Quantifying Movement Coordination in Human-Robot Interaction

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Abstract

This paper investigates movement coordination in Human-Robot Interaction (HRI) during collaborative tasks using tools from dynamical systems theory, specifically Recurrence Quantification Analysis (RQA) and Cross Recurrence Quantification Analysis (cRQA). The study explores how varying robot types and collaboration modes influence task efficiency, human motor performance, and interaction dynamics in a virtual reality (VR) setting. Our findings reveal that sequential collaboration promotes higher determinism and more predictable coordination, while simultaneous collaboration, though initially more demanding, can ultimately improve overall task efficiency. Anthropomorphic designs, exemplified by Baxter, provide smoother and more adaptive interactions but do not always translate into faster completion times. By contrast, less humanoid robots often accelerate task execution at the cost of lower initial coordination. These results underscore the importance of tailoring robot design and interaction modes to balance user experience, trust, and operational efficiency, offering practical insights for industries where human-robot teams must work safely and productively in shared environments.

Keywords: movement coordination; human-robot interaction; cross-recurrence analysis; robot type; collaboration mode.

Introduction

The traditional paradigm of industrial robot operation involves static robots confined within safety cages, performing well-defined steps in the manufacturing process. With technological advancements, we are witnessing the rise of mobile, social, and collaborative robots that freely interact with humans, becoming integral to both workplaces and social environments(Sheridan, 2020; Liu, Guo, Zou, & Duffy, 2024). One of the key challenges in human-robot interaction (HRI) is ensuring that robots can operate safely alongside humans, particularly in shared workspaces where physical proximity increases the risk of accidents. Equally important is building trust, as it facilitates cooperation and encourages humans to rely on robotic systems, ultimately enhancing productivity. Adaptability is another crucial factor—robots must adjust their behavior to align with human expectations to enable intuitive and effective collaboration. Addressing these challenges requires developing new methods to measure and evaluate HRI dynamics (Fiore et al., 2013; Lorenz, Weiss, & Hirche, 2016; Belhassein et al., 2022).

In this work, we propose analyzing movement dynamics as an indicator of interaction quality. For humans, coordinated movement plays a crucial role in non-verbal communication, regulating interactions (Burgoon, Manusov, & Guerrero, 2021); there are, in fact, research programmes that attempt to explain all kinds of social behaviour using the theoretical framework of coordination dynamics (Tognoli, Zhang, Fuchs, Beetle, & Kelso, 2020). During joint actions, people often exhibit high levels of interpersonal coordination, which can predict task performance—though the relationship is not always straightforward(Abney, Paxton, Dale, & Kello, 2015; Wallot, Mitkidis, McGraw, & Roepstorff, 2016; Białek, Zubek, Jackiewicz-Kawka, Adamik, & Białecka-Pikul, 2022). Specific patterns of interpersonal coordination, such as movement synchrony or posture mirroring, correlate with rapport, friendliness ratings, and overall satisfaction with an interaction (Bernieri, 1988; Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007; Ramseyer & Tschacher, 2011).

Movement-based cues are also essential in regulating human-robot interactions(Sciutti, Ansuini, Becchio, & Sandini, 2015; Wollstadt & Krüger, 2022). Thus, operationalisations of some aspects of coordination between human participants and robots during a collaborative task would constitute good prospective measures of the effectiveness of collaboration. We are interested in three different aspects of an interaction: trust, cooperativeness, and task performance. We postulate that robot's characteristics such as anthropomorphic design and responsive behaviour increase trust that a person puts in the robotic system (Roesler, Manzey, & Onnasch, 2021). Increased trust should, in turn, lead to a greater willingness to cooperate with the robot and adapt to its actions. Cooperativeness and adaptation can be quantified through movement coordination measures captured over time. These, in turn, should correlate with task performance, measured by the time required to complete a task. Within this framework, we ask three central research questions to be verified experimentally:

1. How are movement coordination patterns between humans and robots affected by collaboration conditions and variations in robot design?
2. Do task completion times reflect variations in robot design and behaviour?
3. Do people themselves adjust the way they perform a motor task based on the robot they interact with, and are they able to learn effective collaboration strategies over time?

