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The Onset Timing of Exoskeleton Assistance for Motor Cooperation

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MASTER THESIS

The Onset Timing of Exoskeleton Assistance for Motor Cooperation

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Journal Article

1. Daichi Kusumoto, Wen Liang Yeoh, Jeewon Choi, Ping Yeap Loh, and Satoshi Muraki, "Human Motor Responses to Different Assistance Onset Timings During Powered Elbow Flexion," *Applied Ergonomics*. **(Under review)**

Conference Proceeding

1. **Daichi Kusumoto**, Teerapapa Luecha, Wen Liang Yeoh, Ping Yeap Loh, and Satoshi Muraki, "Exploring the Initiation Timing of Assistance in Cooperation with Motion Assist Devices," *The 65th Conference of Japan Human Factors and Ergonomics Society*, vol. 60, Supplement, pp. 2E4-2–2E4-2, 2024. https://doi.org/10.5100/jje.60.2E4-2
2. **Daichi Kusumoto**, Teerapapa Luecha, Jeewon Choi, Wen Liang Yeoh, Ping Yeap Loh, and Satoshi Muraki, "Effects of Start Time in Power-Assisted Elbow Flexion on Human-Motor Cooperation," *The 25th Conference of Society of Instrument and Control Engineers, System Integration Division (SI2024)*, 2024. **(Unpublished)**

Technical Contribution

1. Teerapapa Luecha, Wen Liang Yeoh, Yuan Yang, Jeewon Choi, Ping Yeap Loh, and Satoshi Muraki, "Exploring Grip, Voice, and Electromyography Signals to Initiate Elbow Flexion With a Wearable Robot Arm," *Journal of Robotics*, 2025. https://doi.org/10.1155/joro/4988295
   Contribution: Designed and 3D-printed the housing for the control grip, adjusted the sensitivity of the force sensor, and repaired the experimental system.

Chapter 1 Introduction[1]

1.1 Social Background: Exoskeletons

Exoskeletons are a form of motor augmentation technology designed to externally support human joint movement, reduce physical workload, and compensate for diminished muscle strength (Looze et al., 2016; Lowe et al., 2019). This technology assists with complex, physically demanding tasks, such as material handling in warehouses and patient transfer in nursing care. Often described as superhuman technology, exoskeletons can enable performance beyond natural human capability. They expand the range of human activity beyond natural muscular limits and help mitigate constraints associated with age or disability. Applications include facilitating rescue operations at disaster sites inaccessible to heavy machinery (German Bionic Systems, 2022) and enabling new forms of self-expression in the arts and sports (Yamamura et al., 2023). Such technology supports a diverse and sustainable society in which individuals can pursue their desired lifestyles, regardless of physical capability (Japan Science and Technology Agency, 2024).

However, despite the mechanical advantages provided by exoskeletons, their benefits are limited if users cannot accept and integrate assistive forces into their own movements. More than half of first-time users report concerns about continued use (Davis and Kotowski, 2015; Dufraisse et al., 2025; Siedl and Mara, 2023), and effective use of active exoskeletons often requires 4–12 weeks of practice (Diamond-Ouellette et al., 2024; Manns et al., 2019). Studies also indicate that increased cognitive demands in the workplace may offset these mechanical advantages (Tyagi et al., 2023; Zhu et al., 2021). If unresolved, these user-facing challenges hinder long-term adoption and limit the scope of applications (Elprama et al., 2022).

[1] Portions of this chapter adapted from several of the author's works presented in journal article and conference proceedings. For full bibliographic details, refer to the 'List of Works' section on page vii.

These challenges cannot be solved by hardware improvements alone. In systems where humans and machines act together, insufficient attention to human factors can lead to misuse or overreliance, creating new hazards. Clarifying the operational limits and failure points of human–machine cooperation will enable evidence-based design principles for revising work environments, establishing safety standards, and developing legal frameworks that facilitate safe and widespread societal adoption (Figure 1.1; Muraki et al. (2023)). The importance of this systematic approach has been widely acknowledged. Examples include the Human Factors and Ergonomics Society of Japan's proposed guidelines for the proper use of physical function augmentation technologies (Ebara and Yoshitake, 2022) and the Cabinet Office's Moonshot program, which prioritizes fundamental research on robots that collaborate with humans (Cabinet Office, Government of Japan, 2019).

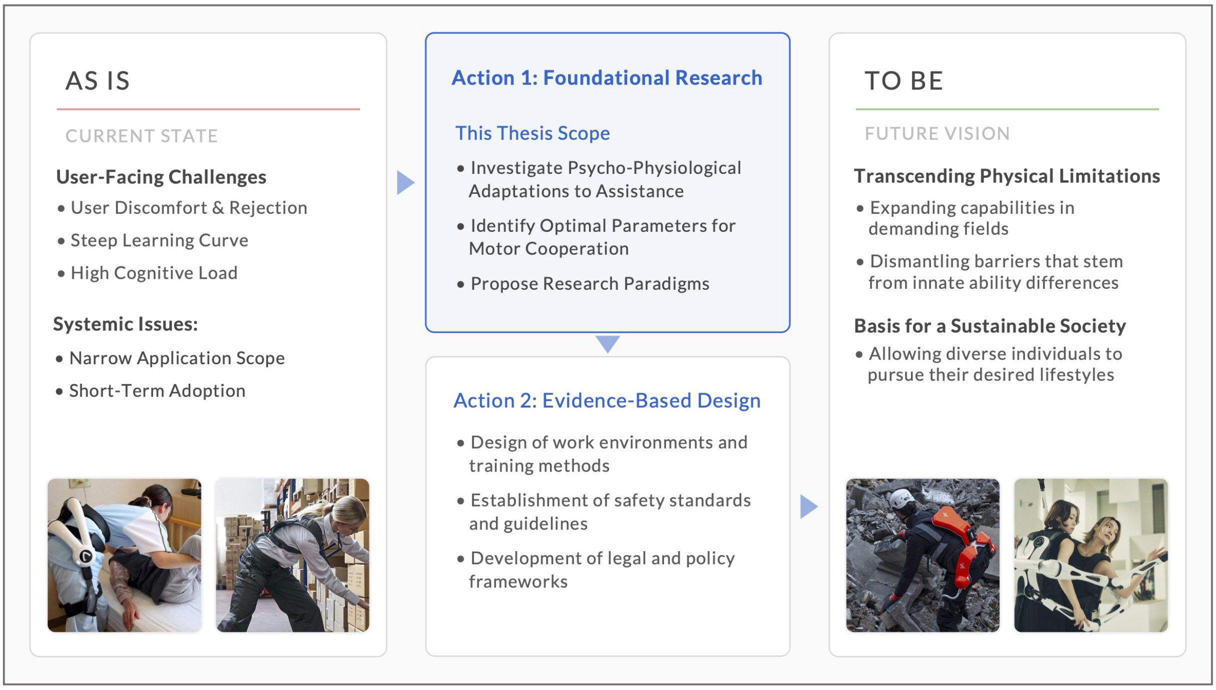

Figure 1.1: Research Positioning. Conceptual roadmap illustrating how this thesis bridges the current challenges and a future vision of exoskeletons.[2]

[2] Photo credits (left to right):

- HAL (Hybrid Assistive Limb), CYBERDYNE, Japan: https://www.cyberdyne.jp/
- LiftSuit, AUXIVO, Switzerland: https://www.auxivo.com/
- Cray X, German Bionic,Germany: https://www.germanbionic.com/
- JIZAI ARMS, JST ERATO Inami JIZAI BODY Project, Japan: https://jizai-arms.com/

1.2 Academic Background: Motor Cooperation & Movement Onset

Humans achieve rapid and accurate motor control by combining feedforward and feedback mechanisms (Wolpert and Bastian (2021); Figure 1.2). Feedforward control is a predictive mechanism that generates motor commands in advance, based on information available before movement begins. In contrast, feedback control is a reactive mechanism that corrects motor error (the discrepancy between desired and actual outcomes) using sensory information obtained during movement, such as visual and somatosensory input (Burdet et al., 2013). For example, when lifting a heavy object, feedforward control predicts the object's mass to prepare the required muscle force, and any deviation from this prediction is corrected by feedback control.

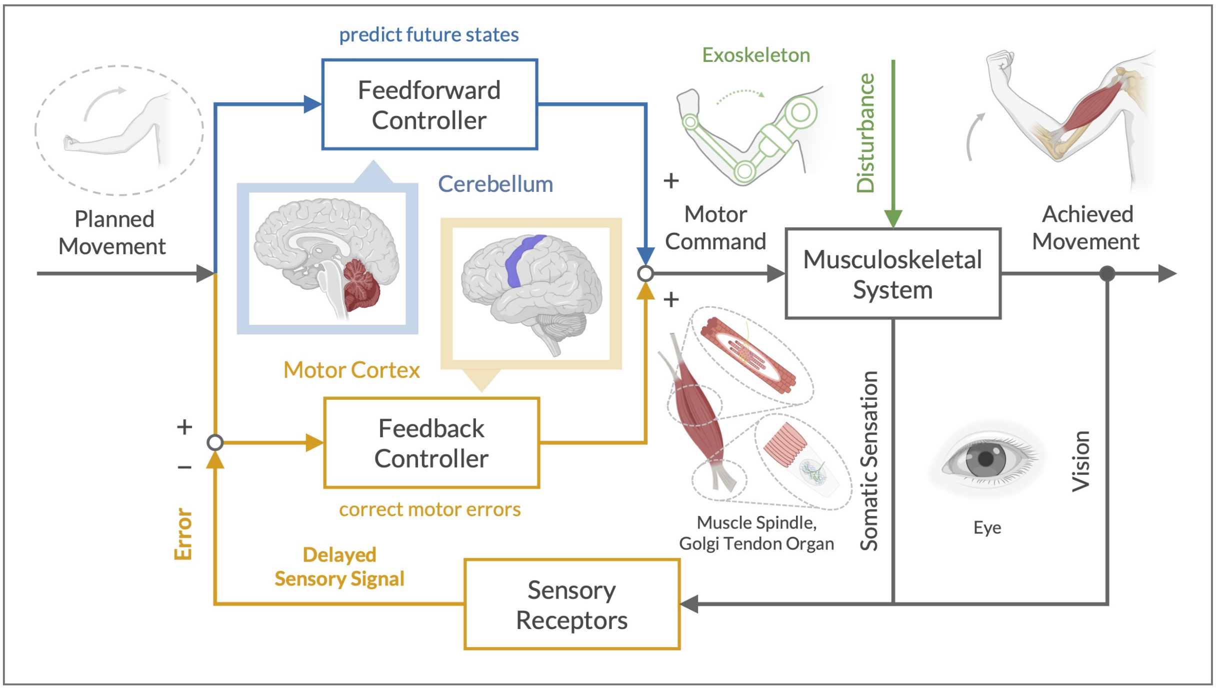

Figure 1.2: Block diagram of human motor control.

This control mechanism is closely related to users' acceptance of exoskeleton assistance. Exoskeletons often provide assistance that exceeds typical user expectations (Massardi et al., 2023), inducing motor errors. Consequently, users must make compensatory muscle adjustments to suppress trajectory overshoots and force perturbations (Afschrift et al., 2023; Choi et al., 2020a). For rapid movements in particular, delays in error correction through sensory feedback can create a mismatch between the user's intention and the actual movement (Desmurget and Grafton, 2000). This mismatch can diminish the sense of agency—the feeling of control over actions and their consequences (Cornelio et al., 2022; Haggard, 2017). In other words, users may feel as if they are being "swung around" by the exoskeleton. To guard against unexpected perturbations, users may maintain continuous muscle tension, which causes frustration and discomfort.

Resolving these challenges requires establishing motor cooperation (Hybart and Ferris, 2023; Inga et al., 2023): a state in which the human and the exoskeleton function as an integrated unit, similar to a familiar tool that feels like a natural limb. Good motor cooperation can be likened to a three-legged race, where both parties anticipate and adjust to each other's movements. When cooperation is poor, assistance conflicts with the user's intent, acting as resistance and creating hazards. When effective, assistance reduces physical burden and creates a synergistic effect that enhances speed and accuracy. Although the components of motor cooperation are debated, this study adopts the following three elements as operational definitions for evaluation:

- Congruence: Alignment of the assisted motion with the user's intended timing and position.
- Agency: Control of one's own movement despite the external assistive force.
- Fluency: Execution of a smooth movement without conscious adjustment to the assistance.

Movement onset is a critical phase because assistance at that moment governs all three core components: congruence, agency, and fluency. First, during rapid movement, delays in sensory feedback control can produce motor error and reduce congruence. Second, unexpected activation of assistance can conflict with self-initiated movements, thereby diminishing agency. Third, the timing of assistance initiation can require additional muscular adjustments, undermining fluency. Thus, the nature of the assistance at movement onset is central to balancing these elements.

1.3 Research Gap

Advances in motion intent estimation using electromyography (EMG) and inertial measurement units (IMUs) have enabled flexible adjustment of assistance onset timing based on anticipatory signals from other limbs or learned motion trajectories (Lee et al., 2024; Molinaro et al., 2024). However, human-factors design guidelines for leveraging this technology have not yet been established because the relationship between assistance parameters and human motor response is not well understood (Figure 1.3). For instance, although assistance that precedes a user's movement intent can enhance task speed (Beck et al., 2023), it may diminish the sense of agency (Wen, 2019). Similarly, higher assistance intensity reduces physical load, whereas lower intensity that preserves user control is often preferable for precision-demanding tasks. Because the tradeoffs among these factors remain unclear, the configuration of assistance parameters currently relies on heuristics and trial and error (Yeoh et al., 2023).

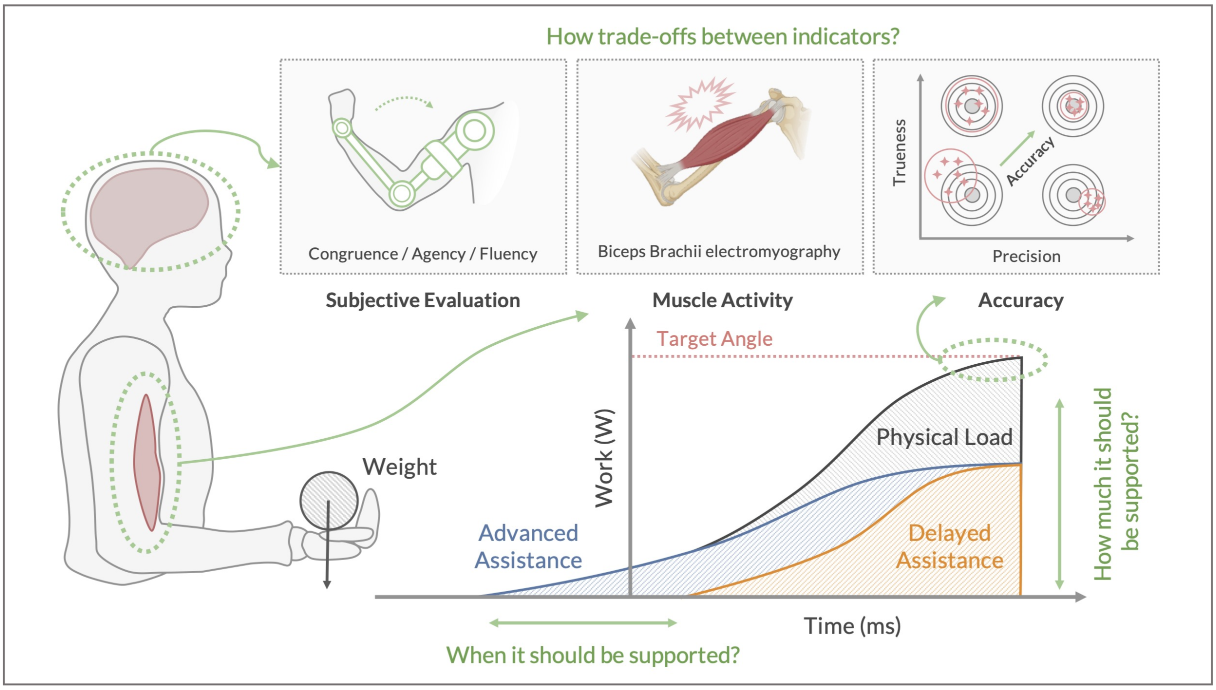

Figure 1.3: Research Questions. Independent (assistance onset and intensity) and dependent (accuracy, muscle activity, and subjective evaluation) variables.

