2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
October 1-5, 2023. Detroit, USA

Impact of Imperfect Exoskeleton Algorithms on Step Characteristics, Task Performance, and Perception of Exoskeleton Performance

Man I Wu[1] and Leia Stirling[2]

Abstract— **Lower-limb exoskeletons may experience errors in operational settings, where an expected assistive torque is missing. These errors may affect user's gait strategies and perception of the exoskeleton's performance, leading to impacted human-exoskeleton fluency and user trust in the system. In this study, we introduced five different exoskeleton control algorithms with fixed error rates up to 10% error (90% accuracy). Two groups of participants (N=22, 11 per group) walked with a bilateral ankle exoskeleton while completing a targeted stepping task and experienced each controller twice, but in different orders. The impact of exoskeleton error rates was assessed on step characteristics (step length and width), task performance (absolute task error), and perception of exoskeleton performance (survey responses). Step characteristics were not impacted by exoskeleton errors, but multiple participants were not able to achieve acceptable task accuracy and increased task error over time across all error rates. Increasing error rates negatively impacted users' perception of algorithm predictability, exoskeleton supportiveness, and probability of future usage. Perceived predictability and future usage probability transitioned from positive to negative between 2% and 5% error. Understanding the effect of increasing exoskeleton error rates informs minimum algorithm accuracy to support human-exoskeleton fluency and performance for gait-assist exoskeletons.**

I. Introduction

Lower-limb exoskeletons have the potential to assist a human user's motor performance in laboratory environments by decreasing energy expenditure [1], [2]. In order for exoskeletons to be adopted in operational settings, they must be robust in uncertain environments. However, while exoskeleton control algorithms are continuously being developed and improved [3], [4], they are unlikely to be perfect and will experience errors. For instance, if gait phase estimation is inaccurate, the exoskeleton may miss an actuation during a stride and affect gait strategies. Gait outcomes arise from the interaction between the human and exoskeleton. As the coordinated meshing of actions between the human and robot is defined as fluency [5], we can consider that human-exoskeleton fluency occurs when the human and exoskeleton's goals align. For example, the human decreasing muscular activity for exoskeletons designed to reduce energy expenditure. Thus, it is important to understand how exoskeleton errors impact gait strategies and human-exoskeleton fluency in order to inform performance requirements for exoskeleton algorithms.

Previous work has begun exploring the impact of imperfect control algorithms when walking with a lower-limb exoskeleton. Wu et al. [6] introduced random errors in exoskeleton operation by not applying an expected exoskeleton torque while participants completed a targeted stepping task. The study used an algorithm with approximately 2% error, or 98% accuracy, and found that step characteristics and task accuracy were not impacted by errors due to adaptations in joint kinematics. The level of error in the study was relatively low, so it is important to understand how more frequent exoskeleton errors will impact stepping strategies and task performance. For instance, it is possible that users will begin to increase muscle activation as they anticipate repeated errors, which is against the goals of the exoskeleton and would impact human-exoskeleton fluency.

The adoption of exoskeletons in real-world environments also depends on the user's perception of the exoskeleton's performance and benefits. Perceived usefulness of technology has been correlated with the current and future usage in the technology acceptance model [7], which has been shown to be applicable to various forms of technology [8]. Similarly, when users interact with exoskeletons, the algorithm's performance informs their perceptions of system usefulness, thus impacting their willingness to adopt the technology. Studies have begun to characterize the perception of exoskeleton performance, such as control parameters [9] and metabolic benefit [10], under nominal laboratory conditions. It is also necessary to understand user perception of exoskeleton usefulness when exposed to exoskeleton errors similar to operational settings.

In this study, we introduce exoskeleton algorithms with defined error rates in order to understand how users respond to more frequent errors. We hypothesized that there would be time-dependent and algorithm-dependent changes in (1) step characteristics (step length and width), (2) task performance (task error), and (3) perception of exoskeleton performance (survey ratings). We also hypothesized that higher levels of error would cause larger changes in the above metrics. These results will be interpreted in the context of perceived exoskeleton usefulness and human-exoskeleton fluency.

