



**HAL**  
open science

## Identifying individual characteristics influencing post-adaptation of motor behavior in upper-limb exoskeleton users

Océane Dubois, Agnès Roby-Brami, Ross Parry, Nathanaël Jarrassé

► **To cite this version:**

Océane Dubois, Agnès Roby-Brami, Ross Parry, Nathanaël Jarrassé. Identifying individual characteristics influencing post-adaptation of motor behavior in upper-limb exoskeleton users. 2024 IEEE-RAS International Conference on Humanoid Robots, Nov 2024, Nancy, France. hal-04812085

**HAL Id: hal-04812085**

**<https://hal.science/hal-04812085v1>**

Submitted on 29 Nov 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Identifying individual characteristics influencing post-adaptation of motor behavior in upper-limb exoskeleton users

Océane Dubois<sup>\*1</sup>, Agnès Roby-Brami<sup>1</sup>, Ross Parry<sup>2</sup> and Nathanaël Jarrassé<sup>1</sup>

**Abstract**—Over the past decade, industrial ergonomics have made significant advances, leading to the development of various occupational exoskeletons. While beneficial, exoskeletons could disrupt motor control due to their distributed interaction with the human body. This study explores individual factors influencing different adaptation patterns following exoskeleton use in asymptomatic individuals. Fifty-five participants used a 4 Degree of Freedom (DoF) arm exoskeleton to perform reaching tasks under low-magnitude force fields. Pre- and post-exposure movements were recorded via motion capture, and personal characteristics were documented. Spectral clustering identified variations in inter-joint coordination after exposition to the exoskeleton, and a random forest classifier linked these patterns to individual anthropometric, demographic and kinematic traits. The model highlighted factors such as laterality, forearm length, and some spontaneous kinematics metrics as key predictors of post-adaptation behavior. These findings underscore the need to consider individual profiles to minimize disruptive motor adaptations and improve exoskeleton safe widespread in industrial applications.

## I. INTRODUCTION

Since 2010, significant advancements in industrial ergonomics have led to the development of various commercially available occupational exoskeletons. These devices, mainly built with spring-based mechanisms, are designed to offset the weight of body parts or tools, thereby providing assistive forces to industrial workers and reducing stress and fatigue during load carrying or prolonged postures [1] [2] [3]. However, it is crucial to acknowledge that, despite their benefits, it is yet unclear if exoskeletons may disrupt motor control due to their close physical interaction with the body, particularly over extended periods. Previous research indicates that while adaptation can occur at the joint level, the end-effector may remain unaffected [4], and individual adaptation to force fields can vary significantly [5]. Nonetheless, the underlying reasons for these variations remain underexplored.

In parallel, there has been increasing attention on personalizing wearable devices to enhance their performance and utility. To date, personalization efforts have predominantly focused on lower-limb devices [6] [7]. Current approaches to personalization typically involve real-time optimization using kinematic data. These methods are complex and necessitate the use of optimal controllers to effectively manage the devices. Given that individuals exhibit different behaviors

even with the same controller, influenced by factors such as morphological characteristics, investigating the impact of personal characteristics on adaptation may offer a more straightforward approach to exoskeleton personalization.

This study aims to investigate the factors and characteristics influencing the adaptation patterns in asymptomatic individuals. Various joint force fields of low magnitude were programmed into a robotic exoskeleton to simulate typical perturbations and physical behaviours. Fifty-five participants, connected to a 4 Degree of Freedom (DoF) arm exoskeleton, performed reaching tasks under different weak magnitude force fields. Their movements, both pre- and post-exposure to the force field, were recorded using optical motion capture, alongside the collection of data on height, weight, arm length, and laterality. Here, the focus is mainly made on inter-joint coordination since previous studies have shown that different adaptation patterns are visible at this level, on the contrary of the end-effector variation [4]. This study aims at examining associations between an observed adaptation behaviour after the exposition to an exoskeleton and initial movement characteristics and personal traits of subjects, such as demographic and anthropometric informations. The subsequent sections detail the experimental protocol, the extraction of various adaptation behaviors, the exploration of the relationships between these behaviors and the subjects' personal characteristics, including natural movement kinematics and demographic or anthropometric informations.

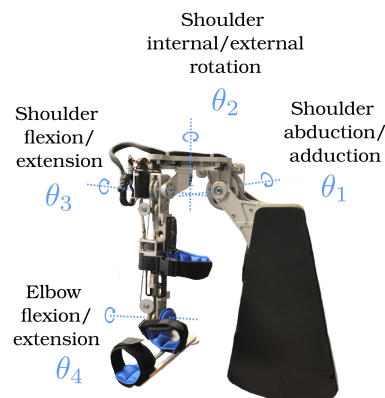


Fig. 1: Able 4 Dof exoskeleton

## II. MATERIAL AND METHODS

This section will initially describe the materials utilized in the experiment, specifically the exoskeleton and the motion

\* dubois@isir.upmc.fr

<sup>1</sup> Institute of Intelligent Systems and Robotics (CNRS-UMR 7222), Sorbonne Université, Paris, France

<sup>2</sup> LINP2, UPL, UFR STAPS, University Paris Nanterre, 200 Avenue de la République, 92001 Nanterre, France

capture system. Subsequently, the methodology will be presented, including the task, protocol, participants details, and data analysis techniques used.

### A. Material

1) *Exoskeleton*: In this experiment, a 4-DoF robotic upper-arm exoskeleton, Able, is employed. This exoskeleton features 3-DoF at the shoulder (abduction/adduction  $\theta_1$ , internal/external rotation  $\theta_2$ , and flexion/extension  $\theta_3$ ) and 1-DoF at the elbow (flexion/extension  $\theta_4$ ), as depicted in Fig. 1. Its mechanical design ensures high efficiency and minimal residual friction torques, facilitated by patented actuators [8]. The length of the exoskeleton arm is fixed, the distance between the shoulder and the elbow is 357mm. In the present study,  $\theta_1$  and  $\theta_2$  were fixed in position, using only  $\theta_3$  and  $\theta_4$ .

