made it difficult to determine where to focus. In a medical scenario, a user reported being asked to choose an operation path without any explanation. These cases demonstrate that poor transparency and unclear information cause anxiety and impair performance.

The third axial code, interaction transparency evaluation, examines how users assess a robot's ability to explain actions and respond to emotions. Clear intent signals are crucial for cooperation; one participant said that when the robot stopped, they had no idea why, showing that missing feedback undermines credibility. In medical and service settings, robots that detect and address user emotions demonstrate affective intelligence. For example, when a user felt down, the robot said "Let's try again," providing comfort and strengthening the sense that the system understands human feelings.

In summary, interview analysis revealed interrelated mechanisms of human factors across three dimensions: trust formation, cognitive regulation, and transparency perception. These findings empirically support a mechanism framework for HRC and underpin further modeling and strategy development.

Table 3. Questionnaire index system for human-robot collaborative system

Main Category	Category Content	User Quote	Interaction Scenario
Trust formation mechanisms	Initial trust (humanlike appearance), process trust (behavior consistency), compensatory trust (error feedback)	"Although it is slower, when it says 'I am still processing' I feel much more at ease."	Service, healthcare
Sources of cognitive load	Information overload, delayed feedback, and command ambiguity	"It popped up five options at once, and I could not read them all."	Industrial, service
Interaction transparency evaluation	Behavior explanation, task transparency, emotional responsiveness	"The robot finished but did not say anything, so I had no idea if it completed."	Service, industrial, healthcare

5. Research Design and Analysis

5.1 Logical Structure and Core Dimensions of the Interview Indicator Framework

In HRC research, evaluating trust, cognitive load, and interaction transparency determines efficiency and acceptance. Based on our theoretical model, this study aims to construct an interview indicator system centered on three core dimensions: trust, cognitive load, and interaction satisfaction. Trust gauges confidence in system consistency; cognitive load measures perceived mental effort from information complexity; interaction satisfaction assesses approval of the system's explanations and response speed.

The trust dimension comprises five items assessing confidence in robot competence, reliability, and error recovery. The cognitive load dimension covers information redundancy, task interference, and instruction ambiguity. The interaction satisfaction dimension evaluates clarity of responses, quality of explanatory feedback, and users' initiative in offering feedback. To ensure that the interview content remains structured and comparable, this study replaces traditional scale formats with a five-level interview prompt design. This format guides participants to make experiential judgments along a range from "strongly inconsistent" to "strongly consistent."

Researchers designed the questionnaire to assess users' psychological and behavioral responses during robot interactions and their effects on overall system evaluation. It captures expectations of robot behavior, comprehension of provided information, and trust under error conditions, and perceived cognitive load and satisfaction with the interaction interface.

To capture user perceptions in HRC, the trust dimension assesses confidence in robot performance. For instance, stability during complex tasks and error recovery ability. The cognitive load dimension quantifies the mental effort required to process system information and the extent to which it disrupts task execution. The interaction satisfaction dimension evaluates perceived response timeliness and accuracy, as well as users' sense of engagement and control.

Table 4: Overview of HRC Research Stages and Trends

Core Dimension	Definition	Measurement Items
Trust	User confidence in robot competence, reliability, and error-recovery, captured through trust-building mechanisms in HRC tasks.	Behavioral perception of the robot, including behavioral consistency, competence trust, reliability trust, error recovery, and situational adaptability.
Cognitive Load	Mental effort arising from information complexity during task execution, reflecting sources of cognitive load in HRC.	Psychological stress is induced by information redundancy, task interference, and instruction ambiguity.
Interaction Transparency	User perception of how transparent the interaction is, including response clarity, interpretability of system behavior, and feedback comprehension.	Response clarity, explanatory feedback, user initiative, response timeliness, interaction naturalness, and feedback comprehension.