II. Methods

A. Participants

Participants (N = 22, age = 25.3±5.0 years (mean±SD), height = 1.67±0.30 m, mass = 68.0±9 kg, leg length =

This work was supported by the National Science Foundation under Grant 1952279. (Corresponding author: Man I Wu.)

This work involved human subjects in the research. Approval of all ethical and experimental protocols was granted by the University of Michigan Institutional Review Board.

[1]Man I Wu is with the Robotics Department, University of Michigan, Ann Arbor, MI 48109 USA. maniwu@umich.edu

[2]Leia Stirling is with the Department of Industrial and Operations Engineering, Robotics Department, University of Michigan, Ann Arbor, MI 48109 USA. leias@umich.edu

2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) | 978-1-6654-9190-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/IROS55552.2023.10341368

903.0±43.7 mm, 12 female and 10 male) provided written informed consent. Participants were excluded if they had a lower extremity injury within the past 6 months or used an assistive walking device. The protocol was approved by the University of Michigan Institutional Review Board (HUM00217656).

B. Experimental Setup

Participants walked on a treadmill in a room equipped with a 10-camera optical motion capture system. Reflective markers were placed on the participants according to the Vicon Plug-in Gait full-body model. Markers were adjusted for the exoskeleton by placing the lower limb markers on the lateral side of the exoskeleton when necessary. Motion capture data were collected at 100 Hz. Study participants wore the Dephy ExoBoot on both legs (Fig. 1) (DpEb504, Dephy Inc, Maynard, MA, USA) [11]. The ExoBoot applied torque at the ankle at push-off during the stance phase of the gait cycle, learned from 25 strides, which is the same as our previous study [6].

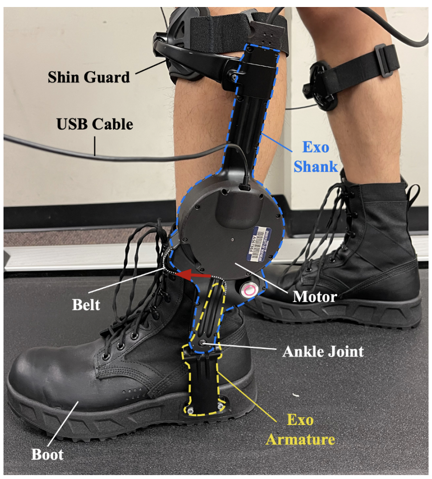

Fig. 1: Powered bilateral ankle exoskeleton, which provides assistance by applying torque via the inelastic belt attached to the exoskeleton armature (DpEb45, Dephy Inc) [9].

C. Protocol

Anthropometric measures were collected prior to walking with the exoskeleton. Leg length was measured as the distance from the anterior superior iliac spine to the medial malleolus. Participants were given a target stepping task, which was a 320 mm-long region marked along the sides of the treadmill, while walking at a fixed speed of 1.2 m/s. A targeted stepping task was chosen as foot placement is an important component of gait and task accuracy may be used to assess prioritization of the task or coordinating with the exoskeleton. Participants were asked to aim their heel at the center-line of the target region at the end of each stride. The length of the stepping target was chosen to be the length of the largest exoskeleton boot size, a Men's size 13.

Participants underwent a training protocol where they walked with the stepping target for 15 minutes with the exoskeleton powered on and torque applied during each stride. Then, participants were separated into two groups (N=11 per group), which experienced the exoskeleton control algorithms in different orders. There were 5 different controllers with 0%, 2%, 5%, 7%, and 10% error. This translates to controller accuracies of 100%, 98%, 95%, 93%, and 90% respectively. Errors were introduced randomly throughout each trial by not actuating the exoskeleton for a single stride. We chose errors of no exoskeleton assistance rather than adjustment of control parameters for this study, as it has been shown that individuals may exhibit different sensitivities toward parameters such as actuation timing [9], which may introduce additional confounding factors. The exoskeleton algorithm also included a recovery period after each error, where the exoskeleton ramps up from 0% to 50% of the normal torque on the first stride after each error, then 80% on the second stride after a error, and finally back to 100% from the third stride onward.

