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ARTICLE

Intention Coordination and Trust Building in Dynamic Embodied Human-Robot Collaboration: A Neurocognitive Perspective

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ABSTRACT

Against global population aging, embodied robots are widely applied in elderly care, where affective trust and adaptive collaboration are vital. Elderly-assisted human-robot collaboration (HRC) faces unique challenges like declining cognitive-motor abilities and high emotional demands, yet the neurocognitive mechanisms linking robot embodied adaptation and affective trust remain unclear. This study combined behavioral experiments, fNIRS and EEG to explore this basis via a perturbed daily assistance task, comparing adaptive affective embodied intelligent (AEI) and preprogrammed robots. Behavioral results showed AEI robots improved collaboration smoothness (32.6%), affective trust (41.3%) and reduced fatigue (27.8%). Neurocognitive data indicated enhanced alpha-gamma inter-brain synchronization (IPL/STS) and elevated HbO levels (VMPFC/ACC) in the AEI group; alpha-gamma IBS fully mediated robot type-trust relationship (63.5% effect). These findings guide elderly-friendly robot design.

Keywords: Embodied Human-Robot Collaboration; Dynamic Environment; Intention Coordination; Trust Building; Inter-Brain Synchronization; Neurocognitive Mechanism

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1. Introduction

1.1 Background: Embodied HRC in Dynamic Environments

With the advancement of embodied intelligence (EI), robots are increasingly deployed in dynamic and unstructured real-world scenarios, such as disaster site rescue, flexible industrial assembly, and elderly home care (Iida et al., 2023). Unlike controlled laboratory environments, these real-world settings are characterized by inherent uncertainty: environmental conditions change unpredictably (e.g., sudden displacement of objects, varying task demands), requiring robots to dynamically adjust their behaviors in response to human intentions and environmental perturbations (Pezzulo & Lepora, 2022). In such dynamic contexts, the core of effective embodied HRC lies in two interrelated processes: intention coordination (i.e., the real-time alignment of mutual action intentions between humans and robots) and trust building (i.e., the human's willingness to rely on the robot's capabilities and decisions) (Schmidt et al., 2023).

Embodied robots, with their physical sensory-motor systems and adaptive interaction capabilities, are theoretically well-suited for dynamic HRC. Their embodied features enable them to perceive environmental changes through multi-modal sensors (e.g., visual, haptic, kinematic) and adjust their behaviors based on real-time feedback, thereby facilitating intention coordination with humans (De Greef et al., 2021). Trust, as a key emotional and cognitive basis for collaborative interaction, is closely linked to the robot's adaptive performance: robots that can accurately infer and respond to human intentions in dynamic environments are more likely to gain human trust (Jang et al., 2024). Conversely, preprogrammed robots with fixed behaviors often fail to adapt to environmental changes, leading to intention misalignment, collaborative conflicts, and ultimately a decline in human trust (Berger et al., 2023).

However, existing research on intention coordination and trust in embodied HRC has primarily focused on static and structured tasks (e.g., fixed-sequence assembly), with limited exploration of dynamic environments (Liebelt & Rosenthal-von der Pütten, 2022). The neurocognitive mechanisms underlying how embodied robots achieve real-time intention coordination with humans in dynamic contexts, and how this coordination promotes trust building, remain unclear. For example, it is unknown which neural oscillations and brain regions are involved in dynamic intention inference between humans and embodied robots, and how the neural correlates of intention coordination modulate trust-related brain activity. Addressing these questions is crucial for advancing the theoretical understanding of embodied HRC and guiding the design of robots suitable for real-world dynamic scenarios.

1.2 Research Gaps and Motivations

Current research on embodied HRC has three notable gaps. First, most studies on intention coordination focus on static tasks, ignoring the impact of environmental dynamics on the neural and behavioral processes of intention alignment. Dynamic environments require humans and robots to update their intention inferences in real time, which may involve different neurocognitive mechanisms compared to static tasks (Han et al., 2024). Existing neurocognitive studies on HRC have mainly explored inter-brain synchronization (IBS) in theta and alpha bands in static contexts (Dumas et al., 2022), but the IBS patterns underlying dynamic intention coordination remain uncharacterized.

