Robotic Individualized Driving Evaluation (RIDE): Design and Preliminary Evaluation

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***Abstract*— Power wheelchair driving entails safety risks, including tips and collisions. Thus, driving assessments are important to safeguard both drivers and their surroundings. However, current driving assessments are deterministic, whereas driving itself is stochastic due to individual and environmental uncertainty. Moreover, disabilities magnify this uncertainty. In this study, a robotic wheelchair was used for a novel function: stochastic assessment of PWC driving. The Robotic Individualized Driving Evaluation (RIDE) is a stochastic assessment that contrasts with deterministic assessments by accounting for individual differences via assessment profiles. The robotic wheelchair acquired the information needed for the stochastic model, and a probabilistic risk score was formulated. The purpose of this preliminary study was to test the effect of assessment profiles within and between driving tasks. Within tasks, there were significant differences in RIDE risk between the profiles. Between tasks, there were significant differences in the new stochastic RIDE metrics but not in the conventional deterministic metrics. Results demonstrated potential for this novel use of robotic wheelchairs to support personalized assessment and training in power mobility rehabilitation.**

I. INTRODUCTION

Power wheelchairs (PWCs) increase autonomy in people with severe mobility impairments [1] insofar as the user can drive effectively. However, functional steering is "extremely difficult" for many PWC users [2]. Day-to-day usage entails safety risks, including tips and collisions [3]. Thus, PWC assessments are used to ensure the safety of both the users and their surroundings. Clinicians perform a comprehensive evaluation of the client's personal and environmental factors. This iterative process of in-clinic evaluations and at-home trials [4] includes clinical ratings and measurements.

Clinical ratings target various levels of the International Classification of Functioning, Disability, and Health [5] (e.g., function [6], activity [7], participation [8]–[10], and environment [11], [12]). Clinical measurements target either wheelchair trajectory (e.g., driving duration, driving error, driving variability, driving speed, and driving acceleration) or human performance (e.g., information processing capacity, reaction time, fatigue, target accuracy, joystick activations, and joystick directional variability) or both [13]–[17].

However, driving contains complexities that are difficult to formalize with ratings and measurements. Driving is a dynamic, stochastic, and nonlinear process [18] involving real-time adaptation mediated by personal and environmental factors. Individual differences in motor skill, cognitive skill, visual acuity, etc., inject uncertainty into the driving process, and disabilities magnify that uncertainty which in turn influences the optimal driving strategy. For example, whereas an unimpaired driver might choose the most efficient trajectory in a given scenario, an impaired driver (i.e., with higher uncertainty in driving control) might instead choose a less efficient trajectory in favor of more safety. By measurements, the impaired driver chose a worse plan (e.g., longer driving time). In practice, they demonstrated good decision-making by accounting for their impairment. These contextual driving decisions are difficult to formalize with ratings and measurements. While a rating may account for some context, it lacks in objectivity and granularity. While a measurement may be objective and granular, it lacks in context.

Stochastic analysis can complement measurement statistics by objectively accounting for contextual differences. A stochastic model can balance task objectives against personal and environmental factors [19]. In this study, a robotic wheelchair was used for a novel function: stochastic assessment of PWC driving. The Robotic Individualized Driving Evaluation (RIDE) was developed on the basis of a Markov model and was configurable via assessment profiles, represented internally as Markov transition models. The robotic wheelchair acquired the information needed for the model, and a probabilistic risk score was formulated. In practice, a clinician would use their expertise to determine a suitable RIDE profile befitting their client's individual differences. The resulting RIDE score would then represent a personalized measure of driving risk. In this preliminary study, the purpose was to test the effect of RIDE profiles within and between driving tasks. It was hypothesized that:

1) within tasks, there will be significant differences in stochastic metrics between assessment profiles; and
2) between tasks, there will be significant differences in stochastic metrics but not deterministic metrics.