Real-world tasks are rarely single-objective. Daily activities, such as carrying a hot, heavy pot or transferring an elderly person in a care setting, require delicacy and caution. Similarly, industrial work often demands a balance of efficiency and accuracy, such as assembling heavy materials within a given takt time. Consequently, an exoskeleton that reduces physical load at the cost of precision or agency is unlikely to meet these multi-faceted demands and will face challenges in user acceptance. This gap in human factors is also closely linked to practical issues such as the safety of augmented physical actions and the attribution of liability in the event of an accident (He et al., 2017; Nussbaum et al., 2019). In short, this knowledge gap is a bottleneck not only to the effective use of exoskeletons but also to the broader adoption of exoskeleton applications.

1.4 Objectives & Approach

To bridge this gap, this study investigates how assistance onset timing affects human motor responses, namely, task accuracy, physical load, and subjective evaluation. The study has three specific objectives:

- O1. Acceptable Range: Identify the boundaries of assistance conditions that significantly impair motor cooperation. This objective informs the establishment of safety standards for unexpected exoskeleton activation.
- O2. Sweet Spot: Propose desirable combinations of assistance onset timing and intensity. This objective supports design guidelines that balance task performance (efficiency, accuracy) and user experience (agency, fluency).
- O3. Evaluation Methodology: Develop an experimental framework for measuring motor cooperation to enable a multifaceted evaluation of exoskeleton acceptability.

This study employed a two-stage approach to fulfill the stated objectives. Chapter 2 characterizes the effects of assistance onset timing, which is a key parameter that influences motor cooperation, especially in voluntary movements. Building on these findings, Chapter 3 introduces assistance intensity as a second variable to investigate the resulting tradeoffs in motor responses and identify the optimal parameter combinations[3]. Finally, Chapter 4 synthesizes the findings to provide recommendations for assistance conditions in terms of safety standards (O1), design guidelines (O2), and an evaluation methodology (O3).

Unilateral elbow flexion was used as the experimental task, providing a simple, controlled environment for analyzing fundamental assistance principles. Focusing on a single-degree-of-freedom (DOF) movement against gravity minimizes confounding factors, such as compensatory movements. This design allowed clear isolation and evaluation of assistance effects. Additionally, the anatomical roles of the agonist and antagonist muscles are well defined, enabling precise analysis of the relationship between muscle activity and movement intent. This fundamental movement model lays the groundwork for understanding human-machine cooperation in more complex daily and occupational activities.

[3] This study prioritizes investigating fundamental assistance parameters (onset timing and intensity) over task-specific variables (e.g., task speed and weight mass). This approach is based on the idea that establishing design guidelines applicable to diverse tasks requires first understanding the principles of motor response under a simplified task.

Chapter 2 Exploring The Effect of Assistance Onset[1]

2.1 Objectives

As discussed in Chapter 1, a central challenge in motor cooperation stems from the discrepancy in timing between human motor intention and the exoskeleton's activation. This chapter investigates how assistance onset timing affects motor response during a simple task and tests the following two hypotheses:

- (H1) Increased temporal offsets significantly impair movement accuracy.
- (H2) Advanced assistance onset disrupts user-initiated movement onset, amplifies discrepancies between intended and actual result, and consequently diminishes the sense of agency.

[1] This chapter primarily based on a manuscript titled "Human Motor Responses to Different Assistance Onset Timings During Powered Elbow Flexion", submitted to Applied Ergonomics and currently under review.

2.2 Methods

2.2.1 Participants

This study recruited 20 young adults (10 males, 10 females) with no history of upper limb musculoskeletal disorders (Table 2.1). The required sample size was determined by an a priori power analysis (Faul et al., 2007) with the following parameters:

- Statistical test: one-way (seven levels) within-subjects analysis of variance
- Alpha level (α): 0.05
- Power ($1 - \beta$): 0.80
- Effect size (f): 0.25 (Midium)
- Nonsphericity correction (ε): 0.75
- Assumed correlation (r): 0.5

The analysis indicated a minimum required sample size of 16 participants. To account for potential attrition, 20 participants were recruited. The Flanders handedness test (Nicholls et al., 2013) was conducted to confirm that all participants were right-handed. Anthropometric measurements were obtained following JIS Z 8500:2002 (Japan Standards Association, 2002). This study was approved by the Research Ethics Committee of the Faculty of Design, Kyushu University (Approval No. 474). All participants provided written informed consent before the experiment.

Table 2.1: Demographic and body dimensions of 1st-experiment participants (mean ± SD)

Measurements	Male (n = 10)	Female (n = 10)
Age (years)	23.0 ± 0.9	25.0 ± 3.5
Stature (cm)	172.1 ± 5.4	161.1 ± 6.2
Body Mass (kg)	60.3 ± 5.7	54.4 ± 7.3
Upper Arm Length (mm)	301 ± 14	274 ± 17
Forearm Length (mm)	248 ± 9.4	229 ± 8.4

2.2.2 Apparatus

An experimental setup was developed (Figure 2.1) to enable participants to adjust elbow flexion for dumbbell lifting with real-time visual feedback. The system was designed to capture the relationship between neuromuscular responses and task performance under external mechanical assistance. It comprised three integrated modules.

The task instruction module provided start cues via a laptop-generated beep and displayed the current, reference, and target angles on a monitor. The task-assistance module applied assistive torque via a mechanical arm based on each participant's muscle strength. To ensure isolated elbow flexion, it included an adjustable fitting and a wrist brace to prevent compensatory movements such as lumbar extension, shoulder flexion, or wrist flexion. The task measurement module recorded motion and EMG data synchronously and stored the data on a laptop.

To ensure that motor torque was effectively translated into elbow flexion without loss, alignment in both the rotational plane and axes was carefully controlled. First, the chair was adjusted so that elbow flexion occurred in a plane parallel to the sagittal plane. Second, the center of the participant's elbow joint was aligned with the rotational axis of the motor. Based on this alignment, the experimenter adjusted the length of the mechanical arm and fitting position according to each participant's anthropometric measurements.

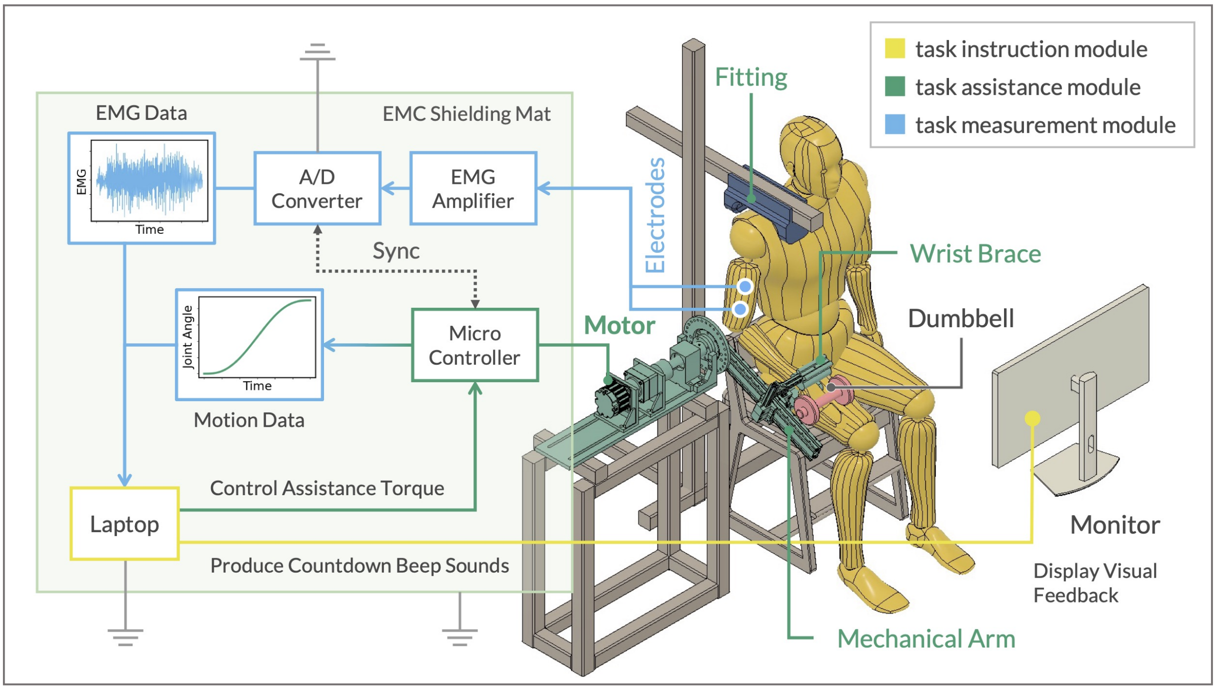

Figure 2.1: Experimental Setup. Schematic of the system for evaluating assisted elbow flexion.

To ensure participant safety throughout the experiment, multiple safety measures were implemented (Table 2.2).

Table 2.2: Safety features implemented in the experimental apparatus

Safety Feature	Description
Fail-Safe	• Physical stoppers were installed to prevent the mechanical arm from rotating beyond the participant's natural range of elbow motion. • The system was designed to automatically shut down upon detecting a strong impact between the arm and these stoppers.
Fool-Proof	• An interlock system was implemented to prevent accidental activation of the mechanical arm. Assistive torque would only be generated when two conditions were met simultaneously: the task start button on the laptop was pressed, and the motor's activation button was engaged. • The arm would never move without a preceding auditory cue.
Mechanical Fuse	• The connection point between the participant and the mechanical arm was intentionally designed as the weakest link. In the event of excessive torque, this component is engineered to fail before any harm is caused to the participant.
Emergency Stop	• A physical emergency stop button was prominently placed, allowing for immediate and forceful shutdown of the system by cutting off the power supply.

2.2.3 Preliminary Measurements: MVC Test

Before the main experiment, muscle strength was assessed to normalize dumbbell mass and assistive torque across participants. Each participant performed a 5-second isometric maximum voluntary contraction (MVC) of elbow flexion at 90° while holding a strap. The MVC test was conducted three times for the biceps brachii (BB), with at least a one-minute rest between trials. To maintain a consistent moment arm, participants were instructed to hold the strap at the center of the wrist.

A tensile sensor, connected to a strap oriented perpendicular to the floor, was used to detect strain induced by the MVC force. The resulting voltage output, proportional to the strain, was amplified 1000-fold using a strain amplifier and digitized using an A/D converter. The most stable 3-second period of force output was visually identified and converted to force (N) using analysis software (LabChart 7; ADInstruments). The MVC force for each participant was calculated by averaging the results from the three trials. These procedures followed methodologies established in previous studies (Choi et al., 2020a) (Figure 2.2).

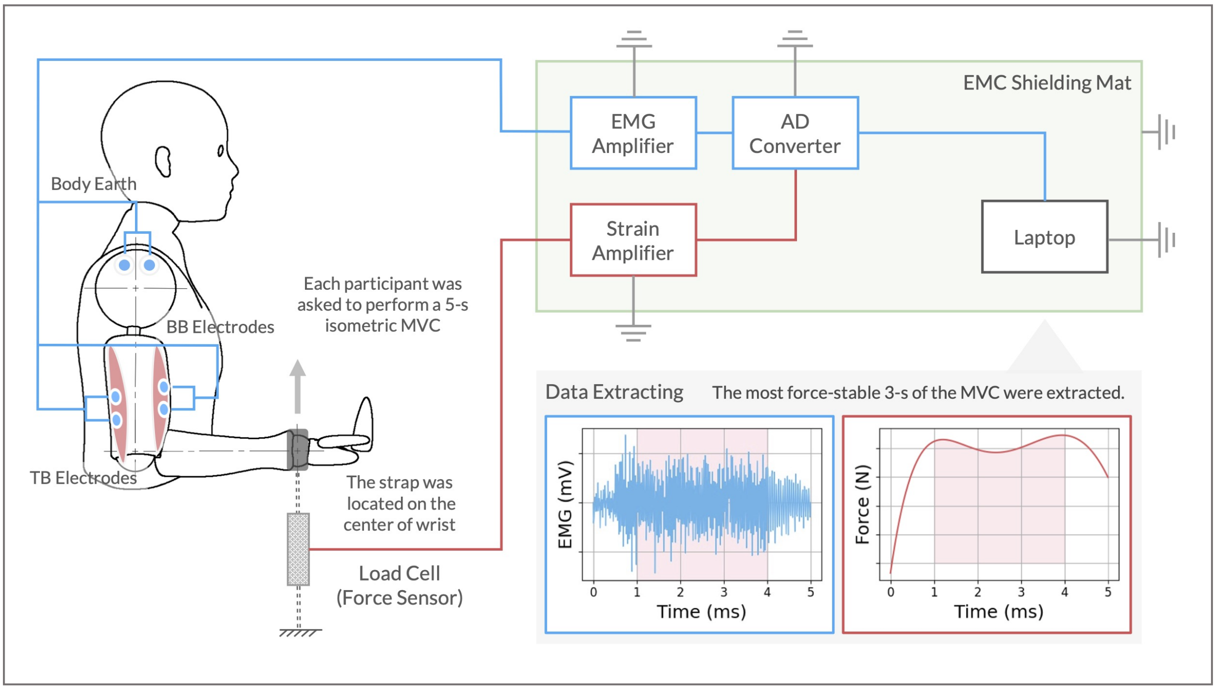

Figure 2.2: MVC Test. A schematic diagram illustrating the setup and data processing for the muscle strength test. The setup shows the measurement of force and EMG during a 5-second isometric elbow flexion, while the processing shows the extraction of a stable 3-second window for EMG normalization.

2.2.4 Main Experiment

» Task Description

Participants performed an elbow flexion task, beginning at 30° and ending at 120° (Figure 2.3A), while lifting a dumbbell weighted at 25% of their BB MVC force. To facilitate motion planning, a countdown beep was given three times at 1-second intervals, starting 3 seconds before the task. A final, main beep signaled the start of the task and served as a timing reference. Participants were required to complete a 90° flexion within 1.15 seconds of the main beep with high accuracy. To assist motor coordination, the system provided real-time visual feedback (Figure 2.3B), a method adopted from previous studies (Yang et al., 2024).

The assistive device applied a constant torque equivalent to 40% of the dumbbell's weight. To prevent overshooting the target angle, assistance was terminated 0.15 seconds before the task ended. The mass of the mechanical arm was offset prior to the experiment to ensure that only the dumbbell and the applied torque influenced the task.