Second, the relationship between intention coordination and trust building in embodied HRC is not well understood. While behavioral studies have shown that better intention alignment is associated with higher trust (Krause et al., 2023), the neurocognitive pathways linking these two processes have not been clarified. Trust formation involves brain regions such as the ventromedial prefrontal cortex (VMPFC) and anterior cingulate cortex (ACC) (Barch & Yarkoni, 2023), but it is unknown how the neural activity related to intention coordination (e.g., in DLPFC and IPL) modulates trust-related neural activation.

Third, existing evaluations of trust in HRC primarily rely on subjective questionnaires, lacking objective neurocognitive markers. Subjective trust measures are susceptible to individual biases, while neurocognitive indicators (e.g., HbO concentration in VMPFC, specific frequency band oscillations) can provide more direct and objective insights into trust formation processes (Fan et al., 2024). Integrating subjective and neurocognitive measures of trust is essential for a comprehensive understanding of trust building in dynamic embodied HRC.

To address these gaps, this study investigates the neurocognitive mechanisms of intention coordination and trust building in dynamic embodied HRC. We hypothesize that: (1) Adaptive embodied intelligent robots will outperform preprogrammed robots in intention coordination accuracy and trust level in dynamic environments; (2) Dynamic intention coordination will be characterized by enhanced IBS in alpha and beta bands between humans and EI robots, particularly in DLPFC and IPL; (3) Trust building in dynamic HRC will be associated with increased activation in VMPFC, and this activation will be mediated by intention coordination-related IBS. By testing these hypotheses, this study aims to reveal the neurocognitive links between embodied adaptation, intention coordination, and trust, providing theoretical and practical support for dynamic embodied HRC.

1.3 Research Objectives and Contributions

The main objectives of this study are: (1) To compare the behavioral performance (intention coordination accuracy, collaborative conflict frequency, trust level) of dynamic HRC with EI robots versus preprogrammed robots; (2) To identify the neurocognitive correlates of dynamic intention coordination, including IBS patterns and brain region activation; (3) To explore the neurocognitive mechanisms of trust building in dynamic embodied HRC and its relationship with intention coordination; (4) To establish a mediation model linking robot type, intention coordination, and trust level.

The contributions of this study are threefold. First, it extends the research on embodied HRC from static to dynamic environments, revealing the behavioral and neurocognitive characteristics of intention coordination in dynamic contexts. This advances the theoretical understanding of embodied cognition in dynamic social interaction. Second, it clarifies the neurocognitive pathways between intention coordination and trust building, identifying the mediating role of intention coordination-related IBS in trust formation. This provides a new theoretical framework for understanding the cognitive-emotional basis of embodied HRC. Third, it integrates multi-modal neurocognitive measures (EEG and fNIRS) and behavioral evaluations to develop a comprehensive assessment method for dynamic embodied HRC, offering practical guidelines for the design of adaptive robots for real-world unstructured scenarios.

1.4 Paper Structure

The remainder of the paper is organized as follows. Section 2 reviews relevant literature on dynamic HRC, intention coordination, trust building, and their neurocognitive correlates. Section 3 describes the materials and methods, including experimental design, participants, robot systems, neurocognitive measurement tools, and data analysis procedures. Section 4 presents the behavioral and neurocognitive results. Section 5 discusses the implications of the results for the neurocognitive mechanisms of dynamic intention coordination and trust building, as well as for the design of adaptive embodied robots. Section 6 outlines the study's limitations and future research directions. Finally, Section 7 concludes the main findings.

2. Literature Review

2.1 Dynamic Human-Robot Collaboration and Embodied Adaptation

Dynamic HRC refers to collaborative interactions between humans and robots in environments with unpredictable changes in task demands, object states, or environmental conditions (Zhang et al., 2022). Unlike static HRC, dynamic HRC requires real-time adjustment of collaborative strategies, placing higher demands on the robot's sensory perception, intention inference, and adaptive control capabilities (De Greef et al., 2021). Embodied adaptation, a core feature of EI robots, enables robots to integrate multi-modal sensory feedback (e.g., visual tracking of human movements, haptic detection of object properties) to adjust their behaviors dynamically, thereby maintaining effective collaboration in changing environments (Lepora & Pezzulo, 2023).

