Subjective Assessment of Individualized Gait Patterns on Enjoyment, Comfort, and Naturalness in Robot-Assisted Walking

MSc Thesis

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I utilized ChatGPT, an AI model based on OpenAI's GPT-3.5 architecture, as a tool for assisting in manuscript preparation.

Severin David Woernle
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***Abstract*—Lower-limb exoskeletons often use trajectory-tracking control to define the device's motion and assistance level. One challenge lies in ensuring a smooth and comfortable interaction between the user and the robotic device by defining a reference trajectory. While recent research has focused on generating individualized gait patterns based on user-specific body characteristics and walking speed, limited research has explored the subjective perception of these patterns and their impact on user experience and rehabilitation outcomes.**

This study investigates user perceptions of individualized versus standard and random gait patterns, focusing on enjoyment, comfort, and naturalness. A predictive gait pattern model, incorporating individual data and walking speed, was developed and tested with human participants using a grounded robotic lower limb device. Participants compared the three gait pattern types and provided subjective feedback through a questionnaire.

Findings indicate no significant preference for any gait pattern in terms of enjoyment, comfort, and naturalness, except for physical strain where the predicted pattern caused significantly more strain than the standard. The analysis also revealed that longer engagement with the device led to increased comfort and naturalness, suggesting an adaptation effect. A general tendency towards preferring the standard pattern was noted, though further research is necessary to determine whether a larger sample size reveals significant differences. Additionally, the perception of different gait patterns and their effect on the rehabilitation outcome should be explored with stroke patients.

***Index Terms*—Robotic gait rehabilitation, Reference joint trajectories, Gait generation, Human factor experiment, Comfort**

I. Introduction

Stroke often leads to partial (paresis) or complete loss (plegia) of motor function [1]. Rehabilitation aims to help patients regain their motor function, with the primary focus frequently being on restoring the ability to walk, depending on the patient's condition and impairment. While spontaneous recovery can occur in post-stroke patients, rehabilitation therapy is commonly essential for regaining lost motor functionalities [2].

Lower-limb exoskeletons have emerged as valuable tools in impaired gait rehabilitation [3]. They are attached to the patient's lower limbs to assist and simulate walking. These devices facilitate task-specific training, enabling ample repetition and intensive training, which are fundamental principles for initiating neural plasticity changes [4]. Moreover, exoskeletons enhance gait rehabilitation by minimizing the need for multiple therapist involvement [5], reducing their physical strain [6], [7], and providing consistent gait simulation, overcoming variability in therapist experience and performance [6]. Additionally, they allow for quantitative assessment of patient performance by evaluating parameters such as walking speed, range of motion, or amount of resisting forces [7], [8]. One drawback of exoskeletons is their complex mechanical structure, limiting natural movement and potentially leading to discomfort and increased energy expenditure [7].

A variety of robotic devices have been developed for gait training, such as Lokomat [6], LOPES [9], G-EO-System [10], ReWalk [11], AIDER [12], and TWIN exoskeleton [13]. One challenge in these systems is ensuring a smooth and comfortable interaction between the user and the robotic device [14], [15]. The most common control strategy employed in these devices is trajectory-tracking control [16]. It involves the use of reference trajectories to define the motion of the device or the level of assistance. Other strategies include neuromuscular control and compliant controllers [16]. Neuromuscular control interprets the user's intentions through biosignals, such as electromyogram (EMG) readings, and adjusts the device's control accordingly. Compliant controllers, conversely, control the device's stiffness (impedance) or its responsiveness (admittance). When used in combination with trajectory-tracking or neuromuscular control, compliant controllers enhance the device's movement flexibility. Particularly in the early phases of rehabilitation training, the exoskeleton is often operated in position control to provide strong support for severely impaired subjects [17]. Thus, the design of these trajectories can have an impact on the patient's comfort and natural movement [15].

Every person's gait pattern is unique [18]. Gait patterns vary due to individual-specific factors, such as age, gender, and body measurements [19], [20]. Moreover, the influence of gait speed on the shape of gait patterns is well-documented [21], [22]. These findings suggest that individualized gait patterns could be beneficial in robotic rehabilitation.

Recent research has focused on creating individualized gait patterns for lower-limb exoskeletons by considering body parameters and desired gait characteristics. Gait pattern generation methods can be categorized into mirroring, model-based, and learning-based approaches. Mirroring methods replicate the walking pattern from the unaffected to the affected leg but are limited to hemiparetic and hemiplegic patients. Their effectiveness is questioned for stroke patients, as the unaffected leg may no longer resemble a natural gait [23]. Model-based methods create gait patterns using mathematical [24], [25] or biomechanical models [26], [27], incorporating parameters like joint angles, muscle forces, and body dynamics. However, a major drawback of these models is that they rely on assumptions about body dynamics and muscle activation that may not fully capture the complexity of human gait. Learning-based methods use machine learning to predict gait patterns from data, without the need for complex kinematic and dynamic human body models [28], [20], [12]. They are becoming increasingly popular due to their versatility in handling a wide range of body parameters and their proven effectiveness in predicting individualized gait patterns at different walking speeds [28], [12]. A drawback is that their success heavily relies on the quantity and quality of the training data [29].

While numerous gait prediction methods have been developed, their accuracy has largely been evaluated using objective quantitative metrics [28], [30], [31]. In contrast, assessments incorporating participants' subjective feedback are markedly underrepresented. Notably, Wu et al. [19] observed that subjects perceived individualized gait patterns as consistent with their natural walking habits. However, the study lacked a thorough exploration of the participants' feedback nor did it provide a comparative analysis with other types of gait patterns, such as standardized ones. There is insufficient evidence that an individualized gait pattern is superior to a normalized one in terms of rehabilitation outcomes [32]. Exploring participants' subjective experiences, such as enjoyment, comfort, and the naturalness of the gait, could provide deeper insights into how different gait patterns affect rehabilitation.

These subjective factors are considered important for several reasons, with their definitions relying on an individual's interpretation due to their subjective nature. Enjoyment of the physical task can be an important motivator for individuals, suggesting that a positive exercise experience may support their ongoing commitment [33]. Furthermore, comfort is an essential factor for user acceptance in human-robot interactions [34]; conversely, discomfort can reduce the motivation of patients to use a system [35]. Additionally, ensuring natural movements is important as deviations from natural movements can cause discomfort, thereby reducing patient motivation to engage with such systems [35]. Research indicated that a lack of motivation can hinder learning [36]. Another point concerning the importance of natural movement relates to the principle of task-specific training, which states that "the best way to learn an activity is to practice that activity" [37]. This suggests that a natural execution of the activity might enhance the rehabilitation of gait by making the training more specific and, consequently, more effective.

The objective of this study is to investigate the perception of walking with individualized gait patterns in comparison to standard and randomly selected gait patterns. The standard pattern reflects the average gait of a healthy population, while the random pattern is chosen from the same group. This comparison seeks to determine if tailoring gait patterns to an individual's body characteristics and walking speed is perceived as favorable. The rationale for including a random pattern as a point of comparison is based on previous studies where a random pattern of a healthy person served as a reference [38], [39].

For the experimental setup, a modified Lokomat® exoskeleton, adapted at ETH Zurich (Zurich, Switzerland) [40], was employed. The modifications aimed to increase realistic walking simulation through improved control of the joint trajectories, particularly in hip abduction/adduction and lateral pelvis movement. Besides that, this device supports the actuation of hip and knee flexion/extension, common features in lower-limb exoskeletons [11], [12], [13].

A key aspect of this study was to develop a new gait prediction model. Previous models often did not predict gait patterns across various speeds [41], [20] or fully account for all the joint movements possible by the modified Lokomat® – particularly, the lateral pelvis movement [28], [12], [42]. To address these limitations, a new gait prediction model based on the approach by Koopman et al. [28], using multiple regression models, was developed.

The study's main contributions are two-fold:

1) Development of a gait pattern prediction model that predicts an individual's gait patterns based on anthropometric, demographic data and walking speed.
2) Subjective assessment of user perception, in terms of enjoyment, comfort, and naturalness, when walking with an individualized gait pattern as compared to a standard or random pattern, using a lower-limb rehabilitation device.

In addition, the interaction between the exoskeleton and the user was evaluated by comparing the actuator position errors and the force measured at the knee for different gait patterns.

Hypotheses

The main hypothesis guiding this study is that participants will show a stronger preference for both standard and personalized predicted gait patterns over random ones. Furthermore, the degree of preference for the predicted gait pattern over the standard one is expected to correlate with the gait prediction model's capability to accurately predict an individual's gait.

Gait Prediction Model Hypothesis: The predicted gait pattern is hypothesized to show a lower root mean square error (RMSE) than the standard pattern, indicating a higher accuracy in mirroring an individual's gait.

Detailed Experiment Hypotheses: Based on the model's expected performance, the following specific hypotheses are proposed:

- *User Experience:* Enjoyment, comfort, and perceived naturalness ratings are predicted to vary, with personalized patterns rated highest, followed by standard and random patterns, indicating a closer similarity to a person's gait.
- *Participant Passivity:* No difference in passivity is expected across gait patterns, due to the exoskeleton's stiff position control mode that is expected to enable passive participation with any gait pattern.
- *Measurement Variations:* Predicted gait patterns are expected to have the lowest actuator position errors and knee forces due to their expected closer replication of an individual's gait, followed by standard, then random patterns.

II. Methods

A. Exoskeleton Design

This study utilizes a modified Lokomat® exoskeleton developed by Hocoma, Switzerland, and further enhanced at ETH Zurich, Switzerland. The Lokomat® is a grounded exoskeleton that consists of robotic legs that attach to the patient's legs and simulate walking on a motor-driven treadmill. It has been modified to enable actuation of hip abduction/adduction and incorporates a compliant pelvis model with six degrees of freedom (DOF): five passive and one active, specifically for lateral pelvis movement [40]. This design utilizes a prismatic actuator to enable the pelvis's lateral movement, while the other DOFs, supported by springs, remain passive to support the user. The pelvis model secures the user's pelvis through two fixtures positioned on either side, as shown in Fig. 1.

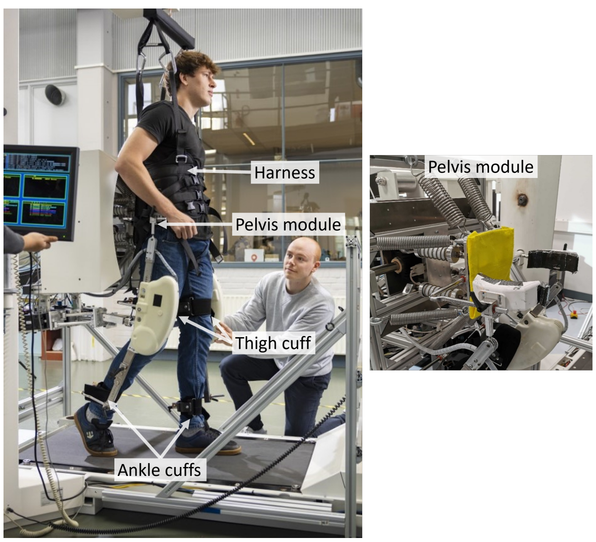

Fig. 1: Modified Lokomat® with a user secured, featuring ankle and thigh cuffs, a safety harness for fall prevention, and a pelvis module (right) with two banana-shaped supports for pelvis stabilization.

The system also features two-DOF hip joint actuation for ad-/abduction and flexion/extension, using four prismatic leg actuators. The knee joint is designed with a single DOF for flexion and extension, operated by a revolute actuator, which is the original mechanism provided by Hocoma. Fig. 2 depicts the kinematic model of the modified Lokomat®, showing all the actuated joints.

B. Gait Prediction Model

A new gait prediction model is established that builds on the methodology developed by Koopman [28]. The original model by Koopman utilized multiple polynomial regression models to predict gait patterns, based on a person's height and walking speed. Our study's model extends this approach by incorporating additional anthropometric and demographic data, such as body weight, age, and gender. These factors are considered influential in determining a person's gait pattern [19], [20]. Additionally, while Koopman's model incorporated various joint trajectories like hip ab-/adduction, hip flexion/extension, and knee flexion/extension, it did not consider lateral pelvis movement, which is included in our model.

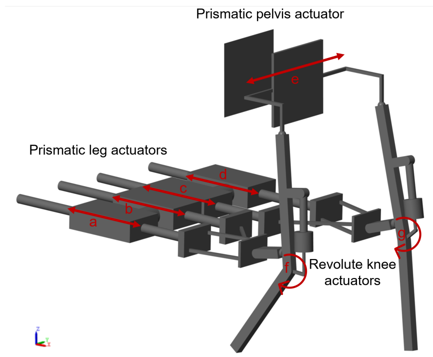

Fig. 2: Kinematic model of the modified Lokomat® in Simulink for gait pattern conversion. It includes four prismatic actuators for ad-/abduction and flexion/extension: (a) right outer, (b) right inner, (c) left inner, (d) left outer; one prismatic pelvis actuator (e) for lateral pelvis movement; and two revolute knee actuators (f) right and (g) left for knee flexion/extension.

1) Dataset: The dataset used for the gait prediction model is from the public gait database provided by the Laboratory of Biomechanics and Motor Control at the Federal University of ABC, Brazil [43]. It includes data from 42 volunteers, split into 24 young adults (21-37 years) and 18 older adults (50-84 years), all free from lower-extremity injuries or conditions affecting gait. Data from both the young and older groups are aggregated for the prediction model. Table I summarizes their anthropometric and demographic characteristics.

TABLE I: Statistical overview of subjects' anthropometric and demographic data [43]

Parameter	Mean	Std.	Min	Max
Age (Years)	42.64	18.62	21	84
Height (cm)	167.12	11.01	147	192
Mass (kg)	67.76	11.24	44.9	95.4

Data collection for the database involved participants walking barefoot on a treadmill at eight different speed levels, ranging from 40% to 145% of their comfortable, self-selected walking speed. Each trial lasted for 90 seconds, with kinematic and kinetic data being recorded during the final 30 seconds.

The dataset includes both raw data, such as marker coordinates and external forces, and pre-processed data like joint angle trajectories for each subject at each speed level. The joint trajectories important for controlling the modified Lokomat® system are specifically knee flexion/extension, hip flexion/extension, hip abduction/adduction, and lateral pelvis movement. While the former three are already provided as pre-processed data, the dataset originally did not contain the lateral pelvis movement. This gap was filled by deriving the lateral pelvis movement from the raw marker data. The derivation method is detailed in Appendix A. Furthermore, the average gait cycle time for each participant's trial was defined, which is also documented in the appendix. All joint trajectories, including the newly computed lateral pelvis movement, are represented as time-normalized ensemble averages for each participant at their respective gait speeds.

Due to the maximum speed limit of 3.2 kph on the commercially available Lokomat® system [44], only a subset of the recorded speeds was selected for training the gait prediction model, to avoid introducing unnecessary complexity and irrelevant patterns. The selected speed levels include: speed level 1 with a mean of 1.80 ± 0.231 kph, speed level 2 with a mean of 2.46 ± 0.336 kph, and speed level 3 with a mean of 3.14 ± 0.410 kph. Details on all speed levels are provided in Appendix B.

2) Gait Prediction Model Architecture:

a) Key events: The key events for joint trajectories – hip abduction/adduction, hip flexion/extension, and knee flexion/extension – were identified similarly to Koopman [28]. For each trajectory, six key events were selected to precisely capture the shape of each waveform, mainly focusing on minimal and maximal position and velocity values. Additionally, the heel strike at the beginning of a gait cycle is also considered a key event. For lateral pelvis movement, key events were determined similarly, emphasizing extreme position and velocity data. However, the heel strike was omitted due to the sinusoidal nature of the waveform, making its inclusion redundant.

These key events are depicted in Fig. 3. Notably, the second key event in the hip flexion/extension trajectory – angle maximum turning point during the stance phase – is excluded from gait pattern reconstruction. This exclusion is based on its relevance mainly to walking speeds exceeding 3.5 kph, as outlined by Koopman. [28], which exceeds the maximum walking speed of the gait prediction model, set at 3.2 kph. The key events were described in terms of several variables: the timing (t), expressed as a percentage of the gait cycle, the angle or displacement (y), (angular) velocity ($\dot{y}$), and acceleration ($\ddot{y}$).

b) Regression Models: Regression models were formulated to establish a relationship between predictor variables and the parameters of the key events. The model predicts timing, position, velocity, and acceleration for each key event, based on a specific set of predictor variables. The regression formula used is:

$$Y = \beta_0 + \beta_1 v + \beta_2 v^2 + \beta_3 \ell + \beta_4 w + \beta_5 a + \beta_6 g, \tag{1}$$

where v represents walking speed, ℓ body height, w body weight, a age, and g gender, encoded as a numerical value where female is -1 and male is 1. The Y variable represents the t, y, $\dot{y}$, or $\ddot{y}$ of a specific key event.

To derive common regression models for the joint trajectories of the left and right legs, the data from their respective joint trajectories were combined. For obtaining the regression coefficients for each parameter of each key event, two steps were followed. First, stepwise regression was conducted to evaluate the significance of the predictor variables. Variables with significant effects ($p < 0.01$) were retained. Second, robust regression with a 'bisquare' weighting function was employed to estimate the final regression coefficients (β_x).