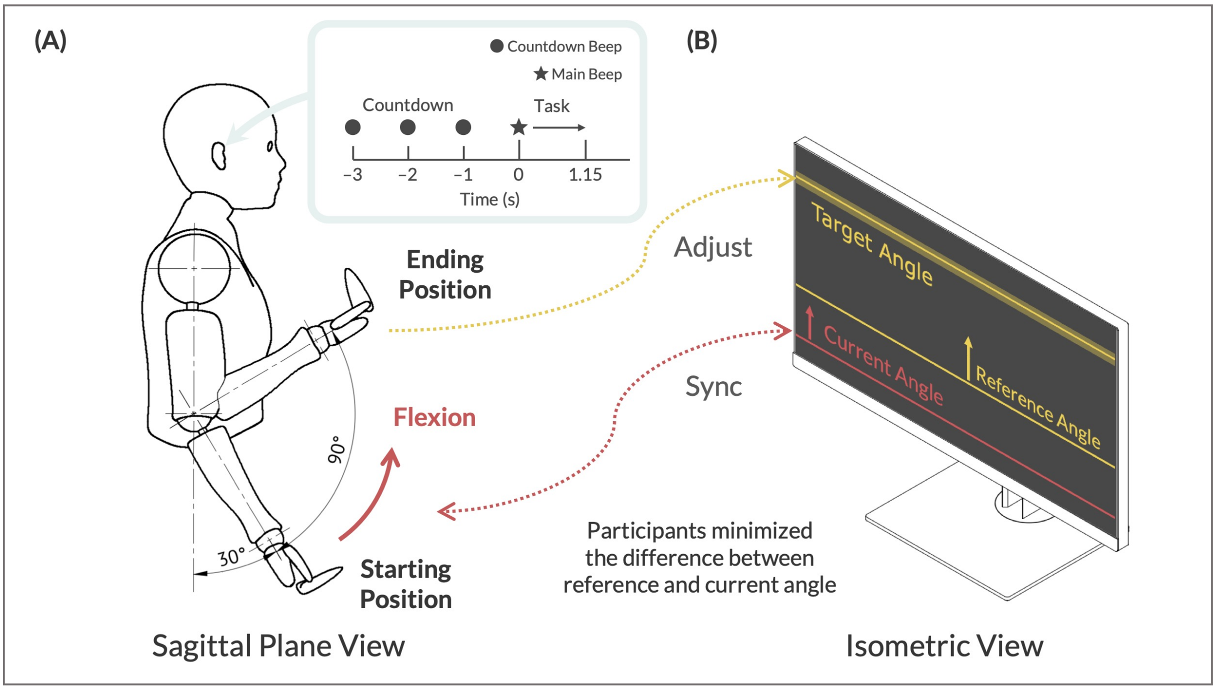

Figure 2.3: Experimental Task. The elbow flexion task, including (A) movement sequence and (B) visual feedback.

» Experimental Conditions & Procedure

Seven onset conditions were examined (Figure 2.4A):

- Immediate assistance (onset at 0 ms, coinciding with the main beep),
- Advanced assistance (onset at -300 ms, -200 ms, or -100 ms), and
- Delayed assistance (onset at $+100$ ms, $+200$ ms, or $+300$ ms).

Additionally, a non-assistance condition was included as a reference to assess the effectiveness of assistance. The main experiment comprised two sessions (Figure 2.4B):

- Familiarization Session: Participants practiced each condition once in a fixed order, followed by two additional rehearsal blocks arranged using a randomized block design (Howell, 2010) to prevent participants from predicting the assistance onset based on pattern recognition.
- Data Collection Session: Participants performed three randomized sets, interspersed with two informed non-assistance trials (one before Set 1 and one after Set 3) to account for potential learning effects or changes in comprehension. Only data from the data collection session were used for analysis.

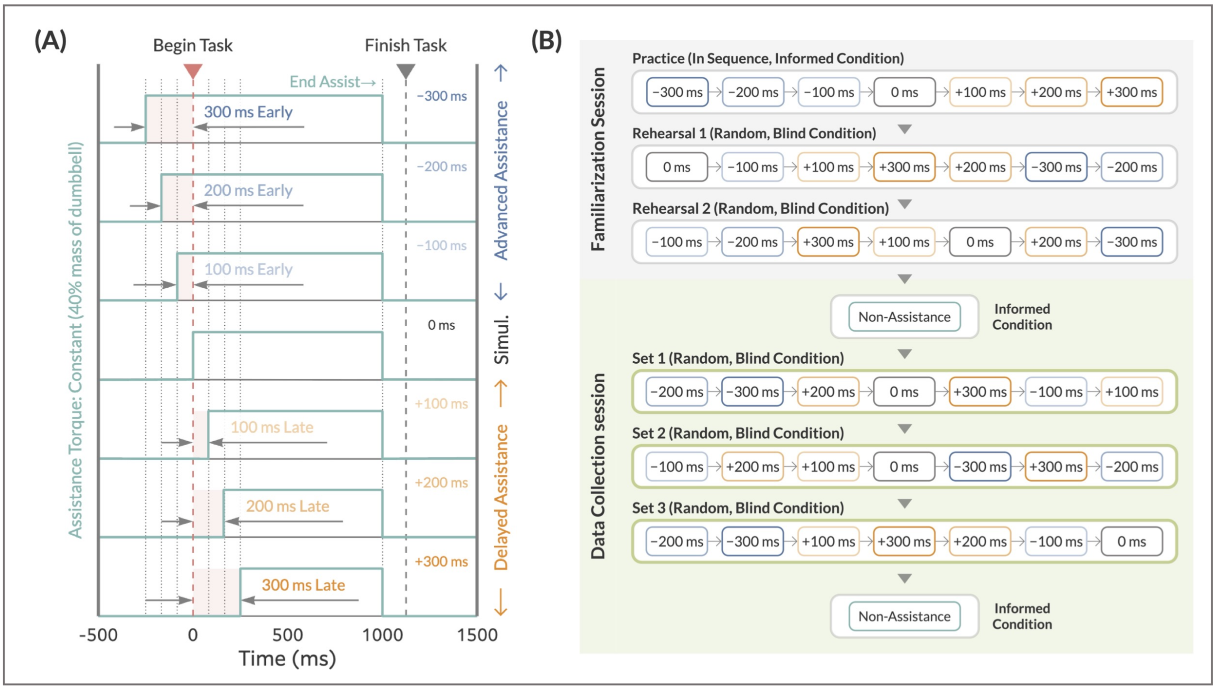

Figure 2.4: 1st-Experimental Design. Overview of (A) the seven assistance onset conditions and (B) the experimental protocol.

2.2.5 Measurements

» Elbow Flexion Angle

Elbow joint angles were recorded using a rotary encoder integrated into the motor. A quadrature encoder pulse module within the microcontroller counted the pulses generated by the rotary encoder. This data was transmitted at a frequency of 120 Hz to a laptop where it was recorded and used to display visual feedback.

» Muscle Activity

Surface EMG was recorded from the BB, the primary agonist in elbow flexion. The skin over the muscle was cleaned using alcohol wipes and scrubbed with a preparation gel. A pair of disposable electrodes were positioned following SENIAM guidelines (Hermens et al., 2000), which specify electrode placement, diameter, and inter-electrode spacing. To eliminate hum noise, all devices were grounded and placed on an electromagnetic compatibility (EMC) shielding mat, in accordance with established recommendations (Clancy et al., 2002).

The EMG amplifier amplified and band-pass filtered (10–500 Hz) the recorded EMG signal. The A/D converter digitized the signal at a 1-kHz sampling rate with 16-bit resolution. The signal amplitude was quantified using the average rectified value method, which involves full-wave rectification and smoothing with a 100-point window (Winter, 2009). The activity for BB muscle was expressed as a percentage of MVC (%MVC) by normalizing each measured EMG value relative to the integral EMG obtained from the MVC tests.

» Subjective Evaluation

After each trial, participants verbally answered two questions regarding their perception of assistance onset timing and movement smoothness as follows:

- Q1 Timing Discrepancy: "To what extent was the assistance onset earlier than you anticipated?" (-5 = "late," $+5$ = "early").
- Q2 Movement Smoothness: "To what extent were your movements smooth throughout the entire motion?" (-5 = "stiff," $+5$ = "smooth")

A semantic differential scale was used, as it is effective in reducing acquiescence bias, particularly when assessing the sense of agency (Bartneck et al., 2009; Haggard, 2017). Each item was rated on an 11-point scale (-5 to $+5$), with 0 anchored to the sensation of lifting the dumbbell without assistance. A pilot study confirmed that the scale was sufficiently sensitive to detect subtle perceptual differences arising from variations in assistance onset. To mitigate response biases such as central tendency and extreme response styles (Bogner and Landrock, 2016), individual ratings were standardized using Z-scores (Howell, 2010). The questionnaire was limited to two items to minimize confusion and reduce participant burden during the rapid sequence of trials.

2.2.6 Data Analysis

For statistical analysis, representative values were extracted from the time-series data of the elbow flexion angle and muscle activity. Following an exploratory inspection of the data, an analysis window was defined, and the data within this window were averaged. The definition of this window and the calculation methods for each metric are described below.

» Elbow Flexion Angle

To assess movement accuracy near the target-reaching time (1150 ms), a 300 ms analysis window was defined from 1000 ms to 1300 ms. Movement accuracy was evaluated in terms of trueness (the closeness of the measured value to the target) and precision (the consistency of repeated measurements). Precision was quantified using the coefficient of variation (CV), which reflects relative variability across repeated trials. For each participant, the CV was calculated under each experimental condition and then averaged to obtain condition-specific mean CVs. CV values exceeding 10% were considered unacceptable (Atkinson and Nevill, 1998).

» Muscle Activity

To evaluate movement agency around task onset (0 ms), a 400 ms analysis window was defined from -200 ms to $+200$ ms. Elevated muscle activation prior to task onset—beyond preparatory activation levels—was interpreted not as self-initiated movement but rather as a reactive adjustment to the assistance. This interpretation was supported by comparisons with time-series muscle activation profiles observed under non-assistance conditions.

2.2.7 Statistical Analysis

A repeated-measures design was employed, with participants completing all seven experimental conditions. Each condition was measured three times to ensure reliability, and the mean of the three trials was used for analysis. The Shapiro–Wilk test confirmed that the data met the assumption of normality across conditions. One-way repeated-measures analysis of variance (ANOVA) was conducted to examine the effect of assistance onset on each outcome measure. Mauchly's test was used to assess the assumption of sphericity; if this assumption was violated, the Greenhouse–Geisser correction was applied. Effect sizes for the ANOVA were reported as generalized eta-squared (η_G^2) and interpreted using benchmarks for small ($\eta_G^2 \geq 0.01$), medium ($\eta_G^2 \geq 0.06$), and large ($\eta_G^2 \geq 0.14$) effects (Bakeman, 2005). When significant main effects were identified, post-hoc comparisons were conducted using paired t-tests with Bonferroni correction. Effect sizes for these comparisons were calculated as Cohen's d and interpreted according to established guidelines (Cohen, 2013): negligible ($|d| < 0.2$), small ($0.2 \leq |d| < 0.5$), medium ($0.5 \leq |d| < 0.8$), and large ($|d| \geq 0.8$). Statistical significance was set at $p < 0.05$. All analyses were conducted using R software (version 4.4.2).

2.3 Results

2.3.1 Elbow Flexion Angle

Figure 2.5A shows the time-series joint angle profile and analysis window (highlighted in green). Advanced assistance tended to result in early arrival and overshooting of the target position (90°), whereas delayed assistance typically resulted in undershooting the target. Figure 2.5B shows the average joint angle of each participant within the analysis window. In terms of median comparisons, the −100 ms condition (89.1°, error: 1.0%) was closer to the target than the baseline 0 ms condition (85.5°, error: 5.0%). ANOVA revealed a significant main effect of onset ($F(6,114) = 25.1$, $p < 0.001$, $\eta^2_G = 0.33$). Post hoc comparisons indicated a significant difference with a large effect size between the −200 ms and 0 ms conditions ($p < 0.01$, $|d| = 1.16$), whereas no significant difference was found between the 0 ms and +200 ms conditions ($p = 0.12$, $|d| = 0.69$), despite a moderate effect size. Examining the medians, the −200 ms condition slightly overshot the target (91.9°, error: 2.1%), while the +200 ms condition substantially undershot the target (79.9°, error: 11.2%).

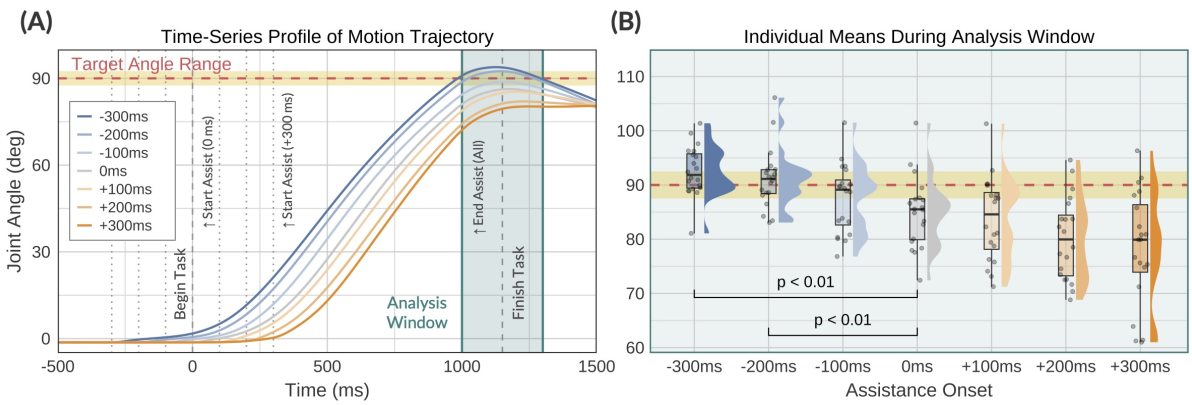

Figure 2.5: Movement Trueness. (A) Time-series motion trajectories and (B) mean joint angles assistance onset conditions.

Figure 2.6 illustrates that the CV across conditions forms an asymmetric U-shaped trend, reaching its minimum at the -100 ms condition and increasing sharply toward the $+300$ ms condition. At $+300$ ms, the mean CV reached 10.1%, exceeding the predefined 10% threshold, thereby indicating that within-subject movement consistency had declined beyond the acceptable range. The violin plot for the $+300$ ms condition displayed a flattened central peak and widened tails, suggesting greater between-subject variability compared to other conditions. Additionally, the 95% confidence interval (CI) for $+300$ ms (7.7–12.5%) did not overlap with that of 0 ms (4.2–6.5%), confirming a statistically significant increase in CV. In contrast, the CI for the -300 ms condition (4.9–7.9%) overlapped with the 0 ms CI, suggesting asymmetry in the effects of advanced versus delayed assistance on movement precision.