Participants experienced each controller twice for a total of 10 trials. Group 1 started with a 0% error controller, increased to 10% error, and then decreased to 0% error. Group 2 started with a 10% error controller, decreased to 0% error, and then increased to 10% error. Details on the groups and control algorithms are shown in Tables I and II. The number of strides for 2% error trials was higher than other trials to ensure an adequate amount of errors within the trial, verified via power analysis. Participants experienced controllers in one of these two fixed orders. A fully randomized order was not selected as it creates difficultly in disambiguating between order and participant effects. By selecting two fixed orders, we can begin to examine the effect of order separate from participant variability.

Trial	Group 1	Group 2	Order
1	0%	10%	1
2	2%	7%	1
3	5%	5%	1
4	7%	2%	1
5	10%	0%	1
6	10%	0%	2
7	7%	2%	2
8	5%	5%	2
9	2%	7%	2
10	0%	10%	2

TABLE I: Trial order of each participant group, where the percentages represent the error rate of each control algorithm. The order represents whether the trial is the first or second time that a participant experiences an error rate.

Error Rate	# of Errors	Total # of Strides
0%	0	300
2%	12	600
5%	15	300
7%	21	300
10%	30	300

TABLE II: The number of errors and total strides for each error rate, where an error consists of not actuating the exoskeleton for a single stride.

	0% Error		2% Error		5% Error		7% Error		10% Error	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p	Estimate	p
Participant	0.511	<0.001	0.595	<0.001	0.574	<0.001	0.465	<0.001	0.524	<0.001
Step Num	<0.001	<0.001	<-0.001	0.125	<-0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Order 1 vs 2	0.038	<0.001	-0.101	<0.001	-0.063	<0.001	0.144	<0.001	0.027	<0.001
Group 1 vs 2	0.030	<0.001	-0.010	0.041	-0.026	<0.001	0.052	<0.001	0.037	0.0145
Step N*Order 2	<-0.001	0.494	<0.001	<0.001	<0.001	<0.001	<-0.001	<0.001	<-0.001	0.002
Step N*Group 2	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.013	<-0.001	0.124
Order 2*Group 2	0.005	0.618	0.086	<0.001	0.153	<0.001	-0.049	<0.001	-0.020	0.049
Step N*O2*G2	<-0.001	<0.001	<-0.001	<0.001	<-0.001	<0.001	<0.001	0.025	<-0.001	0.521

TABLE III: Summary of statistics for linear mixed-effects models (N=22) fitted to normalized step length (NSL) across all error rates. O2 represents Order 2 and G2 represents Group 2.

D. Survey

Participants were given a survey after every trial to rate their perceptions of the control algorithms. The questions analyzed in this study and the associated Likert scales of 1 to 5 are described below:

- Rate how you felt the exoskeleton supports your actions. (1 = extremely hinders actions, 3 = neither hinders nor supports actions, 5 = extremely supports actions)
- Rate your accuracy in completing the stepping task. (1 = not at all accurate, 3 = moderately accurate, 5 = extremely accurate)
- Rate the predictability of the exoskeleton's actions. (1 = not at all predictable, 3 = moderately predictable, 5 = extremely predictable)
- Rate the probability that you would use this controller again. (1 = not probable, 3 = neutral, 5 = very probable)

E. Data Analysis and Statistical Analysis

Gait cycles were segmented with a custom MATLAB script by using the heel marker data from motion capture to identify heel strikes. Normalized step length (NSL), normalized step width (NSW), and task error were calculated using heel marker positions and treadmill velocity. NSL and NSW were calculated as the distance between anterior and lateral foot fall locations, normalized by leg length. Absolute task error was calculated as the absolute value of distance between each heel strike and the center-line of the stepping target. Acceptable absolute task error was determined as $\leq$ 160 mm, which is half of the 320 mm-long target.

Linear mixed-effects models were fit to NSL, NSW, and task error data with the following factors: Participant (random, 22 levels), Step Number (continuous, [1, 600 or 1200]), Group (2 fixed levels), and Order (2 fixed levels). The models were fit using a custom R script and significance level was set to $\alpha = 0.05$. Operationally relevant changes were identified as significant changes in each metric between the beginning and end of a trial that were greater than the mean standard deviation across the trial.