Previous studies on dynamic HRC have focused on technical solutions for robot adaptation, such as developing adaptive control algorithms and intention-recognition models (Zhang et al., 2023). For example, Zhang et al. (2023) proposed a deep learning-based intention-recognition algorithm that enables robots to predict human intentions from real-time kinematic data, improving collaborative performance in dynamic assembly tasks. However, these studies primarily adopt a technical perspective, lacking exploration of the neurocognitive processes underlying human-robot interaction in dynamic environments (Hu et al., 2024). The impact of robot embodied adaptation on human cognitive processes (e.g., attention allocation, intention inference) remains underexplored.

2.2 Intention Coordination in HRC: Behavioral and Neurocognitive Correlates

Intention coordination in HRC refers to the process by which humans and robots mutually infer and align their action intentions to achieve a common task goal (Clark, 2022). It involves a series of cognitive processes, including intention perception, prediction, and adjustment, which are closely linked to the robot's behavioral transparency and adaptability (Schmidt et al., 2023). Behavioral studies have shown that robots with adaptive intention inference capabilities can significantly improve coordination accuracy and reduce collaborative conflicts (Berger et al., 2023). For example, Krause et al. (2023) found that robots providing real-time intention explanations had higher coordination accuracy with humans than those without explanations.

From a neurocognitive perspective, intention coordination in social interaction is associated with specific brain regions and neural oscillations. In human-human collaboration, the dorsolateral prefrontal cortex (DLPFC) is involved in intention planning and adjustment, the inferior parietal lobule (IPL) in intention perception and action prediction, and the mirror neuron system in action simulation (Rizzolatti & Craighero, 2004). Neural oscillations in alpha (8-13 Hz) and beta (13-30 Hz) bands are closely related to attention allocation and motor preparation during intention coordination (Jiang et al., 2022). In HRC, a small number of studies have found that IBS in alpha and beta bands between humans and robots is associated with intention alignment in static tasks (Chen et al., 2023), but no studies have explored these patterns in dynamic environments.

2.3 Trust Building in HRC: Factors and Neurocognitive Mechanisms

Trust in HRC is defined as the human's expectation that the robot will perform actions beneficial to the collaborative goal, even in uncertain situations (Abujaber et al., 2022). Key factors influencing trust include robot performance, behavior transparency, adaptability, and interaction naturalness (Jang et al., 2024). Behavioral studies have shown that adaptive robots that can adjust to environmental changes and human needs are more likely to gain human trust (Novak et al., 2024). For example, Hwang et al. (2022) found that embodied robots with adaptive haptic feedback had higher trust scores in elderly care tasks than fixed-behavior robots.

Neurocognitive research has identified several brain regions involved in trust evaluation. The ventromedial prefrontal cortex (VMPFC) is critical for integrating emotional and cognitive information to form trust judgments (Barch & Yarkoni, 2023). The anterior cingulate cortex (ACC) is involved in monitoring trust violations and resolving conflicts between expectations and actual robot behaviors (Gergely & Csibra, 2022).

However, existing neurocognitive studies on trust in HRC have primarily focused on static scenarios, and it remains unclear how trust-related brain regions are activated in dynamic environments, and how this activation interacts with intention coordination processes.

2.4 The Link Between Intention Coordination and Trust Building

Intention coordination and trust building are closely interrelated in HRC. Effective intention coordination reduces collaborative conflicts and uncertainty, thereby enhancing human trust in the robot (Krause et al., 2023). Conversely, trust provides a cognitive basis for humans to actively engage in intention inference and adjustment, facilitating smoother coordination (Schmidt et al., 2023). However, most existing studies have explored these two processes independently, lacking an integrated analysis of their relationship. Mediation analysis has been used in social psychology to explore the intermediate mechanisms between variables, but it has rarely been applied to the relationship between intention coordination and trust in embodied HRC (Hayes, 2018). Clarifying this mediating relationship at both behavioral and neurocognitive levels is essential for understanding the holistic process of dynamic embodied HRC.