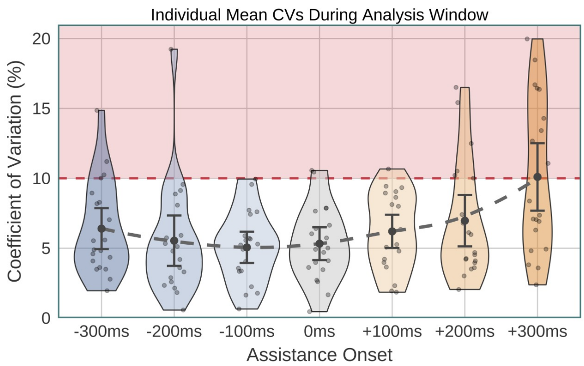

Figure 2.6: Movement Precision. Comparison of the coefficient of variation across assistance onset conditions.

2.3.2 Muscle Activity

Figure 2.7A shows the time-series profile of the BB EMG. Preliminary muscle activation occurred across all conditions, indicating that participants attempted to initiate the task without delay in response to the main beep. In the latter movement phase, BB EMG under non-assistance conditions was substantially higher than that under assisted conditions, confirming that the assistance effectively reduced the muscle load. Within the analysis window, the profiles under delayed assistance nearly overlapped with the non-assistance condition, while advanced assistance produced distinctly elevated BB EMG values. This pattern differs from the self-initiated activation profile under the non-assistance condition.

Figure 2.7B presents participants' mean values within the analysis window. The lowest median BB EMG occurred under the $+100$ ms condition (22.5%MVC), and the highest under the -300 ms condition (34.6%MVC). This 12.1%MVC difference corresponds to approximately 16.5 N (1.6 kgf), given the participants' average MVC of 136 N. ANOVA revealed a significant main effect of onset ($F(3.14,59.58) = 18.67$, $p < 0.001$, $\eta_G^2 = 0.12$). Post hoc tests showed a significant difference with a large effect size between the -200 ms and 0 ms conditions ($p < 0.01$, $|d| = 1.12$), whereas the difference between -100 ms and 0 ms was not significant and had a small effect size ($p = 1.00$, $|d| = 0.42$).

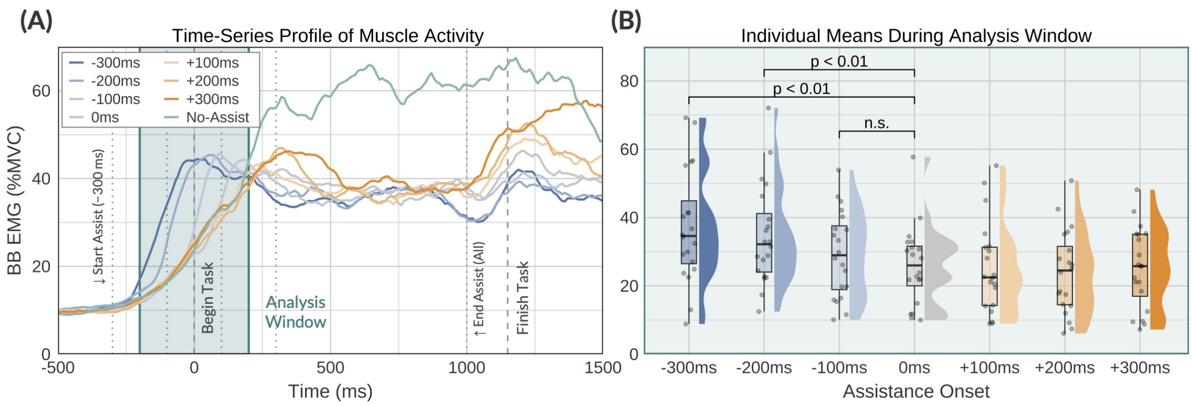

Figure 2.7: Movement Agency. (A) Time-series muscle activity profiles and (B) mean BB EMG during the analysis window.

2.3.3 Subjective Evaluation

Figure 2.8A displays the distribution of subjective timing discrepancy ratings between voluntary movement and assistance onset. Median Z-scores showed a linear trend across conditions, with the 0 ms condition being closest to zero. ANOVA confirmed a significant main effect of onset ($F(6,114) = 47.68$, $p < 0.001$, $\eta^2_G = 0.72$). Post hoc tests showed a significant difference with a large effect size between the 0 ms and 200 ms conditions ($p < 0.01$, $|d| = 1.53$), but no significant difference between 0 ms and $+200$ ms ($p = 0.85$, $|d| = 0.49$). These results suggest that participants perceived the assistance as "too early" or "too late" in an asymmetrical manner.

Figure 2.8B shows the distribution of subjective movement smoothness ratings (Z-scores), which followed an M-shaped pattern. Higher median ratings were observed at the -100 ms and $+100$ ms conditions, with a slightly lower value at 0 ms. ANOVA indicated a significant main effect of onset ($F(3.43,65.17) = 3.10$, $p < 0.05$, $\eta^2_G = 0.14$). However, post hoc tests did not reveal significant differences between any condition pairs. Notably, the $+300$ ms condition exhibited a lower median compared to the others, with moderate effect sizes for certain comparisons—for example, between $+100$ ms and $+300$ ms ($p = 0.12$, $|d| = 0.69$).

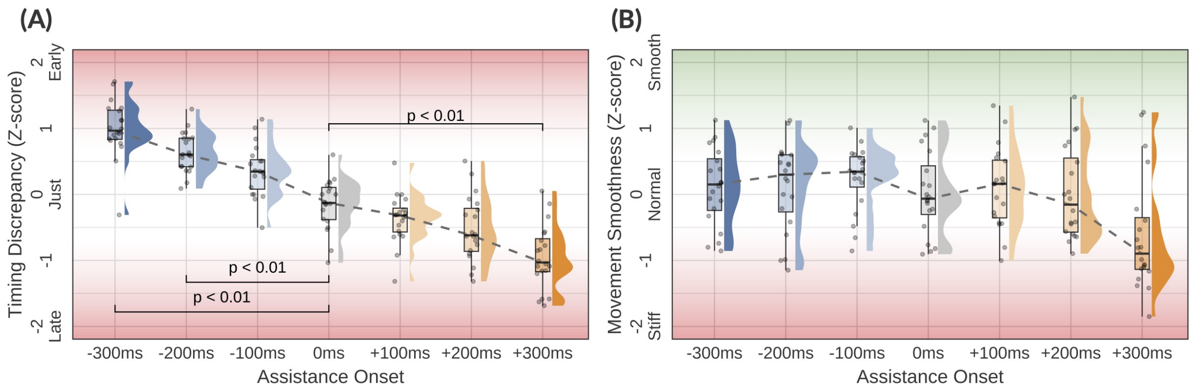

Figure 2.8: Subjective Evaluation. (A) Subjective ratings of timing discrepancy and (B) movement smoothness.

2.4 Discussion

2.4.1 Effects of Advanced Assistance

In this study, the -100ms condition yielded smaller angle errors than the simultaneous assistance (Figure 2.5) suggesting that initiating assistance slightly ahead of voluntary movement helps compensate for inherent delays in sensory feedback. Neurophysiologically, somatosensory signals take approximately 50–100 ms to integrate into motor commands, while visual signals take approximately 100–150 ms (Wolpert and Bastian, 2021). Aligning the assistance onset with this window may alleviate the user's burden of concurrently interpreting incoming sensory feedback (including assistance effects) and adjusting control commands during rapid movement execution. Enabling integration of the external force into the motor plan in advance likely contributed to both the improved accuracy and greater perceived movement smoothness compared to the simultaneous assistance (Figure 2.8B).

However, signs of a diminished sense of agency were observed under excessively advanced assistance. Specifically:

1) A premature elevation in agonist muscle activity occurred before participants' movement intention (Figure 2.7), indicating that movement agency was compromised by external intervention.
2) Overshooting of the target angle was observed (Figure 2.5), reflecting a mismatch between predicted and actual movement outcomes.
3) Subjective evaluation of timing discrepancy showed an increased perception that assistance was "too early" (Figure 2.8A).

These findings suggest impairment of the three prerequisites for the sense of agency: a loss of movement agency, a mismatch between prediction and outcome, and the conscious perception of this mismatch. This pattern was consistently observed at assistance onset timings of -200 ms and earlier. Therefore, we conclude that excessively early assistance diminishes the sense of agency. These results support the second hypothesis (H2).

2.4.2 Effects of Delayed Assistance

Interestingly, despite having the same temporal offset from the 0 ms condition, delayed assistance was perceived to result in fewer timing discrepancies compared with advanced assistance (Figure 2.8A). Furthermore, the +100 ms condition was rated subjectively smoother than the 0 ms condition (Figure 2.8B). One possible explanation involves the electromechanical delay (EMD)—the physiological time lag between the neural activation of a muscle and the generation of contractile force. EMD for the BB muscle during elbow flexion has been reported to range from approximately 30 to 100 ms (Cavanagh and Komi, 1979; Howatson et al., 2009). This suggests that when assistance is delayed by around 100 ms, the ramp-up of assistive torque may coincide more naturally with the actual development of muscle force, thereby reducing the perceived timing discrepancy and enhancing subjective smoothness.

However, excessively delayed assistance impaired movement trueness (Figure 2.5). likely due to a reduced total impulse (force $\times$ time), as the assistive torque terminated uniformly 1000 ms after the start cue regardless of onset timing (Figure 2.4A). As a result, participants were required to compensate with their own muscle force. The increased variability observed at the +300 ms condition—evidenced by a mean CV that exceeded the threshold and a broadened distribution (Figure 2.6)—suggests considerable individual differences in compensatory ability. The corresponding decline in perceived movement smoothness under the +300 ms condition may reflect difficulty in compensation among certain participants (Figure 2.8B). Although no significant pairwise comparisons were found, the median smoothness rating was lower for this condition. In contrast, advanced assistance may have enabled participants to integrate the assistive force into their motor plans, suppress late-phase muscle activity (Figure 2.7A), and avoid excessive overshoot (Figure 2.5A). These findings support first hypothesis (H1); however, the nature of accuracy impairment differed qualitatively between advanced and delayed assistance conditions.

2.4.3 Conclusion

This study demonstrated that the timing of assistance in exoskeletons affects both movement accuracy and the sense of agency. Providing assistance 100 ms before voluntary movement resulted in optimal movement accuracy, likely due to compensation for inherent sensorimotor integration delays. However, assistance initiated more than 200 ms before movement onset diminished the sense of agency, as evidenced by premature muscle activation and subjective evaluations. Delayed assistance preserved the sense of agency but reduced movement accuracy due to insufficient assistive impulse. These findings highlight a tradeoff between movement performance and user experience, which must be carefully considered in exoskeleton design.

Chapter 3 Investigating the Interaction of Assistance Onset & Intensity[1]

3.1 Objectives

The previous chapter revealed a tradeoff between movement accuracy and the sense of agency, identifying a viable range of ± 100 ms for balancing these factors. This chapter investigates how this relationship is modulated by assistance intensity. The objective is to identify and characterize the conditions that maximize overall motor cooperation. Accordingly, four hypotheses are proposed:

- (H3) Higher assistance intensity reduces physical load and exhibits a nonlinear effect that plateaus at higher levels.
- (H4) Physical load is reduced not only by high-intensity assistance but also by advanced assistance.
- (H5) Higher assistance intensity degrades movement accuracy. However, this degradation is mitigated by advanced assistance.
- (H6) Higher assistance intensity diminishes the sense of agency. However, this effect is counteracted by delayed assistance.

[1] The content of this chapter is based on a draft of a paper in preparation for submission to an academic journal.

3.2 Methods

The fundamental methodology for this experiment was identical to that of Chapter 2: participants performed the same elbow flexion task while lifting a dumbbell set to 25% of each participant's BB MVC force. This section details the modifications for the second experiment, namely, the experimental conditions and subjective evaluation items.

3.2.1 Participants

This study recruited 22 young adults (11 males, 11 females) with no history of upper-limb musculoskeletal disorders (Table 3.1). The required sample size was determined via priori power analysis (Faul et al., 2007) to detect the interaction effect with the following parameters:

- Statistical test: two-way (3 × 3) within-subjects analysis of variance
- Alpha level (α): 0.05
- Power ($1-\beta$): 0.80
- Effect size (f): 0.40 (large)
- Assumed correlation (r): 0.0 (conservative)

The analysis indicated a minimum sample size of 20 participants. Therefore, 22 participants were recruited to allow for potential attrition and data loss. All other recruitment criteria were identical to those described in Chapter 2.

Table 3.1: Demographic and body dimensions of 2nd-experiment participants (mean ± SD)

Measurements	Male (n = 11)	Female (n = 11)
Age (years)	25.3 ± 5.5	23.4 ± 2.1
Stature (cm)	173.2 ± 4.9	158.8 ± 6.6
Body Mass (kg)	63.3 ± 5.6	48.0 ± 6.1
Upper Arm Length (mm)	300 ± 10	279 ± 13
Forearm Length (mm)	251 ± 8	222 ± 14

3.2.2 Experimental Conditions & Procedure

The study used a 3 × 3 within-subjects factorial design that manipulating two factors: assistance onset timing and assistance intensity (labelled "assistance rate", Figure 3.1A). Assistance onset timing was set to −100 ms (advanced), 0 ms (simultaneous), or +100 ms (delayed). Assistance intensity was set to 20%, 35%, or 50% of the torque produced by the dumbbell load.

Each participant completed 40 trials (Figure 3.1B)

- Familiarization session (informed; 10 trials): Participants first practiced each experimental condition (3 onsets × 3 intensities) once in a fixed order, followed by a single non-assistance trial. The upcoming condition was announced before each trial.
- Data collection sessions (blinded; three blocks, 30 trials total): Each block corresponded to one assistance intensity (20%, 35%, 50%); block order was randomized per participant to counterbalance order effects. Within a block, participants performed nine assistance trials (three onsets × three repetitions) in random order, followed by one non-assistance trial.

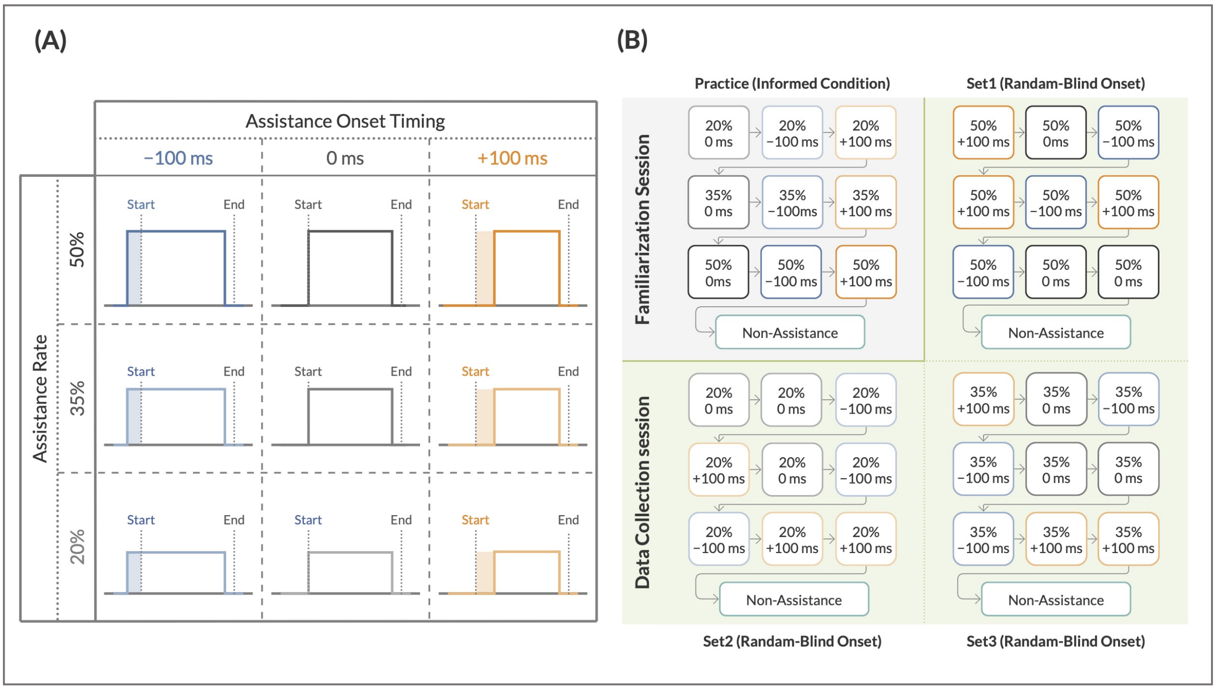

Figure 3.1: 2nd-Experimental Design. Overview of (A) the nine assistance conditions and (B) the experimental protocol.