To answer these questions, we use Recurrence Quantification

Analysis (RQA) techniques to quantify movement coordination of humans and three different collaborative robots, during a simple assembly task simulated in a Virtual Reality environment. Specifically, we demonstrate how RQA measures capture differences in coordination with humanoid and non-humanoid robots, differences between simultaneous and sequential modes of collaboration with a robot, and changes in coordination over time, from trial to trial. We complement this by analysing task completion times, and evaluating learning curves of human participants, revealing the extent to which different robotic designs and collaboration modes influence productivity.

Related Work

Research has shown that movement synchrony fosters interpersonal rapport in educational settings (Bernieri & Rosenthal, 1991) and reflects the quality of relationships in psychotherapy (Ramseyer & Tschacher, 2011). These insights highlight the importance of physical coordination in building trust and facilitating effective interaction. In clinical contexts, (Goldstein, Losin, Anderson, Schelkun, & Wager, 2020) demonstrated that synchronised movements between clinicians and patients not only enhanced trust but also reduced perceived pain, suggesting the profound influence of movement coordination on human relationships. Translating these findings to HRI, (Bartkowski, Nowak, Czajkowski, Schmidt, & Müller, 2023) investigated how movement synchrony affects trust between humans and robots, revealing that synchronised movements significantly increased trust ratings compared to random or repetitive movement patterns. Despite these promising results, Bartkowski et al.'s study relied on an abstract robotic model, leaving open questions about how movement coordination impacts trust and collaboration in task-oriented settings.

Wollstadt and Krüger (2022) recognised the need to quantitatively operationalise cooperation in HRI to guide robot design. They proposed an information-theoretic measure of a synergistic effect of joint actions of two agents working towards a common goal. Their measure goes beyond simple behavioural synchrony as synergy can also be achieved by complementary yet different actions of the two agents. The authors tested the proposed measure with simulated artificial agents, but did not translate it to interactions involving human participants.

Roesler et al. (2021) performed an experimental study in which human participants interacted with a Sawyer robot. They used a behavioural measure of trust operationalised as a mean time required to handover a box between robot and human participant. This measure can interpreted as a rudimentary form of human-robot coordination. Decreasing handover times showed trust development over time.

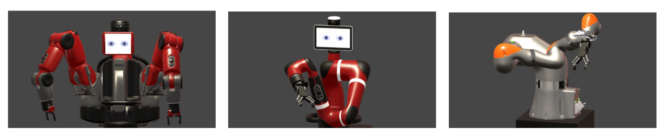
This growing body of research underscores the potential of movement coordination as a mechanism for improving human-robot collaboration. By extending existing work to practical scenarios where humans and robots engage in shared tasks, our research seeks to bridge the gap between abstract studies and real-world applications.

Methodology

Participants and Experimental Setup

The study involved 36 participants (20 male, 16 female) aged between 19 and 26 years (M = 22, SD = 2), recruited from the University of Coimbra. Participants collaborated with three robot types on an assembly task in Virtual Reality (VR) setting. The VR environment developed in Unity simulated a shared workspace where participants and robots worked together to construct interlocking block structures. Apart from robots, the environment included a grid for inserting interlocking building blocks, a shared table, conveyor belt, and block spawners, which enabled appropriate blocks, for both human and robot, when required. There was also a display with a stopwatch timer. The shared workspace was located on a table (200 cm x 80 cm).

The collaborative robots used in the study included the KUKA LBR iiwa, a single-armed industrial-style robot (Figure 1c); Baxter, a two-armed robot with an animated face display developed by Rethink Robotics (Figure 1a); and Sawyer, also from Rethink Robotics, featuring a single arm and an animated face display (Figure 1b). Robots varied in anthropomorphism, with Baxter being the most humanoid (two arms, head-like display) and KUKA the least (single arm, no head).



(a) Baxter (b) Sawyer (c) KUKA LBR iiwa

Figure 1: Overview of the three collaborative robots used in the study: Baxter, Sawyer, and KUKA LBR iiwa, as represented in the VR environment.