In total, regression models were established for all four parameters of the key events, leading to 24 regression models for hip abduction/adduction, hip flexion/extension, and knee flexion/extension (each with 6 key events), and 16 models for the lateral pelvis movement (4 key events). Additionally, a regression model to derive the gait cycle time was also created, using the same predictor variables.

c) Reconstruction of Waveforms: The obtained regression models enable the determination of key event parameters (i.e. t, y, $\dot{y}$, or $\ddot{y}$) for specified predictor variables. To reconstruct continuous kinematic waveforms from these key events, a 5th-order piece-wise quintic splines interpolation method, as proposed by Koopman [28], was employed. This technique effectively creates continuous trajectories.

3) Validation: The validation of the gait prediction method focused on assessing its accuracy using the root mean square error (RMSE) as the evaluation metric. This involved comparing actual gait trajectories with those reconstructed using the leave-one-out cross-validation method.

In this cross-validation approach, spline curves were generated using regression models that omitted data from one subject at a time. The RMSE for the actual versus reconstructed gait trajectories of the excluded subject was then calculated. This procedure was repeated for each of the 42 subjects, with results averaged across all subjects and both left and right gait trajectories.

The RMSE is defined as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} (y_t - \hat{y}_t)^2}{N}}. \tag{2}$$

Here, N represents the number of data points in the gait cycle (101 time-normalized points), y_t corresponds to the actual joint angle/displacement value at time t, and $\hat{y}_t$ denotes the corresponding predicted value.

Additionally, to compare the accuracy of the predicted joint trajectories with the derived standard joint trajectories (Section II-C2b), also the RMSE between the actual gait trajectories of the subjects from the database and the standard gait pattern was calculated.

C. Experiment

1) Participants: Ten subjects participated in the experiment, equally divided into five females and five males. Their ages ranged from 23 to 27 years, with a mean age of 25 ± 1.32 years, average height of 1.76 ± 0.089 m, and weight of 69.25 ± 12.79 kg. None had neurological or orthopedic disorders. This research was approved by the Human Research Ethics Committee of Delft University of Technology. Prior to the experiment, all participants read and signed an informed consent form. The detailed form can be found in Appendix H.

a) Gait Pattern Conversion: The unique control mechanism for hip abduction/adduction and hip flexion/extension via prismatic joints requires the determination of specific actuator position trajectories. In contrast, knee flexion/extension and lateral pelvis movement joint trajectories can be directly used as positional inputs for their corresponding actuators. To derive the position trajectories of the four prismatic leg actuators, a kinematic model of the modified Lokomat® system in Matlab Simulink 2021 with Simscape was employed.

Fig. 2 depicts the kinematic model and actuator movements. The conversion process involved two main steps. Firstly, the

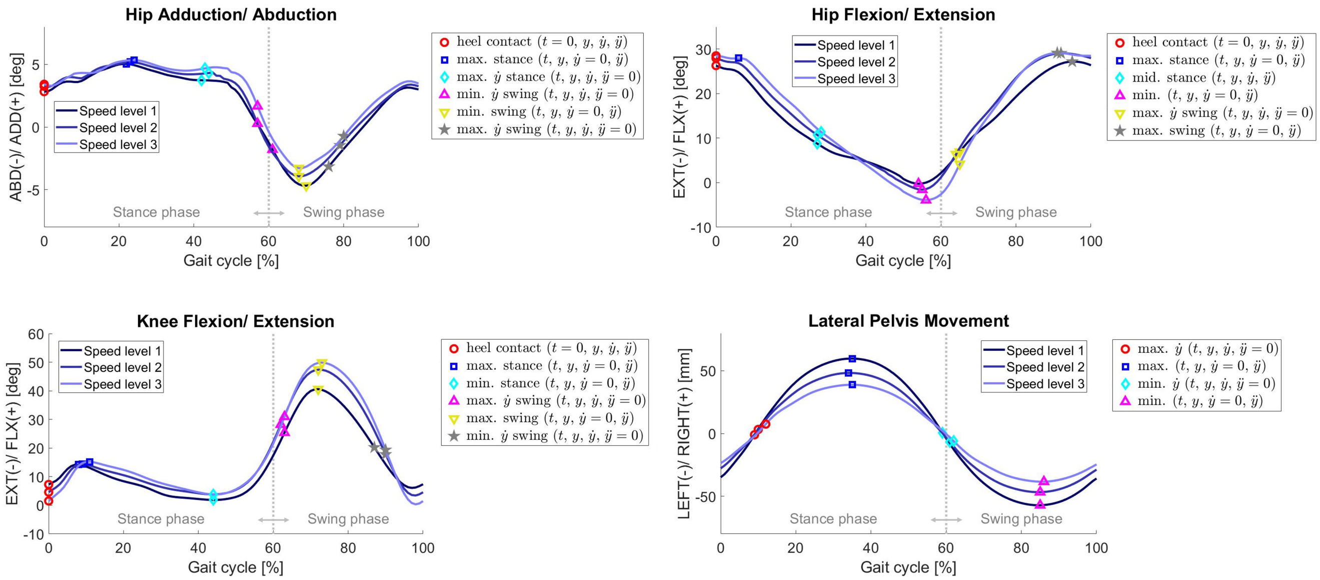

Fig. 3: Key Events: The right leg trajectories of a subject are displayed at walking speed levels 1, 2, and 3, together by their extracted key events. These key events are the same as in Koopman's study [28], except for lateral pelvis movement (not present in their study), for which extreme position and velocity values were chosen. The key events for the left and right joint trajectories were extracted separately. By default, heel strike timing is set to zero (% of the gait cycle), as are the minimum and maximum values for joint position and velocity. These constraints are detailed in the key event legend.

kinematic model was calibrated to match the joint configuration of the real exoskeleton. This adjustment was based on the user's body dimensions, including the width of the pelvis, the frontal position of the hip joint, thigh length, and shank length. Secondly, using the accurately sized kinematic model, the position trajectories of the actuators were determined based on the movement patterns of hip abduction/adduction, hip flexion/extension, and lateral pelvis movement.

b) Control: The exoskeleton is controlled through Matlab Simulink 2013, set up for position tracking control with a system frequency of 500 Hz. The goal of this position control is to closely follow the induced gait patterns, enabling participants to perceive variations in different patterns. The prismatic actuators for the hip and pelvis are configured with a stiff PD controller, using gains of $K_p = 5\,A/mm$ and $K_d = 7.5\,A/(m/s)$, which were adopted from the actuator settings and not manually tuned. Conversely, for the knee actuator, the PD controller was manually tuned to achieve high stiffness, with $K_p = 1$ and $K_d = 0.1$. The input to the controller is the knee angle position error in degrees, and the output is the force in Newtons sent to the knee actuator.

2) Experimental Conditions: In the study, participants underwent three different test conditions using the modified Lokomat® exoskeleton. This exoskeleton, operating in position tracking control, guided the lower limbs of participants in three unique gait patterns: (a) Predicted Gait Pattern, (b) Standard Gait Pattern, and (c) Random Gait Pattern.

a) Predicted Gait Pattern: A gait pattern for each participant is predicted based on individual factors such as gender, age, height, weight, and desired walking speed. Details of this gait prediction model are outlined in section II-B.

b) Standard Gait Pattern: The standard gait pattern was developed using the same gait database referenced by Fukuchi [43], which was also employed in training the gait prediction model. Unlike the predicted pattern using key events for derivation, this standard pattern was derived by averaging the gait patterns of the three lowest walking speed levels. To achieve symmetrical walking, the trajectories of both the left and right legs were combined. The derived averaged gait pattern can be seen in Appendix C.

Furthermore, to estimate the gait cycle time for the standard gait pattern at various speeds, a regression model similar to the gait prediction model was employed (see Section II-B2b). Regression coefficients were calculated to predict an individual's cycle time for the standard gait pattern, specifically based on gait speed and the person's height. Besides gait speed, body height is considered because longer leg length results in a larger step length when the joint trajectories remain constant.

The employed regression formula is expressed as:

$$Y = \beta_0 + \beta_1 v + \beta_2 v^2 + \beta_3 \ell \tag{3}$$

where v represents walking speed, ℓ body height, and Y represents the gait cycle time.

c) Random Pattern: For each participant, a gait pattern was randomly selected from the lowest walking speed level in Fukuchi's database [43] to closely align with the experiment's speed. However, the walking speed of the random patterns varied around the target speed of 1.8 kph, with a standard deviation of ± 0.231 kph. That is why, the replay time was adjusted to ensure similar walking speed across all tested gait pattern types. This adjustment was based on predicting the gait cycle time for 1.8 kph using the regression formula that was also applied for predicting the gait cycle time for the standard gait pattern (Equation 3). Additionally, to ensure a symmetrical gait, the left and right leg joint trajectories of the random pattern were averaged, and the lateral pelvis movement was adjusted for symmetry.

Walking Speed of Experiments: For all conditions, the walking speed was set to 1.8 kph, reflecting the average speed of the lowest walking speed level in the database. However, there might be minor deviations in the actual speed for each gait pattern and subject. This variance arises because the speed is dependent on the playback speed of the gait pattern, which in turn is determined by a predicted gait cycle time specific to each pattern. This prediction may not always align perfectly with the targeted speed of 1.8 kph for every participant. Therefore, to ensure consistency, the treadmill's speed was adjusted as needed to match the playback speed of the gait pattern.

Randomization: Participants tried all the different gait patterns. The gait pattern sequence was randomized across participants. Each of the six possible condition sequences was used once. Then, four more sequences were randomly selected from these six.

3) Experimental Protocol: The experimental protocol consisted of several steps, outlined in the following.

a) Initial Setup: After signing the informed consent, participants were informed about the protocol. The exoskeleton orthosis was then adjusted for the participant's size to align with their hip and knee joints. Furthermore, participants were equipped with a safety harness for fall prevention, but no weight support was provided. Their legs were secured to the exoskeleton with cuffs, and a pelvis module stabilized their pelvis. Fig. 1 shows the setup.

b) Familiarization Phase: During the experiment's initial phase, participants underwent a familiarization process by walking with the exoskeleton in 'transparency mode'. In this mode, the exoskeleton operates with minimal resistance and support, to allow the participant to walk as freely as possible. The participants walked at 1.8 kph, similarly to the speed used in later trials. This phase helped participants get used to walking with the exoskeleton and allowed for checking and adjusting any misalignments between the participant's and the orthosis's joints.

c) Trial Procedure: After the familiarization phase, participants underwent three walking trials, each featuring a different gait pattern. During the trials, the exoskeleton operated in stiff position control. The following procedure was repeated for each trial. Participants started in a predefined start position with the left foot in the air, the exoskeleton gradually increased walking speed to 1.8 kph. As the exoskeleton did not support ankle movement, participants were instructed to actively lift their feet. Aside from this, they were instructed to remain passive, letting the exoskeleton guide their movement without enforcing their walking pattern.

Before each trial started, it was checked if there was sufficient foot clearance between the participant's feet and the treadmill. By increasing the height of the entire exoskeleton, foot clearance could be improved. Additionally, it was checked if there was any slippage, i.e. discrepancies in speed between the feet and the treadmill, and the treadmill's speed was altered accordingly. Each trial lasted two minutes, followed by participants completing a questionnaire on their walking perception (see section II-C5a). To maintain consistency in the fit of the exoskeleton, participants remained in the exoskeleton throughout all conditions. However, adjustments to cuffs, especially ankle cuffs, were made for optimal fit and comfort.

d) Safety Measures: To ensure safety, participants wore a harness. Additionally, an emergency stop button was provided to the participant, and the experimenter had a separate one to halt the experiment if needed.

4) Data Acquisition: The positions of the different actuators within the exoskeleton were recorded, capturing both the desired (induced) and the actual (measured) actuator movements at a frequency of 100 Hz. In addition, the forces exerted on the knee joints were also recorded.

5) Outcome Metrics:

a) Questionnaires: A questionnaire was developed to evaluate participants' perceptions when walking with the three different gait patterns. The complete questionnaire is available in Appendix I. It comprised the following categories, with responses recorded on a 7-point Likert scale, except for open-ended questions:

- *Interest/Enjoyment:* Four questions from the Interest/Enjoyment subcategory of the Intrinsic Motivation Inventory (IMI) [45] were used to assess how appealing and enjoyable participants found the activity. The scores of these four questions were averaged according to the IMI guidelines [45].
- *Passiveness:* This category included four self-designed questions to determine if participants remained passive while using the exoskeleton. Assessing passiveness is important to ensure that the exoskeleton's guidance was predominant, and not overridden by the participant's natural gait. The scores of these four questions were averaged because these questions aim to assess overall participant passiveness through differently phrased questions.
- *Comfort:* Seven self-designed questions evaluating the comfort level experienced by participants while using the exoskeleton. Each question was analyzed individually to capture distinct aspects.
- *Naturalness:* Four self-designed questions evaluating how natural the participants found the movements of the exoskeleton. Each question was analyzed individually to capture distinct aspects.
- *Open-ended questions:* Providing space for additional insights and comments.

Participants also ranked the three gait patterns in terms of overall experience, comfort, and naturalness, and rated their confidence in these rankings.

b) Objective Data Analysis: Besides the subjective feedback, objective data from the exoskeleton was analyzed:

- *Actuator Trajectory Error:* Mean absolute position error between reference and actual actuator trajectories was determined to evaluate the accuracy of the actuators.
- *Knee Joint Forces:* The mean forces exerted at the knee joints were compared across different gait patterns. Appendix D depicts the force direction.

6) Statistical Analysis: The objective of the statistical analysis was to investigate the effects of different gait patterns and trial sequences on participants' perceptions and objective interactions with the exoskeleton. The analysis was performed in R. Statistical significance was set at $p < 0.05$.

a) Questionnaire: To evaluate the effect of gait pattern and trial sequence on participant perceptions across four areas – *Enjoyment/Interest, Passiveness, Comfort,* and *Naturalness* – a regression analysis was conducted. This analysis was performed using the `lmer` function from the `lme4` package in R. The model was defined as:

$$Questionnaire_i = Pattern + Trial + (1|Participant). \quad (4)$$

Here, $Questionnaire_i$ represents the dependent variable, representing questionnaire scores on a 7-point Likert scale. These scores were treated as continuous data for ease of calculation. The independent variables $Pattern$ and $Trial$ were categorical with three levels each. $Pattern$ refers to three gait patterns (Standard, Predicted, and Random), and $Trial$ refers to the experiment sequence (first trial, second trial, and third trial). The model accounted for variability among participants by including $Participant$ as a random factor.

Additionally, ranking outcomes were analyzed using a Friedman test, which is standard to use for ranked measures. The analysis was performed using the `friedman.test` function in R. After identifying significant differences with the Friedman test, a post-hoc Nemenyi Test was conducted to explore pairwise comparisons between groups. This analysis was performed using the `frdAllPairsNemenyiTest` function from the `PMCMRplus` package in R.

b) Objective Data: To evaluate the effect of gait pattern and trial sequence on exoskeleton performance – *Mean absolute position error of actuators* and *Measured mean knee force* – a regression analysis was conducted. This analysis was performed using the `lmer` function from the `lme4` package in R. The model was defined as follows:

$$Interaction_i = Pattern + Trial + (1|Participant). \quad (5)$$

Here, $Interaction_i$ denotes the dependent variables, which include the mean absolute position error for each actuator and the mean knee force. Specifically, position errors were assessed for the pelvis prismatic actuator, Body Weight Support (BWS) prismatic actuator, right and left leg prismatic outer actuators, right and left leg prismatic inner actuators, and both right and left knee revolute actuators. The knee force was evaluated separately for the left and right knee.

Similarly to the questionnaire analysis, the independent variables $Pattern$ and $Trial$ included three gait patterns and three trial sequences, respectively. Participant variability was accounted for by including $Participant$ as a random factor.

III. Results

A. Regression Models

1) Gait Prediction Model: The regression equations derived for the different joint trajectories and their corresponding key events are presented in Appendix E. Additionally, Table II shows the number of times each predictor is used across all 22 key events to determine the key-event parameters (timing t, position y, velocity $\dot{y}$, and acceleration $\ddot{y}$).

TABLE II: Number of predictors used for each parameter (timing, angle/displacement, velocity, acceleration) of the 22 key events in total.

Parameter	Predictors				
	Speed (β_1, β_2)	Height (β_3)	Weight (β_4)	Age (β_5)	Gender (β_6)
Timing (t)	8	4	2	5	4
Angle/ Disp. (y)	7	5	7	10	8
Velocity ($\dot{y}$)	8	5	6	5	5
Acceleration ($\ddot{y}$)	9	5	5	5	8

In terms of timing (t), speed was the primary factor, significantly influencing 8 out of 22 events ($p < 0.01$), followed by age (5 events), and height and gender (4 events each), while weight impacted 2 events. Regarding position (y), age was most influential, affecting 10 events, followed by gender (8 events), and speed and weight (7 events each), with height impacting 5 events. Additionally, the table details how predictors vary in their influence on velocity and acceleration.