2) *Exoskeleton Controller*: Control algorithms are executed on a real-time controller (RTLinux) with a control loop operating at 1 kHz. The default control mode is Gravity Compensation, allowing unrestricted upper-limb motion. This mode implements a feedforward gravity compensation based on a quasi-static model of the exoskeleton. Although this mode minimizes resistance to the user's movements [9], some undesired resistance is present due to the lack of friction and dynamic compensation. This mode will be referred to as the *Transparent* condition in the experiment.

Four additional control modes or perturbative force fields, which can be superimposed on the always-on "transparent" reference condition, were designed to simulate typical perturbing force fields on the two joints  $\theta_3$  and  $\theta_4$ : *elastic*, *viscous*, *increased gravity*, and *decreased gravity*. The force field parameters were experimentally selected to apply a limited yet perceptible perturbation to users.

*Viscous*: In exoskeletons, a viscous field can emerge at the joint level due to uncompensated friction in the transmissions. In this experiment, friction is generated at each joint, depending on each joint's velocity, such that  $\tau = K_v \dot{\theta}$ . Here,  $\tau$  represents the vector of output torque of the exoskeleton joints  $\theta_3$  and  $\theta_4$  provided as feedforward with  $\tau = [\tau_3, \tau_4]$ , and  $K_v$  is a vector of friction coefficients for each joint with  $K_v^T = [2, 0.6]$ .

*Elastic*: An elastic field in exoskeletons can be induced by mechanical elasticity of the structure or by incorrectly adjusted equilibrium points of a spring mechanism. In this mode, a reference position  $\theta_{i,0}$  is defined as the rest position of the user, usually with the arm aligned with the trunk and the elbow slightly bent at  $130^\circ$ . The elastic mode is characterized as  $\tau = K_e(\theta_i - \theta_{i,0})$ , where  $\tau$  denotes the vector of output torque of the exoskeleton joints  $\theta_3$  and  $\theta_4$  provided as feedforward with  $\tau = [\tau_3, \tau_4]$ , and  $K_e$  is a vector of stiffness values for each joint with  $K_e^T = [3.5, 2]$ .

*Decreased Gravity*: Decreased gravity fields are encountered in poorly adjusted passive industrial exoskeletons, causing overcompensation of limb and/or tool weight, resulting in the user's arm feeling lighter. In this mode, decreased gravity corresponds to the overcompensation of 25% of the exoskeleton mobile part weight, giving the user the sensation

of their arm being 750 grams lighter. This is achieved by modulating the gravity vector to 0.75 of the feedforward gravity compensation in the controller.

*Increased Gravity*: Similarly, increased gravity fields can be encountered in improperly adjusted exoskeletons, making the user's arm feel heavier. The increased gravity mode corresponds to the under-compensation of the exoskeleton mobile parts weight by 25% (+750 grams). This is accomplished by modulating the gravity vector to 1.25 of the feedforward gravity compensation.

3) *Motion Capture System and Data Recording*: A motion capture system (OptiTrack, NaturalPoint, USA) is employed to track participant movements using markers placed on their trunk, arm, forearm, and hand. Specific marker placement locations are not required as the calibration algorithm (see II-B.4) does not necessitate specific placements. Four cameras positioned around the participant capture movement data, recording at 120Hz.

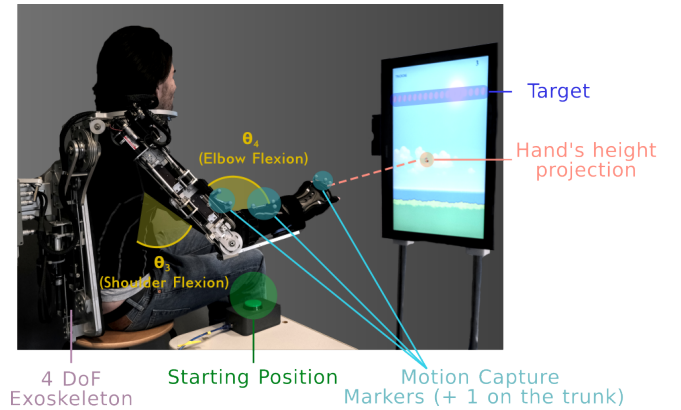


Fig. 2: Set-up

### B. Method

1) *Task and Set-up*: The task was designed to be redundant and represent a first simple case study. It involves a pointing task using one degree of freedom (DoF) controlled by two DoFs of the upper limb. Specifically, the height of the exoskeleton's extremity (representing the user's hand) controls the height of a bird-shaped cursor displayed on a screen placed 2 meters in front of the participant, as well as the targets to reach (Fig. 2). During the experiment, the participant is seated on a stool and instructed to lean against the back structure of the exoskeleton. A button is placed next to the participant so that their hand naturally rests on it in a comfortable position with the elbow slightly bent, approximately  $130^\circ$ . This button defines a repeatable starting position for the hand. For each trial, a target, represented as a horizontal line on the screen, is presented at one of nine heights in a random order. The instruction is to reach the target using two DoFs of the exoskeleton: shoulder ( $\theta_3$ ) and elbow flexion/extension ( $\theta_4$ ). The other two exoskeleton DoFs are blocked, restricting hand movement to a vertical parasagittal plane aligned with the participant's shoulder. The wrist is immobilized using a pre-made orthosis. Due to