Task Design

Participants interacted with the robots one at a time and collaborated to assemble interlocking block structures in two distinct modes of collaboration: sequential and simultaneous. Each robot was paired with the participant for a session, allowing focused exploration of interaction dynamics. The assembly task was designed to simulate real-world applications of collaborative robots, such as manufacturing or logistics, while maintaining simplicity and universality by using Lego-like building blocks with clear affordances. Blocks were color-coded (red for the robots and blue for the human participants) to distinguish roles and ensure clarity during the task.

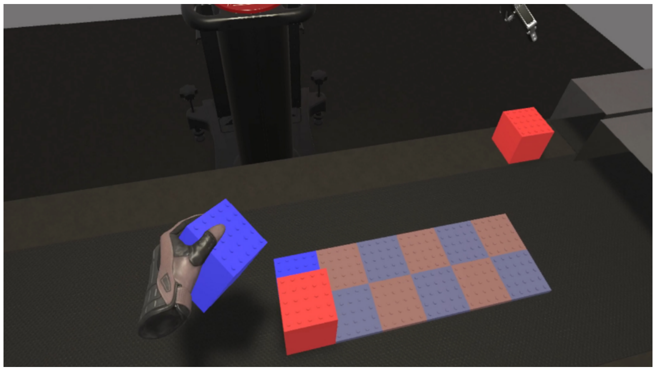


Figure 2: Screen from a VR simulation demonstrating task workspace.

The assembly process required constructing a layered structure on a grid, with designated placement positions shifting with each new layer. Participants and robots alternated their placements in the sequential mode, requiring one agent to complete their placement before the other could proceed. In the simultaneous mode, both agents worked concurrently but still depended on each other to complete their respective placements before advancing to the next layer. These dynamic task conditions allowed for the analysis of movement synchrony, efficiency, and trust under different collaborative scenarios.

To prepare for the task, participants underwent a training phase in a dedicated VR scene where they practised assembling the blocks and became familiar with the controls. During the main task, the sequential delivery of blocks via spawners ensured smooth workflow and minimised errors, while highlighted slots on the grid guided participants in their placements.

Data Collection

Collected dataset comprised a comprehensive array of physiological, behavioural, and psychological measures. However, for the purpose of this study, only the behavioural – movement gathered through the Unity VR engine – was analysed. This movement data consisted of time-series recordings representing the 3D trajectories of the robots' end-effectors and participants' right hands, which were used to manipulate and place the interlocking building blocks. For two-armed robots, such as Baxter, only the trajectory of the left end-effector was considered to maintain consistency across robot configurations. Similarly, all participants used their right hands for task execution, ensuring uniformity in the dataset.

Analysis Framework

To quantify movement coordination between human participants and collaborative robots during the assembly task, we employed the Cross-Recurrence Quantification Analysis (cRQA) method (Marwan, Romano, Thiel, & Kurths, 2007). This approach enables the characterization of the dynamics of coupled systems, such as the predictability, stability, and synchronization of movements, using time-series data. cRQA has been widely applied to analyze interpersonal interactions in various contexts, including movement coordination in joint actions (Abney et al., 2015; Białek et al., 2022).

The first step in cRQA involves reconstructing a multidimensional phase space from the univariate time series using time-delayed embedding, as per Takens' theorem (Takens, 1981). For each time point i, a D-dimensional vector is formed, denoted as

$$\mathbf{h}_i = [h_i, h_{i-d}, \ldots, h_{i-(D-1)d}],$$

where d is the time delay, and D is the embedding dimension. This reconstruction captures the dynamics of the system within a higher-dimensional space, enabling the analysis of complex coordination patterns.

Next, cross-recurrence analysis compares the reconstructed time series of the human participant (H) and the robot (R) by calculating the Euclidean distance between all pairs of embedded vectors $(\mathbf{h}_i^H, \mathbf{h}_j^R)$, where $i, j = 1, \ldots, N$. If the distance between two points is less than a threshold value, the corresponding element in the recurrence matrix, R_{ij}, is set to 1; otherwise, it is set to 0. The structures emerging in the recurrence matrix reveal properties of the coupling between the two systems.