3.2.3 Measurements & Data Analysis

» Muscle Activity

Surface EMG of the biceps brachii (BB) served as an objective indicator of physical load. EMG activity was integrated over a window from -300 ms (onset of movement preparation) to $+1300$ ms (completion of elbow flexion and initiation of dumbbell lowering).

» Subjective Evaluation

After each trial, participants verbally answered two questions regarding perceived effort, agency, and fluency as follows.

- Q1. Rate of Perceived Exertion (RPE): "How intense was the movement during elbow flexion?" (0 = "Nothing at all," 10 = "Extremely strong"). Assessed using the modified Borg Category Ratio 10 (CR-10) scale (Borg, 1982).
- Q2. Agency: "Even with the assistance force, did you feel you could perform the movement as you intended?" (-5 = "Not at all as intended," $+5$ = "Perfectly as intended").
- Q3. Fluency: "To achieve smooth movement, to what extent did you feel conscious adjustment to the assistance force was necessary?" (-5 = "Much conscious adjustment," $+5$ = "No conscious adjustment").

Q1 tested the predicted reduction in physical load (H3). Q2 targeted the sense of agency (H6), and Q3 assessed fluency as a component of motor cooperation. Unlike the simple smoothness rating in Chapter 2, Q3 emphasized cognitive effort rather than kinematic outcomes. Scores from the 11-point scales (Q2 and Q3) were standardized using z-score within participants before statistical analysis to control for individual response bias.

» Post-Experiment Interview

Unstructured interviews were conducted to complement interpretation of the quantitative results with qualitative insights into participant interpretations, unexpected reactions, and control strategies; they were not intended to provide direct evidence for hypothesis testing. Questions were adapted in real time based on each participant's behavior; consequently, their wording and order varied across interviews, and some topics were omitted due to time constraints.

Responses were not audio-recorded; instead, the experimenter documented key points in immediate notes. To support neutral interpretation during analysis, responses containing both positive and negative judgments were extracted, allowing contrast between the advantages and disadvantages of each condition. Key example questions are listed in Table 3.2.

Table 3.2: Key Question Examples from the Post-Experiment Interview.

Category	Key Question Examples
Perception	• How did you perceive the differences in assistance intensity and onset timing? • Which assistance conditions was the easiest to operate, and why?
Motor Control	• To accurately reach at the target angle range, what strategies, if any, did you consciously use? • When you felt a discrepancy between your intention and the device's movement, how did you try to correct for it?
Adaptation	• Did your strategy for handling the device or your own movements evolve from the beginning to the end of the experiment? If so, how? • After becoming accustomed to the assistance, what did it feel like to move without any assistance? What specific aspects stood out to you (e.g., the perceived weight, movement timing, or effort required)?

3.2.4 Statistical Analysis

A two-way repeated-measures analysis of variance (ANOVA) was performed on each dependent variable, with assistance onset timing and assistance intensity as within-subject factors. Specifically, the main effect of assistance intensity tested the predicted reduction in physical load (H3), and the main effect of assistance onset timing tested its influence on physical load (H4). The interaction between assistance onset timing and assistance intensity was examined to assess whether their combined effects varied across outcomes, including movement accuracy (H5) and the sense of agency (H6). When a significant interaction was detected, simple effects (simple main effects) were tested, followed by Bonferroni-adjusted pairwise comparisons.

3.3 Results

3.3.1 Physical Load

» Muscle Activity

Figure 3.2A compares the three assistance intensities (labeled “rates” in the figure) at simultaneous onset (0 ms) against the no-assistance condition. In all assisted conditions, the BB EMG trends were nearly identical for the first 200 ms of the task, after which the profiles diverged by assistance intensity. From 200 ms to 1150 ms, the 20% condition was approximately 5–10%MVC higher than the other two conditions. The 35% profile was slightly higher than the 50% profile between 200 ms and 500 ms, after which the two became nearly identical.

Figure 3.2B shows the mean BB EMG for each participant. Under the 0 ms condition, the mean BB EMG was 34.4%, 29.2%, 26.9%, and 25.4%MVC for the non-assistance (0%), 20%, 35%, and 50% assistance intensities, respectively. Because assistance (20%, 35%, 50%) was applied to a 25%MVC dumbbell load, the theoretical load reductions were 5%, 8.75%, and 12.5%MVC. The actual reductions were 5.2%, 7.5%, and 9.0%MVC, indicating that only the 20% condition matched its theoretical value, whereas the higher intensities fell short.

ANOVA revealed a significant main effect of assistance rate ($F(2,42) = 21.1$, $p < 0.001$, η^2_G = 0.015). Post-hoc tests indicated a medium effect size between the 20% and 35% conditions ($|d|$ = 0.62), and a small effect size between the 35% and 50% conditions ($|d|$ = 0.49). ANOVA revealed no significant main effect for onset($F(2,42)$ = 0.68, p = 0.68, η^2_G < 0.001), or interaction effect ($F(4,48)$ = 0.46, p = 0.77, η^2_G < 0.001).

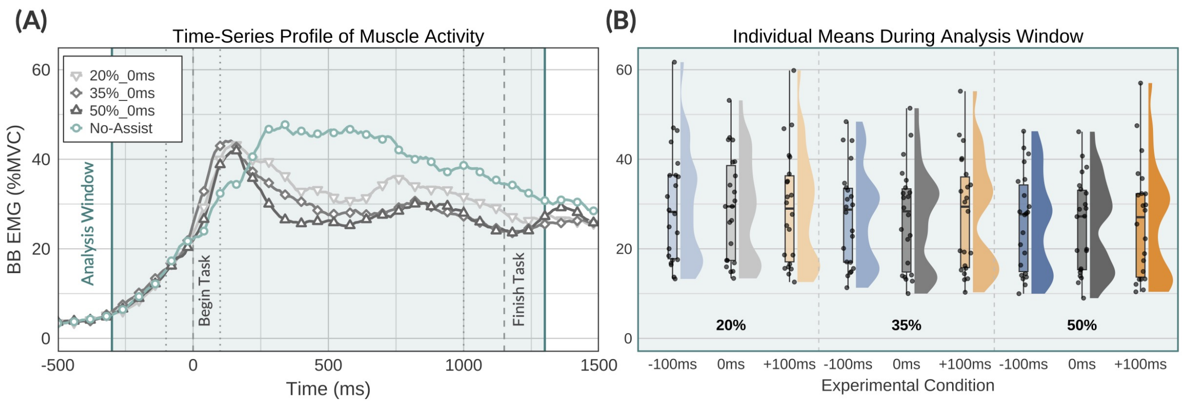

Figure 3.2: Muscle Activity. (A)Time-series BB EMG profiles and (B) mean BB EMG values during the analysis window.

» Rate of Perceived Exertion (RPE)

Figure 3.3A illustrates RPE scores across experimental conditions. Under the 0 ms onset, the median scores for the non-assistance, 20%, 35%, and 50% intensities were 4.28, 2.71, 2.38, and 2.21, respectively. ANOVA revealed significant main effects of assistance rate (F(2,42) = 18.4, $p < 0.001$, $\eta^2_G = 0.04$) and onset timings (F(2,42) = 3.9, $p < 0.05$, $\eta^2_G = 0.004$), while the interaction effect was not significant (F(4,48) = 0.5, $p = 0.7$, $\eta^2_G = 0.001$). Post-hoc comparisons for assistance intensity showed a large effect between the 20% and 35% conditions ($|d| = 0.82$) and a negligible effect between the 35% and 50% conditions ($|d|| = 0.21$). For onset timing, post-hoc comparisons indicated a negligible effect size between -100 ms and 0 ms ($|d| = 0.14$) and a small effect between +100 ms and 0 ms ($|d| = 0.28$).

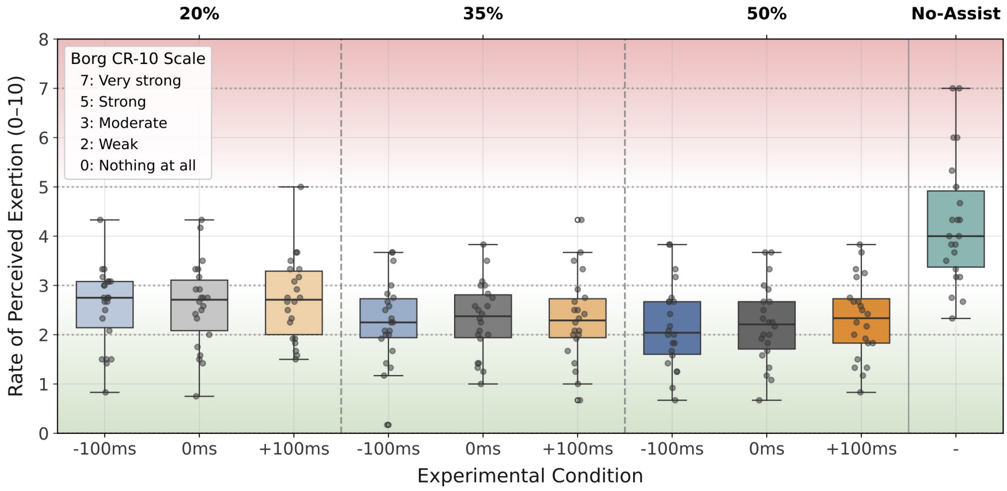

Figure 3.3: Rate of Perceived Exertion. Boxplots showing the distribution of RPE scores across experimental conditions.

3.3.2 Movement Accuracy

» Trueness

Figure 3.4A shows the time-series profile of joint angles during the task. The joint angle at the end of the task tended to align with the 90° target regardless of assistance rate. This high level of trueness is also evident in Figure 3.4B, which displays the distribution of participants' mean joint angles within the analysis window. Except for several overshoots in the 50% condition, most participants remained within the target range.

Because the data violated the normality assumption, an ANOVA was not performed. All condition medians also fell within ±3°, indicating no practically meaningful differences; therefore, additional models, such as a generalized linear model, were also omitted. The broad distributions and outliers suggest that precision (movement consistency) is a more sensitive measure, so subsequent analyses focused on this metric.

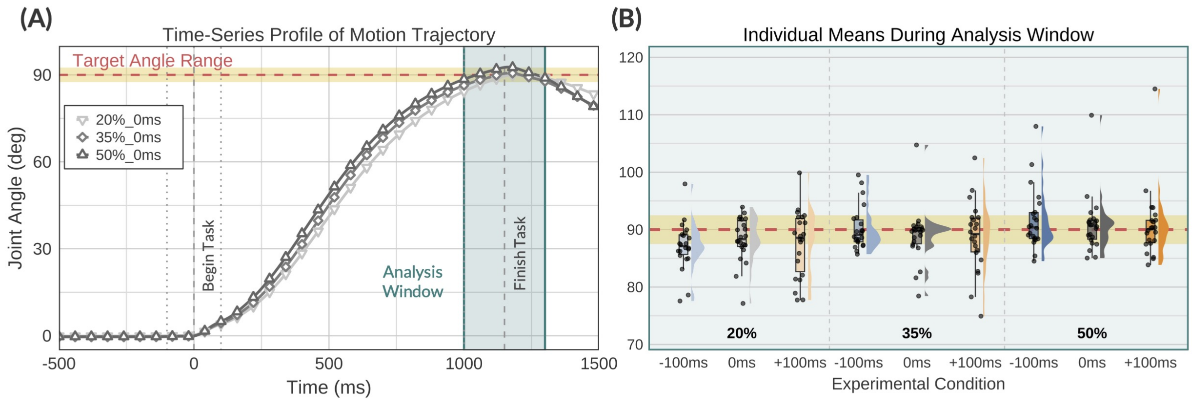

Figure 3.4: Movement Trueness. (A) Time-series motion trajectories and (B) mean joint angles across assistance conditions.

» Precision

Figure 3.5A shows the coefficient of variation (CV) across all experimental conditions. The mean CV remained below the 10% threshold under all conditions, and all pairs showed overlapping 95% confidence intervals. However, the violin plots indicated that the upper tail of the distribution widened as the assistance rate increased. Moreover, in the 50% condition, some participants exhibited CV values exceeding 20%. These trends suggest that precision deteriorates with increasing assistance rate.

The relationship between assistance rate and onset displayed a noteworthy pattern, visualized by the saddle-shaped response surface in Figure 3.5B. The surface illustrates that the two factors did not act independently but rather influenced each other. Under a low assistance rate (20%), advanced assistance (-100 ms) improved precision; under a high assistance rate (50%), it worsened precision. In contrast, delayed assistance ($+100$ ms) worsened precision under a low assistance rate but maintained it under a high assistance rate.

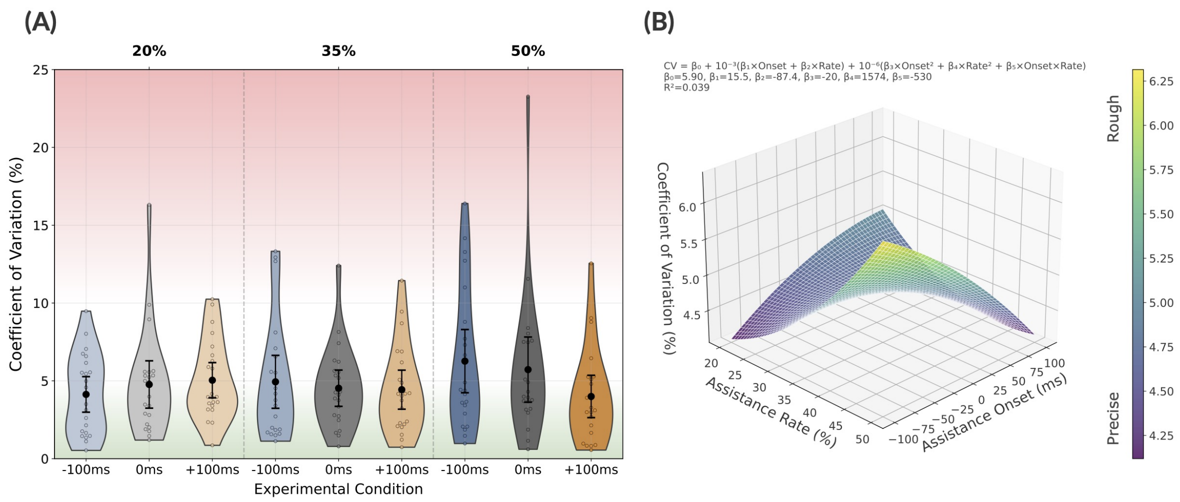

Figure 3.5: Movement Precision. (A) Violin plots showing the distribution of the CV for the elbow flexion angle across the nine experimental conditions. (B) A saddle-shaped response surface modeling the CV as a function of assistance rate and onset.