Furthermore, the derived regression equation for predicting the gait cycle time is shown in equation 6, showing that gait cycle time (Y) is dependent on speed (v) and age (a), with other factors being non-significant ($p < 0.01$).

$$\begin{aligned} Y = 2.7662 - 0.7458v + 0.0903v^2 + 0\ell + 0w \\ - 0.0037a + 0g. \end{aligned} \quad (6)$$

2) Standard/Random Gait Pattern: For both the standard and random gait patterns, one regression equation was derived to estimate the gait cycle time, as presented in equation 3. It shows that gait cycle time (Y) is dependent linearly and quadratically on speed (v), as well as on height (ℓ).

$$Y = 1.8993 - 0.6909v + 0.0789v^2 + 0.3928\ell. \quad (7)$$

3) Leave-One-Out Cross-Validation: The accuracy of the reconstructed gait pattern was assessed through the Root Mean Square Error (RMSE), with results averaged across subjects and walking speeds presented in Table III.

TABLE III: RMSE for the reconstructed and the standard trajectories

Joint	RMSE[a] Act-Rec	RMSE_Train[a] Act-Rec	RMSE[a] Act-Standard
Hip abd/add (deg)	2.906	2.552	2.772
Hip flex/ext (deg)	7.573	6.709	6.953
Knee flex/ext (deg)	5.809	5.449	6.385
Pelvis lateral (mm)	6.321	5.473	6.779

[a] Only the three lowest speed levels were considered for regression model and standard pattern determination.

To evaluate the risk of overfitting, RMSE was calculated for the training sets (RMSE_Train Act-Rec) and compared with the RMSE for the reconstructed trajectories (RMSE Act-Rec). The RMSE values for the training sets are lower than those for the reconstructions, indicating a modest decrease in performance on new, unseen data.

Additionally, RMSE comparisons between standard and actual measured gait patterns of subjects were made to determine which pattern – predicted or standard – more accurately reflects the actual gait. Results show that for hip movements, the standard pattern's RMSE values are slightly lower. Conversely, for knee and pelvis movements, the reconstructed trajectories had slightly lower RMSE.

B. Experimental Results

The final treadmill speeds for each trial varied between 1.8 and 2.0 kph. A detailed overview of the speeds for each trial is provided in Appendix F-A.

1) Statistical analysis: A detailed overview of the questionnaire responses and actuator data collected from various participants is provided in Appendix F-B. It showcases the results from questionnaires and actuator recordings through boxplots, organized by gait pattern and experimental position. Furthermore, it displays the distribution of participants' rankings for each gait pattern and experimental position.

a) Questionnaire: The results of the questionnaire analysis are summarized in the following tables: *Interest/Enjoyment* (IMI) and *Passiveness* in Table IV, *Comfort* in Table V, and *Naturalness* in Table VI. The analysis for both the *Interest/Enjoyment* (IMI) and *Passiveness* metrics revealed no significant differences, neither in terms of gait pattern nor experimental position.

In contrast, the analysis of *Comfort* revealed some significant differences. Each question was evaluated individually, due to the distinct aspects. Findings showed a significant preference for the third trial over the first in terms of overall movement comfort ($\beta = 1.43,\ t = 2.94,\ p = 0.01$). No significant differences were found regarding the comfort of movement in specific areas of the body such as hips, knees, ankles/feet, and cuffs. Notably, a significant difference was observed in the perception of physical strain; participants reported more strain under the predicted gait pattern than the standard pattern ($\beta = 1.07,\ t = 2.86,\ p = 0.011$). The sense of security with the device showed no significant differences.

The *Naturalness* category also presented significant findings, particularly regarding trial order. The third trial was significantly perceived as more natural compared to the first trial ($\beta = 1.35,\ t = 2.79,\ p = 0.013$), and as more similar to the participants' own way of walking ($\beta = 1.85,\ t = 3.59,\ p = 0.002$). Questions related to the smoothness of movements and whether the limbs were pushed beyond their natural range did not show significant differences.

Table VII presents the outcomes of the Friedman test conducted for the ranking analysis. The analysis did not reveal any significant differences in rankings among the gait patterns in terms of overall preference, comfort, and naturalness. However, significance was found for comfort and naturalness across experimental positions. The third trial was perceived as more comfortable ($p = 0.037$) and more natural ($p = 0.037$) compared to the first trial. Additionally, participants demonstrated high confidence in their rankings, scoring 8.2 ± 0.92 regarding overall preference, 8.3 ± 1.06 regarding the most comfortable gait pattern, and 7.6 ± 1.51 regarding the most natural gait pattern, on a scale from 1 (not confident at all) to 10 (very confident).

b) Objective Data: The analysis of the exoskeleton's data recordings is summarized in two tables: the Mean Absolute Error (MAE) of actuator positions in Table VIII and the Mean Absolute Force at the knee actuators in Table IX.

The MAE of actuator positions revealed a significant difference in the pelvis actuator error between predicted and standard gaits ($\beta = 1.46,\ t = 3.78,\ p = 8.67e-4$), with the standard showing a smaller error. Similarly, the Body Weight Support (BWS) actuator showed a significant difference between random and standard gaits ($\beta = 0.71,\ t = 3.24,\ p = 0.005$), where the standard had again a smaller error.

Further analysis identified significant differences for both outer prismatic leg actuators, which followed the reference trajectory more accurately under the predicted gait compared to the standard gait ($\beta = -0.53,\ t = -3.85,\ p = 0.001$ right; $\beta = -0.52,\ t = -3.84,\ p = 0.001$ left). Additionally, the position error for these actuators was significantly smaller in random gaits compared to standard gaits ($\beta = -1.13,\ t = -8.17,\ p = 4.20e-7$ right; $\beta = -1.08,\ t = -7.95,\ p = 6.04e-7$ left).

The right inner prismatic leg actuator showed a significantly lower MAE for the predicted compared to the standard pattern ($\beta = -0.98,\ t = -2.45,\ p = 0.022$), whereas the left actuator slightly missed the significance threshold for these two gaits ($p = 0.053$). In addition, both inner prismatic leg actuators and knee actuators showed significant reductions in position error from the first to the second trial, exemplified by the right inner actuator ($\beta = -0.92,\ t = -2.30,\ p = 0.030$). Detailed results for the other actuators are given in the table. A significant difference between the first and third trials, however, was only observed for the right knee actuator, with the third trial showing a smaller MAE ($\beta = -0.48,\ t = -2.99,\ p = 0.009$).

Regarding the Mean Absolute Force at both knee actuators, the force was significantly higher for random gaits compared to standard gaits ($\beta = 68.7,\ t = 3.6,\ p = 0.002$ right; $\beta = 84.5,\ t = 4.1,\ p = 0.001$ left).

2) Qualitative Data: The responses to the open-ended questions are listed in Appendix F-C. Participants repeatedly cited discomfort at ankle cuffs, describing them as "uncomfortable" (P2, P8). Others specified feeling "discomfort at ankles" (P5) and "discomfort in my ankles" (P9). Hip movements emerged as another significant source of discomfort, with participants experiencing hips "swaying outside the range" (P3), "over-exaggerated" hip movement (P4), "a lot of lateral hip movement" (P8), and hips moving "too much towards the outside" (P6), all of which were described as uncomfortable across various gait patterns. Unnatural joint movements, particularly regarding the ankles, were a common theme. Participants reported an "unnatural" trajectory of knees and ankles (P10, predicted) and high discomfort due to "unnatural motion for my legs to walk with" (P9, predicted). Complaints included "unnatural movement at the heel strike" (P9, standard) and not walking "in a straight line" (P6, standard), indicating issues across different patterns. Additionally, the random pattern was reported to cause legs to move "more to the outside when extending the leg" (P7, random) and make ankles feel "pushed inwards" (P10, random), contributing to the sense of unnatural movement.

Positive remarks were also given, with the standard gait pattern being described as "straighter, which made it more similar to my gait" (P10, standard), and the random pattern being stated as "much better compared to the first two gait patterns" (P6, random). Foot placement also varied among participants, with one reporting their "feet were too close to

TABLE IV: Linear mixed model results for the questionnaire metric *Enjoyment/Interest (IMI)* and *Passiveness*

Variable	Enjoyment/Interest (IMI)[1]				Passiveness[1]			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	5.01	0.3	16.58	**5.28E-10*****	5.68	0.36	15.60	**2.37E-14*****
Predicted pattern	0.2	0.15	1.34	0.199	-0.30	0.36	-0.84	0.413
Random pattern	0.13	0.15	0.85	0.409	-0.29	0.36	-0.81	0.429
2nd Trial	0.01	0.15	0.08	0.933	0.10	0.36	0.27	0.792
3rd Trial	0.02	0.15	0.12	0.907	0.10	0.36	0.28	0.781

[1] 7-point Likert Scale: (1) Not true at all - (4) Somewhat true - (7) Very true
*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

TABLE V: Linear mixed model results for the questions regarding *Comfort*

Variable	Overall Comfort of Movements[1]				Comfort of Movements at Cuffs[1]			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	3.29	0.52	6.31	**1.35E-06*****	3.81	0.49	7.82	**2.88E-07*****
Predicted pattern	-0.75	0.49	-1.53	0.145	0.40	0.35	1.17	0.260
Random pattern	-0.4	0.49	-0.83	0.419	0.41	0.35	1.20	0.249
2nd Trial	0.96	0.49	1.97	0.067	0.14	0.35	0.41	0.688
3rd Trial	1.43	0.49	2.94	**0.01****	0.10	0.35	0.29	0.774
Variable	Comfort of Movements at Hips[1]				Comfort of Movements at Knees[1]			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	4.39	0.63	7.02	**2.42E-07*****	5.16	0.57	9.00	**2.72E-09*****
Predicted pattern	-0.26	0.58	-0.45	0.655	-0.15	0.53	-0.29	0.779
Random pattern	-0.04	0.58	-0.07	0.945	-0.55	0.53	-1.03	0.320
2nd Trial	0.60	0.58	1.03	0.317	-0.45	0.53	-0.86	0.405
3rd Trial	0.22	0.58	0.38	0.705	0.06	0.53	0.11	0.911
Variable	Comfort of Movements at Ankle/Feet[1]				Physical Strain[2]			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	4.05	0.53	7.64	**6.37E-08*****	2.10	0.43	4.86	**6.14E-05*****
Predicted pattern	-0.44	0.47	-0.94	0.362	1.07	0.37	2.86	**0.011***
Random pattern	-0.28	0.47	-0.60	0.559	0.44	0.37	1.19	0.252
2nd Trial	0.17	0.47	0.36	0.722	0.44	0.37	1.19	0.252
3rd Trial	0.62	0.47	1.30	0.212	-0.26	0.37	-0.70	0.492
Variable	Sense of Security in Device[2]							
	Estimate (β)	**Std. Error**	**t value**	**p-value**				
(Intercept)	5.15	0.45	11.44	**8.22E-10*****				
Predicted pattern	-0.13	0.32	-0.41	0.687				
Random pattern	0.22	0.32	0.69	0.497				
2nd Trial	0.22	0.32	0.69	0.497				
3rd Trial	0.54	0.32	1.67	0.114				

[1] 7-point Likert Scale: (1) Very uncomfortable - (4) Neutral - (7) Very comfortable
[2] 7-point Likert Scale: (1) Not true at all - (4) Somewhat true - (7) Very true
*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

each other" (P1) and another finding discomfort in their "feet being too distant from each other" (P6), across all gait patterns.

IV. Discussion

A. Gait Pattern Generation

The small decline in the RMSE for the training sets compared to the test sets implies good model generalization with limited overfitting. Furthermore, contrary to the hypothesis, the developed gait prediction model did not outperform the standard gait pattern in terms of accuracy regarding root mean square error (RMSE). The analysis revealed that the standard pattern had slightly lower RMSE for hip movements, whereas the model's reconstructed patterns showed lower RMSE for knee and pelvis movements, suggesting comparable accuracy in approximating gait for both predicted and standard patterns using RMSE.

A comparison with Koopman's [28] findings (see Table X) reveals lower RMSEs in their study, likely due to the use of a less diverse gait database limited to fifteen middle-aged individuals. A comparative analysis between databases in Appendix G revealed that different databases can have different kinematic variability. It further indicates that databases with a broader population range show increased kinematic variability. Thus prediction models evaluated on more diverse databases likely show reduced accuracy due to the challenge of capturing greater kinematic variability.

Furthermore, Semwal [46] used the same database to develop and validate their gait prediction model, employing a deep learning framework that integrates Long Short-Term

TABLE VI: Linear mixed model results for the questions regarding *Naturalness*

Variable	Naturalness of Movements[1]				Similarity to Own Way of Walking[1]			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate** (β)	**Std. Error**	**t value**	**p-value**
(Intercept)	2.68	0.52	5.20	**2.25E-05*****	2.56	0.51	4.98	**4.01E-05*****
Predicted pattern	-0.71	0.49	-1.45	0.165	-0.76	0.51	-1.50	0.154
Random pattern	-0.17	0.49	-0.35	0.728	-0.58	0.51	-1.14	0.272
2nd Trial	1.28	0.49	2.64	0.018	1.24	0.51	2.45	0.026
3rd Trial	1.35	0.49	2.79	**0.013****	1.82	0.51	3.59	**0.002****
Variable	Smoothness of Movements[1]				Limbs Pushed Beyond Natural Range[2]			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate** (β)	**Std. Error**	**t value**	**p-value**
(Intercept)	4.61	0.40	11.42	**2.09E-10*****	2.00	0.40	5.04	**5.21E-05*****
Predicted pattern	0.16	0.31	0.52	0.614	-0.09	0.32	-0.29	0.777
Random pattern	0.11	0.31	0.35	0.728	-0.42	0.32	-1.35	0.197
2nd Trial	0.11	0.31	0.35	0.728	-0.24	0.32	-0.77	0.453
3rd Trial	0.49	0.31	1.58	0.134	-0.33	0.32	-1.06	0.306

[1] 7-point Likert Scale: (1) Very unnatural/ dissimilar/ abrupt - (4) Neutral - (7) Very natural/ similar/ smooth
[2] 7-point Likert Scale: (1) Not true at all - (4) Somewhat true - (7) Very true
*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

TABLE VII: Friedman test results for participant rankings, including p-values from post-hoc pairwise comparisons for significant findings. The analysis compares rankings across patterns – standard (S), predicted (P), and random (R) – and evaluates rankings across experimental trials – 1st: T1, 2nd: T2, 3rd: T3.

Comparison Groups	Ranking	Friedman test			Post-hoc pairwise comparisons		
		χ^2	df	p-value	[1]S vs. P/ [2]T1 vs. T2	[1]S vs. R/ [2]T2 vs. T3	[1]P vs. R/ [2]T1 vs. T3
Conditions[1] (Patterns)	Overall preferred pattern	4.1	2	0.122	-	-	-
	Most comfortable pattern	3.2	2	0.202	-	-	-
	Most natural pattern	2.6	2	0.272	-	-	-
Trial order[2] (Experimental positions)	Overall preferred pattern	5.6	2	0.061	-	-	-
	Most comfortable pattern	6.2	2	**0.045***	0.261	0.644	**0.037***
	Most natural pattern	6.2	2	**0.045***	0.261	0.644	**0.037***

*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

Memory (LSTM) and Convolutional Neural Network (CNN) techniques. Their approach achieved lower RMSE values than our regression model, with $2.41°$ for hip and $3.49°$ for knee flexion/extension. However, they split the training and test data in such a way that both datasets include gait patterns from the same individuals but at different walking speeds, possibly limiting extrapolation to subjects outside of this dataset.

B. Experimental Findings

1) Questionnaire: Contrary to the hypothesis, the perceived *Interest/Enjoyment* (IMI), *Comfort*, and *Naturalness* of the predicted, standard, and random gait patterns showed no significant differences, except for physical strain, where the predicted pattern resulted in significantly higher strain than the standard. This increased physical strain could be due to the way the prediction model works, predicting trajectories of the different joints separately, which may lead to a gait pattern where the movements of different joints are not well-coordinated. Conversely, the standard pattern, derived from averaging multiple healthy gait datasets, might provide smoother joint trajectories, resulting in less strain. Although no significant preferences (aside from physical strain) among gait patterns were found, a tendency favoring the standard pattern was observed. This preference might be attributed to its potentially smoother and more harmonious joint coordination.

Interestingly trial order appeared to influence participants perception. Participants rated the questions related to the overall comfort, naturalness, and smoothness of the exoskeleton's movements significantly better in the third trial than in the first, suggesting an adaptation to the system over time, leading to an enhanced walking experience. Similarly, the results of the Friedman test regarding the rankings revealed a significant effect of trial order, supporting the observation of users becoming used to the system. However, it is crucial to note that the observed order effect introduces an interaction between the trial sequence and condition preference (pattern), diminishing the validity of the Friedman test results. Thus, the lack of significant differences in the ranking of the patterns could be due to this ordering effect, which may mask real preferences.

Furthermore, as hypothesized, gait patterns did not influence participants' ability to remain passive, with high passivity scores across all patterns. This shows that participants did not actively interfere with the intended gait patterns.

The questionnaire results indicate that the comfort and naturalness of the gait pattern could be improved. However, the discomfort during movements may not only be due to the gait pattern itself, but also to the overall discomfort of the device, as indicated by the participants' responses regarding discomfort at the cuffs, particularly the ankle cuff.