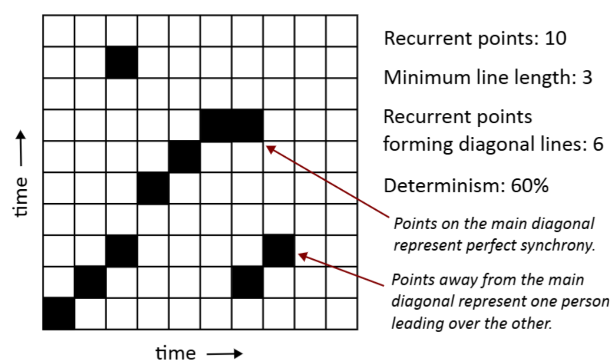


Figure 3: An example of a cross-recurrence matrix. Determinism is defined as the fraction of recurrent points forming diagonal lines longer than the minimum length. (Reproduced from Zubek and Łucznik (2024) with permission.)

One of the primary metrics derived from the recurrence matrix is *Determinism (DET)*, which measures the proportion of recurrence points that form diagonal lines of a minimum length $l_{\min}$. These diagonal lines represent periods during which the two systems exhibit predictable and stable coordination. Higher Determinism indicates smoother and more predictable interactions, reflecting improved synchronization and coordination quality.

The primary input time series for cRQA consisted of the human hand and robot end-effector positions along the X-axis.

This axis was chosen because movements from block spawners to the destination grid predominantly occurred along it. To evaluate coordination dynamics using cRQA, we modelled DET values with a linear mixed-effects model, incorporating robot type, collaboration mode, and their interaction as fixed effects. We hypothesized that more anthropomorphic robots (Baxter) and more ordered interaction mode (sequential condition) will lead to higher cRQA determinism.

Additionally, we analysed the stability of human hand motion during the interaction using Recurrence Quantification Analysis (RQA), a univariate version of cRQA which examines how a single dynamical system revisits similar states over time. For this analysis, the primary input time series was the scalar acceleration of the participant's hand, which captures overall changes in movement dynamics during block placement. Here, "trial" referred to the ordinal number of each block placement by the human participant in the sequence of the task. RQA was applied to windows corresponding to the duration of each individual block placement, allowing us to capture dynamic changes in motion stability throughout the task. By isolating the acceleration data for each block placement, we modelled DET values as a function of trial progression, collaboration mode, and robot type, including their interaction effects. We hypothesized that hand movement stability (operationalised as RQA DET) and its rate of adaptation over time will be larger for more anthropomorphic robots.

Finally, to assess time effectiveness, we examined both the time required by participants to place each block during the assembly task and the total time needed to complete the assembly. The first analysis evaluated how subtask completion times changed across trials (learning rates) and whether this change varied by collaboration mode and robot type. The second analysis compared the total time required to complete the full assembly structure across conditions. Here, we hypothesized that in conditions with higher DET task completion times will also be lower. Additionally, we expected the simultaneous mode to lead to shorter total assembly time, but longer subtask completion times of human participant, as it should be more demanding with respect to coordination.

To evaluate coordination dynamics using RQA methods, as well as to analyze time effectiveness, we used a script written in R. The dataset and R code used for these analyses are publicly available on OSF: `https://osf.io/g65mt/?view_only=b3869de02c244c50b4ce5b633b70b0d3`.

Results

Significant effects of robot type and collaboration mode on movement coordination, assessed via cRQA, were observed (Table 1a). DET was lower when interacting with Kuka (Est. $= -0.130, p = 0.003$) and Sawyer (Est. $= -0.195, p < 0.001$) compared to Baxter. Simultaneous collaboration resulted in significantly lower DET than sequential collaboration (Est. $= -0.127, p = 0.004$). A marginal interaction between Kuka and simultaneous collaboration (Est. =

Effect	**Est.**	**SE**	**t**	**p**
Intercept	0.590	0.033	18.043	<0.001***
Kuka (vs. B)	-0.130	0.044	-2.973	0.003**
Sawyer (vs. B)	-0.195	0.044	-4.467	<0.001***
Sim (vs. Seq)	-0.127	0.044	-2.908	0.004**
Kuka:Sim	0.121	0.062	1.960	0.052.
Sawyer:Sim	-0.036	0.062	-0.578	0.564

(a) cRQA (HR Movement Coordination). Formula: `DET ~ robot * mode + (1 | subject)`.