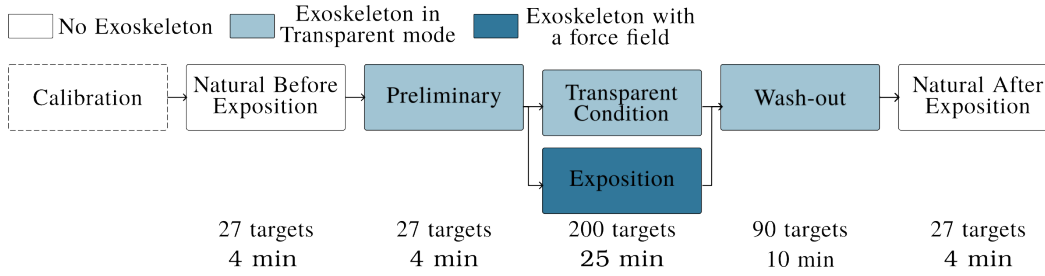


Fig. 3: Experimental protocol. The time indication can vary between subject and take into account the time to put and remove the exoskeleton

redundancy, the target can be reached by an infinite number of hand positions along an anteroposterior line at the target height in the sagittal plane. In the natural condition, reaching without the exoskeleton (but with the trunk blocked and wrist orthosis), the task can be performed with four DoFs (three shoulder DoFs and elbow flexion/extension, trunk always blocked and wrist with the orthosis).

2) *Protocol*: The experimental protocol consists of six distinct phases (Fig. 3). During the *Calibration* phase, the participant performs random, slow, and large movements without the exoskeleton for one minute. The experiment is designed to maximize the participant’s exposure to the exoskeleton, thereby enhancing the potential effects of the device. The other phases are structured to ensure sufficient repetition and data collection, while prioritizing the main exposure phase. The *Natural Before Exposition* and *Natural After Exposition* phases occur without the exoskeleton. In these phases, the participant encounters 27 targets (each of the 9 targets presented 3 times in random order). They press the button to initiate the reaching task; the target appears on the screen, and the participant then reaches for it naturally, utilizing their arm’s 4 DoFs. Once the hand remains steady at the target height for 2 seconds, the target is confirmed, and the participant can proceed to the next target by pressing the button. In the *Preliminary* and *Washout* phases, participants wear the exoskeleton in *Transparent* mode, with the first two joints blocked. They encounter 27 targets (3 times each target) and 90 targets (10 times each target) respectively, presented randomly and follow the same reaching procedure. In the *Exposition* phase, participants wear the exoskeleton with the first two joints blocked and experience one force field while reaching 200 targets (40 times for each of the 5 exposed targets). Each participant is exposed to a unique force field among the four to prevent any interference between different force field impacts. One group is exposed only to the *Transparent* force field. Participants can take breaks as needed. The exposure lasts 15 to 25 minutes.

3) *Participants*: Eleven participants were exposed to each force field and eleven to the transparent mode only, totaling 55 participants. All participants were aged between 18 and 34 years old. Height, weight, number of men and women as well as left- and right-handed participants were balanced between groups (see Table I). Each subject completed the Edinburgh inventory [10] to rate their handedness between

-100 (completely left-handed) and 100 (completely right-handed).

The study was approved by the local ethics committee at Sorbonne University, and participants provided informed consent prior to participation.

4) *Data Processing*: Motion capture markers’ raw positions and orientations were used to identify the participant’s joint rotation centers using a calibration algorithm [11]. This algorithm provides the positions of each joint rotation center (shoulder and elbow). Data were filtered using a low-pass filter with a 5Hz cutoff frequency. From the shoulder and elbow positions, joint angles were extracted using the exoskeleton joint angle sequence:  $\theta_1$ ,  $\theta_2$ ,  $\theta_3$ , and  $\theta_4$  (see Fig. 1). Movements were then segmented into single movements, starting with the button press and ending with target validation.

For each protocol phase, end-effector and joint metrics were computed: task time, overshoot (i.e., the distance between the end-effector maximum height and the target height), distance covered by the end-effector, maximum end-effector velocity, time taken to reach maximum end-effector velocity, and individual joints’ range of motion (ROM). This study focuses on participants’ reactions once the exoskeleton is removed. Therefore, for all metrics listed above, the relative differences between the pre- and post-exposure force field exposure results were computed to highlight modifications in participants’ own behavior.

In this study, the variations of inter-joints coordinations are also measured. Inter-joint coordination refers to the way joints are coordinated together in a spatial and temporal way in order to produce a movement. Both aspects are measured using dedicated metrics : Joint contribution variation based on Principal Component Analysis (JcvPCA) for spatial inter-joint coordination, and Joint synchronization variation based on Continuous Relative Phase (JsvCRP) for temporal inter-joint coordination [4]. JcvPCA uses Principal Component Analysis to compare 2 datasets. A first PCA is computed on the first dataset, defining a new reference frame. Then the second dataset is projected in this new reference frame. A second PCA is done over the projected dataset, representing the difference between the first dataset and the second dataset concerning the joints contribution. JsvCRP is based on a well known metric named CRP [12], [13] used in biomechanics to quantify the coordination between two movements. It provides a way to measure the dynamic relationship between

| Condition           | Num. of Subjects | Sex (F/M/Non-Binary) | Laterality  | Weight (kg) | Height (cm)  |
|---------------------|------------------|----------------------|-------------|-------------|--------------|
| Transparent         | 11               | 4/7/0                | 63.3 ± 36.0 | 67.7 ± 11.0 | 175.0 ± 12.6 |
| Increase of gravity | 11               | 3/8/0                | 69.7 ± 53.6 | 69.5 ± 10.3 | 176.8 ± 8.7  |
| Decrease of gravity | 11               | 3/8/0                | 50.8 ± 59.3 | 68.6 ± 6.7  | 175.6 ± 10.4 |
| Viscous             | 11               | 6/4/1                | 48.1 ± 62.5 | 67.7 ± 13.4 | 173.2 ± 12.5 |
| Elastic             | 11               | 4/7/0                | 54.2 ± 54.7 | 68.6 ± 11.2 | 173.2 ± 8.7  |

TABLE I: Characteristics of the participants by group condition

two body segments or joints in motion. Since the force field affects only shoulder and elbow flexions, we monitored only variations in their contribution to the movement (JcvPCA Shoulder Flexion and JcvPCA Elbow Flexion) and their temporal synchronization (JsvCRP Shoulder/Elbow) post-exposition to the exoskeleton.