ANOVAs were fit to the responses of each survey question with the factors of Participant (random) and Error Rate (5 fixed levels) with significance level set to $\alpha = 0.05$. Spearman's rank correlation coefficients (r_s) were calculated for the survey results to assess if survey scores were monotonically related.

III. Results

A. Step Characteristics

While there were significant main effects of Participant, Step Number, Order, Group, and interaction effects on normalized step length (NSL) across select error rates (Table III), most were not operationally relevant. Pooled NSL across all participants at all error rates are shown in Fig. 2 (left). Using the definition of operationally relevant changes, only participants in Group 2 increased NSL at an error rate of 2% at Order 1 (mean=15.0% increase, SD=6.4%), despite significant factors in the linear-mixed effects models.

There were significant main effects of the Participant, Step Number, Order, Group, and interaction effects for normalized step width (NSW) across select error rates, shown in Table IV. Pooled NSW across all participants at all error rates are shown in Fig. 2 (middle). When using the definition of operational relevance, there were no relevant changes in NSW across all error rates despite significant fitted slopes in the linear models.

B. Task Accuracy

There were significant main effects of Participant, Step Number, Order, Group, and interaction effects on absolute task error (Table V). While most participants were able to achieve acceptable task accuracy ($\leq$160 mm), some participants (10 of 22, 45%) had significantly higher task error in at least one trial (Table VI). A majority of participants (20 of 22, 91%) also experienced a relevant operational change in task accuracy over time (VII) in at least one trial, as defined in Section II.E. A plot of abs. task error across all error rates is shown in Fig. 2 (right).

C. Survey Results

The mean and standard deviation of the survey responses across all error rates are shown in Table VIII. The factor of Error Rate was significant for perceived algorithm predictability ($F(4, 104) = 20.83$, $p < 0.001$), exoskeleton supportiveness ($F(4, 104) = 28.10$, $p < 0.001$), probability of future usage ($F(4, 104) = 28.10$, $p < 0.001$), and perceived task accuracy ($F(4, 104) = 4.45$, $p = 0.002$). There was a moderate negative correlation between perceived predictability and error rates ($r = -0.40$, $p < 0.001$), a very weak negative correlation between supportiveness and error

	0% Error		2% Error		5% Error		7% Error		10% Error	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p	Estimate	p
Participant	0.127	<0.001	0.119	<0.001	0.121	<0.001	0.121	<0.001	0.124	<0.001
Step Num	<-0.001	0.183	<0.001	0.001	<0.001	0.517	<0.001	<0.001	<-0.001	0.851
Order 1 vs 2	<-0.001	<0.001	0.013	<0.001	<-0.001	0.560	-0.002	0.286	-0.004	0.008
Group 1 vs 2	<0.001	0.689	0.009	<0.001	0.009	<0.001	0.014	<0.001	0.013	<0.001
Step N*Order 2	<0.001	0.414	<-0.001	<0.001	<0.001	0.731	<-0.001	0.008	<0.001	0.026
Step N*Group 2	<-0.001	0.914	<-0.001	0.001	<-0.001	0.926	<-0.001	0.003	<-0.001	0.796
Order 2*Group 2	0.004	0.0.62	-0.018	<0.001	-0.008	<0.001	-0.008	<0.001	-0.009	<0.001
Step N*O2*G2	<-0.001	0.605	<0.001	<0.001	<-0.001	0.746	<0.001	0.122	<-0.001	0.999

TABLE IV: Summary of statistics for linear mixed-effects models (N=22) fitted to normalized step width (NSW) across all error rates. O2 represents Order 2 and G2 represents Group 2.