Effect	**Est.**	**SE**	**t**	**p**
Intercept	0.706	0.022	31.798	<0.001***
Trial	0.003	0.004	0.732	0.464
Sim(vs. Seq)	-0.071	0.016	-4.340	<0.001***
Kuka (vs. B)	-0.080	0.020	-4.026	<0.001***
Sawyer (vs. B)	-0.132	0.020	-6.641	<0.001***
Trial:Sim	0.015	0.004	4.018	<0.001***
Trial:Kuka	0.011	0.004	2.575	0.010*
Trial:Sawyer	0.013	0.004	2.940	0.003**

(b) RQA with Trial and Robot Interaction. Formula: `DET ~ trial * mode + robot * trial + (1 | subject)`.

Effect	**Est.**	**SE**	**t**	**p**
Intercept	2133.01	215.37	9.904	<0.001***
Trial	-13.77	32.57	-0.423	0.672
Sim (vs. Seq)	1411.46	145.64	9.691	<0.001***
Kuka (vs. B)	-527.25	178.38	-2.956	0.003**
Sawyer (vs. B)	-14.43	178.38	-0.081	0.936
Trial:Sim	-200.63	32.57	-6.161	<0.001***
Trial:Kuka	23.38	39.89	0.586	0.558
Trial:Sawyer	-50.48	39.89	-1.266	0.206

(c) Time Effectiveness Analysis (units in ms). Formula: `time ~ trial * mode + trial * robot + (1 | subject)`.

Effect	**Est.**	**SE**	**t**	**p**
(Intercept)	46240.9	504.0	91.740	<2e-16***
Kuka (vs. B)	-3401.2	592.9	-5.736	4.12e-08***
Sawyer (vs. B)	-7849.2	592.9	-13.238	<2e-16***
Sim (vs. Seq)	-3782.2	484.1	-7.812	4.78e-13***

(d) Aggregated Trial Duration Analysis (units in ms). Linear mixed-effects. Formula: `aggregated_time ~ robot + mode + (1 | subject)`.
Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Note: Est. = Estimate; **SE** = Standard Error; **t** = t-value; **p** = p-value. Significance codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$. B = Baxter; Seq = Sequential; Sim = Simultaneous.

Table 1: Results of Linear Mixed Models for cRQA, RQA and block placement times.

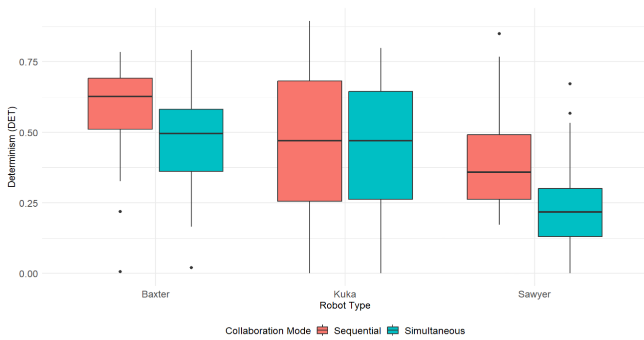


Figure 4: Boxplot of Determinism (DET) values from cRQA analysis, representing movement coordination along the X-axis. DET values are grouped by robot type and collaboration mode.

$0.121, p = 0.052$) suggests that the effect of collaboration mode on DET might vary depending on the robot. No significant interaction was found for Sawyer ($p = 0.564$).

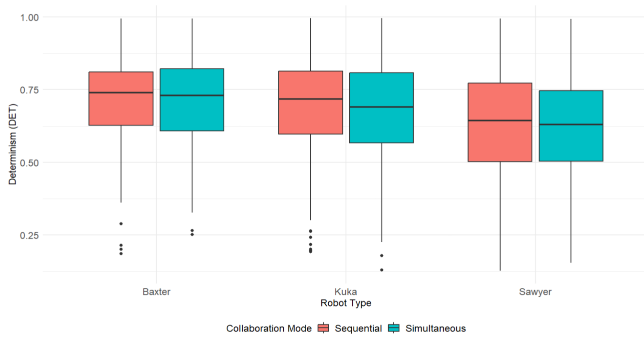


Figure 5: Boxplot of Determinism (DET) values from RQA analysis, representing human hand acceleration profiles. DET values are grouped by robot type and collaboration mode.