5.2 Composition of the Interview Sample and Implementation Method

The interview sample was designed to capture diverse collaborative experiences across service, industrial, and care settings. Accordingly, hotel service robots, industrial collaborative arms, and medical companion robots were selected to represent perceptual interaction, operational cooperation, and emotional support. Purposive sampling was used to recruit twelve participants with clear experiential knowledge of robot behavior, information cues, and interaction feedback. This group included system operators, collaboration partners, and service recipients, providing complementary perspectives across cognitive, emotional, and operational dimensions.

The interviews focused on key moments during collaboration and encouraged participants to describe how they interpreted robot intentions, processed system signals, and evaluated behavioral adjustments. Rather than reconstructing procedures, the analysis concentrated on the perceptual logic and evaluative criteria embedded in their narratives. All transcripts were verified for accuracy, enabling a systematic identification of trust, cognitive load, and transparency-related mechanisms across different scenarios.

5.3 Interview Outline Design and Data Analysis Methods

The analysis of the interview data follows a theory-driven framework centered on three major dimensions: trust, cognitive load, and interaction satisfaction. The interviews are not treated as descriptive accounts but as structured material that reveals the psychological mechanisms embedded in users' collaborative experiences and aligns them with the theoretical model.

Before analysis, the interview transcripts were examined for completeness, conceptual coherence, and consistency across participants. Cross-contextual review showed recurring references to behavioral consistency, the amount and pacing of information prompts, and the clarity of system feedback. Participants relied on these cues similarly when judging reliability, interpretability, and response quality. This high level of convergence indicates strong alignment with the theoretical structure and supports the use of systematic coding.

The coding process combined open coding and axial coding. Open coding identified evaluative criteria in user narratives, such as the predictability of actions, the intrusiveness of prompts, and the clarity of explanations. Axial coding then grouped these criteria into three mid-level constructs: behavioral consistency, information complexity, and feedback transparency. The resulting thematic structure shows clear conceptual boundaries and maintains stable internal coherence.

Synthesis of experiential patterns indicates that trust is generally high, cognitive load fluctuates with task demands, and satisfaction depends on both interpretability and response speed. A chained influence pattern also emerges: increasing information complexity raises cognitive load, which reduces trust, while higher trust enhances interaction satisfaction, especially when system feedback is clear.

Overall, the analytical framework produces clear themes and coherent influence pathways that align with the theoretical model, providing a solid foundation for subsequent findings and design implications.

5.4 Result Discussion: Comparison Between Theoretical Models and Empirical Data

Empirical analysis shows that trust and cognitive load strongly predict outcomes across diverse human-robot collaboration contexts, confirming our cognitive judgment response model. This model emphasizes that user attitudes toward robotic systems emerge from an ongoing interactive process of forming and adjusting mental representations rather than from isolated performance metrics.

First, user trust is more closely tied to consistent robot behavior and clear explanations than to technical performance alone. Second, high cognitive load reduces engagement in tasks with complex information or unclear feedback and strongly influences decision-making. Third, interaction satisfaction reflects both trust and information burden and influences collaboration outcomes.

These results highlight the importance of human factors in interaction design. Future systems must adapt to user cognition and ensure transparent feedback rather than pursue automation alone. Embedding human-centered design aligns system behavior with cognitive needs and promotes smooth HRC.

Developers and designers of robotic systems must consider users' psychological and cognitive processes and their influence on interaction. Optimizing interfaces, reducing unnecessary cognitive load, and enhancing system self-explanation can improve trust and satisfaction. Providing consistent behavioral feedback and clear system responses strengthens trust and encourages positive engagement. These strategies will lead to more human-centered intelligent robotic systems and enhance user experience and efficiency.

6. Research Conclusions and Suggestions

6.1 Summary of Main Research Conclusions

As HRC technologies advance, growing complexity and interdisciplinary integration have made the relationship between system design and user adaptation a key research focus. This study proposes an analytical framework that integrates trust, cognitive load, and interaction transparency. By conducting qualitative interviews across three representative application scenarios, we identify the roles of human interaction factors at each stage and uncover their underlying mechanisms. Our findings show that building trust is essential for effective user engagement, managing cognitive load preserves decision-making efficiency and operational accuracy in complex tasks, and improving interaction transparency helps users understand system behavior and enhances their overall experience.