TABLE VIII: Linear mixed model results for position error: *Mean Absolute Error (MAE)* of the different actuators

Variable	Pelvis Prismatic Actuator: MAE - Position (mm)				BWS Prismatic Actuator: MAE - Position (mm)			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	4.05	0.36	11.29	**2.61E-11*****	2.54	0.21	11.96	**1.48E-11*****
Predicted pattern	1.46	0.39	3.78	**8.67E-04****	0.44	0.22	2.02	0.060
Random pattern	0.58	0.39	1.50	0.147	0.71	0.22	3.24	**0.005****
2nd Trial	0.53	0.39	1.37	0.181	0.23	0.22	1.03	0.317
3rd Trial	0.14	0.39	0.37	0.713	0.05	0.22	0.22	0.827
Variable	Right Outer Prismatic Actuator: MAE - Position (mm)				Right Inner Prismatic Actuator: MAE - Position (mm)			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	8.35	0.15	56.41	**8.77E-28*****	5.96	0.37	15.99	**1.23E-14*****
Predicted pattern	-0.53	0.14	-3.85	**0.001****	-0.98	0.40	-2.45	**0.022***
Random pattern	-1.13	0.14	-8.17	**4.20E-07*****	-0.12	0.40	-0.30	0.770
2nd Trial	-0.20	0.14	-1.48	0.157	-0.92	0.40	-2.30	**0.030***
3rd Trial	-0.18	0.14	-1.32	0.205	-0.32	0.40	-0.81	0.425
Variable	Left Outer Prismatic Actuator: MAE - Position (mm)				Left Inner Prismatic Actuator: MAE - Position (mm)			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	8.48	0.15	58.43	**3.26E-28*****	5.95	0.38	15.83	**1.53E-14*****
Predicted pattern	-0.52	0.14	-3.84	**0.001****	-0.82	0.40	-2.04	0.053
Random pattern	-1.08	0.14	-7.95	**6.04E-07*****	-0.13	0.40	-0.32	0.753
2nd Trial	-0.19	0.14	-1.36	0.193	-0.94	0.40	-2.33	**0.028***
3rd Trial	-0.19	0.14	-1.38	0.186	-0.35	0.40	-0.87	0.394
Variable	Right Knee Revolute Actuator: MAE - Position (deg)				Left Knee Revolute Actuator: MAE - Position (deg)			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	2.87	0.20	14.15	**2.95E-12*****	3.06	0.27	11.46	**4.91E-09*****
Predicted pattern	-0.14	0.16	-0.84	0.411	-0.02	0.17	-0.14	0.888
Random pattern	0.26	0.16	1.65	0.118	0.27	0.17	1.60	0.128
2nd Trial	-0.47	0.16	-2.96	**0.009****	-0.49	0.17	-2.94	**0.010***
3rd Trial	-0.48	0.16	-2.99	**0.009****	-0.25	0.17	-1.48	0.157

*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

TABLE IX: Linear mixed model results for mean absolute force at knee actuators

Variable	Right Knee: Mean Absolute Force (N)				Left Knee: Mean Absolute Force (N)			
	Estimate (β)	**Std. Error**	**t value**	**p-value**	**Estimate (β)**	**Std. Error**	**t value**	**p-value**
(Intercept)	153.4	20.5	7.5	**8.22E-08*****	140.0	24.1	5.8	**5.78E-06*****
Predicted pattern	22.2	18.9	1.2	0.257	42.1	20.9	2.0	0.061
Random pattern	68.7	18.9	3.6	**0.002****	84.5	20.9	4.1	**0.001****
2nd Trial	-19.7	18.9	-1.0	0.313	-17.7	20.9	-0.8	0.409
3rd Trial	-25.6	18.9	-1.4	0.193	-19.2	20.9	-0.9	0.372

*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

TABLE X: Comparsion of RMSE to benchmark study

Joint	RMSE This study	RMSE Koopman [28]
Hip abd/add (deg)	2.91	1.46
Hip flex/ext (deg)	7.57	2.42
Knee flex/ext (deg)	5.81	3.49
Pelvis lateral (mm)	6.32	-

This discomfort could be due to improperly timed toe-off and heel strike, which are particularly noticeable at the ankle cuff. Moreover, participants commonly mentioned excessive lateral pelvis movement, causing the body to move uncomfortably and unnaturally sideways. Several factors contribute to this, such as the pelvis actuator's slight overshoot (Appendix F-D) and the compliant pelvis module potentially causing additional lateral movements due to its spring system (Fig. 1). Instructing participants to remain passive may have led to them allowing the exoskeleton to flop their upper body from side to side, possibly adding to the sensation of excessive lateral movement. Another factor resulting in potential discomfort is the lack of an ankle support mechanism to facilitate toe-off might have contributed to discomfort at the ankle. A participant also remarked that the slow walking speed of the exoskeleton felt unnatural, indicating that slow speeds may feel generally unnatural. Furthermore, joint misalignments between the participant and the exoskeleton during dynamic movements, inherent to the system due to the relative motion of the human body within the exoskeleton, likely resulted in increased discomfort from additional interaction forces [47].

2) Objective Data: The actuators successfully replicated the reference gait pattern with relatively low errors, enabling a comparison of different gait patterns. The predicted gait pattern, other than hypothesized, did not significantly reduce actuator position errors and knee forces, nor was the random pattern consistently worse than the standard or predicted patterns. Some actuators showed significantly lower position errors with the predicted pattern compared to the standard pattern, while others showed no significant difference or performed better with the standard pattern. Similarly, knee forces were significantly higher for the random pattern compared to the standard pattern, but actuator position errors varied with the random pattern – being significantly higher, significantly lower, or showing no significant difference, depending on the actuator. The observed differences in actuator position errors and knee forces among the gait pattern conditions might be due to unique peculiarities in their trajectories. These peculiarities might stem from the methodologies used to derive the different gait patterns: averaging for the standard pattern, quintic spline fitting for the predicted, and directly using a pre-recorded gait for the random pattern.

The results also revealed an effect of trial order. Participants may have gotten used to the system, creating fewer interaction forces, although this trend was primarily observed in the second trial rather than in the third. The discrepancy between the second and third trials indicates that the adaptation trend is not consistent, or that the different results for the second and third trials might be due to the small sample size.

C. Limitations

This study's gait prediction model has several limitations. The reconstruction of gait patterns relied on selecting six key events per joint (except lateral pelvis movement) based on the researchers' expertise in the study by Koopman [28]. However, there was no optimization process for determining the ideal number of key events to improve fit. An alternative selection of key events could potentially enhance the prediction accuracy. Additionally, the dataset utilized in this study, provided by Fukuchi [43], primarily comprises data from the Brazilian population. This poses questions about the model's efficiency across different demographic profiles, for example, considering the average height differences between Dutch and Brazilian males and females [48]. Moreover, the database only includes data from young and elderly participants, omitting middle-aged individuals, which further limits the model's generalizability.

There are also certain limitations regarding the experiment and its findings. The study included only healthy participants, which limits the applicability of the results to individuals with gait impairments, such as those experienced by stroke survivors. There were also uncontrolled factors in this experiment, e.g., personal footwear, that were controlled in the reference data [43], which may have influenced performance. In addition, the lack of defined terms in the questionnaire could lead to subjective interpretations, affecting the consistency of the responses among participants.

The small sample size and the treatment of ordinal data from a 7-point Likert scale as continuous data may affect the validity of the statistical analysis. Moreover, the presence of an order effect diminishes the reliability of the Friedman test results. Regarding the actuator position analysis, improvements could be made by converting actuator trajectories back into joint angle trajectories. This would provide a clearer understanding of the magnitude of the position errors in terms of actual joint trajectories.

D. Future research

Future research should explore other gait prediction models to examine their effects on users' perceptions of individualized gait patterns. Enhancing the accuracy of these models is crucial for accurately predicting an individual's gait pattern, which may involve exploring a wider and more varied set of input variables. Moreover, expanding the gait database to cover a more diverse population and further walking speeds is essential for improving the performance of these prediction models. Exploring how stroke patients perceive different gait patterns and the effect of these perceptions on their rehabilitation training and outcomes is another important area for future research. Additionally, studies with larger sample sizes are needed for conclusive statistically significant results. Furthermore, feedback in this study highlighted that many individuals find the current reference gait patterns to be unnatural and uncomfortable. Future work should not only aim to accurately predict individual gait patterns but also to refine these patterns based on patient feedback to better meet specific needs. Adjusting spatial or temporal aspects of gait, such as step length and width, provides more flexibility in generating gait patterns. Such adjustments could make gait patterns feel more comfortable and natural to patients. Engaging directly with stroke patients to gather and analyze their feedback on gait adjustments should be a central focus in future research.

V. Conclusion

This study explored user perceptions of individualized versus standard and random gait patterns, focusing on enjoyment, comfort, and naturalness. A predictive gait model was developed incorporating individual anthropometric, demographic data, and walking speed. Analysis of prediction accuracy using root mean square error indicated that both predicted and standard gait patterns approximate an individual's gait similarly well.

In an experiment, participants walked with a robotic lower limb device across these gait patterns and provided feedback through a questionnaire. The findings revealed no significant differences in gait pattern perceptions, except for physical strain, where the predicted pattern resulted in significantly more strain than the standard. Further analysis indicated that trial order influenced perception, suggesting that longer use of the system leads to an improved walking experience in terms of comfort and naturalness.

Although no significant differences were observed except in terms of physical strain, a tendency towards the standard pattern was observed. This preference exists despite RMSE results suggesting similar accuracy between the standard and predicted gait patterns. This highlights the importance of experiments involving humans in evaluating physical human-robot interactions.

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Supplementary Material

Subjective Assessment of Individualized Gait Patterns on Enjoyment, Comfort, and Naturalness in Robot-Assisted Walking

Appendix A
Calculation of the Lateral Pelvis Movements from the Gait Database

The modified Lokomat® employed in this study can enable lateral pelvis movements. However, these movements are not originally included in the post-processed data of the used gait database by Fukushi et al. [1]. Therefore, the lateral pelvic movements were determined using the raw data of marker positions. This appendix details the methodology for calculating lateral pelvis movements for the different recorded walking trials.

A. Marker Positions

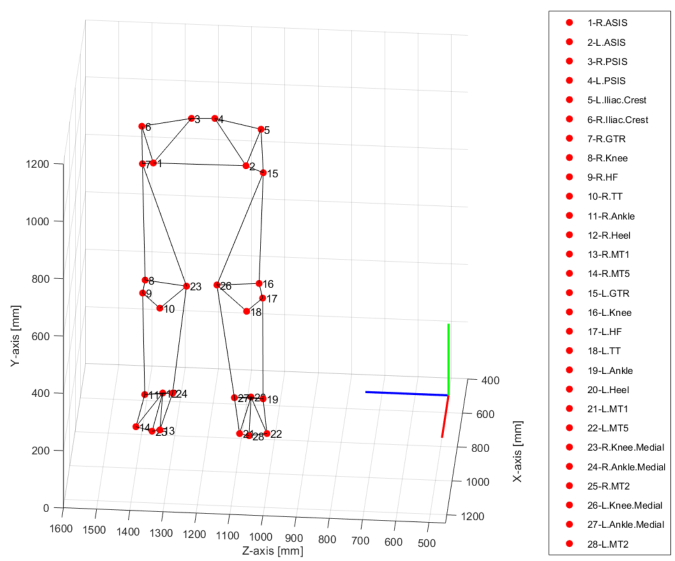


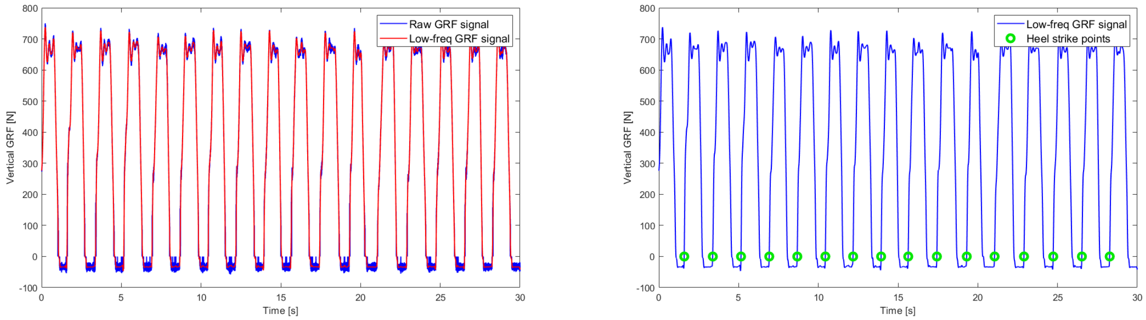
Fig. 4: Illustration of marker placements on the pelvis [1].

Fig. 4 illustrates the placement of markers on the participants' body. To determine lateral pelvis movement, the markers placed on the participants' pelvis were used. These included the left and right Anterior Superior Iliac Spine (ASIS) - marked as 1-R.ASIS and 2-L.ASIS, the left and right Posterior Superior Iliac Spine (PSIS) - marked as 3-R.PSIS and 4-L.PSIS, and the left and right iliac crest - marked as 5-R.Iliac.Crest and 6-L.Iliac.Crest. The markers were used in calculating the average lateral displacement (in the z-direction) during the walking trials.

B. Determination of Lateral Pelvis Movement

The gait database comprises raw marker data in the XYZ directions and ground reaction force (GRF) data for each 30-second walking trial, which consists of multiple gait cycles. The approach to determining lateral pelvis movement involves analyzing individual marker signals and subsequently computing the ensemble average across the six considered markers. The following sections describe the employed procedure in more detail.

1) Identifying Heel Strike: First, heel strikes are identified using the GRF data to determine the start of gait cycles. This step is important to align the lateral pelvis movement with the already existing joint angle trajectories of the database [1]. The determination of heel strike, which is based on the methodology of Fukuchi et al. [2], involves filtering the GRF signal with a fourth-order low-pass Butterworth filter (cut-off frequency: 10 Hz) and detecting heel strike when the vertical GRF exceeds a threshold value of 20 N (Fig. 5). These heel strike points are then used to calculate the step frequency, essential for further noise reduction in pelvis marker data, and average gait cycle time.

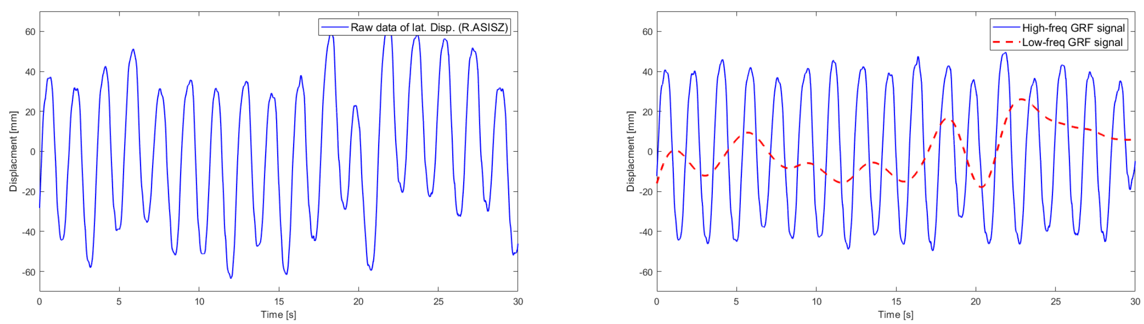


(a) Low-pass filtering step

(b) Identifying heel strike locations

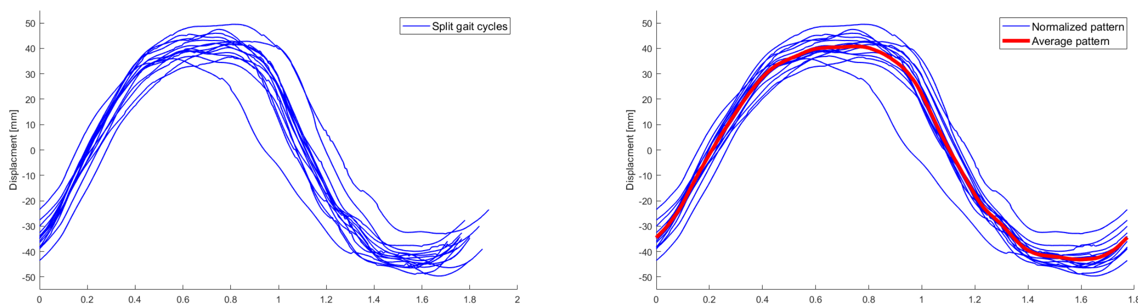
Fig. 5: Pre-Processing of GRF Data: Example of data subject 1 at walking speed level 1. (a) Low-pass filtering of raw GRF data to eliminate high-frequency noise. (b) Determination of heel strike when the vertical GRF exceeds a threshold value of 20 N.

2) Pre-Processing of Marker Data: To analyze the lateral pelvis displacement (Z-axis) of the pelvis marker, a fourth-order, high-pass Butterworth filter (cut-off frequency: half the step frequency) is employed to reduce low-frequency noise. This specific frequency effectively filters out low-frequency noises, as determined by visual inspection (Fig. 6a, 6b). The use of the filter is crucial for accurate data processing, as subjects naturally shift laterally while walking on a treadmill. These shifts can introduce noise into the data, potentially obscuring the true pelvis movement patterns when walking in a straight line. The high-pass filter effectively minimizes these variations, ensuring a clearer analysis of the pelvis's lateral movements. Following the filtering process, the raw pelvis marker data are segmented into individual gait cycles (Fig. 6c), based on the heel strike points determined with the GRF data. These cycles are normalized to the mean cycle duration and subsequently averaged to represent the lateral pelvis movement of a marker (Fig. 6d).