5) *Methodology used to identify individual characteristics influencing post-adaptation behavior*: This process involved four main steps:

- 1) **Clustering Participants Based on Post-Adaptation Behaviors** : Participants were grouped into distinct post-adaptation behaviors by clustering their inter-joint coordination metric values using Spectral Clustering algorithm [14]. The optimal number of cluster is determined using an graphical method [15]. This clustering identifies different patterns of post-adaptation among subjects.
- 2) **Building a Random Forest Model** : A random forest model [16] was built using the clustered data to identify and enhance the relationships between individual characteristics (e.g., natural movement kinematics and demographic and anthropometric informations) and the observed post-adaptation behaviors. Parameters of the model are optimized via randomized search with cross-validation.
- 3) **Model Validation** : The random forest model was tested and validated to ensure the accuracy and reliability of the results. This step is used to confirm that the model accurately predicts post-adaptation behaviors based on individual characteristics.
- 4) **Main Feature Extraction** : Key features contributing to the classification of post-adaptation behavior groups were extracted. These features reveal the main factors influencing the decision-making process of the random forest model regarding the assignment of subjects to specific post-adaptation behavior groups.

### III. RESULTS

*a) Variety of adaptation behaviors*: A previous study [4] attempted to extract global reactions to different force fields. Post adaptation patterns were measured using the variations in shoulder flexion contribution (JcvPCA Shoulder), elbow flexion contribution (JcvPCA Elbow), and synchronization between shoulder and elbow flexion (JscCRP Shoulder/Elbow). However, the results were difficult to analyze, with no significant differences observed in the adaptation patterns among the various force field groups.

Yet, when examining the reaction behavior of individual subjects within a single force field, differences in their post-

adaptation pattern become apparent. Figure 4b illustrates how participants exposed to the *Viscous* force field exhibit varied responses. For example, participant 68 (yellow) shows significant changes in both elbow and shoulder contributions, as well as in shoulder-elbow synchronization after exposure to the force field. In contrast, participant 22 (pink) maintains consistent joint contributions but alters joint synchronization. Meanwhile, participant 53 (purple) adjusts shoulder contribution without modifying elbow contribution or joint synchronization. Diverse patterns can be observed in all the different post-adaptation patterns of all the different force fields, as shown for exemple in Figure 4a for the Transparent force field and Figure 4c for the Decrease of Gravity force field.

These plots demonstrate that, despite being exposed to the same condition, individuals may adapt differently. In the following work, we will analyze which individual factors could influence the different adaptation patterns of subjects exposed to a same force field.

*b) Clustering Participants on Post-Adaptation Behaviors*: The three inter-joint coordination metrics were presented in the previous section as a radar chart, but they can also be represented as a 3D scatter plot. To extract groups of reaction behaviors, the 3D data of all subjects (1 point = 1 subject) were clustered using the Spectral Clustering Algorithm, with the three clusters as defined by the graphical method.

The dataset of 55 subjects was clustered into these three groups, each exhibiting distinct adaptation behaviors. These behaviors involve either increasing or not the desynchronization of elbow/shoulder flexion, and increasing either the shoulder or the elbow contribution to the movement (see Table II and Fig. 5). Since, in this task, shoulder and elbow contributions are linked, a decrease in elbow flexion necessitates increased shoulder flexion to reach a given target.

This table highlights that certain adaptation strategies are preferred among the subjects. Regarding the desynchronization of the shoulder/elbow, almost half of the subjects (22/55) tend to desynchronize their elbow and shoulder. In the second group, approximately 30% (18/55) of the subjects, they did not change their elbow/shoulder synchronization, increased their elbow contribution to the task and maintaining the same shoulder flexion. Finally, for the third group, around 27% (15/55) of the subjects increased the contribution of their shoulder joint and maintained the same synchronization.

As indicated earlier, the type of force field might not be the only factor influencing these groups of inter-joint modification behaviors after exposure to a joint-level force

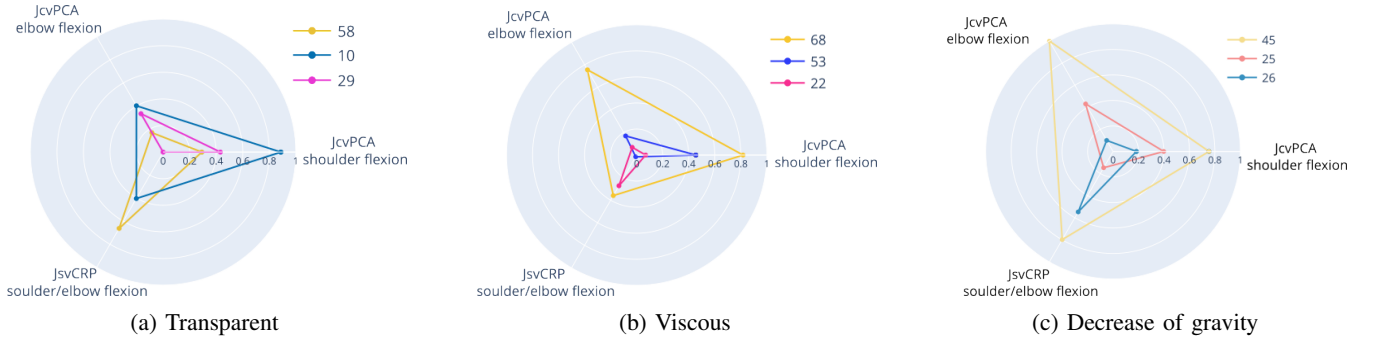


Fig. 4: Reaction behavior for 3 different participants exposed to the different force field