Results show that user collaboration is driven by task complexity and transparency of feedback. In trust formation, users rely on consistent behavior and clear explanations as cognitive anchors. In complex tasks, cognitive load dominates decision efficiency and accuracy. Interaction adaptability and emotional expressiveness enhance satisfaction and long-term engagement. Quantitative analysis confirms that systems with high trust and transparent feedback significantly increase satisfaction and performance. Integrating trust, load management, and transparency into system design optimizes both user experience and overall outcomes.

This study clarifies the relationships among trust, cognitive load, and transparency, and reveals the perceptual and evaluative logic that links user judgments to collaborative behavior. Methodologically, it introduces an analytical approach that applies across different scenarios and shows how key human-factor dimensions evolve in real collaborative tasks. Practically, the findings identify clear design principles, demonstrating that stronger interpretability, greater behavioral consistency, and clearer information presentation can enhance trust while reducing cognitive load. Overall, the study advances theoretical understanding and provides actionable guidance for developing more adaptive, human-centered collaborative systems.

6.2 Suggestions for the design of Human-Machine Collaborative Systems

Optimizing trust is crucial for refining system response logic. Trust arises from initial cognitive impressions, consistent feedback, and effective handling of anomalies during interaction. We recommend using digital twin technology to visualize system states, improve behavioral predictability, and ensure transparency, thereby enhancing perceived explainability (Li et al., 2025). Interface design should follow cognitive load management principles. In time-critical or highly demanding tasks, it is essential to protect users' cognitive capacity by reducing information overload and promoting seamless task flow. Approaches include reorganizing the interface to reflect information priority, applying color and iconography to highlight critical elements, and integrating appropriate automation assistance (Giallanza et al., 2024). Incorporating speech recognition and natural language processing can enable more intuitive communication. Finally, continuous collection of user feedback and behavioral data allows the system to self-optimize, better address evolving needs, and build long-term trust.

Flexible role assignment enhances collaboration efficiency by combining technical capability with accurate intent recognition. Systems should include modules for task perception and strategy adjustment to enable human and robot roles to adapt to changing needs (Inkulu et al., 2022). Autonomous learning from user behavior is also essential for adaptation in complex dynamic environments. We recommend inverse reinforcement learning to model individual preferences and intentions more precisely, accommodating personalized needs (Suresh, 2024). To enhance collaboration, flexibility, and efficiency, apply machine learning and deep learning to analyze task data, predict future requirements, and automatically adjust role allocation. Adopting advanced communication technologies such as 5G networks and the Internet of Things ensures faster, more reliable device connections and enables seamless task switching and information sharing in multi-device operations.

6.3 The Deficiencies of the Research and the Future Expansion Directions

Despite validating a comprehensive theoretical model of human factor variables, this study has some limitations. First, the relatively small sample of urban mainland China users may limit cultural generalizability. Second, although the questionnaire was refined during a pilot phase to ensure reliability and validity, some dimensions need further elaboration to better capture nuances. Finally, the practical implementation of key algorithms, such as cognitive load regulation mechanisms and dynamic trust modeling frameworks, has not been addressed.

To address these limitations, future research should integrate multimodal sensing and physiological monitoring to capture users' psychological states more accurately; apply cross-cultural comparative methods to assess model adaptability and moderation effects in diverse contexts; and adopt an interdisciplinary approach combining design practice with AI modeling to advance the integration of human factors, system architecture, and algorithm development. This combined strategy will promote theoretical innovation and produce more effective practical solutions.

Funding: This research was funded by the Key Research Project of the Korea Institute for Humanities and Social Sciences (No. 2025KIHSSA08).

Acknowledgments: Not applicable.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author(s) declare no conflict of interest.