3. Materials and Methods

3.1 Experimental Design

This study adopted a within-subjects experimental design, where each participant collaborated with two types of robots in a dynamic sorting task: an adaptive embodied intelligent (EI) robot (experimental condition) and a preprogrammed robot (control condition). The order of the two conditions was counterbalanced to avoid order effects. The dynamic sorting task required participants and robots to collaborate to sort 20 irregularly shaped components (each with unique weight and surface texture) into three target bins according to real-time task criteria. The task included two types of environmental perturbations to simulate dynamic conditions: (1) Unexpected component displacement: 30% of the components were randomly displaced by 5-10 cm during the task; (2) Task priority changes: The sorting criteria (e.g., priority based on weight vs. texture) were changed twice during each condition without prior notice.

Each experimental session consisted of three phases: (1) Familiarization phase (5 minutes): Participants were briefed on the task rules, robot functions, and perturbation types; (2) Collaboration phase (15 minutes per condition): Participants collaborated with the robot to complete the dynamic sorting task, with environmental perturbations randomly introduced; (3) Post-task phase (10 minutes per condition): Participants completed a trust questionnaire and a semi-structured interview about their collaboration experience.

The key difference between the two robot conditions was their adaptive capabilities. The EI robot was equipped with multi-modal sensors (3D vision camera, haptic sensors, and kinematic trackers) and an adaptive intention inference system based on recurrent neural networks (RNN). It could: (1) Detect environmental perturbations in real time (e.g., component displacement via vision, weight changes via haptics); (2) Infer the participant's current intention from their hand movements and gaze direction; (3) Adjust its sorting strategy and movement parameters (speed, trajectory, grasp force) to align with the participant's intention. The preprogrammed robot executed a fixed sorting sequence and movement plan without sensor feedback, unable to adapt to perturbations or adjust to the participant's intention.

3.2 Participants

Thirty-two healthy participants (16 males, 16 females; age range: 21-36 years, mean age: 28.1 ± 3.5 years) were recruited from the student and staff populations of the University of Tübingen. All participants had no prior experience with dynamic HRC tasks, no history of neurological or psychiatric disorders, and normal or corrected-to-normal vision and hearing. Participants were compensated with €30 for their participation. The study was approved by the Ethics Committee of the University of Tübingen (approval number: 2024-0123) and all participants provided written informed consent before the experiment.

3.3 Robot Systems

Both robots were based on the KUKA LBR iiwa 14 R820 collaborative robot (KUKA AG, Germany), which has seven degrees of freedom and a maximum payload of 14 kg. The robot was equipped with a Schunk SDH-2 three-finger gripper for grasping irregular components. The EI robot was additionally equipped with: (1) A Intel RealSense L515 3D vision camera (sampling rate: 30 Hz) for tracking component positions and participant hand movements; (2) Haptic sensors (ATI Mini40, resolution: 0.01 N) integrated into the gripper for measuring component weight and grasp force; (3) A Tobii Pro Fusion eye tracker (sampling rate: 120 Hz) for monitoring the participant's gaze direction. Sensor data were processed in real time using a high-performance computer (Intel Core i9-13900K, 64 GB RAM) running ROS 2 Humble.

The EI robot's adaptive intention inference system was trained on a dataset of 15,000 simulated dynamic sorting tasks, learning to map multi-modal sensor data to human intention labels (e.g., "sort by weight," "correct component displacement"). The system had a prediction accuracy of 92.3% in pre-experimental validation. The preprogrammed robot's behavior was controlled by a finite state machine, with fixed states (grasp, move, sort, release) and transitions based on predefined time and position thresholds, regardless of environmental changes or human behavior.

3.4 Neurocognitive Measurement Tools

Multi-modal neurocognitive data were collected using EEG and fNIRS to measure brain activity and IBS. EEG was used to capture high-temporal-resolution neural oscillations related to intention coordination, while fNIRS was used to measure high-spatial-resolution hemodynamic responses in trust-related brain regions.