TABLE I
MARKOV DECISION PROCESS (MDP) FORMULATION

		Driving	Implementation
State	$s \in S$	Position	Directed acyclic graph
Action	$a \in A(s)$	Heading	Rigid body dynamics
Reward	$R(s)$	Environment	Infrared depth point cloud
Transition	$P(s'\|s, a)$	Uncertainty	Assessment profiles

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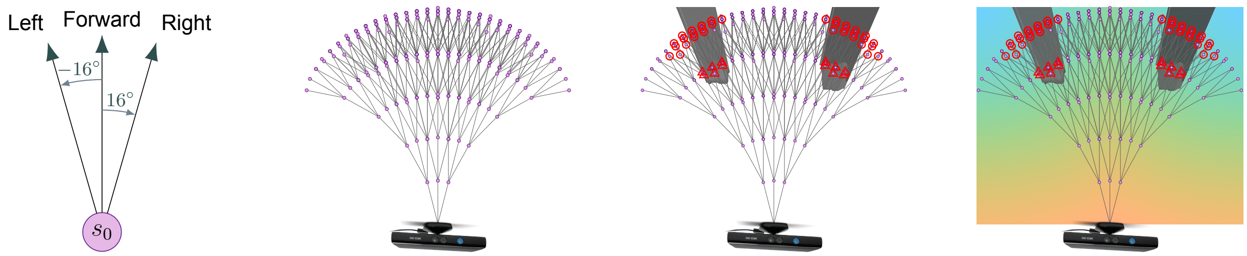


(a) Actions (b) States (c) Environment (d) Rewards

Fig. 1. Markov decision process components. (a) The action space consists of left-, for-, and rightward actions. (b) The state space is formed by propagating actions into a 3-branch, 6-depth directed acyclic graph. (c) The state graph is overlaid on a point cloud with two obstacles. (d) The point cloud is further overlaid on a Markov reward function that penalizes obstacles based on proximity and directness of path.

II. SYSTEM DESIGN

The RIDE algorithm was based on a first-order Markov decision process (MDP) [20], consisting of a set of states (i.e., wheelchair positions), set of actions (i.e., wheelchair headings), probability distribution of movement transitions (i.e., movement uncertainty), and reward function (i.e., environmental cues) (Table I). These components were used to model PWC driving as a sequence of MDP decisions, accounting for differences in driving skill and environmental context. Driving risk was determined by contrasting the driver's observed actions with the MDP's computed actions.

A C300 power wheelchair (Permobil, Inc., Lebanon, TN) was robotized, although computational navigation functionality was not used; the participants retained full driving control, as the purpose of the study was to assess their own driving. The robotic wheelchair facilitated the capture and extraction of information needed for the MDP—i.e., the driver's actions and the environment's context.

To capture the driver's actions, an Arduino Mega 2560 R3 (Smart Projects SRL, Strambino, Italy) was interfaced with the joystick's microcontroller board to intercept `FORE_AFT` and `LEFT_RIGHT` voltages. The model's action space $A(s)$ (Fig. 1a) consisted of three discrete actions: left ($-16°$), forward ($0°$), and right ($16°$). These actions were propagated into the state space S (Fig. 1b): a directed acyclic graph with three branches and six levels. To determine the driver's action $a \in A(s)$ in a given state s, the PWC heading was computed. The turning of a PWC is actuated via differential steering, in which new headings are based on relative wheel torques. For example, the PWC actuates a right turn by increasing the left wheel's velocity relative to the right wheel's velocity. In this study, joystick excursions were used to ascertain the wheel velocities, which in turn were used to compute the PWC headings:

$$\begin{array}{ccccccc} \text{Joystick} & & \text{Wheel} & & \text{PWC} & & \text{MDP} \\ \text{excursion} & \mapsto & \text{velocities} & \mapsto & \text{heading} & \mapsto & \text{action} \\ (r,\theta) & & \langle \mathbf{v}_L, \mathbf{v}_R \rangle & & \theta & & a \in A(s) \end{array}$$

Joystick excursions fell within eight regions, each with its own excursion-velocity mapping. The regions were bounded by the polar angles 0, ϕ_1, $\frac{\pi}{2}$, $\pi - \phi_1$, π, $\pi + \phi_2$, $\frac{3\pi}{2}$, and $-\phi_2$ (Fig. 2a). The boundary angles and output velocities were parameterized by five constants, which were derived from empirical testing on the standard speed setting of the indoor driving profile. The linear velocities were computed from angular velocities based on the PWC's wheel radius. Using the resultant wheel velocity tuple, the PWC heading θ was computed via rigid body dynamics (Fig. 2b),

$$\theta = \frac{v_L - v_R}{2Af_s} \tag{1}$$

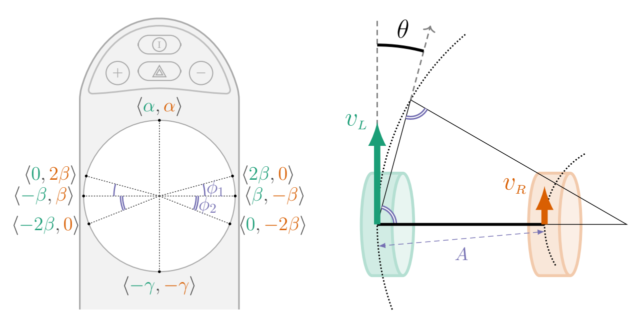
where v_L and v_R were the wheel velocities, A was the axle length, and f_s was the sampling frequency.