	0% Error		2% Error		5% Error		7% Error		10% Error	
	Estimate	p	Estimate	p	Estimate	p	Estimate	p	Estimate	p
Participant	78.65	<0.001	112.10	<0.001	92.98	<0.001	88.34	<0.001	82.23	<0.001
Step Num	0.06	<0.001	0.01	<0.001	0.05	<0.001	0.05	<0.001	0.07	<0.001
Order 1 vs 2	23.68	<0.001	-7.06	<0.001	-8.00	<0.001	7.17	0.025	11.58	<0.001
Group 1 vs 2	29.53	<0.001	1.84	0.328	13.23	<0.001	11.49	<0.001	17.56	<0.001
Step N*Order 2	-0.01	0.033	-0.006	0.01	-0.01	0.100	0.001	0.889	-0.05	<0.001
Step N*Group 2	-0.06	<0.001	-0.004	0.150	-0.01	0.071	0.07	<0.001	-0.003	<0.001
Order 2*Group 2	-24.10	<0.001	-2.08	0.434	6.937	0.051	8.91	0.061	-10.35	0.003
Step N*O2*G2	0.02	0.030	0.01	0.006	-0.01	0.495	-0.07	<0.001	0.01	0.190

TABLE V: Summary of statistics for linear mixed-effects models (N=22) fitted to absolute task error across all error rates. O2 represents Order 2 and G2 represents Group 2.

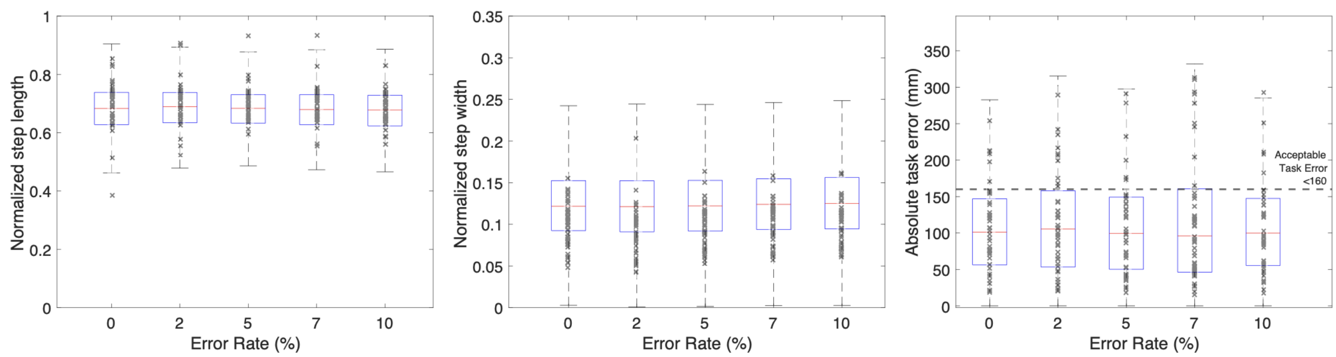

Fig. 2: (left) Normalized step length (NSL), (middle) normalized step width (NSW), and (right) absolute task error pooled from all participants (N=22) across all error rates. Each 'x' marker represents the mean abs. task error of a single trial for one participant. Each box includes 25th to 75th percentile and whisker length is 1.5*IQR.

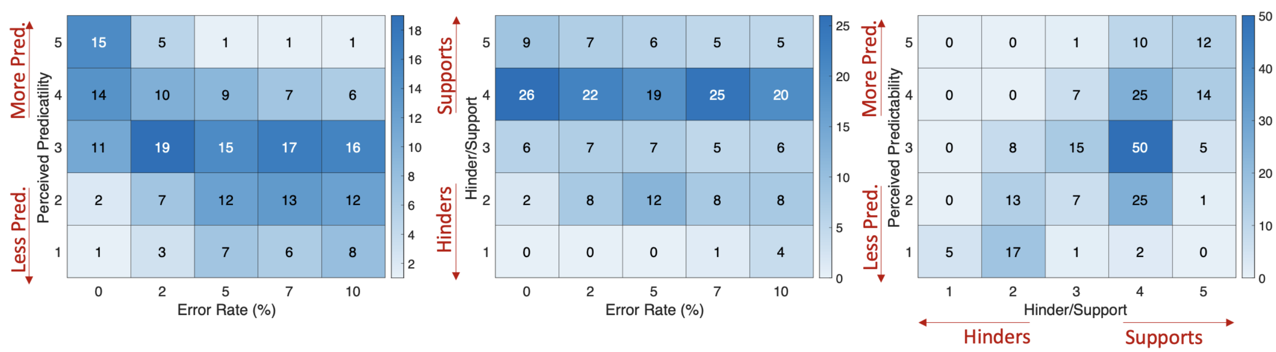

Fig. 3: (left) Perceived predictability vs. trial error rate ($r = -0.40$, $p < 0.001$), (middle) perceived supportiveness vs. trial error rate ($r = -0.17$, $p = 0.01$), and (right) perceived predictability vs supportiveness for all participants and trials ($r = 0.60$, $p < 0.001$). The numbers are the count of data-points for each combination of predictability, supportiveness, and error rate.