(a) Raw R.ASISZ signal

(b) High-pass filtering step

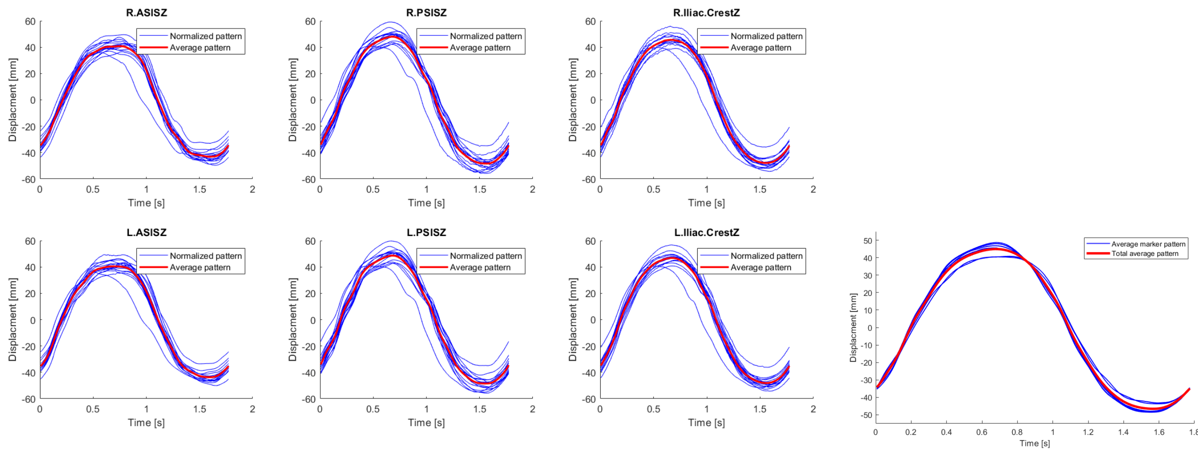


(c) Split gait cycles

(d) Normalize gait cycle

Fig. 6: Pre-Processing of Marker Data (Part 1): Example of data subject 1 at walking speed level 1. (a) Raw displacement data of the R.ASISZ marker in the lateral direction. (b) High-pass filtering of raw marker data to eliminate low-frequency noise. (c) Segmentation of the marker data into single gait cycles based on identified heel strike locations. (d) Normalization of split gait cycle segments to average cycle time, followed by the computation of an average pattern from these normalized patterns.

3) Ensemble Average Lateral Pelvis Movement: To determine the average lateral movement of the pelvis during a walking trial, the individual averaged trajectories of the six pelvis markers are time-normalized and subsequently averaged (Fig. 7). This method produces the ensemble average of the subject's lateral pelvis movement. This movement is then stored as a time-normalized gait pattern, similar to the already calculated joint angle trajectories in the gait database.



(a) Normalized and averaged pattern of all markers

(b) Total average pattern

Fig. 7: Pre-Processing of Marker Data (Part 2): Example of data subject 1 at walking speed level 1. (a) Similar to the marker R.ASISZ in Fig. 6, the average lateral movements are calculated for all six pelvis markers. (b) A combined average gait pattern is derived from these six markers.

Appendix B
Overview of Walking Speed Data in Fukuchi's Database

Table XI provides the mean speeds and standard deviations for the different speed levels of the database by Fukuchj [43]. Specifically, data from the three lowest speed levels were selected for training the prediction model.

TABLE XI: Overview of the mean and standard deviation of speeds at various speed levels from the database by Fukuchi [43]. A speed level contains the speeds of participants related to walking with a certain percentage of their comfortable, self-selected walking speed. Speed levels included for the gait prediction model are highlighted in bold.

Speed Levels (% of Self-Selected Speed)	Mean (kph)	Std. (kph)
Level 1 (40%)	**1.80**	0.231
Level 2 (55%)	**2.46**	0.336
Level 3 (70%)	**3.14**	0.410
Level 4 (85%)	3.81	0.493
Level 5 (100%)	4.48	0.582
Level 6 (115%)	5.15	0.670
Level 7 (130%)	5.83	0.765
Level 8 (145%)	6.45	0.812

APPENDIX C
STANDARD GAIT PATTERN

The standard gait pattern used in this study is depicted in Fig. 8 and was derived by averaging the gait patterns of the three lowest walking speed levels from the database by Fukuchi [1]. Including only these lower speeds, all below the exoskeleton's maximum speed of 3.2 kph [3], ensures that the pattern is representative of the exoskeleton's operational capabilities.

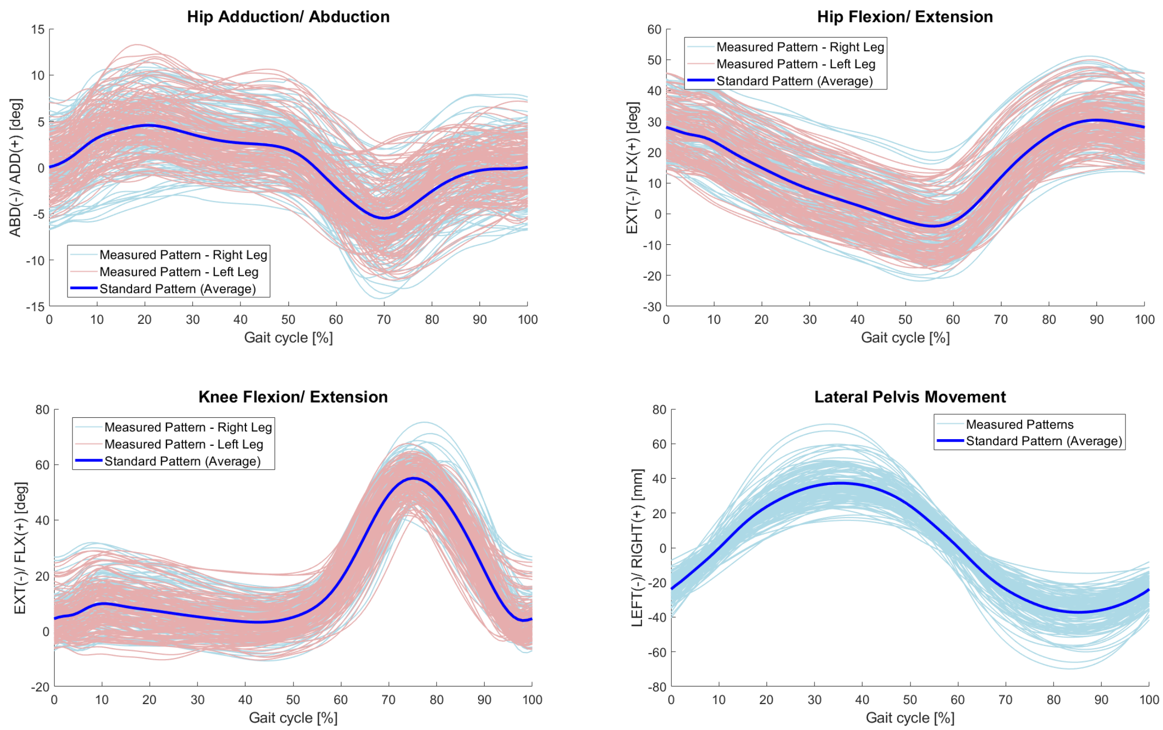


Fig. 8: Standard Gait Pattern: Calculated by averaging the gait patterns of all test subjects of the three lowest speed levels, the light red line represents the left leg and the light blue line the right leg.

APPENDIX D
REVOLUTE KNEE JOINT MECHANICS

Fig. 9 depicts the inside of the knee actuator in the Lokomat® system. The force measured at the knee joint reflects the longitudinal force produced along the main axis of the spindle drive, indicating the magnitude of force exerted on the knee actuator.

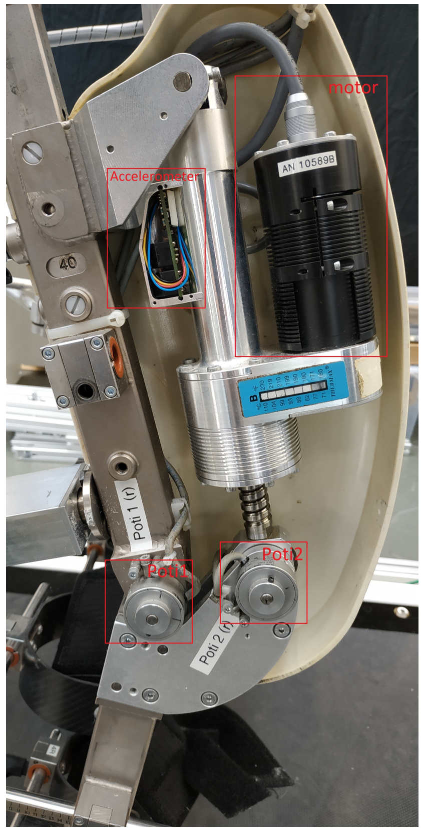


Fig. 9: Image of the inside of the knee actuator in the Lokomat® system. Source: HRI Wiki, TU Delft [4]

APPENDIX E
REGRESSION EQUATIONS OF JOINT TRAJECTORIES

The regression coefficients derived for the different joint trajectories and their corresponding key events are listed as follows: hip abduction/adduction in Table XII, hip flexion/extension in Table XIII, knee flexion/extension in Table XIV, and lateral pelvis movement in Table XV.

TABLE XII: Regression equations for the parameter values of the key events of hip abduction/adduction.

Hip abduction/adduction								
Key event	Parameter	β_0 (Intercept)	β_1 (Speed)	β_2 (Speed^2)	β_3 (Height)	β_4 (Weight)	β_5 (Age)	β_6 (Gender)
Heel contact	Timing (t)	0	-	-	-	-	-	-
	Angle (y)	0.0400	-	-	-	-	-	-
	Vel. ($\dot{y}$)	0.0222	-	0.0075	-	-	-	−0.0343
	Acc. ($\ddot{y}$)	0.0390	-	0.0042	-	-	-	−0.0182
Max. stance	Timing (t)	35.8245	-	-	−10.0179	-	-	0.7653
	Angle (y)	15.0676	-	-	−8.2105	0.0568	-	−1.3062
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	−0.0914	-	-	-	-	0.0006	0.0108
Max. $\dot{y}$ stance	Timing (t)	41.0000	-	-	-	-	-	-
	Angle (y)	17.5024	-	-	−12.0096	0.0790	-	−0.5726
	Vel. ($\dot{y}$)	−0.0130	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-
Min. $\dot{y}$ swing	Timing (t)	58.3550	-	-	-	-	-	-
	Angle (y)	−4.0730	-	-	-	-	0.0479	-
	Vel. ($\dot{y}$)	−2.3595	-	−0.0138	1.4393	−0.0105	0.0034	-
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-
Min. swing	Timing (t)	74.1734	−1.7955	-	-	-	-	-
	Angle (y)	−19.8236	-	-	8.9280	−0.0598	0.0725	-
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	0.2778	-	-	−0.1289	0.0013	−0.0008	−0.0190
Max. $\dot{y}$ swing	Timing (t)	69.8878	-	-	-	0.0891	0.0331	-
	Angle (y)	−5.2261	-	-	-	-	0.0444	-
	Vel. ($\dot{y}$)	0.4375	−0.0366	-	-	0.0037	−0.0030	−0.0956
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-

Note: "-" indicates that a parameter has no significant impact on the regression model. The regression equations were generated using data from all 42 subjects. By default, heel strike timing is set to zero (% of the gait cycle), as are the minimum and maximum values for joint angle and angular velocity.

TABLE XIII: Regression equations for the parameter values of the key events of hip flexion/extension.

Hip flexion/extension								
Key Event	Parameter	β_0 (Intercept)	β_1 (Speed)	β_2 (Speed^2)	β_3 (Height)	β_4 (Weight)	β_5 (Age)	β_6 (Gender)
Heel contact	Timing (t)	0	-	-	-	-	-	-
	Angle (y)	24.4160	-	-	-	-	0.0830	-
	Vel. ($\dot{y}$)	−0.8169	0.1166	-	0.1915	-	-	-
	Acc. ($\ddot{y}$)	−0.3435	0.0775	-	-	-	-	0.0147
Max. stance[a]	Timing (t)	15.6875	-	-	−5.6864	-	-	-
	Angle (y)	30.1610	-	-	-	-	-	-
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	−1.0905	-	-	0.7260	−0.0043	-	-
t=50% Stance	Timing (t)	31.4315	−2.3754	0.3413	-	-	-	-
	Angle (y)	5.4895	-	-	-	-	0.0868	-
	Vel. ($\dot{y}$)	−1.2312	−0.1953	-	0.6511	-	-	-
	Acc. ($\ddot{y}$)	0.0601	-	−0.0017	-	-	−0.0005	-
Min.	Timing (t)	63.4402	−4.7863	0.6803	-	-	-	-
	Angle (y)	−4.5359	-	-	-	-	-	1.9210
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	0.1171	0.0117	-	-	-	-	-
Max. $\dot{y}$ swing	Timing (t)	75.3750	−9.3496	1.6596	-	0.0719	-	−1.2761
	Angle (y)	8.4660	-	-	-	-	-	-
	Vel. ($\dot{y}$)	3.2209	0.0980	-	−1.2215	0.0081	−0.0033	−0.0829
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-
Max. swing	Timing (t)	90.6226	−1.0169	-	-	-	0.0474	-
	Angle (y)	61.8406	2.0764	-	−21.7837	-	-	1.4937
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	−0.1080	-	-	-	-	-	-

[a] This key event is excluded from the spline fitting procedure due to its relevance only for walking speeds exceeding 3.5 kph [5], whereas the developed regression model focuses on speeds up to 3.2 kph.

TABLE XIV: Regression equations for the parameter values of the key events of knee flexion/extension.

Knee flexion/extension								
Key Event	Parameter	β_0 (Intercept)	β_1 (Speed)	β_2 (Speed^2)	β_3 (Height)	β_4 (Weight)	β_5 (Age)	β_6 (Gender)
Heel contact	Timing (t)	0	-	-	-	-	-	-
	Angle (y)	-18.4403	-	-0.3887	10.1799	-	0.1908	-
	Vel. ($\dot{y}$)	-0.8710	0.7016	-0.0875	-	-	-	0.0664
	Acc. ($\ddot{y}$)	-0.5245	0.2494	-	-	-	-	0.0490
Max. stance	Timing (t)	11.643	-	-	-	-	-	-
	Angle (y)	-2.2525	-	0.4534	-	-	0.2254	2.1273
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	-0.3389	-	-	0.3752	-0.0074	-0.0017	0.0743
Min. stance	Timing (t)	32.4633	-	-	-	-	0.1521	1.9152
	Angle (y)	16.7077	-	-	-	-0.2192	-	3.2653
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	0.1067	0.0202	-	-0.0980	0.0012	-	-
Max. $\dot{y}$ swing	Timing (t)	77.1875	-7.9539	1.1427	-	-	-	-0.4295
	Angle (y)	37.1826	1.4471	-	-	-0.0980	-	-
	Vel. ($\dot{y}$)	3.2140	-	-	-	0.0061	-	-0.1909
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-
Max. swing	Timing (t)	81.719	-5.0453	0.8888	-	-	-	-
	Angle (y)	52.1027	4.7823	-	-	-0.1198	-	-
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	-0.9725	0.0768	-	0.1608	-	0.0014	0.0297
Min. $\dot{y}$ swing	Timing (t)	88.3116	-	0.1551	-	-	-	-
	Angle (y)	17.7490	-	-	-	-	0.1429	-
	Vel. ($\dot{y}$)	-3.9013	-0.4602	-	-	0.0143	0.0098	-
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-

TABLE XV: Regression equations for the parameter values of the key events of lateral pelvis movement.

Lateral pelvis movement								
Key Event	Parameter	β_0 (Intercept)	β_1 (Speed)	β_2 (Speed^2)	β_3 (Height)	β_4 (Weight)	β_5 (Age)	β_6 (Gender)
Max. $\dot{y}$	Timing (t)	12.7882	-	-	-	-	-0.0266	-
	Angle (y)	6.9961	-	-	-	-	-0.0735	-1.7287
	Vel. ($\dot{y}$)	7.1648	-0.7182	-	-2.0033	0.0210	-0.0142	-
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-
Max.	Timing (t)	26.1353	-	-	5.6096	-	-	-
	Angle (y)	60.1065	-9.2432	-	-	-	-	-
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	-0.1353	-	0.0031	-	-	-	-
Min. $\dot{y}$	Timing (t)	62.9191	-	-	-	-	-0.0243	-
	Angle (y)	4.2084	-	-	-	-0.1631	0.0582	3.1179
	Vel. ($\dot{y}$)	-4.7921	0.7730	-	-	-	-	-
	Acc. ($\ddot{y}$)	0	-	-	-	-	-	-
Min.	Timing (t)	75.8100	-	-	5.6217	-	-	-
	Angle (y)	-60.1309	9.2839	-	-	-	-	-
	Vel. ($\dot{y}$)	0	-	-	-	-	-	-
	Acc. ($\ddot{y}$)	0.0387	-	-0.0018	-	0.0014	-	-0.0212

APPENDIX F
EXPERIMENTAL RESULTS

A. *Treadmill Speed Settings of Trials*

The final treadmill speeds for each trial of the participants are summarized in Table XVI. The data indicates that, for the majority of participants, no adjustment to the treadmill speed was necessary, indicating that the predicted gait cycle time for the gait patterns matched the desired speed of 1.8 kph. However, some participants gave feedback suggesting an increase in treadmill speed to minimize discrepancies between treadmill speed and foot movements.