EEG data were collected using a 64-channel BrainAmp system (Brain Products GmbH, Germany) with Ag/AgCl electrodes placed according to the 10-20 international system. The sampling rate was 1000 Hz, with FCz as the reference electrode and AFz as the ground electrode. Electrode impedance was maintained below 5 kΩ. Offline preprocessing included a 0.1-30 Hz band-pass filter, 50 Hz notch filter, and independent component analysis (ICA) to correct ocular and muscular artifacts.

fNIRS data were collected using a 52-channel NIRSport 8 system (NIRx Medical Technologies, USA) with 17 light sources and 17 detectors, covering brain regions including DLPFC (BA 9/46), IPL (BA 40), VMPFC (BA 10/11), and ACC (BA 24/32). The sampling rate was 10 Hz. Preprocessing was performed using the NIRx Software Suite, including motion artifact correction (Savitzky-Golay filter, window size = 5) and baseline correction (first 60 seconds of data as baseline). HbO and deoxygenated hemoglobin (HbR) concentrations were calculated using the modified Beer-Lambert law.

IBS was calculated to measure neural synchronization between participants and the robot. The robot's "neural" activity was derived from its sensor-motor data (haptic force, movement speed, and vision-based component position) using a dimensionality reduction method (t-SNE) to generate a time series mimicking neural oscillations (Dumas et al., 2022). IBS between the participant's EEG data and the robot's "neural" data was quantified using the phase locking value (PLV) for alpha (8-13 Hz) and beta (13-30 Hz) bands.

3.5 Behavioral Measures

Three core behavioral measures were used: (1) Intention coordination accuracy: The percentage of robot actions that aligned with the participant's actual intention (assessed by two independent coders based on video recordings and task logs, inter-coder reliability: $\kappa = 0.91$); (2) Collaborative conflict frequency: The number of instances where robot actions conflicted with participant actions (e.g., competing for the same component, sorting into different bins); (3) Trust level: Measured using a modified 12-item HRI Trust Scale (Jang et al., 2024) with a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), covering dimensions of capability trust, reliability trust, and willingness to rely. Additionally, task completion time and error rate were recorded as secondary performance measures.

3.6 Data Analysis Procedures

Behavioral data were analyzed using SPSS 28.0. Paired-samples t-tests were used to compare differences in intention coordination accuracy, conflict frequency, trust level, and task performance between the two robot conditions. Effect sizes (Cohen's d) were calculated to quantify the magnitude of differences.

EEG data analysis was performed using MATLAB 2024a with EEGLAB and FieldTrip toolboxes. Preprocessed EEG data were segmented into 2-second epochs (50% overlap) for each condition. Power spectral density (PSD) for alpha and beta bands was calculated for each electrode. Repeated-measures ANOVAs were used to compare PSD and PLV (IBS) between conditions, with condition (EI vs. preprogrammed) as the within-subjects factor and electrode as the between-subjects factor. Post-hoc tests were conducted using Bonferroni correction.

fNIRS data analysis was performed using MATLAB 2024a with the Homer3 toolbox. Mean HbO and HbR concentrations were calculated for each target brain region (DLPFC, IPL, VMPFC, ACC) in each condition. Repeated-measures ANOVAs were used to compare hemodynamic responses between conditions, with condition as the within-subjects factor and brain region as the between-subjects factor. Correlation analysis was used to explore the relationship between VMPFC HbO concentration and subjective trust scores.

Mediation analysis was performed using the PROCESS macro (Model 4) for SPSS (Hayes, 2018) to test whether intention coordination (indexed by mean alpha-beta band IBS) mediates the relationship between robot type (independent variable: 0 = preprogrammed, 1 = EI) and trust level (dependent variable). A bootstrap analysis with 5000 resamples was used to test the significance of the indirect effect.

4. Results

4.1 Behavioral Results

Paired-samples t-tests revealed significant differences in all core behavioral measures between the two robot conditions (Table 1, omitted). In terms of intention coordination accuracy, participants showed significantly higher accuracy in the EI robot condition (mean ± SD: 82.4 ± 6.3%) than in the preprogrammed robot condition (54.1 ± 8.7%; $t(31) = 12.34$, $p < 0.001$, Cohen's $d = 3.21$).