3.3.3 Motor Cooperation

» Agency

Figure 3.6A shows the Z-scores for subjective agency across all experimental conditions. Agency decreased as assistance rate increased. The -100 ms onset consistently produced low scores across rates; this pattern was most pronounced at 50%, where the -100 ms onset yielded the lowest mean among all conditions. In contrast, scores were relatively preserved under the $+100$ ms onset.

ANOVA revealed significant main effects of both assistance rate ($F(2,42) = 11.5$, $p < 0.001$, $\eta^2_G < 0.19$) and onset ($F(2,42) = 4.1$, $p < 0.05$, $\eta^2_G = 0.04$). However, no significant interaction effect was found ($F(4,84) = 0.73$, $p = 0.57$, $\eta^2_G = 0.01$), suggesting that the two factors independently reduced the sense of agency. Post-hoc analysis for assistance rate showed a small effect size between the 20% and 35% pairs ($|d| = 0.3$) and a medium effect size between the 35% and 50% pairs ($|d| = 0.5$). For assistance onset, a small effect size was observed between the -100 ms and 0 ms pairs ($|d| = 0.39$), whereas the effect size between the 0 ms and $+100$ ms pairs was negligible ($|d| = 0.15$).

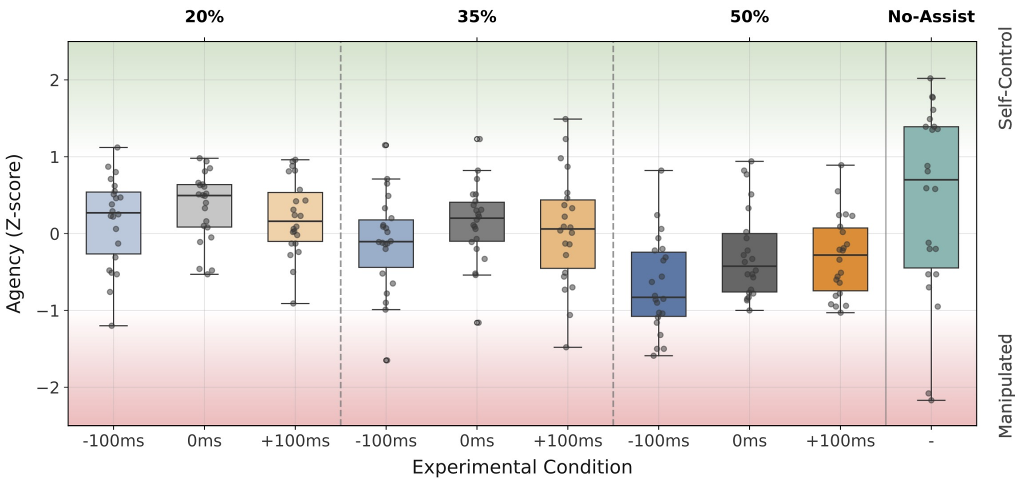

Figure 3.6: Agency. Boxplots showing the distribution of Z-scores from the subjective evaluation of Agency (Q2).

» Fluency

Figure 3.7A show the Z-scores for subjective fluency across all experimental conditions. Mean Z-scores decreased as the assistance rate increased, but this effect varied with the assistance onset. ANOVA revealed a significant main effect of assistance rate ($F(2,42) = 9.7, p < 0.001, \eta^2_G = 0.17$), but not of assistance onset ($F(2,42) = 3.0, p = 0.06, \eta^2_G = 0.03$). A significant interaction between rate and onset was detected ($F(4,84) = 3.0, p < 0.05, \eta^2_G = 0.03$); simple-effects tests were not significant, indicating a crossover interaction.

The response surface illustrates this interaction (Figure 3.7B). Along the -100 ms onset line, fluency decreased sharply with increasing assistance rate, whereas along the $+100$ ms line, the decrease was gradual. Consequently, the -100 ms onset yielded higher fluency at low assistance rates, but the $+100$ ms onset became superior at high rates. This differential slope across assistance rates represents the detected interaction.

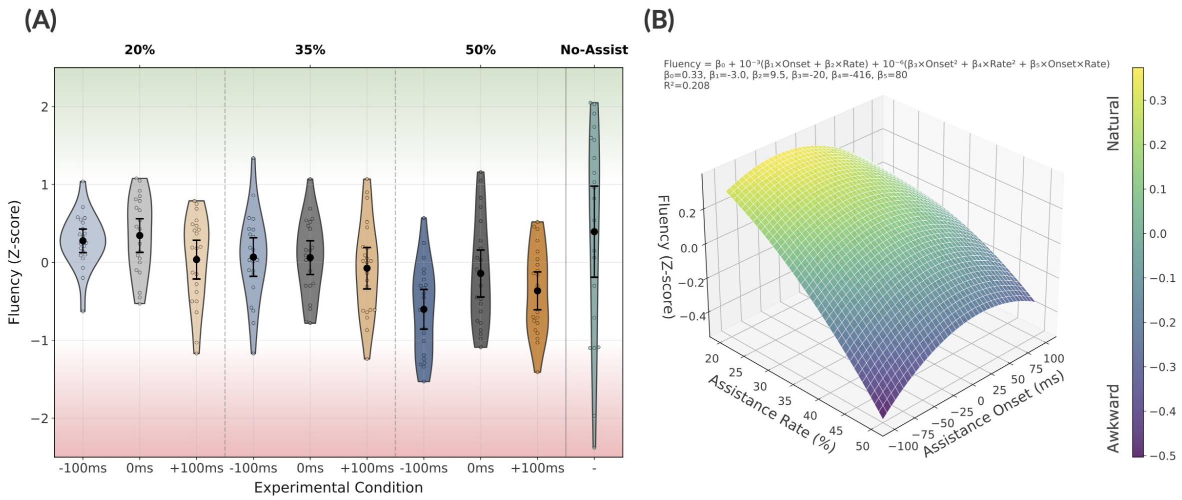

Figure 3.7: Fluency. (A) Boxplots showing the distribution of Z-scores from the subjective evaluation of Fluency (Q3). (B) A response surface modeling the fluency Z-score as a function of assistance rate and onset.

» Post-Experiment Interview

Selected participant responses from the post-experiment interviews are presented in Table 3.3.

Table 3.3: Selected participant responses from the post-experiment interviews.

Category	Selected Responses
Perception	• With strong assistance, it felt like the exoskeleton was toying with me. It gave me a powerful boost at first, then seemed to shut down right before the target. I worried the dumbbell might drop, so I consciously supported it myself. • When the assistance was weak, I couldn't reach the target angle, so I had to add my own force. It's hard to hit the target by accelerating; I'd rather apply the brakes to fine-tune the position. • When the assistance was early, it was easy to control because I just had to follow the leading torque. It felt like pedaling on an e-bike; I could accelerate effortlessly. • With delayed assistance, it was less startling. I could move naturally at my own pace.
Motor Control	• I focused on keeping my elbow relaxed to accurately reach the target accurately. I feel that if I try to force the deceleration, I'll actually undershoot. • When I felt a discrepancy between my intention and the assistance, I wanted to correct the error, but by the time I noticed, it was too late.
Adaptation	• Before I got used to it, I tried to initiate the movement myself and ended up fighting the exoskeleton, which made my motion jerky. I learned to let the device initiate the movement and just focused on stopping it at the right time. • After getting used to weak assistance, the non-assistance condition felt like 'the dumbbell is heavy.' In contrast, after getting used to strong assistance, it felt like 'my own body was heavy.'

3.4 Discussion

3.4.1 Physical Load

Significant main effects of assistance rate were observed for both muscle activity (Figure 3.2) and RPE (Figure 3.3), with effect sizes decreasing as the assistance rate increased. Notably, the mean difference in BB EMG between the 35% and 50% assistance rates was only 1.5%MVC, substantially lower than the theoretical difference of 3.75%MVC. This saturation effect may reflect participants' adoption of a conservative motor strategy, such as conscious control to prevent overshoot (Choi et al., 2020a) and preparation for the impact of the abrupt cessation of assistance. These findings support hypothesis (H3).

No interaction between assistance rate and onset was observed for either BB EMG or RPE. Although a statistically significant main effect of onset was found for RPE, the effect size was negligible ($\eta_G^2 = 0.004$). From the perspective of physical load, this suggests that the optimal onset timing remains constant regardless of the assistance rate. Therefore, hypothesis (H4) was not supported.

This absence of interaction may be attributable to the temporal profile of the assistive torque. In a previous study that reported an interaction (Yang et al., 2024), a smooth bell-shaped torque curve was used, which made it easier for participants to anticipate assistance. In contrast, for simplicity, this study employed a pulse-like torque curve (Figure 3.1). As a result, participants experienced abrupt "surges" and "plunges" (Table 3.3) and needed to maintain constant muscle tension. Consequently, any potential interaction between the assistance onset and assistance rate may have been masked. Specifically, the discontinuous torque profile may have counteracted the potential benefits of different timing strategies. Advanced assistance may reduce inertial resistance at low rates, whereas delayed assistance may mitigate overshoot at high rates; both effects may have been offset.

3.4.2 Movement Accuracy

Objective movement accuracy remained high across all conditions. Trueness was high, as evidenced by median elbow angles remaining within $\pm 3^\circ$ of the target (Figure 3.4). Precision was also acceptable, with the mean coefficient of variation (CV) not exceeding the 10% threshold (Figure 3.5). Based on these objective metrics, a decline in accuracy with increasing assistance intensity, as predicted in hypothesis (H5), was not observed. However, subjective fluency decreased significantly as the assistance rate increased (Figure 3.7). This result suggests that a mismatch between assistance and participants' intent requires conscious control. In other words, although objective accuracy did not decrease, it likely came at the cost of greater cognitive effort to make adjustments.

Another key finding was the interaction effect between assistance intensity and onset. This interaction was statistically significant for subjective fluency, and a similar trend was observed for precision, with the CV forming a saddle-shaped response surface. This consistent pattern indicates that the optimal assistance onset timing reverses depending on assistance intensity. This can be explained from two perspectives.

The first involves an intra-task control strategy. Humans predict the intensity and trajectory of a movement and switch their control strategy accordingly (Wolpert and Ghahramani, 2000). Under low assistance rates, where participants must generate more of their own force, advanced assistance likely facilitates smooth initiation aligned with the participant's predictive motor plan. In contrast, under high assistance rates, the primary challenge was braking to prevent an overshoot (Table 3.3). In this context, delayed assistance may have been more congruent with the strategy of gradually applying force to counteract the excessive external power.

The second perspective concerns the inter -task adaptation strategy. When moving under uncertainty, humans tend to plan the next action based on the average of past experiences, or statistical expectation (Kording and Wolpert, 2004). This is a rational strategy for maintaining flexibility in the face of unpredictable events. In a blinded experiment like this one, participants likely adapted to an implicit baseline corresponding to the most moderate condition experienced (intensity: 35%, onset: 0 ms). The conditions that deviated most from this baseline were "low-intensity delayed assistance" and "high-intensity advanced assistance." It is plausible that the decline in fluency under these extreme conditions was caused by the large discrepancy between the actual assistance and participants' expectations.

3.4.3 Sense of Agency

The first half of hypothesis (H6), namely that higher assistance intensity diminishes the sense of agency, was supported by a significant main effect, with effect size increasing with assistance intensity (Figure 3.6). However, the latter half of the hypothesis, that this decline could be counteracted by delaying assistance onset, was not supported because no interaction was found. Under the 50% assistance condition, delaying onset by $+100$ ms was insufficient to fully compensate for the decline in agency scores. This suggests that the effects of excessive mechanical intervention are sufficiently strong that minor timing adjustments alone cannot overcome them.

A significant main effect of assistance onset on the sense of agency was nevertheless observed. Notably, an early onset of -100 ms consistently lowered agency scores regardless of assistance rate. This pattern indicates a "negativity bias" in the perception of agency (Morewedge, 2009): users are highly sensitive to a perceived "loss" of agency when they are moved by the machine against their will (Takahata Keisuke, 2012), whereas movements that align with their intentions are taken for granted and are less likely to be perceived as an "enhancement" of agency. This perceptual asymmetry (also suggested in Chapter 2) likely underlies the difficulty of fine-tuning assistance timing.

This bias was further substantiated by unexpected ratings in the "non-assistance" trials (Figure 3.6). Despite the questionnaire's anchor for a $+5$ score being "the sensation of moving with one's own body" and participants being informed beforehand that no assistance would be provided, some participants gave remarkably low agency scores. In a situation where absent bias should have been rated $+5$, these low ratings indicate that the discrepancy from assistance expectations built up over prior trials was experienced as a strong sense of incongruity. This suggests that participants adapted to the exoskeleton's characteristics and formed unconscious motor predictions within a short period.

3.4.4 Toward an Optimal Assistance Strategy

A significant interaction between assistance onset and assistance rate on subjective fluency was observed. It became evident that advanced assistance at low assistance rates and delayed assistance at high assistance rates reduced the need for conscious adjustments. Which strategy is more desirable can be assessed by examining trends in the effects of assistance rate. As supported by hypothesis (H3), the physical-load-reduction benefit began to saturate at an assistance rate of approximately 35%. In contrast, consistent with the first part of hypothesis (H6), the sense of agency declined steadily as the assistance rate increased.

Considering this asymmetry between benefits and drawbacks, a desirable strategy would be to combine advanced assistance (-100 ms) with an assistance rate up to 35%, the point where the load-reduction effect begins to plateau. This parameter set allows efficient gains in load reduction while minimizing loss of the sense of agency. However, this theoretical optimal solution may not always be desirable. Final parameters should be determined based on the specific requirements of the task and user priorities.

3.4.5 Conclusion

This study investigated how assistance intensity modulates the effects of assistance onset on motor cooperation. The load-reduction effect, measured by BB EMG and RPE, saturated at high assistance rates. Movement accuracy was maintained across conditions; however, participants required more conscious control to adapt to changing assistance conditions. This difficulty was reflected in subjective evaluations as a crossover interaction in fluency: at low assistance rates, advanced assistance was perceived as more fluent, whereas at high assistance rates, this relationship reversed.

Chapter 4 General Discussion

4.1 Summary

This study addresses disruptions in motor control that arise when exoskeleton-assistance timing is misaligned with users' movement intent. Such misalignment can make users feel driven by the machine rather than in control, and its impact is particularly pronounced during rapid movements, where even small onset offsets can degrade performance. These disruptions not only compromise movement quality and safety but also undermine user confidence, thereby hindering acceptance and widespread adoption of exoskeleton technology. Against this backdrop, this thesis investigates how assistance onset timing affects human motor responses—movement accuracy, physical load, and subjective evaluations (Chapter 1).

While most existing research has taken reactive approaches—sensing human states (posture, motion, muscle activity) and providing immediate assistance—this study proposes a timing-based approach that leverages deliberate temporal offsets aligned with the inherent temporal characteristics of the human sensorimotor system. The first experiment showed that slightly advanced assistance enhanced movement accuracy, whereas slightly delayed assistance improved subjective movement smoothness. These findings suggest that the optimal assistance onset for motor cooperation need not coincide with the moment of motor intention; instead, introducing temporal offsets that account for neuromuscular delays may be preferable (Chapter 2).