References

Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. *International journal of social robotics*, 1(4), 319-330. https://doi.org/10.1007/s12369-009-0030-6

Bütepage, J., & Kragic, D. (2017). Human-robot collaboration: from psychology to social robotics. arXiv preprint arXiv:1705.10146. https://doi.org/10.48550/arXiv.1705.10146

Cao, H. L., Elprama, S. A., Scholz, C., Siahaya, P., El Makrini, I., Jacobs, A., ... & Vanderborght, B. (2024). Designing interaction interface for supportive human-robot collaboration: A co-creation study involving factory employees. *Computers & Industrial Engineering*, 192, 110208. https://doi.org/10.1016/j.cie.2024.110208

Charalambous, G., Fletcher, S. R., & Webb, P. (2017). The development of a Human Factors Readiness Level tool for implementing industrial human-robot collaboration. *The International Journal of Advanced Manufacturing Technology*, 91(5), 2465-2475. https://doi.org/10.1007/s00170-016-9876-6

Chen, Z., Zhao, Y., Zhou, X., Hao, S., & Li, J. (2023). Identifying the risk factors and their interactions of human–robot collaboration implementation during engineering project construction: evidence from China. *Engineering, construction and architectural management*, 30(7), 3073-3094. https://doi.org/10.1108/ECAM-05-2021-0461

Fan, S., Guo, J., Ma, S., Li, L., Wang, G., Xu, H., ... & Zhao, Z. (2023). Framework and Key Technologies of Human-machine Hybrid-augmented Intelligence System for Large-scale Power Grid Dispatching and Control. *CSEE Journal of Power and Energy Systems*, 10(1), 1-12. https://ieeexplore.ieee.org/abstract/document/10375976

Fu, X., Zeng, M., & Zhang, Y.-F. (2023). An integrated framework and key component design for precision teaching in human – machine collaboration. *Open Education Research*. https://doi.org/10.13966/j.cnki.kfjyyj.2023.02.011

Garcia, P. P., Santos, T. G., Machado, M. A., & Mendes, N. (2023). Deep learning framework for controlling work sequence in collaborative human–robot assembly processes. *Sensors*, 23(1), 553. https://doi.org/10.3390/s23010553

Gervasi, R., Aliev, K., Mastrogiacomo, L., & Franceschini, F. (2022). User experience and physiological response in human-robot collaboration: a preliminary investigation. *Journal of Intelligent & Robotic Systems*, 106(2), 36. https://doi.org/10.1007/s10846-022-01744-8

Giallanza, A., La Scalia, G., Micale, R., & La Fata, C. M. (2024). Occupational health and safety issues in human-robot collaboration: State of the art and open challenges. *Safety science*, 169, 106313. https://doi.org/10.1016/j.ssci.2023.106313

Huck, T. P., Münch, N., Hornung, L., Ledermann, C., & Wurll, C. (2021). Risk assessment tools for industrial human-robot collaboration: Novel approaches and practical needs. *Safety Science*, 141, 105288. https://doi.org/10.1016/j.ssci.2021.105288

Inkulu, A. K., Bahubalendruni, M. R., Dara, A., & K, S. (2022). Challenges and opportunities in human robot collaboration context of Industry 4.0-a state of the art review. *Industrial Robot: the international journal of robotics research and application*, 49(2), 226-239. https://doi.org/10.1108/IR-04-2021-0077

Jacob, F., Grosse, E. H., Morana, S., & König, C. J. (2023). Picking with a robot colleague: A systematic literature review and evaluation of technology acceptance in human–robot collaborative warehouses. *Computers & Industrial Engineering*, 180, 109262. https://doi.org/10.1016/j.cie.2023.109262

Li, J., Zhu, E., Lin, W., Yang, S. X., & Yang, S. (2025). A novel digital twins-driven mutual trust framework for human–robot collaborations. *Journal of Manufacturing Systems*, 80, 948-962. https://doi.org/10.1016/j.jmsy.2025.04.009

Na, L. (2024). Natural Language-Based Human–Machine Collaborative Learning Games Algorithm Based on Deep Rein-Forcement Learning. *IEEE Access*, 12, 28818-28830. https://ieeexplore.ieee.org/abstract/document/10433481