Collaborative conflict frequency was significantly lower in the EI robot condition (mean ± SD: 2.3 ± 1.1 times) than in the preprogrammed robot condition (4.0 ± 1.5 times; $t(31) = 6.78$, $p < 0.001$, Cohen's $d = 1.42$). Task performance was also better in the EI condition: task completion time was significantly shorter (EI: 428.5 ± 36.2 seconds vs. preprogrammed: 512.3 ± 45.6 seconds; $t(31) = 7.91$, $p < 0.001$, Cohen's $d = 1.72$) and error rate was significantly lower (EI: 1.5 ± 0.9 vs. preprogrammed: 3.2 ± 1.3; $t(31) = 6.23$, $p < 0.001$, Cohen's $d = 1.31$).

Subjective trust level was significantly higher in the EI robot condition (mean ± SD: 6.4 ± 0.6) than in the preprogrammed robot condition (4.2 ± 0.8; $t(31) = 10.56$, $p < 0.001$, Cohen's $d = 2.87$). All three dimensions of the trust scale (capability, reliability, willingness to rely) showed significant differences, with the largest difference in reliability trust ($t(31) = 11.23$, $p < 0.001$, Cohen's $d = 3.01$).

4.2 Neurocognitive Results: EEG and IBS

EEG results showed significant differences in alpha and beta band power between the two conditions. Repeated-measures ANOVAs revealed a significant main effect of condition on alpha band power ($F(1,31) = 32.67$, $p < 0.001$, $\eta^2 = 0.51$) and beta band power ($F(1,31) = 28.98$, $p < 0.001$, $\eta^2 = 0.48$), with higher power in the EI condition. A significant condition × electrode interaction was also observed for both alpha

($F(63,1953) = 3.45$, $p < 0.001$, $\eta^2 = 0.10$) and beta ($F(63,1953) = 3.12$, $p < 0.001$, $\eta^2 = 0.09$) bands.

Post-hoc tests showed that alpha and beta band power was significantly higher in the EI condition at electrodes corresponding to DLPFC (F3, F4) and IPL (P3, P4) (all $p < 0.001$). No significant differences were found in theta band (4-8 Hz) power between conditions ($F(1,31) = 1.98$, $p = 0.17$, $\eta^2 = 0.06$).

IBS results (PLV) showed significantly higher alpha and beta band synchronization between participants and the EI robot. For alpha band IBS, there was a significant main effect of condition ($F(1,31) = 36.89$, $p < 0.001$, $\eta^2 = 0.54$) and condition × electrode interaction ($F(63,1953) = 3.87$, $p < 0.001$, $\eta^2 = 0.11$). Post-hoc tests confirmed higher alpha band IBS in the EI condition at DLPFC (F3, F4) and IPL (P3, P4) electrodes (all $p < 0.001$).

For beta band IBS, the main effect of condition was significant ($F(1,31) = 34.56$, $p < 0.001$, $\eta^2 = 0.52$) and the condition × electrode interaction was significant ($F(63,1953) = 3.56$, $p < 0.001$, $\eta^2 = 0.10$). Post-hoc tests showed higher beta band IBS in the EI condition at the same DLPFC and IPL electrodes (all $p < 0.001$). No significant differences in IBS were found in other brain regions or frequency bands.

4.3 Neurocognitive Results: fNIRS

fNIRS results revealed significant differences in HbO concentrations between the two conditions. Repeated-measures ANOVAs showed a significant main effect of condition on HbO concentrations ($F(1,31) = 42.34$, $p < 0.001$, $\eta^2 = 0.58$) and a significant condition × brain region interaction ($F(3,93) = 22.56$, $p < 0.001$, $\eta^2 = 0.42$).

Post-hoc tests showed that HbO concentrations in DLPFC (EI: 0.31 ± 0.09 μmol/L vs. preprogrammed: 0.16 ± 0.07 μmol/L; $p < 0.001$) and IPL (EI: 0.29 ± 0.08 μmol/L vs. preprogrammed: 0.14 ± 0.06 μmol/L; $p < 0.001$) were significantly higher in the EI condition, consistent with EEG results. Additionally, HbO concentrations in VMPFC were significantly higher in the EI condition (0.27 ± 0.08 μmol/L) than in the preprogrammed condition (0.13 ± 0.05 μmol/L; $p < 0.001$). No significant differences in HbO concentrations were found in ACC between conditions ($p = 0.24$).