The second experiment further showed that the optimal assistance onset varied with assistance intensity. A crossover interaction emerged: advanced assistance yielded higher subjective fluency at low assistance intensities, whereas delayed assistance was superior at high intensities. This pattern indicates that as assistance intensity increases, users' conscious effort to maintain precision also increases, necessitating different timing strategies for compensation. Additionally, while load-reduction benefits plateaued at high assistance intensities, agency scores consistently declined with increasing intensity. These results suggest that subjective measures (agency and fluency) are as crucial as objective measures (muscle-load reduction and accuracy) for exoskeleton acceptance (Chapter 3).

The following sections discuss the implications of these findings for industrial implementation and exoskeleton design, and then examine the study's limitations and directions for future research.

4.2 Implications

Unanticipated exoskeleton activation is a critical hazard that can lead to falls and collisions (Massardi et al., 2023). Consequently, international standards for exoskeletons stipulate that risk assessments be conducted to prevent the application of excessive torque at unexpected times (ASTM International, 2017; International Organization for Standardization, 2014). Nevertheless, quantitative criteria and test methods remain largely unestablished (Li-Baboud et al., 2023). This study examined how assistance onset timing affects motor intention and showed that temporal offsets within ± 100 ms of voluntary movement balance movement accuracy and the sense of agency. It also identified risks when deviating from this range, including a compromised sense of agency with advanced assistance (-200 ms) and impaired precision with delayed assistance ($+300$ ms).

This study also showed that users can adapt to exoskeleton assistance within a short period. One participant reported, "After getting used to strong assistance, it felt like my own body was heavy, not the dumbbell" (Table 3.3). This suggests that exoskeleton use may alter body schema. Performing tasks in this state can lead to accidents associated with motor control disruptions, such as dropping tools or falling. To mitigate this risk, safety measures include implementing a cool-down period that gradually decreases assistance after high-intensity tasks and cautioning users to proceed carefully immediately after doffing the device.

To ensure safety in practical settings, a design philosophy that considers the user's subjective experience is essential. Exoskeleton assistance torque has traditionally been optimized for specific objectives, such as metabolic cost or movement accuracy (Franks et al., 2022; Kim et al., 2022). However, the sense of discomfort accompanying motor control disruption remains an issue that is often addressed by developer intuition (Yeoh et al., 2023). This study systematically investigated how assistance intensity and onset timing affect physical load, movement accuracy, and subjective evaluations. The results showed that, even when objective movement accuracy was maintained, subjective fluency decreased as a hidden cost.

This phenomenon can be explained by the interaction between assistance intensity and onset timing. Specifically, advanced assistance enhanced fluency ratings at low intensity, whereas delayed assistance did so at high intensity, suggesting that users unconsciously switch control strategies according to task load. Therefore, in exoskeleton design, it is crucial not to pursue a single optimal value but to understand user acceptance of assistance and to adjust parameters dynamically to the task situation.

4.3 Limitations & Future Work

This study focused on elbow flexion to ensure interpretability. However, elbow extension may involve more conservative motor control strategies. For instance, in nursing care, patients must be carefully lowered into beds or wheelchairs (Davis and Kotowski, 2015). Consequently, users may reject abrupt assistance and prioritize control stability. Additionally, extension involves eccentric muscle contraction, which imposes a greater physical load than flexion (Powers and Howley, 2018). Thus, users may avoid forceful or rapid movements. As task demands change in these ways, the timing of the desired assistance onset may also vary. Future research should examine how the tradeoff relationships identified in this study (accuracy, load reduction, and agency) shift under elbow extension conditions.

Another limitation was the focus on single-arm movements. Bilateral movements pose challenges for achieving coordinated motion (Choi et al., 2020b). For example, vehicle operation requires simultaneous manipulation of the steering wheel and gear shift. Under divided attention, coordinating the dominant and non-dominant hands may lead users to prioritize agency over load reduction. Assembly tasks require precision and symmetry. Mismatches in assistance onset between the left and right arms may necessitate additional adjustments to maintain balance. Therefore, future research should test the applicability of these findings to bilateral movements and establish acceptable ranges for left-right assistance onset discrepancies.

Future research will require expanding the experimental paradigm. One promising approach involves enhancing assistance predictability through sensory priming (Stoykov and Madhavan, 2015). Providing anticipatory cues, such as tactile vibrations or auditory signals, before the onset of assistance (Harshe et al., 2024) could facilitate motor coordination. Additionally, adaptation to temporal offsets between sensory modalities (temporal recalibration) warrants attention (Bubna et al., 2022). Users who initially experience timing-related discomfort may recalibrate their sensorimotor predictions through repeated exposure (Matsubara et al., 2020). However, the rate and extent of this adaptation vary among individuals. Understanding individual differences in these learning curves can inform the personalization of training protocols for exoskeleton deployment.

4.4 Conclusion

This thesis demonstrates how assistance onset timing affects motor cooperation during elbow flexion. The main contributions are twofold: first, an experimental framework was established by defining the components of motor cooperation for quantitative evaluation; second, experiments showed that an intentional ± 100 ms offset in assistance onset enhances movement accuracy and subjective fluency. The study also revealed tradeoffs among key metrics, including accuracy, physical load, and agency, and showed that the optimal timing depends on assistance intensity. These findings provide guidelines for designing intuitive exoskeletons that operate without conscious adjustment. Future work should extend these findings to more complex tasks, including elbow extension and multijoint movements.

Appendix

Table AP 1: Specification of Experiment Setup

Item	Model No.	Manufacturer
Monitor	LCD- MF321XDB-B	I-O DATA, Japan
Dumbbell	STW-109	SINTEX, China
Wrist Brace	Wrist Brace with 3 Stays	FREETOO, Hong Kong
Load Cell	1269f2, T.K.K.1269f	TAKEI KIKI KOGYO, Japan
Strain Amplifier	TSA-210	TAKEI KIKI KOGYO, Japan
Motor	M-3411P-LN-08D	Teknic, USA
Microcontroller	TMS320F28379D	Texas Instruments, USA
EMG Electrodes	BuleSensor, P-00-S	Ambu, Malaysia
BIO Amplifier	Bioamp, ML132	ADInstruments, New Zealand
A/D Converter	PowerLab, 16/30	ADInstruments, New Zealand
EMC Shielding Mat	MaP1000 Series, S-10-1	SUNTECH JAPAN, Japan
Alcohol Cotton Pad	Alwety, 31078	SUZURAN MEDICAL, Japan
Skin Preparation Gel	skinPure, YZ-0019	NIHON KOHDEN, Japan
Surgical Tape	Transpore, 25mm	3M, USA

実験質問紙 1枚目 / Experiment Questionnaire Page 1

Q1. 主観的運動強度 / Rate of Perceived Exertion

肘屈曲中に感じた運動の程度は、どの程度でしたか？

How intense was the movement during elbow flexion?

0 何も感じないほど弱い *Nothing at all*
0.5 極めて弱い *Extremely weak*
1 とても弱い *Very weak*
1.25
1.5
1.75
2 弱い *Weak*
2.25
2.5
2.75
3 普通 *Moderate*
3.5
4
5 きつい *Strong*
6
7 とてもきつい *Very strong*
8
9
10 極めてきつい *Extremely strong*

試行が終わりましたら、実験者に口頭で回答ください。
Please verbally respond to the experimenter when you have completed each trial.

Figure Ap 1: Questionnaire of The 2nd Experiment (Q1:RPE)

実験質問紙 2枚目 / Experiment Questionnaire Page 2

Q2. 主体感 / Agency

支援力が加わっても、自分の意図通りに動作できましたか？
Even with the assistance force, did you feel you could perform the movement as you intended?

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
○	○	○	○	○	○	○	○	○	○	○

全く意図通りでない Not at all as intended	どちらともいえない Neutral	完璧に意図通り Perfectly as intended

Q3. 流暢さ / Fluency

滑らかな運動を実現するために、支援力に対する意識的な調整はどの程度必要でしたか？
To achieve smooth movement, to what extent did you feel conscious adjustment to the assistance force was necessary?

-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
○	○	○	○	○	○	○	○	○	○	○

強く意識した Much concious adjustment	どちらともいえない Neutral	全く意識しなかった No concious adjustment

試行が終わりましたら、実験者に口頭で回答ください。
Please verbally respond to the experimenter when you have completed each trial.

Figure Ap 2: Questionnaire of The 2nd Experiment (Q2:Agency, Q3:Fluency)

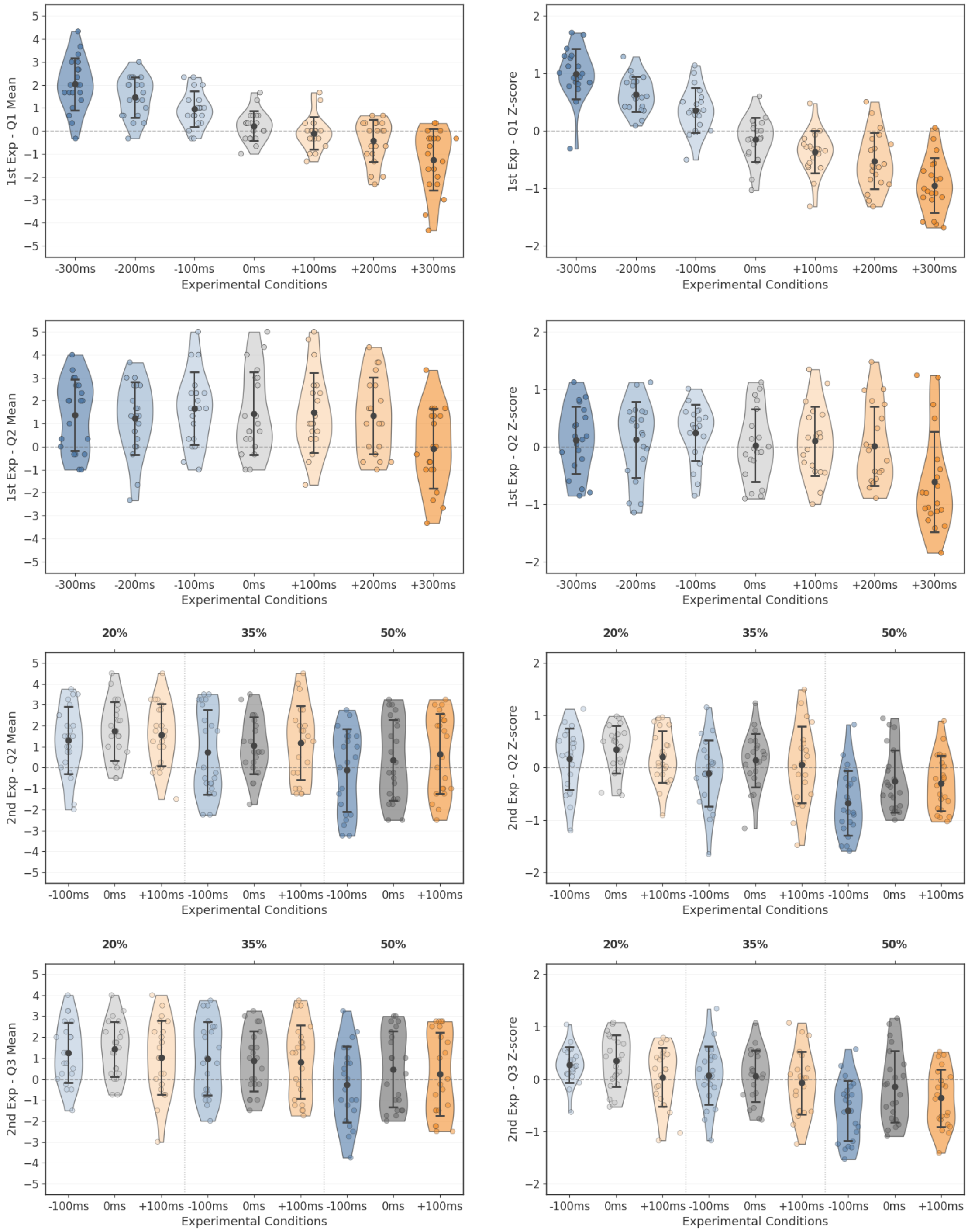

Figure Ap 3: Comparison of Raw and Standardized Subjective Ratings. Distributions of raw scores (left) and their Z-score (right) for four metrics—timing discrepancy, smoothness, agency, and fluency—from two experiments across all tested conditions.

Listing Appendix.1: R: Sample Size Calculation for Main Effects in One-way Repeated Measures ANOVA

```r
# --- Parameter settings ----------------------------------
alpha  <- 0.05    # significance level
target <- 0.80    # desired power
f      <- 0.25    # effect size
k      <- 1       # levels of between factor (grouping factor)
m      <- 7       # number of repeated measures (conditions)
# Note: For a one-way repeated-measures ANOVA, k = 1
#       (i.e., no between-subjects factor), and m is the number of
#       repeated measures (conditions) within the subjects.
eps    <- 0.75    # -GreenhouseGeisser epsilon
rho    <- 0.5     # correlation between repeated measures

power_rm_anova <- function(N, alpha, f, k, eps, rho) {
  df1    <- (m - 1) * eps                 # numerator degrees of freedom
  df2    <- (N - k) * (m - 1) * eps       # denominator df (GG-corrected)
  u       <- m / (1 - rho)                # adjustment for correlation
  lambda <- f^2 * u * N                   # non-centrality parameter
  Fcrit  <- qf(1 - alpha, df1, df2)       # critical F value
  1 - pf(Fcrit, df1, df2, ncp = lambda)   # statistical power
}

# --- Search for required sample size ---------------------
N_seq <- 8:40
pow   <- sapply(N_seq, power_rm_anova,
                alpha = alpha, f = f, k = k, eps = eps, rho = rho)
N_need <- N_seq[min(which(pow >= target))]

# --- Display result --------------------------------------
cat("Required sample size =", N_need, "participants\n")

# (Optional) Plot power curve
plot(N_seq, pow, type = "l", lwd = 2,
     xlab = "Sample Size N", ylab = "Statistical Power",
     main = "Power Curve for 1-way Repeated-Measures ANOVA")
abline(h = target, v = N_need, lty = 2)
text(N_need, target,
     labels = paste0("  N = ", N_need), pos = 4)
```

Listing Appendix.2: Python: Counterbalanced Experimental Schedule Generation Using Randomized-Block Design

```python
import random
import csv

# Settings
num_subjects = 20
conditions = ['-300ms', '-200ms', '-100ms', '0ms', '+100ms', '+200ms','+300ms']
num_sections = 5

def generate_experiment_schedule(num_subjects=20, conditions = conditions, num_sections=5):
  all_schedules = []

  for subject in range(num_subjects):
    subject_schedule = []
    previous_section = []

    for section in range(num_sections):
       while True:
        current_section = random.sample(conditions, len(conditions))
        if current_section != previous_section:
          subject_schedule.append(current_section)
          previous_section = current_section
          break

    all_schedules.append(subject_schedule)

  return all_schedules

# Generate the schedule
schedules = generate_experiment_schedule(num_subjects, conditions, num_sections)

#Export as CSV
with open('experiment_schedule.csv', 'w', newline='') as csvfile:
  fieldnames = ['Participants', 'Section', 'Trial', 'Condition']
  writer = csv.DictWriter(csvfile, fieldnames=fieldnames)
  writer.writeheader()

  for subject_id, schedule in enumerate(schedules, 1):
    for section_id, section in enumerate(schedule, 1):
      for trial_id, condition in enumerate(section, 1):
        writer.writerow({
          'Participants': subject_id, 'Section': section_id,
          'Trial': (section_id - 1) * len(conditions) + trial_id,
          'Condition': condition
})
print("The CSV File was generated: experiment_schedule.csv")
```