TABLE XVI: Overview of adjusted treadmill walking speeds for each participant and trial condition (predicted, standard, and random).

Participant	Final walking speed (kph)		
	Predicted	Standard	Random
1	1.8	1.8	1.8
2	1.8	1.8	1.8
3	1.8	1.8	1.8
4	2.0	2.0	2.0
5	1.8	1.8	2.0
6	1.8	1.8	1.8
7	2.0	1.8	1.8
8	2.0	2.0	2.0
9	1.8	1.8	1.8
10	1.8	1.8	1.8

B. *Questionnaire and Actuator Data Results*

This section presents the results of questionnaires and recorded actuator data collected from various subjects, using boxplots for illustration. The outcomes are displayed across different experimental conditions (standard, predicted, and random patterns), and for the different trial stages (T1, T2, T3). Specifically, the questionnaire results are categorized and presented in the following manner: *Interest/Enjoyment* (IMI) and *Passiveness* are depicted in figure 10, *Comfort* in figure 11, and *Naturalness* in figure 12. Additionally, the distribution of participants' rankings for each gait pattern and experimental position is displayed in figure 13.

The analysis of the actuator data is also visualized through boxplots, comparing outcomes across the same experimental conditions and trial stages. The specific metrics investigated include: the Mean Absolute Error (MAE) of the actuators' positions in figure 14, and the Mean Absolute Force at the knee actuators in figure 15.

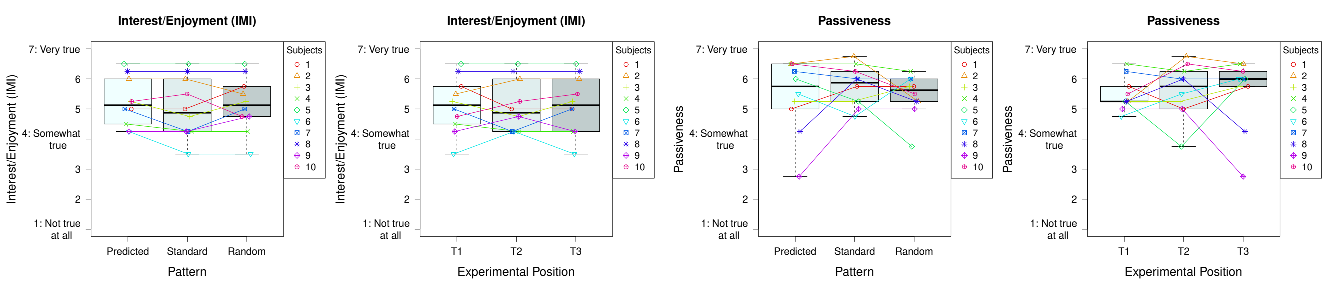


Fig. 10: Boxplots displaying the questionnaire outcomes for *Interest/Enjoyment* (IMI) and user *Passiveness* during trials, evaluated on a 7-point Likert scale (see appendix I. Each category's outcome is the average of several related questions. The data is organized into separate boxplots to provide a detailed view: for each category, the left plot shows the results across different experimental conditions (standard, predicted, and random pattern), and the right plot shows the outcomes at each trial stage (T1, T2, T3).

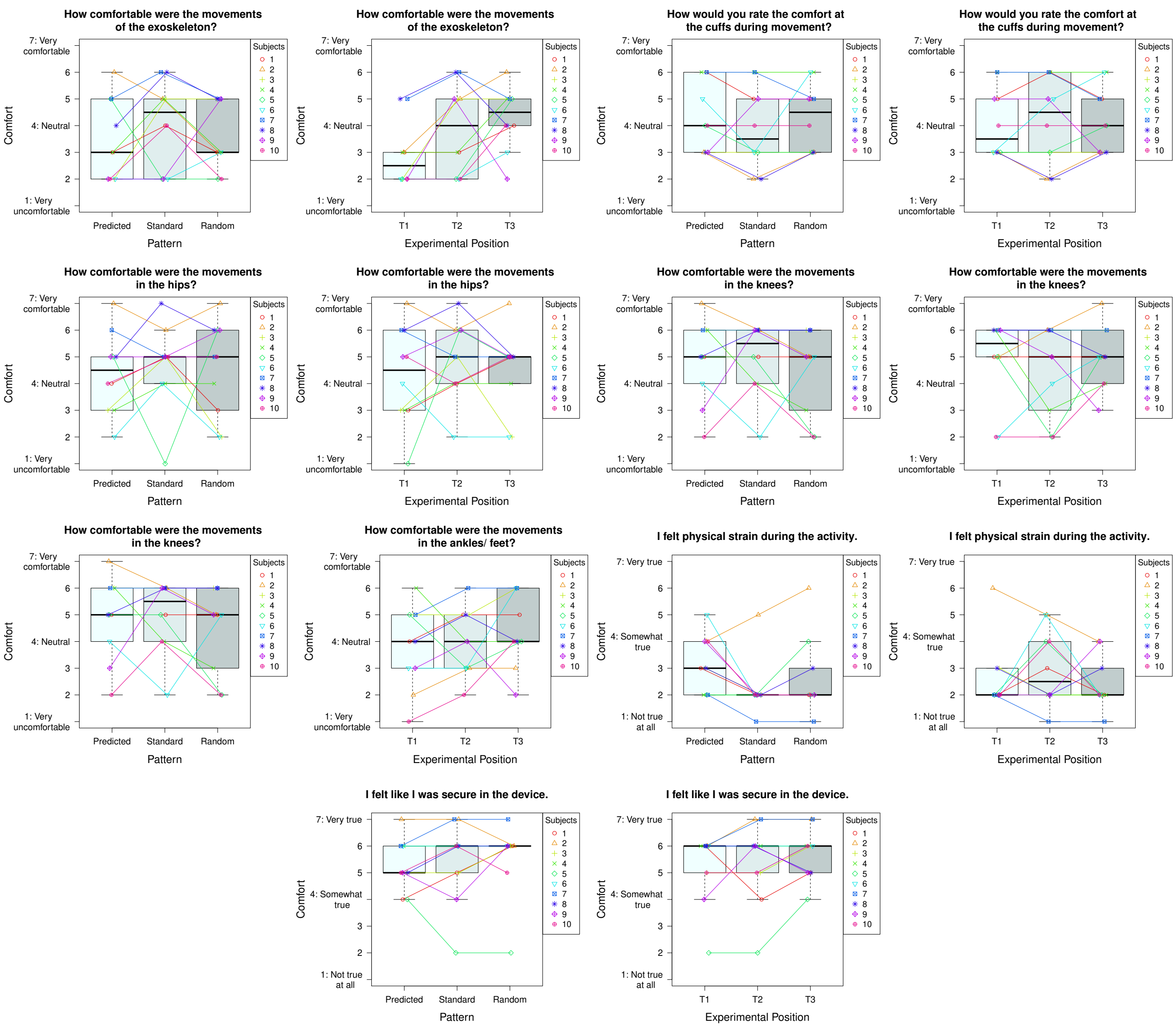


Fig. 11: Boxplots displaying the questionnaire outcomes related to *Comfort*, with each question analyzed separately, evaluated on a 7-point Likert scale (see appendix I. The data is organized into separate boxplots to provide a detailed view: for each category, the left plot shows the results across different experimental conditions (standard, predicted, and random pattern), and the right plot shows the outcomes at each trial stage (T1, T2, T3).

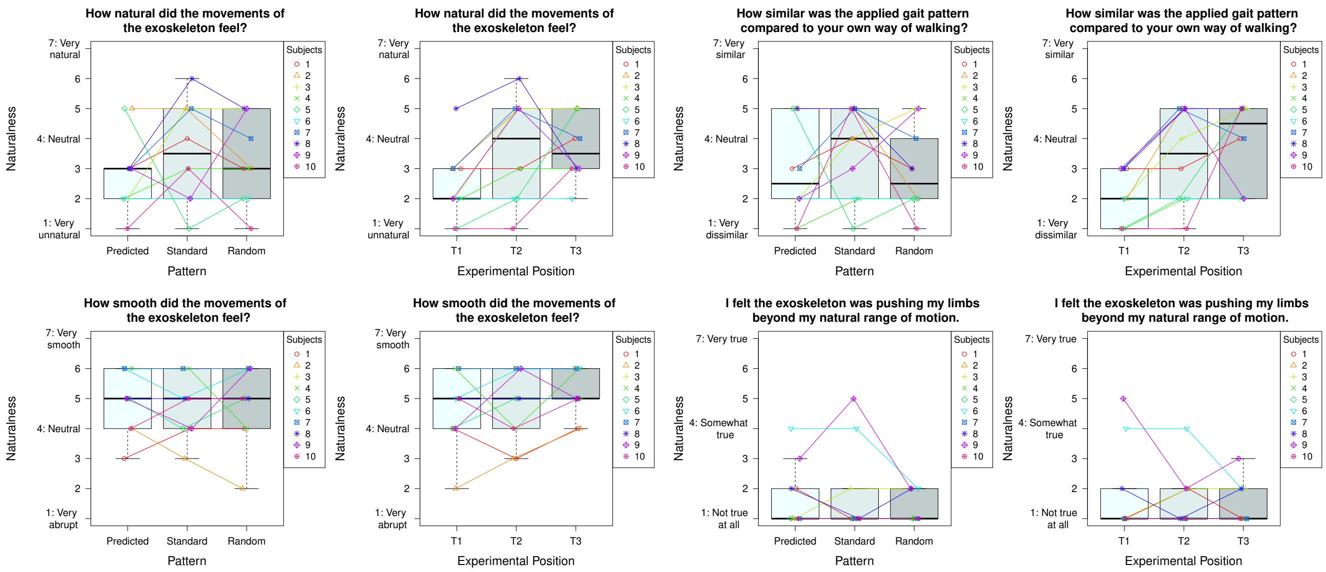


Fig. 12: Boxplots displaying the questionnaire outcomes related to *Naturalness*, with each question analyzed separately, evaluated on a 7-point Likert scale (see appendix I. The data is organized into separate boxplots to provide a detailed view: for each category, the left plot shows the results across different experimental conditions (standard, predicted, and random pattern), and the right plot shows the outcomes at each trial stage (T1, T2, T3).

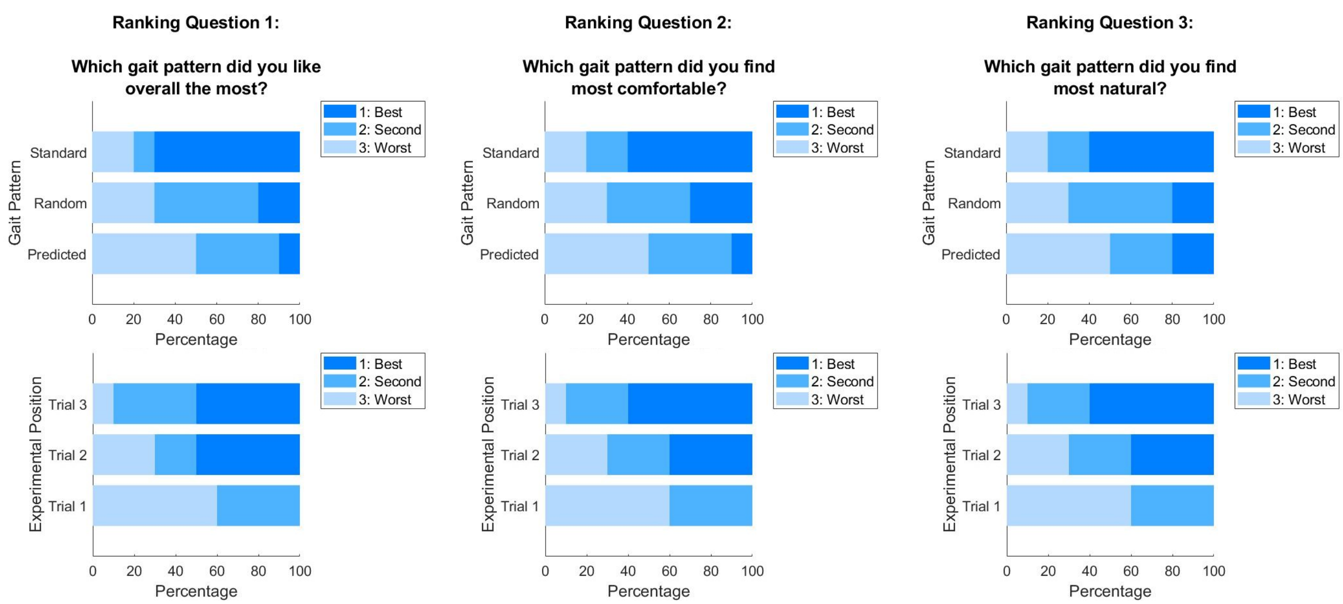


Fig. 13: Distribution of rankings for each gait pattern and experimental position across ranking categories: overall preferred gait pattern (left), most comfortable gait pattern (middle), and most natural gait pattern (right). The top plots illustrate the distribution of rankings for each gait pattern, while the bottom plots detail the distribution for each experimental position.

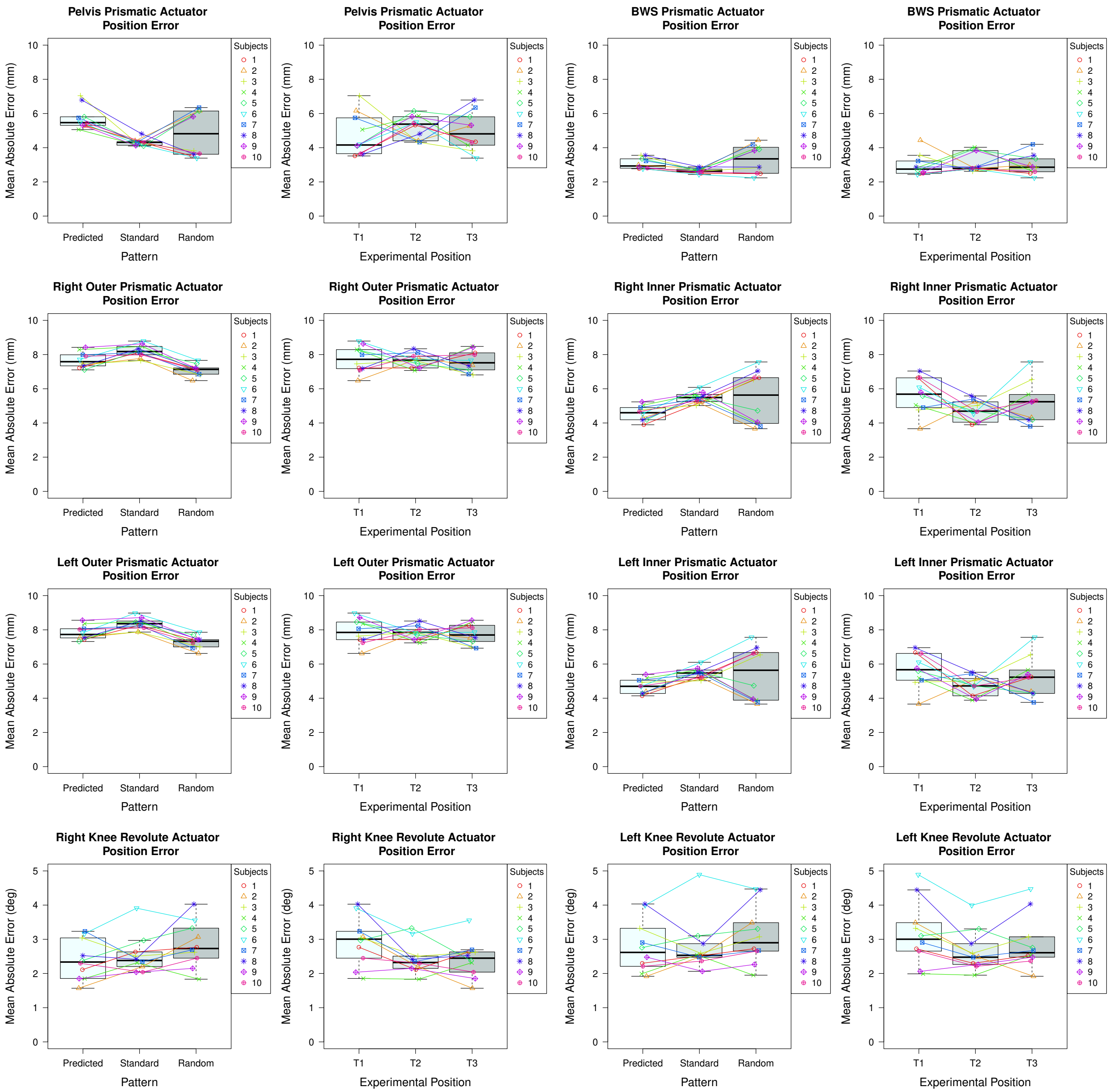


Fig. 14: Boxplots displaying the Mean Absolute Error(MAE) in the actuators' positions, i.e. the error between the reference and measured pattern at each actuator. The data is organized into separate boxplots to provide a detailed view: for each actuator, the left plot shows the MAE across different experimental conditions (standard, predicted, and random pattern), and the right plot shows the MAE at each trial stage (T1, T2, T3).