| Group | Num. of Subject | Inter-joint coordination |              |             | Force field repartition |                |                |      |       |
|-------|-----------------|--------------------------|--------------|-------------|-------------------------|----------------|----------------|------|-------|
|       |                 | JsvCRP Shou./Elb.        | JcvPCA Shou. | JcvPCA Elb. | Transp.                 | Incr. of grav. | Decr. of grav. | Ela. | Visc. |
| 1     | 22              | +                        | /            | /           | 5                       | 4              | 5              | 6    | 2     |
| 2     | 18              | -                        | -            | +           | 2                       | 4              | 2              | 3    | 7     |
| 3     | 15              | -                        | +            | -           | 4                       | 3              | 4              | 2    | 2     |

TABLE II: Inter-joint coordination pattern groups.

'+' means that there is an important variation in the metric and a '-' means that the modification of the metric is minor  
 Name of the conditions : Transp. = Transparent / Incr. of grav. = Increase of gravity / Decr. of grav. = Decrease of Gravity / Ela = Elastic / Visc = Viscous

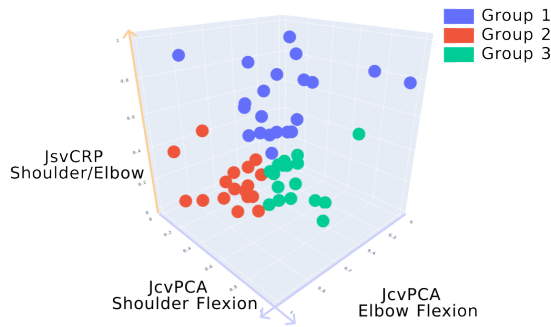


Fig. 5: Clustering of inter-joint coordination metrics

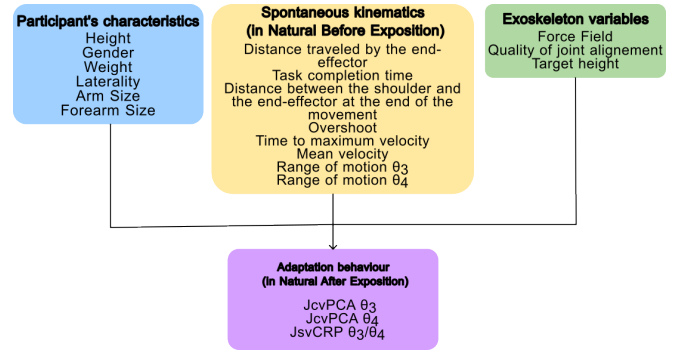


Fig. 6: Variables used for the random forest classifier

field applied by an exoskeleton. Indeed, the three different adaptation behaviors are found across all five force field groups (see the last columns of Table II). A hypothesis is that the chosen adaptation behavior might also depend on individual characteristics.

*c) Building and validating the random forest model:*  
 The goal of this section is to explore the link between demographic informations, anthropometric informations and kinematic characteristics and adaptation behavior, as summarized by Figure 6. In order to extract the complex relationships between the variables and predict the post-adaptation inter-joint coordination pattern, a random forest classifier is constructed.

The inputs include anthropometric variables (height, weight, laterality, arm, and forearm size), demographic variables (such as sex), exoskeleton variables (force field and quality of joint alignment), and spontaneous kinematic variables (mean velocity, task time, joint range of motion, etc., recorded before exposure to the exoskeleton), for a total of 18 variables. The H2O algorithm [17] is used as it can handle

categorical variables such as force field, sex, and alignment. The dataset is randomly split into 80% training and 20% test data. Each participant is present several times in each dataset since they've reached 9 different targets height, resulting in the same amount of lines in the dataset (data are averaged by participant and by target height). The model achieve 97% accuracy over the testing dataset for predicting the adaptation behavior group (see Confusion matrix on Figure 7). On the test dataset, the Root Mean Square Error (RMSE) is 0.226, and the corresponding logarithmic loss (that quantifies the uncertainty of the predictions, the closer to 0 the better) is 0.20.

*d) Main Features Extraction:* The most influential variables were extracted and are shown in Figure 8. Notably, the force field emerged as only the second most important factor in predicting reaction behavior. Anthropometric and demographic variables played a significant role, with 5 of the 9 most important features being from this category. The most critical variable was participant laterality. In contrast, spontaneous kinematic variables of the end-effector, such as

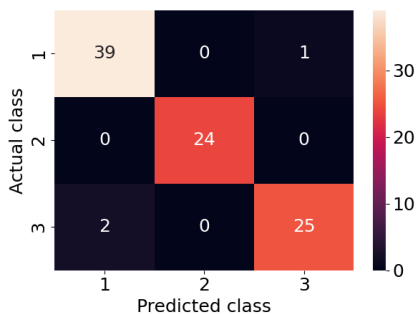


Fig. 7: Confusion matrix for the random forest classifier built over the dataset of 55 participant exposed 30min to an exoskeleton

overshoot and task time, ranked 8th and 9th, respectively, while spontaneous joint range of motion did not appear among the top predictors. The low ranking of end-effector variables and the absence of joint range of motion suggest that a large portion of exoskeleton personalization, aimed at minimizing motor control disruption, can be achieved by focusing on users' personal characteristics.