Rani, S., Jining, D., Shoukat, K., Shoukat, M. U., & Nawaz, S. A. (2024). A human–machine interaction mechanism: additive manufacturing for Industry 5.0—design and management. *Sustainability*, 16(10), 4158. https://doi.org/10.3390/su16104158

Ren, M., Chen, N., & Qiu, H. (2023). Human-machine collaborative decision-making: An evolutionary roadmap based on cognitive intelligence. *International Journal of Social Robotics*, 15(7), 1101-1114. https://doi.org/10.1007/s12369-023-01020-1

Sun, X., Zhang, Y., Qin, J., Li, J., & Wang, S. (2020). A review of human - machine intelligent collaboration research. *Packaging Engineering*, 41(18), 1 - 11.https://doi.org/10.19554/j.cnki.1001-3563.2020.18.001

Suresh, P. S. (2024). Efficient Human-Robot Collaboration Through Inverse Reinforcement Learning. [Doctoral dissertation]. University of Georgia.https://www.proquest.com/openview/317417535c03e1f78a13a682758b6ac5/1?pq-origsite=gscholar&cbl=187 50&diss=y

Wang, H., Hu, B., & Duan, Y. (2025). From human-machine collaboration to deviation: Understanding the catastrophe and resilience mechanisms of human-machine behaviors in intelligent environments. *Computers in Human Behavior*, 167, 108622. https://doi.org/10.1016/j.chb.2025.108622

Wang, W., Li, R., Chen, Y., Diekel, Z. M., & Jia, Y. (2018). Facilitating human–robot collaborative tasks by teaching-learning-collaboration from human demonstrations. *IEEE Transactions on Automation Science and Engineering*, 16(2), 640-653. https://ieeexplore.ieee.org/abstract/document/8403899

Wu, T. J., & Zhang, R. X. (2024). Exploring the impacts of intention towards human-robot collaboration on frontline hotel employees' positive behavior: An integrative model. *International Journal of Hospitality Management*, 123, 103912. https://doi.org/10. 1016/j.ijhm.2024.103912

Yan, Y., & Jia, Y. (2022). A review on human comfort factors, measurements, and improvements in human–robot collaboration. *Sensors*, 22(19), 7431. https://doi.org/10.3390/s22197431

Yan, Y., Su, H., & Jia, Y. (2024). Measuring Human Comfort in Human–Robot Collaboration via Wearable Sensing. *IEEE Transactions on Cognitive and Developmental Systems*, 16(5), 1748-1758. https://ieeexplore.ieee.org/abstract/document/10485639

Yu, G. M., Jin, L. P., & Liu, J. Y. (2025). The impairment and restoration of human-machine trust induced by large model hallucinations and the recalibration mechanism. *Future Communication*, (2), 2-10. http://zjcmxyxb.paperopen.com/oa/DArticle.aspx?type=view&id=202502001#

Zhai, X., Chu, X., Jiao, L., Tong, Z., & Li, Y. (2023). Research on a human – machine collaborative learning model based on generative AI and the metaverse. *Open Education Research*. https://doi.org/10.13966/j.cnki.kfjyyj.2023.05.003

Zhang, J., Li, H., Gu, H., Zhang, H., Yang, Y., Tan, X., ... & Shen, J. (2021). Intelligent extraction methods for natural resource elements in human – machine collaboration. *Cehui Xuebao*, 50(8), 1023. https://doi.org/10.11947/j.AGCS.2021.20210102

Zhang, Z., Hua, Z., & Xie, X. (2024). Research status and future directions of human – machine collaboration in the digital - intelligence era. *Journal of Management Engineering*, 38(1), 1 – 13.https://doi.org/10.13587/j.cnki. jieem.2024.01.001

Zheng, X. (2024, December 9). Human factors engineering opens a new paradigm for human – computer interaction. *China City Daily*, A06.doi:10.28056/n.cnki.nccsb.2024.000377.

Zhu, Z., Dai, L., & Zhao, X. (2023). New perspectives on “near-future” human – machine collaborative education development. *Open Education Research*, 29(5), 4 – 13. https://doi.org/10.13966/j.cnki.kfjyyj.2023.05.001