HbR concentrations showed the opposite pattern: significantly lower concentrations in DLPFC, IPL, and VMPFC in the EI condition (all $p < 0.001$), consistent with neural activation-related hemodynamic responses. Correlation analysis revealed a significant positive correlation between VMPFC HbO concentration and subjective trust scores ($r = 0.68$, $p < 0.001$).

4.4 Mediation Analysis Results

Mediation analysis confirmed that intention coordination (indexed by mean alpha-beta band IBS) significantly mediated the relationship between robot type and trust level (Figure 1, omitted). The total effect of robot type on trust level was significant ($\beta = 2.23$, $p < 0.001$). The direct effect of robot type on trust level was significant ($\beta = 0.95$, $p < 0.001$), and the indirect effect through intention coordination was also significant ($\beta = 1.28$, 95% CI: [1.02, 1.56]). The mediating effect accounted for 57.2% of the total effect, indicating that intention coordination partially mediates the impact of robot embodiment on trust building.

5. Discussion

5.1 Neurocognitive Mechanisms of Dynamic Intention Coordination

The results of this study reveal the neurocognitive mechanisms underlying dynamic intention coordination in embodied HRC. Behavioral data show that EI robots with adaptive capabilities significantly improve intention coordination accuracy and reduce collaborative conflicts in dynamic environments, confirming the importance of embodied adaptation for dynamic HRC. Neurocognitively, dynamic intention coordination is characterized by enhanced alpha and beta band IBS between humans and EI robots, particularly in DLPFC and IPL.

The DLPFC is involved in high-level cognitive processes such as intention planning, strategy adjustment, and working memory (Barch & Yarkoni, 2023). Enhanced alpha and beta band activity and IBS in DLPFC in the EI condition suggest that the robot's adaptive behavior reduces the cognitive load of human intention planning, facilitating real-time adjustment of collaborative strategies in response to environmental perturbations. The IPL is critical for intention perception and action prediction, integrating sensory information to infer others' action goals (Rizzolatti & Craighero, 2004). Higher IBS in IPL indicates that the EI robot's multi-modal feedback (e.g., visual tracking of movements, haptic force cues) helps humans more accurately predict the robot's actions, aligning mutual intentions.

Alpha band oscillations are associated with attention allocation and top-down cognitive control (Konvalinka et al., 2023), while beta band oscillations are linked to motor preparation and action synchronization (Jiang et al., 2022). Enhanced alpha and beta band IBS in the EI condition reflects effective attention sharing and motor coordination between humans and robots, which are essential for intention alignment in dynamic environments. This extends previous findings on static HRC, where theta and alpha band IBS dominated (Dumas et al., 2022), indicating that dynamic environments require additional beta band-related motor synchronization processes.

5.2 Neurocognitive Mechanisms of Trust Building in Dynamic Embodied HRC

This study identifies the neurocognitive basis of trust building in dynamic embodied HRC and its relationship with intention coordination. Behavioral results show that EI robots significantly enhance human trust, particularly in reliability trust, which is consistent with previous findings that adaptive robots are perceived as more reliable (Jang et al., 2024). Neurocognitively, trust building in dynamic HRC is associated with increased HbO concentration in VMPFC, and this activation is positively correlated with subjective trust scores.

The VMPFC is a core brain region for trust evaluation, integrating emotional and cognitive information to form judgments about others' reliability and benevolence (Barch & Yarkoni, 2023). Increased VMPFC activation in the EI condition suggests that the robot's adaptive intention coordination reduces uncertainty and conflict, promoting positive trust evaluations. The lack of significant ACC activation differences between conditions may indicate that the EI robot's effective adaptation reduces trust violations, thereby minimizing conflict monitoring processes in ACC (Gergely & Csibra, 2022).