It is also noteworthy that joint alignment quality ranked fourth, highlighting its potential influence on behavior, even after the exoskeleton is removed. Since joint alignment can easily shift during exoskeleton use due to slippage, this characteristic might significantly impact post-exoskeleton use behavior. Additionally, arm and forearm size ranked highly, which may be related to non-adjustable exoskeleton segments causing misalignment with the participant's joint rotation center. This misalignment could amplify or reduce the exoskeleton's effects.

Interestingly, sex did not emerge as a significant factor in this experiment. However, sex-related morphological differences, such as weight and arm/forearm size, could influence other important variables.

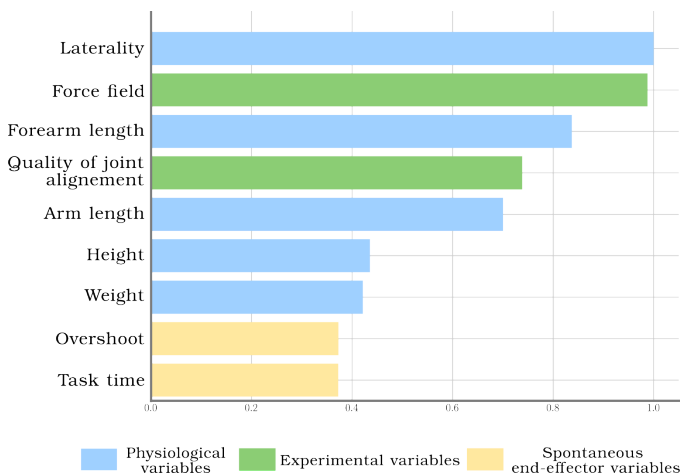


Fig. 8: Main variable importance for adaptation behavior prediction, scaled between 1 (the most important) and 0.

Based on the previous results, it may be tempting to clas-

sify individuals solely based on the most important factors and predict their post-adaptation pattern to a specific force field. However, the relationships between these variables are complex, and correlation should not be mistaken for causation. As shown in Figure 9, the importance of these factors demonstrates statistically significant differences in their distribution across the three post-adaptation groups. A Kruskal-Wallis test was performed for each variable to assess differences in distribution between groups. For laterality score, the  $p$ -value was  $< 0.001$ , indicating a significant effect, with similar results for forearm ( $p < 0.001$ ) and arm length ( $p < 0.001$ ). This suggests that a participant's laterality score, arm length, and forearm length significantly influence the type of post-adaptation they exhibit.

Although it may seem appealing to conclude that participants with lower laterality scores are more likely to belong to post-adaptation group 2 (characterized by an increased elbow contribution), the absence of clearly defined thresholds for individual factors makes such direct classification difficult. The random forest model captures complex, multivariate relationships by considering multiple factors simultaneously to predict post-adaptation responses to force field perturbations. Therefore, it is crucial to account for these intricate interactions rather than relying on any single factor to predict behavior.

#### IV. DISCUSSION AND CONCLUSION

This study demonstrates that participants exhibit different post-adaptation and retention patterns, even when exposed to the same perturbation. This work proposes a novel methodology to extract these distinct inter-joint coordination post-adaptation patterns and investigate potential relationships between these post-adaptation patterns and participants' individual characteristics—ranging from anthropometric and demographic data to kinematic metrics—and experimental conditions, such as force fields, task height, and participant-exoskeleton alignment. The methodology involves using a Spectral Clustering algorithm to identify post-adaptation patterns, followed by a Random Forest classifier to explore how various factors contribute to these patterns. By analyzing the importance of each variable in the final decision process, we observe that anthropometric and demographic data, such as *laterality*, *arm* and *forearm sizes* emerge as critical factors. This suggests that these personal characteristics play a significant role in determining how participants adapt their inter-joint coordination. Then, variables linked to the exoskeleton are also important to take into account such as the *force field* and the *joint alignment*. Importantly, the distribution of key variables among the post-adaptation groups often shows statistically significant differences, though no single variable offers a clear threshold to categorize participants alone. This underlines the need to consider interactions among multiple factors when predicting post-adaptation patterns. Based on these findings, guidelines could be developed for exoskeleton use to minimize disruptive changes in inter-joint coordination patterns. However, many occupational exoskeletons lack customization guidelines for individual users based on weight

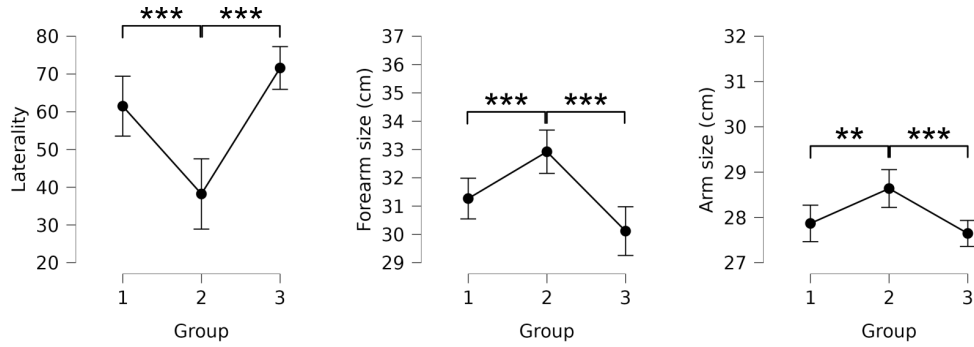


Fig. 9: Mean and average values of factors of importance per group for the short term dataset, where \* means  $p \leq 0.05$ , \*\* means  $p \leq 0.01$  and \*\*\* means  $p \leq 0.001$

or laterality, increasing the likelihood of undesirable motor post-adaptations.