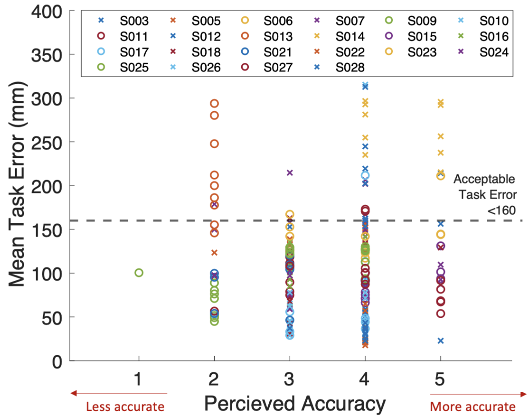

Fig. 4: Mean absolute task error plotted against the users' rating of perceived task accuracy, where 1 represents low accuracy and 5 represents high accuracy. Each marker represents the data from one trial for one participant.

		Order 1		Order 2	
Error	$\leq$ 160mm?	N	$\overline{\lvert TaskError \rvert}$	N	$\overline{\lvert TaskError \rvert}$
0	Y	18	85.14 mm	19	95.02 mm
	N	4	189.85 mm	3	223.45 mm
2	Y	16	85.38 mm	18	83.82 mm
	N	6	207.35 mm	4	221.87 mm
5	Y	19	92.50 mm	19	84.80 mm
	N	3	235.86 mm	3	219.82 mm
7	Y	17	80.21 mm	18	82.72 mm
	N	5	245.88 mm	4	285.29 mm
10	Y	19	92.53 mm	18	86.12 mm
	N	3	227.15 mm	4	201.94 mm

TABLE VI: Table of absolute task error data for acceptable ($\leq$160 mm) and non-acceptable (>160 mm) task performance. N represents the number of participants in each group and $\overline{\lvert TaskError \rvert}$ is the mean absolute task error per group.

rate ($r = -0.17$, $p = 0.013$), and a strong positive correlation between perceived predictability and supportiveness ($r = 0.60$, $p < 0.001$) (Fig. 3).

IV. Discussion

This study explored the effect of imperfect algorithms on step characteristics, task performance, and perceptions of exoskeleton performance. We introduced algorithms with 0%, 2%, 5%, 7%, and 10% error (100%, 98%, 95%, 93%, and 90% accuracy, respectively). Participants experienced each controller twice, but in different orders. We evaluated the impact of error rate with respect to the participant's group, if it was their first or second exposure to the algorithm (Order), and over trial time (Step Number). Operationally significant changes were defined as changes in metrics over time that were greater than the standard deviation.

Overall, participants were able to maintain their step characteristics across error rates for the assessed Orders and Groups. The data do not support the first hypothesis that there would be time-dependent changes in step characteristics. Only participants within Group 2 during the first exposure

	Order 1		Order 2	
Error	N	$\Delta\lvert TaskError \rvert$	N	$\Delta\lvert TaskError \rvert$
0	13	+53.78 mm	7	+56.98 mm
2	7	+49.21 mm	6	+57.89 mm
5	12	+52.22 mm	8	+69.67 mm
7	10	+111.12 mm	10	+75.92 mm
10	11	+82.56 mm	8	+64.76 mm

TABLE VII: Table of operationally relevant changes in task error across all error rates. N is the number of participants that experienced changes and $\Delta\lvert TaskError \rvert$ is the mean change in abs. task error for each error rate and Order.