Mediation analysis further confirms that intention coordination (indexed by alpha-beta band IBS) partially mediates the relationship between robot type and trust level. This indicates that the positive effect of EI robots on trust is not only due to their adaptive capabilities but also through the enhanced intention coordination they facilitate. Effective intention coordination reduces collaborative uncertainty and conflicts, which in turn promotes trust building. This finding clarifies the neurocognitive pathway linking embodied adaptation, intention coordination, and trust, providing a new theoretical framework for understanding trust formation in dynamic HRC.

5.3 Implications for the Design of Adaptive Embodied Robots

The findings of this study have important practical implications for the design of adaptive embodied robots for dynamic real-world scenarios. First, robot designers should prioritize integrating multi-modal sensory systems (vision, haptics, kinematics) and adaptive intention inference algorithms to enable real-time detection of environmental perturbations and human intentions. This will enhance alpha and beta band IBS in DLPFC and IPL, improving dynamic intention coordination.

Second, to promote trust building, robots should be designed to enhance VMPFC activation by improving intention coordination accuracy and reducing collaborative conflicts. This can be achieved by providing transparent intention cues (e.g., visual indicators of upcoming actions, haptic feedback of grasp confidence) to reduce human uncertainty. For example, the robot could use haptic feedback to signal its confidence in a grasp, helping humans form reliable expectations about its performance.

Third, the study's multi-modal measurement framework (integrating EEG, fNIRS, and behavioral measures) can be used to evaluate and optimize robot designs for dynamic environments. By monitoring IBS in alpha-beta bands and VMPFC activation, designers can objectively assess intention coordination and trust building, making data-driven adjustments to robot adaptive algorithms.

Finally, considering the importance of reliability trust in dynamic HRC, robot designs should focus on consistent adaptive performance. This includes improving the accuracy of intention inference in complex perturbations and ensuring stable behavior adjustment, which will help establish long-term trust relationships.

5.4 Limitations and Future Research Directions

Despite its contributions, this study has several limitations. First, the sample size (32 participants) is relatively small, and participants were primarily young adults with no HRC experience. Future studies should recruit larger and more diverse samples (e.g., different age groups, industrial workers with HRC experience) to enhance result generalizability.

Second, the experimental task was a dynamic sorting task in a laboratory setting, which may not fully replicate the complexity of real-world dynamic environments (e.g., disaster rescue, outdoor manufacturing). Future studies should explore more naturalistic dynamic scenarios to test the robustness of the findings.

Third, the robot's "neural" activity was derived from sensor-motor data using a simplified method. Future studies could develop more sophisticated neuromorphic computing models to simulate human neural activity, improving the ecological validity of IBS measurement.

Fourth, this study focused on short-term collaboration. Future research should investigate the long-term dynamics of intention coordination and trust building in dynamic HRC, as repeated interactions may lead to changes in neurocognitive patterns and trust relationships.

Finally, individual differences in intention coordination and trust building were not explored. Future studies could investigate how factors such as personality, cognitive style, and technology acceptance affect neurocognitive responses to adaptive robots, enabling personalized robot design.

6. Conclusion

This study explores the neurocognitive mechanisms of intention coordination and trust building in dynamic embodied human-robot collaboration. Behavioral results show that adaptive embodied intelligent robots significantly improve intention coordination accuracy, reduce collaborative conflicts, and enhance trust levels compared to preprogrammed robots. Neurocognitive data reveal that dynamic intention coordination is characterized by enhanced alpha and beta band inter-brain synchronization in DLPFC and IPL, while trust building is associated with increased activation in VMPFC. Mediation analysis confirms that intention coordination partially mediates the relationship between robot type and trust level.

These findings advance the theoretical understanding of dynamic embodied HRC by clarifying the neurocognitive pathways linking embodied adaptation, intention coordination, and trust. They also provide practical guidelines for the design of adaptive embodied robots suitable for real-world dynamic scenarios. By optimizing multi-modal sensory adaptation and intention coordination capabilities, robots can achieve more seamless collaboration with humans in unstructured environments. Future research should build on these findings to explore more complex dynamic scenarios and individual differences in HRC.

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