However, this study has several limitations. First, participants were exposed to force fields for only 25 minutes which is far less than the multi-hour exposures expected in industrial settings. Thus, it is unclear whether the same retention patterns would occur with prolonged and repeated exposure and the generalization of actual results is therefore limited. A longer-term study with repeated exposure is necessary to determine whether these results can be reliably generalized.

Regarding the methodology, to enhance the robustness of the results,  $k$ -fold cross-validation could have been employed. In this approach, the dataset is divided into  $k$  subsets (referred to as "folds"). The model is trained and validated  $k$  times, with each iteration using a different fold as the validation set, while the remaining  $k - 1$  folds are used for training. This process is repeated until each fold has served as the validation set once. This method provides a more reliable assessment of a model's ability to generalize to unseen data and helps mitigate the risk of overfitting. In our case, the model-building process was conducted by running multiple iterations with different random splits of the dataset, ensuring that similar results were produced in each iteration. However, adopting a systematic cross-validation methodology, such as  $k$ -fold cross-validation, would have further strengthened the robustness and reliability of the results.

Moreover, retention patterns in exoskeleton use remain underexplored. While studies such as [5] and [18] identified two retention patterns, our study identified three. It is possible that increasing the number of subjects in this experiment might have revealed additional subgroups, particularly within Group 1, which could distinguish participants based on whether they increased elbow or shoulder contribution. Notably, around half the participants maintained their initial elbow/shoulder synchronization, while the other half modified it, indicating no clear preference for a specific post-adaptation pattern.

Similarly, participants in Groups 2 and 3 displayed varied behaviors, with some increasing shoulder contribution and others favoring elbow contribution. This suggests that post-adaptation is highly individualized, with each participant adjusting their inter-joint coordination based on how their

central nervous system (CNS) interprets task constraints and completion strategies. This reinforces the idea that there is no single "correct" way to coordinate joints during adaptation. The diversity of adaptation patterns highlights that joint coordination is a personal and complex process, resulting in optimal solutions unique to each individual's specific context. Similar observations were made by [19], where participants exhibited different movements under varying levels of arm support, with no consistent trends in arm adaptation. Each asymptomatic participant developed their own unique way to adapt to different support levels. In the short term, none of these post-adaptations can be classified as inherently 'good' or 'bad.' The primary concern arises if these adaptations, which emerge within minutes of exposure to perturbation, persist for several hours or even days. Shifting the load to different joints or body parts to manage the perturbation may increase the risk of overuse injuries, such as tendinopathy [20].

The dominance of demographic and anthropomorphic parameters in predicting post-adaptation behaviors might arise from the absence of force field normalization to individual participants' physiology. In this experiment, the force fields were not customized to account for differences in participants' body morphologies, future studies should take this parameter into account in order to maybe lower the importance of anthropomorphic parameters. In addition, concerning the importance of the weight of the participants in the decision variables it is important to note that different body weights are linked to differences in body weight distribution, resulting in differences in limbs inertia that could lead to different ways of moving. [21] has also shown a link between Body Mass Index (BMI) and shoulder range of motion, showing a decrease in the range of motion with an increase of the BMI, potentially then leading in different movements strategies since the available range of motion is narrowed. Additionally, the fixed size of the robotic exoskeleton means that the same torque applied by the robot may be perceived differently by participants due to variations in the location of force application. In industrial settings, exoskeletons should be personalized for each user, with support levels adjusted according to their specific morphology and the task at hand. For instance, a constant level of assistance may be



experienced differently depending on the user's physical characteristics, resulting in variations in the actual support provided. Future research could benefit from frameworks like the one proposed by [22], which may enhance exoskeleton personalization and reduce the influence of anthropomorphic variables on retention patterns. However, despite the lack of personalized force fields in this experiment, it is important to note that the applied forces remained low in magnitude and were manageable for all participants. Even without individual calibration, participants were able to effectively adapt to the perturbations introduced by the exoskeleton.

This finding underscores the necessity of personalizing exoskeletons to minimize the influence of anthropomorphic and demographic factors on retention behaviors, particularly concerning user morphology (e.g., arm size, weight) and arm dominance. One aspect that remains insufficiently explored is how exoskeletons affect the dominant versus non-dominant arm. As demonstrated in [23], dominant and non-dominant arms may require different levels of support. While bilateral support is common in industrial applications and asymmetric training is used in rehabilitation, most occupational exoskeletons apply uniform settings to both arms. Our results suggest that applying the same force field to the dominant and non-dominant arms can lead to different retention behaviors, increasing the risk of appearance of asymmetrical behaviors. Customizing exoskeleton support for the dominant arm may help minimize disruptions in inter-joint coordination and prevent asymmetrical motor patterns from developing.

Further research is necessary to better understand the specific role of each factor and to determine how to optimally adjust and control exoskeletons based on these factors, thereby reducing motor control modifications. Research on the long-term effects of exoskeleton use and the post-adaptation movement patterns following repeated exposure to exoskeletons should also be conducted.