Error	Support	Accuracy	Predictability	Usage Prob.
0%	3.98 (0.74)	3.81 (0.76)	3.93 (1.01)	3.95 (0.95)
2%	3.64 (0.97)	3.66 (0.83)	3.16 (1.05)	3.23 (1.34)
5%	3.43 (1.04)	3.45 (0.82)	2.66 (1.05)	2.82 (1.26)
7%	3.57 (1.00)	3.41 (0.88)	2.64 (0.99)	2.82 (1.18)
10%	3.33 (1.19)	3.37 (0.93)	2.53 (1.03)	2.14 (1.06)

TABLE VIII: Summary of survey responses, where users rated the exoskeleton's supportiveness, perceived task accuracy, algorithm predictability, and possibility of future usage on a scale from 1 (low) to 5 (high). The mean and standard deviation are reported across all error rates (mean (SD)).

to 2% error increased NSL by 15.0%. This change in NSL may have been motivated by the relatively low error rate compared to the previous 5-10% error controllers that the Group 2 participants experienced first. Participants may have relearned to trust the exoskeleton when it performed with lower error, which allowed for improved collaboration with the exoskeleton torque and thus increased NSL over time. The data had no observed significant changes in NSW, which can be considered an indicator of mediolateral stability [12].

Our second hypothesis predicted that there would be time-dependent changes to task accuracy and was supported by these data. There was a significant increase in absolute task error over each trial. The changes in task accuracy were observed in multiple participants (91%), regardless of their mean absolute task error, Group, and the Order (Table VI). Multiple participants (45%) were also unable to achieve acceptable absolute task accuracy of $\leq$160 mm (Table VII). The changes in task error with the consistent NSL and NSW indicates that participants may be adjusting their position on the treadmill over time rather than changing NSL to reach the stepping target. Participants with significant increases in task error likely shifted further back along the treadmill. The significant task error changes may suggest that users directed less attention to completing the stepping task or were unable to match the treadmill speed and may have slowed down if they had been on a self-paced treadmill or were overground.

The trend in task accuracy is different from our previous study [6], where participants were able to consistently achieve acceptable task accuracy when walking with a controller with 2% error. The difference in task performance between studies may arise as this study's participants had experience with controllers with relatively poorer accuracy, impacting their overall trust in the system and human-exoskeleton fluency. If participants were less trusting of the system, they may either focus more on coordinating with the exoskeleton's torque, adjust their kinematics in anticipation of errors, or begin to fight the system by stiffening their muscles to restrict joint movement, thus leading to deviations in task performance. Changes in trust may be linked to the perception of exoskeleton performance, which was qualitatively assessed through post-trial surveys.

Survey responses on exoskeleton performance and future usage were impacted by the frequency of controller errors, which supports our third hypothesis of algorithm-dependent changes in survey responses. As error rates increased, the average score for supportiveness, predictability, and future usage probability significantly decreased (Table VIII). At 0% error, participants on average felt that the exoskeleton moderately supports their actions with a very predictable control algorithm that they would likely use again, enabling them to achieve very accurate task performance. When errors were more frequent, users' perceptions of the exoskeleton become more neutral and tended towards negative. At 10% error, participants on average felt that the exoskeleton neither hindered nor supported their actions; users found the algorithm to be slightly to moderately predictable and rated it slightly improbable that they would use the controller in the future. As perceived predictability of the exoskeleton's algorithm decreased, users also reported that the exoskeleton no longer supported their actions (Fig. 3). As errors increased from 2% to 5%, users transitioned to feeling neutral about predictability and future usage. The transition from positive to negative perception of exoskeleton performance between 2 to 5% error should inform minimum accuracy requirements for exoskeletons designed to support gait.

Users' perception of task accuracy was consistently between moderate and very accurate across all error rates (Table VIII). Although 10 participants (45%) had a mean task error of >160 mm in at least one trial across all controllers (Fig. 4), indicating that some users may overestimate their task performance. Additionally, 20 participants (90%) significantly increased task error in at least one trial across all controllers. Differences in perceived and actual task accuracy may prevent users from making accurate adjustments to their stepping strategies to support acceptable task accuracy.