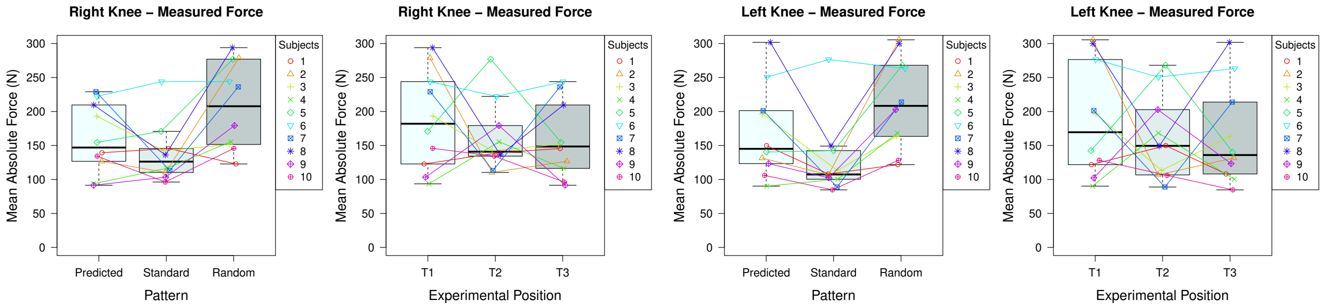


Fig. 15: Boxplots displaying the Mean Absolute Force at the left and right knee actuators. The data is organized into separate boxplots to provide a detailed view: for each actuator, the left plot shows the Mean Absolute Force across different experimental conditions (standard, predicted, and random pattern), and the right plot shows the Mean Absolute Force at each trial stage (T1, T2, T3).

C. Open-ended Question Results

The results of the open-ended questionnaire are organized into the tables below: Table XVII contains responses related to discomfort and unusual sensations; Table XVIII contains responses related to aspects influencing comfort or discomfort; and Table XIX includes additional thoughts or comments provided by participants.

TABLE XVII: Participant responses regarding the open-ended question about discomfort and unusual sensations, sorted by gait patterns (standard, predicted, random).

Participant	**Open-ended question:** Did you experience any discomfort in terms of physical strain or unusual sensations during the walking session with the Lokomat? If so, please specify the level of discomfort as well as the areas of discomfort, e.g., on which cuffs, joints, or other body parts.		
	Standard	**Predicted**	**Random**
1	"I felt like there was some weight on my feet which made it difficult to remain passive. Discomfort level: 6/10."	"I felt discomfort with how much weight was applied on my feet. Because of this it was hard to remain passive. Discomfort level: 7/10."	"I felt some discomfort at the hips (6/10)."
2	"Cuffs at the ankles still uncomfortable as [during the random pattern]. Much less strain to keep foot position"	"Very similar to [standard pattern]."	"Yes, the machine was too low while walking and my feet did not have room to go back. At the same time if the machine was higher the ankle cuffs pressed too much against my calf. Also having to keep my feet as horizontal as possible was tiring."
3	"I still felt strain around the ankle cuffs seemingly pushing my calf muscles up, although it was less compared to the last trial. I also felt some chafing around the hip bone this time; minor but there"	"Ankle cuffs keep pushing the muscles of my calves up (on and off). This creates a kind of cramped feeling sometimes. Also by nature of the device it feels a little as if the space between my thighs is larger than it normally would be (but this may be due to the fittings there)."	"This pattern resulted in the least chafing for me, if none, but the experiment progressed, the excessive hip swaying began to hurt at the hip bone. Also the ankles started to chafe again as everything progressed."
4	-	-	"Yes, a slight discomfort in the knees."
5	"Yes, particularly uncomfortable on the hips."	"Slight discomfort at ankles (especially left)."	"Light discomfort on calf cuff. Medium discomfort at ankle and knee."
6	-	"My muscles got a bit sour since you relax your muscles except for the calves because of the ankle movements."	"No, this was much better compared to the first two gait patterns. However, this could also be because I got used to it."
7	-	-	-
8	"Ankle cuffs a bit uncomfortable."	"Ankle cuffs uncomfortable."	"Right ankle cuff was sometimes a bit uncomfortable."
9	"I felt slight discomfort in my ankles when walking with the exoskeleton. The joints were moved in an unnatural position."	"I experienced some discomfort in my legs around the cuffs, because my legs were pushed beyond natural range of motion."	"No physical strain."
10	-	"Mild discomfort on the outer part of my feet when landing after every step."	-

TABLE XVIII: Participant responses regarding the open-ended question about aspects promoting comfort or discomfort, sorted by gait patterns (standard, predicted, random).

Participant	**Open-ended question:** Were there any specific aspects of the gait pattern that contributed to your comfort or discomfort? If so, please specify. For example, consider aspects such as an unusual movement of a particular joint, a small/ large range of motion, jerking of the trajectory, or unsymmetrical gait pattern between left and right leg.		
	Standard	**Predicted**	**Random**
1	"My feet were moving too close to each other which was unnatural for me."	"Again I felt like my feet were too close to each other during the trial."	"I felt like my feet were a bit too close to each other when walking, which was unnatural for me."
2	"Acceleration still a bit abrupt." (referred to random pattern)	"I felt the accelerations were less abrupt compared to the other two conditions."	"I felt the forward acceleration phase was unnaturally fast."
3	"My hips were still swaying quite far sideways. This time it was less problematic because the movement was less so and my body partially countered the weight distributions during. This made it feel less like my body was being thrown left to right by the hips."	"Too felt my hips were swaying outside the range my legs (or really where my feet are positioned on the ground), creating a sensation as if I would fall [if] I [have] to walk like this outside of the device."	"There was once again excessive hip swaying, the worst of the three conditions."
4	-	-	"Not sure about the source but my knees felt rather stiff."
5	"The trajectory was moving my waist left and right, making the hip movement less pleasant and natural."	"My left leg was pushed a bit towards the right, making the left ankle acting a bit shaky at the end of the motion."	"Yes, my legs were positioned more forward than their natural position, this implied better movement for the hip but worse for the knee. It was difficult to raise the tip of the foot enough."
6	"The gait pattern was somewhat counterintuitive since it felt like I wasn't walking in a straight line."	"The lower limb movement was ok, but my feet were towards the centre. Also, hips are moved too much towards the outside → uncomfortable!"	"Now, I know why it was uncomfortable; feet are too distant from each other, so you have to compensate with your hips → uncomfortable."
7	"This time my legs seemed to move from the outside to the inside when extending the leg to the front. This felt more similar to my usual gait."	"I felt like the legs were sometimes moving from the inside to the outside during leg extension to the front. Depending on if I was leaning more to the right or left it was unsymmetrical."	"The hips were moving less from side to side in my opinion this made it more comfortable. But the legs were moving more to the outside when extending the leg. This was a bit unnatural."
8	"Also a lot of lateral hip movement."	"Also lateral hip movement [uncomfortable]."	"Too much lateral movement of my hips felt funny."
9	"The gait pattern moved my feet in an unnatural movement at the heel strike."	"My discomfort was high because there was an unnatural motion for my legs to walk with."	"Comfort in my ankles was higher due to smaller movement/ slower jerking motions compared to 1st trial [standard pattern]."
10	"I felt this time the steps were wider and the trajectory the foot followed from start to end of the step was straighter, which made it more similar to my gait."	"The trajectory of my knees/ankles felt unnatural because it went in and out before landing the step."	"Ankles were pushed inwards, which made it feel unnatural. Also, knee movement had some overshoot and then retrieved a bit before landing the feet."

TABLE XIX: Participant responses regarding the open-ended question on additional thoughts or comments, sorted by gait patterns (standard, predicted, random).

Participant	Open-ended question: Would you like to share any other thoughts or comments?		
	Standard	**Predicted**	**Random**
1	-	-	-
2	-	-	-
3	-	-	"1) Despite the points above, the legs movement & time felt the most natural for this [trial]. The legs felt too spread & the hip swaying felt like I would fall. The legs movements overall felt quite natural somehow. 2) Sometimes the machine movements felt a little odd during this trial, as if it would speed up very briefly, it did this maybe twice so it might not be anything (just an observation)."
4	"The hip movement felt a bit unusual, perhaps slightly exaggerated."	"It wasn't discomfort per se but the hip movement felt over-exaggerated."	-
5	-	"I felt that my weight was placed more on the right leg, like a 60-40 subdivision of the weight."	-
6	-	"Because of the unnatural movements, I really had to focus on what I was doing instead of letting go and naturally walk."	-
7	-	-	-
8	-	-	-
9	"Rest of gait pattern as moved natural."	"I think the unnatural movements were contributing to the strain/discomfort around the cuffs, but I am not sure."	-
10	-	-	-

D. Overshoot of Pelvis Actuator

Figure 16 illustrates the pelvis actuator's overshoot in one subject's trial; however, this phenomenon was observed across multiple subjects. The overshoot causes a slightly larger lateral pelvis movement.

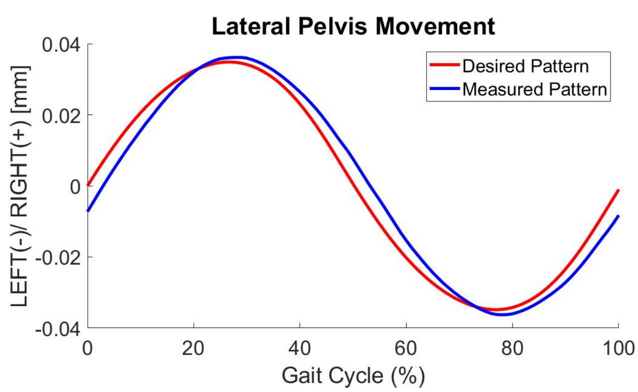


Fig. 16: Recordings of a subject showing slight actuator overshoot in the lateral pelvis movement trajectory compared to the desired trajectory.

APPENDIX G
COMPARSION OF OFFSET AND AMPLITUDE VARIABILITY BETWEEN DATABASES

This appendix presents a comparative analysis of the gait databases from Fukuchi et al. [1], which provided the basis for the regression models in this study, and Theunissen et al. [6], another publicly available gait database. The aim is to explore the origins of the observed variability within Fukuchi's dataset, investigating whether the variability of Fukuchi's database is comparable to that of another database.

A. Overview of Datasets

Section II-B1 of the main paper provides detailed information about the gait database developed by Fukuchi [1]. Conversely, the subsequent paragraph delves into the specifics of the Theunissen database [6].

In the Theunissen database [6], participants walked on the treadmill, similar to the protocol used by Fukuchi. However, one notable difference in the experimental set-up was that the participants in Fukuchi's study walked barefoot, while the participants in Theunissen's study wore standardized shoes designed to closely mimic the dynamics of barefoot walking. The database includes pre-processed trajectories of joint angles for each subject at each speed level. The joint angle movements, including knee flexion/extension, hip flexion/extension, and hip abduction/adduction, are presented as time-normalized ensemble averages for each participant.

A comparative overview of the databases by Fukuchi and Theunissen is shown in Table XX, highlighting differences in anthropometric and demographic data of the subjects, as well as the range of walking speeds included. These speeds are expressed as percentages of the subject's self-determined comfortable walking speed. Furthermore, for a more differentiated comparison, a subset of the Fukuchi database focusing on younger participants is included. This subgroup was selected because its demographic composition better matches that of the subjects in Theunissen's database, allowing a more direct comparison between the two data sets.

TABLE XX: Gait Database Characteristics Comparison

Parameter	**Fukuchi**	**Fukuchi (Young Group)**	**Theunissen**
Subject number	42 (24 male/ 18 female)	24 (14 male/ 10 female)	18 (9 male/ 9 female)
Age (years)	42.64 ± 18.63	27.6 ± 4.4	24.8 ± 3.3
Height (m)	1.67 ± 0.11	1.711 ± 0.105	1.71 ± 0.081
Weight (kg)	67.72 ± 11.24	68.4 ± 12.2	65.9 ± 8.1
Speeds	40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of the self-selected walking speed[a]	40%, 55%, 70%, 85%, 100%, 115%, 130%, and 145% of the self-selected walking speed[a]	60%, 80%, 100%, and 120% of the self-selected walking speed[a]

[a]Self-paced walking speed corresponds to the comfortable walking speed of a person.

To ensure a valid comparison of the offset and amplitude variability between the two databases, comparisons were conducted among specific speed-level groups of the two datasets. Because the two databases contain different speed levels, closely aligned speed levels were selected for the comparison. Table XXI presents an overview of the mean speeds and their corresponding standard deviations for the various speed levels being compared.

TABLE XXI: Comparison of Mean Walking Speeds and Standard Deviations Across Studies

	Speed level[a]	**Fukuchi**	**Fukuchi (Young Group)**	**Theunissen**
Mean speed ±	100%	4.48 ± 0.582	4.48 ± 0.549	4.63 ± 0.539
Std. deviation	85%[b]/80%[c]	3.81 ± 0.493	3.81 ± 0.467	3.76 ± 0.446
(kph)	70%[b]/60%[c]	3.14 ± 0.410	3.14 ± 0.388	3.00 ± 0.395

[a]Percentage of self-paced walking speed. [b]Speed level of Fukuchi database. [c]Speed level of Theunissen database.

B. Metrics

The offset standard deviation σ_{offset}, defined in equation 8, is used as a metric to quantify the variability of gait patterns in the two databases in terms of offset. It provides a measure of the spread or dispersion of offset values around the mean offset.

$$\sigma_{\text{offset}} = \sqrt{\frac{\sum_{i=1}^{N}(o_i - \bar{o})^2}{N}}, \tag{8}$$

Where: σ_{offset} is the offset standard deviation,

o_i represents the offset of each subject's trajectory,

(where o_i is the mean value across the whole gait cycle),

$\bar{o}$ is the mean (average) offset across all subjects' trajectories, and

N is the total number of subjects in the dataset.

The amplitude standard deviation $\sigma_{\text{amplitude}}$, defined in equation 9, is used as a metric to quantify the variability of gait patterns in the two databases in terms of amplitude. It provides a measure of the spread or dispersion of amplitudes around the mean amplitude.

$$\begin{aligned} &\sigma_{\text{amplitude}} = \sqrt{\frac{\sum_{i=1}^{N}(a_i - \bar{a})^2}{N}}, \\ &\text{Where:} \quad \sigma_{\text{amplitude}} \text{ is the amplitude standard deviation,} \\ &\qquad a_i \text{ represents the amplitude of each subject's trajectory,} \\ &\qquad \bar{a} \text{ is the mean (average) amplitude across all subjects' trajectories, and} \\ &\qquad N \text{ is the total number of subjects in the dataset.} \end{aligned} \tag{9}$$

C. Results

Table XXII presents the results of offset standard deviation analyses for the different gait pattern databases: Fukuchi, Fukuchi (Young Group), and Theunissen, across various walking speeds. These results show distinct differences among the database groups. The full Fukuchi database, which includes all participants, reveals a higher offset standard deviation compared to its subgroup of only young participants. Furthermore, when comparing the Fukuchi-Young group subset with the Theunissen database, the offset standard deviations for hip abduction/adduction and knee flexion/extension show similar results. However, a larger discrepancy is observed in hip flexion/extension, where the Fukuchi-Young group demonstrates a notably higher standard deviation. Specifically, this group has a higher offset standard deviation of up to 2.92° higher at 100% comfortable walking speed compared to the Theunissen database. For other walking speeds, the discrepancies are slightly smaller, namely 2.59° at 85%/80% and 2.64° at 70%/60% of comfortable walking speed.

TABLE XXII: Comparison of the Fukuchi, Fukuchi (Young Group), and Theunissen gait pattern databases in terms of offset standard deviation across different walking speeds.

Walking speed	**Database**	**Offset standard deviation**			
		Hip abduction (deg)	**Hip flexion (deg)**	**Knee flexion (deg)**	**Lateral pelvis movement (mm)**
100% comfortable speed	Fukuchi	2.50	7.33	4.08	0.05
	Fukuchi (Young)	2.33	**6.57**	3.01	0.05
	Theunissen	2.14	**3.65**	2.90	-
85%[1]/ 80%[2] comfortable speed	Fukuchi[1]	2.52	7.68	4.71	0.075
	Fukuchi (Young)[1]	2.23	**6.81**	3.50	0.083
	Theunissen[2]	2.19	**4.22**	3.12	-
70%[1]/ 60%[2] comfortable speed	Fukuchi[1]	2.57	7.86	4.92	0.051
	Fukuchi (Young)[1]	2.28	**6.88**	4.08	0.09
	Theunissen[2]	2.25	**4.24**	3.68	-

Table XXIII presents the results of amplitude standard deviation analyses for the different gait pattern databases: Fukuchi, Fukuchi (Young Group), and Theunissen, across various walking speeds. Similarly to the offset variability, these results show distinct differences among the database groups. The full Fukuchi database, which includes all participants, reveals a higher amplitude standard deviation compared to its subgroup of only young participants. Again, when comparing the Fukuchi-Young group subset with the Theunissen database, the amplitude standard deviations for hip abduction/adduction and knee flexion/extension show more similar results. A larger discrepancy is observed in hip flexion/extension, but this time the Fukuchi-Young group demonstrates a notably lower standard deviation. Specifically, this group has a lower amplitude standard deviation of up to 1.82° lower at 100% comfortable walking speed compared to the Theunissen database. For other walking speeds, the discrepancies are slightly smaller, namely 1.49° at 85%/80% and 1.38° at 70%/60% of comfortable walking speed.