## REFERENCES

- [1] Y. Xu, V. Crocher, J. Fong, Y. Tan, and D. Oetomo, "Inducing Human Motor Adaptation without Explicit Error Feedback: A Motor Cost Approach," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 1403–1412, 2021.
- [2] S. Iranzo, A. Piedrabuena, F. García-Torres, J. L. Martínez-De-Juan, G. Prats-Boluda, M. Sanchis, and J. M. Belda-Lois, "Assessment of a Passive Lumbar Exoskeleton in Material Manual Handling Tasks under Laboratory Conditions," *Sensors*, vol. 22, no. 11, pp. 1–29, 2022.
- [3] E. Rayssiguie and M. S. Erden, "A Review of Exoskeletons Considering Nurses," *Sensors*, vol. 22, no. 18, 2022.
- [4] O. Dubois, A. Roby-Brami, R. Parry, and N. Jarrassé, "Short term after-effects of small force fields applied by an upper-limb exoskeleton on inter-joint coordination," *Icra*, 2024.
- [5] T. Proietti, E. Guigon, A. Roby-Brami, and N. Jarrassé, "Modifying upper-limb inter-joint coordination in healthy subjects by training with a robotic exoskeleton," *J. Neuroeng. Rehabil.*, vol. 14, no. 1, 2017.
- [6] P. Slade, M. J. Kochenderfer, S. L. Delp, S. H. Collins, and E. D. Fig, "Personalizing exoskeleton assistance while walking in the real world," vol. 610, no. October, 2022.
- [7] K. L. Poggensee and S. H. Collins, "How adaptation, training, and customization contribute to benefits from exoskeleton assistance," *Sci. Robot.*, vol. 6, no. 58, 2021.
- [8] P. Garrec, Y. Friconneau, Y. Méasson, Y. Perrot, P. Garrec, Y. Friconneau, Y. Méasson, Y. P. Able, and T. Exoskeleton, "ABLE , an Innovative Transparent Exoskeleton for the To cite this version : HAL Id : cea-01588401 ABLE , an Innovative Transparent Exoskeleton for the Upper-Limb," *Int. Conf. Intell. Robot. Syst. INRIA*, 2008.
- [9] N. Jarrassé, M. Tagliabue, J. V. Robertson, A. Maiza, V. Crocher, A. Roby-Brami, and G. Morel, "A methodology to quantify alterations in human upper limb movement during co-manipulation with an exoskeleton," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 4, pp. 389–397, 2010.
- [10] R. C. Oldfield, "The assessment and analysis of handedness: The Edinburgh inventory," *Neuropsychologia*, vol. 9, no. 1, pp. 97–113, 1971.
- [11] J. F. O. Brien and J. K. Hodgins, "Automatic Joint Parameter Estimation from Magnetic Motion Capture Data," no. February 2015, pp. 1–8, 2000.
- [12] R. Burgess-Limerick, B. Abernethy, and R. J. Neal, "Relative phase quantifies interjoint coordination," *J. Biomech.*, vol. 26, no. 1, pp. 91–94, 1993.
- [13] N. Dounskaia, A. W. Van Gemmert, and G. E. Stelmach, "Interjoint coordination during handwriting-like movements," *Exp. Brain Res.*, vol. 135, no. 1, pp. 127–140, 2000.
- [14] D. A. Spielman and S. H. Teng, "Spectral partitioning works: Planar graphs and finite element meshes," *Linear Algebra Appl.*, vol. 421, no. 2-3 SPEC. ISS., pp. 284–305, 2007.
- [15] T. M. Kodinariya and P. R. Makwana, "Review on determining of cluster in K-means," *Int. J. Adv. Res. Comput. Sci. Manag. Stud.*, vol. 1, no. 6, pp. 90–95, 2013. [Online]. Available: <https://www.researchgate.net/publication/313554124>
- [16] M. Schonlau and R. Y. Zou, "The random forest algorithm for statistical learning," *The Stata Journal*, vol. 20, no. 1, pp. 3–29, 2020. [Online]. Available: <https://doi.org/10.1177/1536867X20909688>
- [17] E. LeDell and S. Poirier, "H20 automl: Scalable automatic machine learning," *7th ICML Workshop on Automated Machine Learning (AutoML)*, July 2020.
- [18] N. Nibras, C. Liu, D. Mottet, C. Wang, D. Reinkensmeyer, O. Remy-Neris, I. Laffont, and N. Schweighofer, "Dissociating Sensorimotor Recovery and Compensation During Exoskeleton Training Following Stroke," *Front. Hum. Neurosci.*, vol. 15, no. April, pp. 1–14, 2021.
- [19] M. Coscia, M. Coscia, M. Coscia, V. C. K. Cheung, V. C. K. Cheung, P. Tropea, P. Tropea, A. Koenig, A. Koenig, V. Monaco, V. Monaco, V. Monaco, V. Monaco, C. Bennis, C. Bennis, S. Micera, S. Micera, P. Bonato, and P. Bonato, "The effect of arm weight support on upper limb muscle synergies during reaching movements," *Journal of NeuroEngineering and Rehabilitation*, 2014.
- [20] J. Kaux, J.-F. Kaux, B. Forthomme, B. Forthomme, C. L. Goff, C. L. Goff, J.-M. Crielaard, J.-M. Crielaard, J.-L. Croisier, and J.-L. Croisier, "Current opinions on tendinopathy," *Journal of Sports Science and Medicine*, 2011.
- [21] W. Allen, W. Allen, J. Lin, J. J. Lin, W. B. Barfield, W. B. Barfield, R. A. Friedman, R. J. Friedman, R. J. Friedman, J. K. Eichinger, and J. K. Eichinger, "Shoulder motion decreases as body mass increases in patients with asymptomatic shoulders," *JSES International*, 2020.
- [22] O. J. Ott, L. Ralfs, and R. Weidner, "Framework for qualifying exoskeletons as adaptive support technology," *Frontiers in Robotics and AI*, 2022.
- [23] D. Park, C. Di Natali, M. Sposito, D. G. Caldwell, and J. Ortiz, "Elbow-side WINDER (Elbow-side Wearable INDUSTRIAL Ergonomic Robot): design, control, and validation of a novel elbow exoskeleton," *Front. Neurobot.*, vol. 17, 2023.