Overall, participants maintained step characteristics when walking with an exoskeleton controlled by imperfect algorithms, but task accuracy and perceptions of exoskeleton performance and future usage were impacted. Multiple participants were not able to achieve acceptable task accuracy and most participants showed increases in absolute task error over time for at least one error level. Users also reported that they perceived exoskeleton algorithms as less predictable and less likely to be used in the future as the frequency of errors increased. It is important to note that users' survey responses are dependent on their interpretation of terms such as "predictability" and "supportiveness." For instance, it is possible that users felt that the exoskeleton was supportive if they were able to feel the applied torque, regardless of if the exoskeleton assisted or opposed their motions. Further research should explore differences between actual and perceived exoskeleton goals and the emergent torques. Alternate exoskeletons and error types (i.e. changes in different control parameters) may also yield different responses across error ranges. Future work will analyze the joint kinematics and muscle activity data collected with this dataset to understand the underlying adaptations across this range of error frequency and further define algorithm accuracy requirements for gait-assist exoskeleton controllers.

V. Conclusion

This study explored the impact of imperfect exoskeleton algorithms with up to 10% error on step characteristics, task error, and perceived exoskeleton performance. Users maintained step characteristics, but multiple participants did not achieve acceptable task accuracy and increased task error over time across all error rates. Users' perception of exoskeleton performance was negatively impacted as the error frequency increased, thus decreasing the probability of future usage. Understanding the effect of the various error rates will inform minimum exoskeleton algorithm accuracy to support human-exoskeleton fluency and system performance.

Acknowledgment

The authors would like to thank Tarek El Bsat for his support in data processing.

References

[1] L. M. Mooney, E. J. Rouse, and H. M. Herr, "Autonomous exoskeleton reduces metabolic cost of human walking during load carriage," *Journal of neuroengineering and rehabilitation*, vol. 11, no. 80, 2014.

[2] J. Zhang, P. Fiers, K. A. Witte, R. W. Jackson, K. L. Poggensee, C. G. Atkeson, and S. H. Collins, "Human-in-the-loop optimization of exoskeleton assistance during walking," *Science*, vol. 356, no. 6344, pp. 1280–1284, 2017.

[3] M. K. Shepherd, D. D. Molinaro, G. S. Sawicki, and A. J. Young, "Deep learning enables exoboot control to augment variable-speed walking," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 3571–3577, 2022.

[4] I. Kang, P. Kunapuli, and A. J. Young, "Real-time neural network-based gait phase estimation using a robotic hip exoskeleton," *IEEE Trans. on Medical Robotics and Bionics*, vol. 2, pp. 28–37, 2020.

[5] G. Hoffman, "Evaluating fluency in human–robot collaboration," *IEEE Trans. on Human-Machine Systems*, vol. 49, no. 3, pp. 209–218, 2019.

[6] M. I. Wu, B. S. Baum, H. Edwards, and L. Stirling, "Users maintain task accuracy and gait characteristics during missed exoskeleton actuations through adaptations in joint kinematics," in *2022 44th Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC)*, 2022, pp. 1809–1813.

[7] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 09 1989.

[8] W. R. King and J. He, "A meta-analysis of the technology acceptance model," *Information Management*, vol. 43, no. 6, pp. 740–755, 2006.

[9] X. Peng, Y. Acosta-Sojo, M. I. Wu, and L. Stirling, "Actuation timing perception of a powered ankle exoskeleton and its associated ankle angle changes during walking," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 869–877, 2022.

[10] R. L. Medrano, G. C. Thomas, and E. J. Rouse, "Can humans perceive the metabolic benefit provided by augmentative exoskeletons?" *J. Neuroeng. Rehabil.*, vol. 19, no. 1, p. 26, Feb. 2022.

[11] M. Luke and D. Jean-Francois, "Unidirectional actuated exoskeleton device," Patent, 2020.

[12] M. Arvin, M. Mazaheri, M. J. M. Hoozemans, M. Pijnappels, B. J. Burger, S. M. P. Verschueren, and J. H. van Dieën, "Effects of narrow base gait on mediolateral balance control in young and older adults," *Journal of Biomechanics*, vol. 49, pp. 1264–1267, 2016.