Listing Appendix.3: Python: Low-pass Signal Filtering Using 4th-order Butterworth Filter

```
# Required Libraries
from scipy.signal import butter
from scipy.signal import filtfilt

# Function to apply IIR filter to the data
def apply_iir_filter(data, cutoff=10, fs=1000, order=4):
    nyquist = 0.5 * fs
    normal_cutoff = cutoff / nyquist
    b, a = butter(order, normal_cutoff, btype='low', analog=False)
    filtered_data = filtfilt(b, a, data)
    return filtered_data
```

Listing Appendix.4: Python: Derivatives Calculation Using Five-Point Central Difference Method

```
# Required Libraries
import pandas as pd

# Function to calculate the first derivative using 5-point central difference
def central_difference_5pt(data, dx=0.01):
    d_data = (-data[4:] + 8 * data[3:-1] - 8 * data[1:-3] + data[:-4]) / (12 * dx)
    return [0, 0] + list(d_data) + [0, 0]

# Function to process motion-related columns (position, speed, acceleration)
def process_motion_columns(df):
    df['motor_pos'] = apply_iir_filter(df['motor_pos'].values)
    df['motor_speed'] = central_difference_5pt(df['motor_pos'].values)
    df['motor_acceleration'] = central_difference_5pt(df['motor_speed'].values)
    df['motor_jerk'] = central_difference_5pt(df['motor_acceleration'].values)
    return df
```

Listing Appendix.5: Python: EMG Signal Processing: Full-wave Rectification and Temporal Smoothing

```
import pandas as pd

# Settings
ROLLING_WINDOW = 100

def process_emg(df, channel):
    df = df.copy()
    #Avoiding errors when myoelectric values contain missing values
    df[channel] = pd.to_numeric(df[channel], errors='coerce')

    #full-wave rectification
    df[channel] = df[channel].abs()

    #temporal smoothing (time averaging)
    df[channel] = df[channel].rolling(ROLLING_WINDOW, center=True).mean()
    return df
```

Listing Appendix.6: R: Standardization Using Z-score Transformation

```
# Required Libraries
library(dplyr)

# Load the CSV file
# Replace "path/to/csv" with the actual file path of your dataset
data <- read.csv("path/to/csv")

# Calculate Z-scores for ANSWER by Subject
data_zscore <- data %>%
  group_by(Subject) %>%                # Group by Subject
  mutate(
    ANSWER_mean = mean(ANSWER, na.rm = TRUE),  # Calculate mean of ANSWER
    ANSWER_sd = sd(ANSWER, na.rm = TRUE),      # Calculate standard deviation of ANSWER
    ANSWER_Z = (ANSWER - ANSWER_mean) / ANSWER_sd      # Calculate Z-score for ANSWER
  ) %>%
  select(-ANSWER_mean, -ANSWER_sd)             # Optionally drop intermediate columns

# View the processed data
print(data_zscore)

# Optionally, save the Z-score results to a new CSV file
write.csv(data_zscore, "Zscore_Results.csv", row.names = FALSE)

# The above program assumes a CSV file structure like this:
| Subject | Condition | Answer |
|---------|-----------|--------|
| S01     | -100ms    |  1.00  |
| S01     | -200ms    |  2.33  |
| S01     | -300ms    |  3.00  |
| S01     | +100ms    | -0.33  |
| S01     | +200ms    |  0.00  |
```

Listing Appendix.7: R: Data Preprocessing: Missing Value Detection, Outlier Identification, and Normality Testing

```
# Packages
library(tidyverse)

# 1) Missing value detection
check_missing <- function(df){
  list(counts = colSums(is.na(df)),
       positions = which(is.na(df), arr.ind = TRUE),
       has_missing = anyNA(df))
}

# 2) Outlier detection by IQR within each condition
check_outliers <- function(df){
  df %>%
    group_by(Test_Condition) %>%
    mutate(Q1 = quantile(mean_val, .25),
           Q3 = quantile(mean_val, .75),
           IQR = Q3 - Q1,
           is_out = mean_val < (Q1 - 1.5*IQR) | mean_val > (Q3 + 1.5*IQR)) %>%
    filter(is_out) %>%
    select(Subject, Test_Condition, mean_val) %>%
    {list(outliers = ., has_outliers = nrow(.) > 0)}
}

# 3) Average three trials for each Subject × Condition
average_trials <- function(df){
  df %>% group_by(Subject, Test_Condition) %>%
    summarise(mean_val = mean(mean_val), .groups = "drop")
}

# 4) Normality check per condition (–ShapiroWilk)
check_normality <- function(df){
  df %>% group_by(Test_Condition) %>%
    summarise(stat = shapiro.test(mean_val)$statistic,
              p    = shapiro.test(mean_val)$p.value,
              normal = p > .05)
}

# Wrapper to execute all checks
run_checks <- function(path){
  raw <- read_csv(path) %>%
    mutate(across(c(Subject, Test_Condition), as.factor))
  avg <- average_trials(raw)
  list(missing   = check_missing(raw),
       outliers  = check_outliers(raw),
       averaged  = avg,
       normality = check_normality(avg))
}
```

Listing Appendix.8: R: 1-way Repeated Measures ANOVA with Bonferroni-corrected Post-hoc Tests

```r
# Packages
library(ez)        # repeated-measures ANOVA
library(tidyverse) # data wrangling
library(rstatix)   # pairwise t-tests (wrapper around stats::pairwise.t.test)
# Data import
data <- read.csv("path/to/csv")
df <- read_csv(data_path) %>%
  mutate(
    Test_Condition = factor(
      Test_Condition,
      levels = c("-300ms", "-200ms", "-100ms", "0ms", "+100ms", "+200ms", "+300ms")
    )
  )
# Repeated-measures ANOVA
anova_res <- ezANOVA(
  data     = df,
  dv       = .(mean_val),
  wid      = .(Subject),
  within   = .(Test_Condition),
  detailed = TRUE
)
# Bonferroni-corrected post-hoc tests
posthoc_res <- pairwise_t_test(
  df,
  mean_val ~ Test_Condition,
  paired          = TRUE,
  p.adjust.method  = "bonferroni"
)
# Effect size ('Cohens d for paired samples)
cohens_d_paired <- function(x, y) {
  d  <- mean(x - y) / sd(x - y)               # 'Cohens d
  se <- sqrt((4/length(x)) + (d^2/(2*length(x))))
  tibble(d = d, ci_lower = d - 1.96 * se, ci_upper = d + 1.96 * se)
}
effect_size_res <-
  expand.grid(c1 = levels(df$Test_Condition),
              c2 = levels(df$Test_Condition),
              KEEP.OUT.ATTRS = FALSE) %>%
  filter(c1 != c2) %>%
  pmap_dfr(function(c1, c2) {
    tmp <- df %>%
      filter(Test_Condition %in% c(c1, c2)) %>%
      pivot_wider(names_from = Test_Condition, values_from = mean_val)
    est <- cohens_d_paired(tmp[[c1]], tmp[[c2]])
    tibble(condition1 = c1,
           condition2 = c2,
           d          = est$d,
           ci_lower   = est$ci_lower,
           ci_upper   = est$ci_upper)
  })
```

Listing Appendix.9: R: Sample-size calculation for a 3 × 3 within-subjects 2-way repeated ANOVA interaction

```
library(Superpower)
set.seed(123)                          # reproducible simulation

### 1.  Design & population parameters  ---------------------------------------
alpha_level   <- 0.05   # Type-I error rate (two-sided)
desired_power <- 0.80   # Target statistical power
f             <- 0.40   # 'Cohens f (-mediumlarge interaction)
r             <- 0.0   # Assumed correlation between repeated measures

### 2.  Search grid for per-condition sample size -----------------------------
ns         <- 17:23                     # candidate n per condition
power_est <- numeric(length(ns))        # container for simulated power

for(i in seq_along(ns)){                # iterate through candidate n
  n <- ns[i]

  # Population means arranged to yield the desired A × B interaction (size f)
  delta  <- f
  mu_vec <- c(-delta, 0, delta,
             0,     0,    0,
             delta, 0, -delta)

  design <- ANOVA_design(design = "3w*3w",
                         n      = n,
                         mu     = mu_vec,
                         sd     = 1,
                         r      = r,
                         label_list = list(A = c("A1","A2","A3"),
                                           B = c("B1","B2","B3")),
                         plot   = TRUE)

  sim_res <- ANOVA_power(design,
                         alpha_level = alpha_level,
                         nsims       = 2000,    # ↑ increase for higher precision
                         verbose     = FALSE)

  # Store simulated power for the A × B interaction (convert from %)
  power_est[i] <- sim_res$main_result["anova_A:B", "power"] / 100
}

### 3.  Determine required n ---------------------------------------------------
res_df <- data.frame(n = ns, power = round(power_est, 3))
print(res_df)                           # inspection table for appendix

n_req <- ns[which(power_est >= desired_power)[1]]
cat(sprintf(
  "Minimum per-condition sample achieving %.2f power for the interaction: n = %d\n",
  desired_power, n_req))
```

Listing Appendix.10: Python: Counterbalanced Experimental Schedule Generation Using Randomized-Block Design

```
import pandas as pd
import random

# Experiment parameters
N_PARTICIPANTS = 22
ASSIST_LEVELS = ["20%", "35%", "50%"]
ONSET_LEVELS = ["-100ms", "0ms", "+100ms"]
REPS_PER_ONSET = 3

# Fixed practice block order
PRACTICE_ORDER = [
    ("20%", "0ms"), ("20%", "-100ms"), ("20%", "+100ms"),
    ("35%", "0ms"), ("35%", "-100ms"), ("35%", "+100ms"),
    ("50%", "0ms"), ("50%", "-100ms"), ("50%", "+100ms"),
]

random.seed(42)
records = []

for pid in range(1, N_PARTICIPANTS + 1):
    trial_num = 1

    # Practice block
    for assist_pct, onset_ms in PRACTICE_ORDER:
        records.append({"Subject": f"S{pid:02d}", "Trial": f"{trial_num:02d}",
                        "block": "prep", "Assist_Rate": assist_pct, "Onset": onset_ms})
        trial_num += 1
    records.append({"Subject": f"S{pid:02d}", "Trial": f"{trial_num:02d}",
                    "block": "prep", "Assist_Rate": "No-Assist", "Onset": "No-Assist"})
    trial_num += 1

    # Experimental blocks (randomized)
    assist_order = random.sample(ASSIST_LEVELS, 3)
    for blk_idx, assist_pct in enumerate(assist_order, 1):
        # Randomize onset trials
        onset_trials = [ol for ol in ONSET_LEVELS for _ in range(REPS_PER_ONSET)]
        random.shuffle(onset_trials)

        for onset_ms in onset_trials:
            records.append({"Subject": f"S{pid:02d}", "Trial": f"{trial_num:02d}",
                            "block": f"set{blk_idx}", "Assist_Rate": assist_pct, "Onset":
                                onset_ms})
            trial_num += 1
        records.append({"Subject": f"S{pid:02d}", "Trial": f"{trial_num:02d}",
                        "block": f"set{blk_idx}", "Assist_Rate": "No-Assist", "Onset": "No-
                            Assist"})
        trial_num += 1

# Save to CSV
pd.DataFrame(records).to_csv("path/to/csv/exp_design.csv", index=False)
```

Listing Appendix.11: R: 2-way RM ANOVA with Bonferroni-corrected Post-hoc Tests

```
# Load required libraries
library(readr)
library(dplyr)
library(rstatix)

# Data import and preprocessing
rpe_data <- read_csv(path/to/csv) %>%
  filter(Rate != "0%" & Onset != "No-Assist") %>%
  mutate(
    Subject = factor(Subject),
    Rate = factor(Rate, levels = c("20%", "35%", "50%")),
    Onset = factor(Onset, levels = c("-100ms", "0ms", "+100ms")),
    RPE = Q1_mean
  )

# Normality test (Shapiro-Wilk test)
normality_test <- rpe_data %>%
  group_by(Rate, Onset) %>%
  summarise(shapiro_p = shapiro.test(RPE)$p.value)

# Two-way repeated measures ANOVA
anova_result <- rpe_data %>%
  anova_test(dv = RPE, wid = Subject, within = c(Rate, Onset))

# Post-hoc tests for significant interaction
if (anova_result$ANOVA[anova_result$ANOVA$Effect == "Rate:Onset", "p"] < 0.05) {
  # Simple main effects of Onset at each Rate level
  simple_effects_rate <- rpe_data %>%
    group_by(Rate) %>%
    anova_test(dv = RPE, wid = Subject, within = Onset) %>%
    adjust_pvalue(method = "bonferroni")

  # Simple main effects of Rate at each Onset level
  simple_effects_onset <- rpe_data %>%
    group_by(Onset) %>%
    anova_test(dv = RPE, wid = Subject, within = Rate) %>%
    adjust_pvalue(method = "bonferroni")

  # Pairwise comparisons with Bonferroni correction
  pairwise_rate <- rpe_data %>%
    group_by(Rate) %>%
    pairwise_t_test(RPE ~ Onset, paired = TRUE, p.adjust.method = "bonferroni")

  # Cohen's d effect size for paired t-tests
  cohen_d <- function(x, y) {
    diff <- x - y
    mean(diff) / sd(diff)
  }
}
```

Listing Appendix.12: Python: 3D Mesh Plot with Polynomial Regression

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D

# Load data and filter out No-Assist condition
data = pd.read_csv("path/to/csv")
df = data[data['Onset'] != 'No-Assist'].copy()

# Convert strings to numeric values
df['Rate_num'] = df['Assist_Rate'].str.replace('%', '').astype(float)
onset_map = {'-100ms': -100, '0ms': 0, '+100ms': 100}
df['Onset_num'] = df['Onset'].map(onset_map)

# Build polynomial regression model
# Design matrix: intercept, Onset, Rate, Onset^2, Rate^2, Onset×Rate
X = np.column_stack([
    np.ones(len(df)),
    df['Onset_num'],
    df['Rate_num'],
    df['Onset_num'] ** 2,
    df['Rate_num'] ** 2,
    df['Onset_num'] * df['Rate_num']
])
y = df['Q2_mean'].values

# Calculate coefficients using least squares
coefficients = np.linalg.lstsq(X, y, rcond=None)[0]

# Create prediction grid
onset_grid, rate_grid = np.meshgrid(
    np.linspace(-100, 100, 40),
    np.linspace(20, 50, 40)
)

# Predict on grid
X_pred = np.column_stack([
    np.ones(onset_grid.size),
    onset_grid.flatten(),
    rate_grid.flatten(),
    onset_grid.flatten() ** 2,
    rate_grid.flatten() ** 2,
    onset_grid.flatten() * rate_grid.flatten()
])
z_matrix = (X_pred @ coefficients).reshape(onset_grid.shape)

# Create 3D plot
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.plot_surface(onset_grid, rate_grid, z_matrix, cmap='viridis', alpha=0.8)
plt.show()
```

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