For the stability of human hand motion, as assessed using RQA of acceleration profiles, both robot type and collaboration mode had significant effects (Table 1b). Simultaneous collaboration led to lower DET (Est. $= -0.071, p < 0.001$), suggesting less predictable hand motion. DET was also lower with Kuka (Est. $= -0.080, p < 0.001$) and Sawyer (Est. $= -0.132, p < 0.001$) compared to Baxter. Although trial progression alone was not significant (Est. $= 0.003, p = 0.464$), its interaction with collaboration mode was significant (Est. $= 0.015, p < 0.001$), indicating a faster improvement in human motion stability in simultaneous collaboration. Trial-by-robot interactions for Kuka (Est. $= 0.011, p = 0.010$) and Sawyer (Est. $= 0.013, p = 0.003$) suggest motion stability improved more over trials with these robots.

Time effectiveness was analyzed at two levels: (1) total task completion time and (2) block placement time (excluding robot movement) (Table 1c,1d). For the total task duration, participants working with Kuka (Est. $= -3401.2, p < 0.001$)

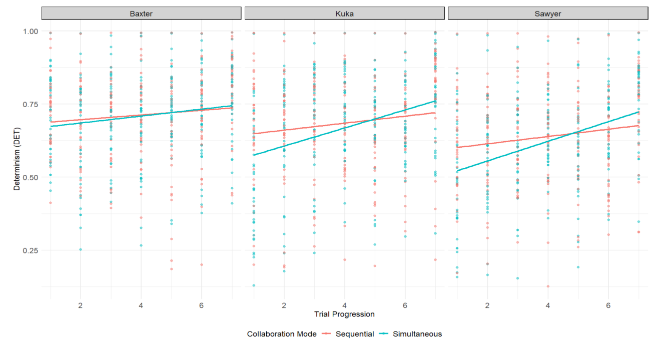


Figure 6: Mean Determinism (DET) values from RQA analysis over trials, grouped by collaboration mode, with trends depicted for each robot type. This figure illustrates the progression of movement stability over time.

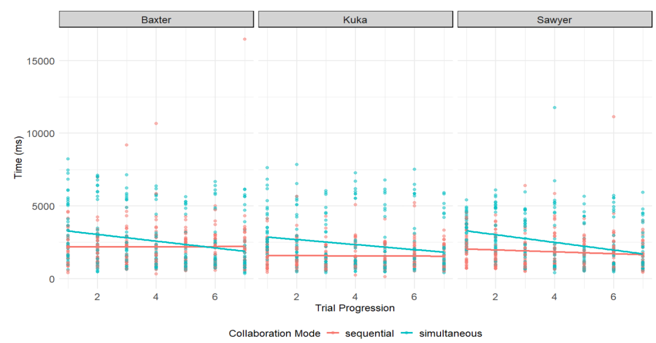


Figure 7: Mean time required for human participants to place each block over successive trials, grouped by collaboration mode and robot type.

and Sawyer (Est. $= -7849.2, p < 0.001$) completed the task more quickly than those collaborating with Baxter. Simultaneous collaboration further reduced overall completion time (Est. $= -3782.2, p < 0.001$), as concurrent actions helped accelerate the process.

At the block placement level, simultaneous collaboration increased movement duration per block (Est. $= 1411.46, p < 0.001$), indicating higher time costs for human actions. However, placement times in this condition decreased more rapidly across trials than in the sequential condition (Est. $= -200.63, p < 0.001$), suggesting faster adaptation. Robot type also affected placement times, with Kuka enabling faster placements than Baxter (Est. $= -527.25, p = 0.003$), while Sawyer showed no significant difference (Est. $= -14.43, p = 0.936$). This aligns with total task duration results, where Kuka and Sawyer were associated with shorter times. These findings suggest that while DET was higher with Baxter, its execution speed was lower, possibly due to actuation speed or workspace design.