TABLE XXIII: Comparison of the Fukuchi, Fukuchi (Young Group), and Theunissen gait pattern databases in terms of amplitude standard deviation across different walking speeds.

Walking speed	**Database**	**Amplitude standard deviation**			
		Hip abduction (deg)	**Hip flexion (deg)**	**Knee flexion (deg)**	**Lateral pelvis movement (mm)**
100% comfortable speed	Fukuchi	4.07	4.07	4.35	9.72
	Fukuchi (Young)	3.63	**2.54**	3.79	8.86
	Theunissen	3.81	**4.36**	3.77	-
85%[1]/ 80%[2] comfortable speed	Fukuchi[1]	3.74	3.90	4.78	10.82
	Fukuchi (Young)[1]	3.35	**2.43**	4.24	8.57
	Theunissen[2]	3.77	**3.92**	4.33	-
70%[1]/ 60%[2] comfortable speed	Fukuchi[1]	3.53	4.32	5.74	13.56
	Fukuchi (Young)[1]	3.24	**2.85**	4.88	11.51
	Theunissen[2]	3.90	**4.23**	5.64	-

D. Discussion

The comparison of the Fukuchi and Theunissen databases shows distinct variations in offset and amplitude especially for hip flexion/extension, with the Fukuchi database showing a higher offset standard deviation and the Theunissen database showing a greater amplitude standard deviation. The differences in offset and amplitude for hip abduction/adduction and knee flexion/extension are less pronounced between the two databases.

These discrepancies can be attributed to several factors, such as calibration differences in measurement devices, variations in data collection protocols, and differences in data filtering and analysis algorithms. Moreover, the diversity in anthropometrics and demographics within each study's population influences the kinematic variations. It is observed that gait databases covering a wider range of anthropometric and demographic profiles, such as the Fukuchi database when considering its full scope versus a subset of young subjects, show increased variability in kinematic data.

These observations emphasize the challenge of comparing gait analysis results from different studies due to methodological differences in data collection and population diversity.

APPENDIX H
INFORMED CONSENT FORM

Informed Consent Form – Version 13-07-2023

Development and Validation of an Individualized Gait Pattern Generator for the Lokomat® Exoskeleton

Participant Information

You are being invited to participate in a research study titled "Development and Validation of an Individualized Gait Pattern Generator for the Lokomat® Exoskeleton". This study is being performed at the Motor Learning and Neurorehabilitation (MLN) Laboratory at the TU Delft, Cognitive Robotics Department.

Purpose

The purpose of this research study is to evaluate the perceived comfort, satisfaction, and naturalness of walking with different types of gait patterns in a lower-limb exoskeleton, namely a modified version of the Lokomat® exoskeleton (Hocoma, Switzerland). The study aims to gain better understanding of the necessity for individualized gait patterns during lower-limb rehabilitation training with robotic devices. The study will take approximately 60 minutes to complete.

Procedure

In this experiment, you will wear a modified Lokomat® exoskeleton, a lower-limb robotic device of Hocoma, Switzerland, which has been further modified at ETH Zurich (Zurich, Switzerland), to enhance hip and pelvis movements. Your task will be to experience walking with the exoskeleton, whereby the exoskeleton will do the actual walking and guide your lower limbs to mimic various gait patterns. You are expected to remain passive within the exoskeleton, letting it direct your movements. Multiple trials will be conducted, with a rest period after each trial, and some questionnaires will also be completed. The robot will be operated using an assistive controller to mimic a certain gait pattern. During the experiment, your legs will be fastened to the orthosis through cuffs attached to thighs and shanks. In addition, you will also be wearing a bodyweight support harness for extra safety to ensure you're protected from falls to the front or side. An experimenter will always be present, providing specific instructions before and during the experiment. You can withdraw at any time during the experiment.

Eligibility

The intended population of this research study are neurologically healthy participants who do not have orthopedic disorders. If you have a neurologic condition or orthopedic disorder then unfortunately you are not eligible to participate. Furthermore, the study is limited to participants between the ages of 18 and 60. These eligibility criteria have been established to ensure the safety and well-being of all participants.

Collected Data

For this experiment, we will collect your age, gender, body height, and body weight. We will use such parameters to generate an individualized gait pattern tailored to you. Additionally, we will record signals from the robot kinematic and force/torque interaction sensors throughout the experiment. Also, during and after the experiment, you will be asked to complete some questionnaires and share your feedback about the user experience with the robot. Your personal data and answers will remain confidential. The collected data will be pseudo-anonymized immediately after collection and can only be identified via a separately stored link. Before the study is published, this link will be destroyed to ensure data anonymization. The collected data will be used to further develop the device, create reports, publications, presentations, and support teaching.

Risks

Because the device you will test is a prototype, it cannot be excluded that a failure or malfunction occurs, potentially resulting in discomfort or minor injury. Additionally, the assistive controller involves haptic forces aligning your lower limbs with the intended pattern, possibly resulting in mild discomfort. To ensure participant comfort and the natural execution of the implemented gait pattern, a preliminary test will be conducted to assess limb mobility. During the experiment, you may experience minor tiredness in your legs, mitigated by several pauses between trials. Besides that, no physical, emotional, or reputational risks are expected. Risks of minor injury during the interaction with the robot have been mitigated by following safety procedures following the TU Delft safety protocol. There is a risk of Covid-19 transmission through equipment surfaces or face-to-face encounters, mitigated by disinfection of the robot.

Voluntary Participation

Participation in this study is entirely voluntary, and you can withdraw at any time during the experiment. You are free to omit any questions. You have the right to request access to and/or deletion of your collected data until either the publication of the study or a maximum period of one month after participation, whichever comes first.

Participant Information

Name: ____

E-mail Address: ____

Identification Number: ____

Explicit Consent Points

<table>
<tr><th>PLEASE TICK THE APPROPRIATE BOXES</th><th>Yes</th><th>No</th></tr>
<tr><td>A: GENERAL AGREEMENT</td><td></td><td></td></tr>
<tr><td>1. I have read and understood the study information dated 13-07-2023, or it has been read to me. I have been able to ask questions about the study, and my questions have been answered to my satisfaction.</td><td>☐</td><td>☐</td></tr>
<tr><td>2. I consent voluntarily to be a participant in this study and confirm that I am aware of the eligibility criteria. I understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.</td><td>☐</td><td>☐</td></tr>
<tr><td>3. I understand that taking part in the study involves:
I will receive instructions about the tasks and the systems that I will test and evaluate.
I will conduct walking trials using the exoskeleton. The experimenter will always be present, and I will receive specific instructions prior to the experiment.
I will use a research prototype device for walking training and will execute a variety of walking trials with this device. Sensor data from the robot will be recorded during these trials.
The device is capable of generating haptic forces at the different joints of the legs. While performing the tasks, I will feel the interaction forces via the device as it guides my legs.
I will have to complete a set of questionnaires regarding the user experience when walking with the device.</td><td>☐</td><td>☐</td></tr>
<tr><td>4. I understand that compensation will be provided for my participation in the form of a gift card. The compensation rate is ~10 € per hour. Considering that the experiment is expected to last 120 minutes, I will receive 20 € for the entire duration. It is important to note that compensation will be provided regardless of my performance, and that for incomplete participation in the experiment, I will still receive partial compensation.</td><td>☐</td><td>☐</td></tr>
<tr><td>5. I understand that the study will take about 60 minutes.</td><td>☐</td><td>☐</td></tr>
<tr><td>B: POTENTIAL RISKS OF PARTICIPATING (INCLUDING DATA PROTECTION)</td><td></td><td></td></tr>
<tr><td>6. I understand that taking part in the study involves the following risks:
The device that will be evaluated is a research prototype and not a CE-certified device. It can, therefore, not be excluded that a mechanical or</td><td>☐</td><td>☐</td></tr>
</table>

<table>
<tr><th>PLEASE TICK THE APPROPRIATE BOXES</th><th>Yes</th><th>No</th></tr>
<tr><td>electrical failure or a software malfunction occurs, and I may experience a minor injury due to collision with the robot.
• I may experience minor discomfort and tiredness in the legs during the tasks.
• I may experience exposure to COVID-19.
I understand that these will be mitigated by:
• An in-depth risk assessment was performed by the developers and the risks of injury were mitigated in accordance with the TU Delft protocol. For instance, the treadmill is equipped with two emergency stop buttons, one of which can be activated by the operator and the user, and one stop button for the orthosis, which can only be activated by the operator. Throughout the experiment, an experimenter will be present at all times and will stop the orthosis immediately if requested by the participant.
• Appropriate resting time is assigned between trials, and I am allowed to press the emergency stop button on the treadmill and request to stop the orthosis at any time without justification.
• All equipment will be disinfected before and after use. All relevant Covid-19 regulations and recommendations of the Dutch government during the time of the experiment will be complied with.</td><td></td><td></td></tr>
<tr><td>7. I understand that taking part in the study also involves collecting specific personally identifiable information (PII) such as my name, gender, age, and contact details and associated personally identifiable research data (PIRD) with the potential risk of my identity being revealed to all researchers involved in this study. No PII or PIRD will be made publicly available unless explicit consent is given (see questions 11 – 15).</td><td>☐</td><td>☐</td></tr>
<tr><td>8. I understand that the following steps will be taken to minimize the threat of a data breach, and protect my identity in the event of such a breach:
• All data will be stored according to a data management plan that was developed and approved by an expert at TU Delft.
• The collected data will be stored on a server located at the TU Delft and backed up at TU Delft Gitlab.
• The collected data will be pseudonymized. Every participant will receive a unique identifier.
• The keys for the unique identifier – participant allocation will be stored on a separate drive.
• The informed consent sheet will be stored in a locked cabinet.</td><td>☐</td><td>☐</td></tr>
<tr><td>9. I understand that personal information collected about me that can identify me will not be shared beyond the study team.</td><td>☐</td><td>☐</td></tr>
<tr><td>10. I understand that the keys for the unique identifier will be destroyed prior to the publication of the study results.</td><td>☐</td><td>☐</td></tr>
<tr><td>C: RESEARCH PUBLICATION, DISSEMINATION AND APPLICATION</td><td></td><td></td></tr>
<tr><td>11. I understand that after the research study the de-identified information I provide will be used for further development of the device, report(s), publication(s), presentation(s), and teaching.</td><td>☐</td><td>☐</td></tr>
</table>

PLEASE TICK THE APPROPRIATE BOXES	Yes	No
12. I agree that my responses, views or other input can be quoted anonymously in research outputs.	☐	☐
D: (LONGTERM) DATA STORAGE, ACCESS AND REUSE		
14. I give permission for the de-identified research data (e.g., task metrics, questionnaire results, age, gender) that I provide to be archived in 4TU Data Center repository so it can be used for future research and learning.	☐	☐
15. I understand that access to this repository is open.	☐	☐

Signatures

________________________ ________________________ ________

Name of participant [printed] Signature Date

I, as researcher, have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

________________________ ________________________ ________

Researcher name [printed] Signature Date

APPENDIX I
QUESTIONNAIRE

Development and Validation of an Individualized Gait Pattern Generator for the Lokomat® Exoskeleton

Subject Information

Participant ID: __________________
Gender (Male, Female, Other): __________________
Age: __________________
Height (in cm): __________________
Weight (in kg): __________________
Thigh length (in cm): __________________
Shank length (in cm): __________________

	No.	Yes, once.	Yes, less than 3 times.	Yes, less than 10 times.	Yes, more than 10 times.
Do you have experience walking with an exoskeleton?	○	○	○	○	○
If yes, please specify which exoskeleton.					

Questionnaire – Test condition 1/2/3

Please make sure to read the questions carefully and answer them truthfully to the best of your ability. If any question is unclear, feel free to ask the experimenter for clarification. Please note that the questions should be answered based on walking at the final speed. The acceleration and deceleration phase should not be considered.

Category: Interest/ Enjoyment from the Intrinsic Motivation Inventory (IMI) [45][1]

I enjoyed doing this activity very much.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

I thought this was a boring activity.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

I thought the task was very interesting.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

This activity was fun to do.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

Category: Passiveness (Self-designed questions)[1]

I remained passive during the activity.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

I resisted the movements of the exoskeleton.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

I allowed the exoskeleton to guide my lower limbs.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

I actively tried to control or influence the movements of the exoskeleton.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

[1]Text in *cursive* was not part of the original questionnaire.

Questionnaire – Test condition 1/2/3

Category: Comfort (Self-designed questions)[1]

How comfortable were the movements of the exoskeleton?						
◯ Very uncomfortable	◯ Uncomfortable	◯ Somewhat uncomfortable	◯ Neutral	◯ Somewhat comfortable	◯ Comfortable	◯ Very comfortable

How would you rate the comfort at the cuffs during movement?						
◯ Very uncomfortable	◯ Uncomfortable	◯ Somewhat uncomfortable	◯ Neutral	◯ Somewhat comfortable	◯ Comfortable	◯ Very comfortable

How comfortable were the movements **in the hips**?						
◯ Very uncomfortable	◯ Uncomfortable	◯ Somewhat uncomfortable	◯ Neutral	◯ Somewhat comfortable	◯ Comfortable	◯ Very comfortable

How comfortable were the movements **in the knees**?						
◯ Very uncomfortable	◯ Uncomfortable	◯ Somewhat uncomfortable	◯ Neutral	◯ Somewhat comfortable	◯ Comfortable	◯ Very comfortable

How comfortable were the movements **in the ankles/ feet**?						
◯ Very uncomfortable	◯ Uncomfortable	◯ Somewhat uncomfortable	◯ Neutral	◯ Somewhat comfortable	◯ Comfortable	◯ Very comfortable

I felt physical strain during the activity.						
◯ Not true at all	◯	◯	◯ Somewhat true	◯	◯	◯ Very true

I felt like I was secure in the device.						
◯ Not true at all	◯	◯	◯ Somewhat true	◯	◯	◯ Very true

Questionnaire – Test condition 1/2/3

Category: Naturalness (Self-designed questions)[1]

How natural did the movements of the exoskeleton feel?						
○ Very unnatural	○ Unnatural	○ Somewhat unnatural	○ Neutral	○ Somewhat natural	○ Natural	○ Very natural

How similar was the applied gait pattern compared to your own way of walking?						
○ Very dissimilar	○ Dissimilar	○ Somewhat dissimilar	○ Neutral	○ Somewhat similar	○ Similar	○ Very similar

How smooth did the movements of the exoskeleton feel?						
○ Very abrupt	○ Abrupt	○ Somewhat abrupt	○ Neutral	○ Somewhat smooth	○ Smooth	○ Very smooth

I felt the exoskeleton was pushing my limbs beyond my natural range of motion.						
○ Not true at all	○	○	○ Somewhat true	○	○	○ Very true

Open-ended questions:

Did you experience any discomfort in terms of physical strain or unusual sensations during the walking session with the Lokomat? If so, please specify the level of discomfort a well as the areas of discomfort, e.g. on which cuffs, joints, or other body parts.

Were there any specific aspects of the gait pattern that contributed to your comfort or discomfort? If so, please specify. For example, consider aspects such as an unusual movement of a particular joint, a small/ large range of motion, jerking of the trajectory, or unsymmetrical gait pattern between left and right leg.

Would you like to share any other thoughts or comments?

Final Questionnaire (After All Conditions)

Ranking:

	1st condition	**2nd condition**	**3rd condition**
Which gait pattern did you like overall the most? Rank most (1) to least (3).			
How confident are you with the ranking? Rank from 1 (not at all) to 10 (very).			
Which gait pattern did you find most comfortable? Rank most (1) to least (3).			
How confident are you with the ranking? Rank from 1 (not at all) to 10 (very).			
Which gait pattern did you find most natural? Rank most (1) to least (3).			
How confident are you with the ranking? Rank from 1 (not at all) to 10 (very).			

References for Appendices

[1] C. A. Fukuchi, R. K. Fukuchi, and M. Duarte, "A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals," *PeerJ*, vol. 2018, p. e4640, 4 2018. [Online]. Available: https://peerj.com/articles/4640

[2] R. K. Fukuchi, C. A. Fukuchi, and M. Duarte, "A public dataset of running biomechanics and the effects of running speed on lower extremity kinematics and kinetics," *PeerJ*, vol. 2017, p. 3298, 2017.

[3] *Technical Data Lokomat® Pro*, Hocoma AG, Industriestrasse 4, CH-8604 Volketswil, Switzerland, Feb 2023, device Version 6.3. [Online]. Available: https://www.hocoma.com/solutions/lokomat/techincal-data-sheet/

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[5] B. Koopman, E. van Asseldonk, and H. van der Kooij, "Speed-dependent reference joint trajectory generation for robotic gait support," *Journal of Biomechanics*, vol. 47, no. 6, pp. 1447–1458, 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0021929014000682

[6] K. Theunissen, B. Van Hooren, G. Plasqui, and K. Meijer, "Dataset of energetics and biomechanics of self-paced and fixed speed treadmill walking at multiple speeds," *Data in Brief*, vol. 41, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352340922001275