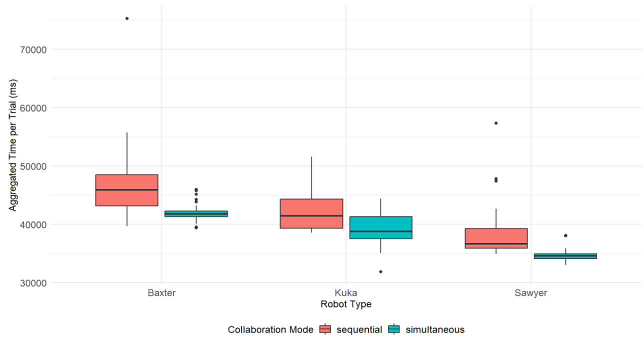


Figure 8: Boxplot of total task completion times, showing differences between collaboration modes and robot types.

Discussion

The results provide a nuanced understanding of how robot design and collaboration mode influence movement coordination and motor performance in human-robot interactions. In line with our hypotheses, Baxter—the most anthropomorphic robot—consistently produced higher determinism (DET) scores, indicating smoother and more predictable interactions. In contrast, Kuka and Sawyer yielded lower DET scores, with Sawyer posing particular challenges. This may be due to its mixture of anthropomorphic elements (e.g., an animated face display) and its unconventional single-arm kinematics. Robots that appear somewhat human-like yet lack fundamental features of biological motion may be more difficult for participants to interpret, as their intentions are not clearly conveyed by their movements (Sciutti et al., 2015; Vignolo et al., 2017). Additionally, the juxtaposition of human-like and nonhuman-like characteristics could evoke a version of the uncanny valley effect (Mori, 2012), which merits further research.

As expected, collaboration mode had a significant impact in both the cRQA and RQA analyses. Sequential collaboration consistently yielded higher DET scores, indicating more stable and predictable interactions. This mode likely allowed participants to focus on their actions without the added complexity of real-time synchronization, facilitating clearer action delineation and reducing cognitive load. In contrast, simultaneous collaboration required participants to adjust dynamically to the robot's movements, amplifying challenges posed by less anthropomorphic or mechanically unpredictable designs such as Kuka and Sawyer.

The interaction between collaboration mode and trial progression, particularly in the RQA analysis, revealed that participants adapted differently to each mode over time. During sequential collaboration, the predictability of hand motion improved steadily as participants became familiar with the robot's behaviour. However, in simultaneous collaboration, the rate of improvement was slower, suggesting that the cognitive and motor demands of real-time coordination presented greater adaptation challenges.

While Baxter supported smoother coordination, participants took significantly longer to complete the assembly task when working with this robot. Its predictability and movement-coordination advantages did not necessarily translate into higher overall performance. By contrast, Kuka and Sawyer, despite their lower DET scores, enabled faster assembly completion—likely due to their movement speed or interaction dynamics. These findings suggest a key trade-off: while Baxter enhanced movement coordination, Kuka and Sawyer provided greater efficiency. This aligns with previous work indicating that a higher degree of anthropomorphism, though beneficial for subjective trust, can hinder task performance (Pilacinski et al., 2023).

Simultaneous collaboration further highlighted these efficiency trade-offs. The longer block placement times in the simultaneous condition suggest that real-time coordination imposes additional cognitive and motor demands. However, participants in sequential collaboration improved their placement times more rapidly, indicating that structured, turn-based interaction allowed for faster adaptation.

Conclusions

This study contributes to the field of human-robot interaction by quantifying movement coordination using RQA and cRQA and exploring the effects of collaboration modes and robot types. We found out that sequential collaboration offers predictability, while simultaneous collaboration encourages adaptability and efficiency gains. Additionally, humanoid robots, such as Baxter, enhanced motor performance and interaction quality compared to less humanoid designs.

This study demonstrates the potential of VR environments to simulate real-world scenarios, enabling safe and flexible experimentation. These insights not only advance the understanding of human-robot collaboration but also provide practical guidance for designing human-centred robotic systems.

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