To capture the environment's context, the headrest was retrofitted with a Kinect (Microsoft Corporation, Redmond, WA), containing a depth sensor with 11-bit depth, 57° horizontal field of view, 43° vertical field of view, and 4 m radial distance. Each depth image was transformed into a point cloud of obstacles onto which the state graph was overlaid (Fig. 1c). The reward function $R(s)$ (Fig. 1d) was then used to determine the reward value at each graph node. Obstacle nodes and their descendent nodes were penalized inversely by the distance from the driver,

$$R(s) = \lambda\sqrt{(x_{\max} - |x_s|)^2 + (y_{\max} - |y_s|)^2}, \quad \lambda < 0 \tag{2}$$

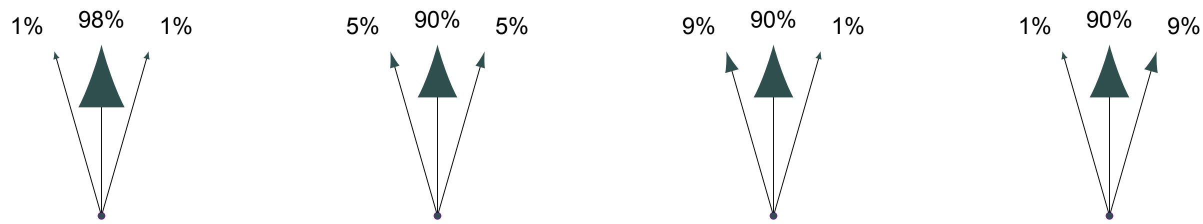
where x_s and y_s were the coordinates of state s, and λ was a negative penalty coefficient. Thus, $R(s)$ was scaled both for proximity and directness of path to the driver.

The joystick data and depth images were acquired simultaneously using MATLAB (The MathWorks, Inc., Natick, MA) at sampling frequencies of 2 Hz and 10 Hz, respectively.



(a) Wheel Velocities $\langle v_L, v_R \rangle$ (b) Wheelchair Heading θ

Fig. 2. Heading derivation. (a) Wheel velocities were first extracted from joystick excursions using a microcontroller board. (b) Wheelchair heading was then computed from the wheel velocities using rigid body dynamics.



(a) Unimpaired (b) Bilateral (c) Unilateral Left (d) Unilateral Right

Fig. 3. The four assessment profiles for the stochastic model. The profiles were represented internally as Markov transition models. (a) The unimpaired profile contained 2% overall variability. (b)–(d) The bilateral and unilateral assessment profiles each contained 10% overall variability.

III. EXPERIMENT DESIGN

A. Protocol

The experiment was conducted in a university building hallway. Two driving tasks were defined per [7]:

1) turn left 90° while moving forward and
2) turn right 90° while moving forward.

To prevent interference from passersby, the hallway was cordoned off for the duration of the protocol. Three healthy participants completed the experiment. The impairment level of the participants was not relevant, as the purpose of the study in this preliminary stage was to test the effect of assessment profiles versus tasks. Each participant was a right-handed joystick user and was given time to acclimate to the wheelchair and joystick before performing the experimental task. Each task was repeated twice with brief resting periods in between. The joystick data and depth images were extracted from the robotic wheelchair for offline analysis.

B. Data Analysis

For each driving trial, two deterministic and four stochastic metrics were analyzed. The deterministic metrics included driving duration and joystick variability per [15]. The stochastic metrics included four RIDE risk scores (i.e., one per profile) computed from the Markov model.

Markov decisions were optimized into a policy of actions maximizing the driver's expected utility according to the Bellman equation,

$$U(s) = R(s) + \gamma \max_{a \in A} \sum_{s' \in S} P(s'|s,a)U(s'), \quad 0 < \gamma < 1 \tag{3}$$

where $U(s)$ was the utility value for state s, $R(s)$ was the reward for state s, γ was a discount factor, and $P(s'|s,a)$ was the transition model for transitioning to state s' given the current state s and action a.

For PWC driving, a transition model with higher or lower variability suggests a driver with stronger or milder impairments, respectively. This transition model $P(s'|s,a)$ can be viewed as an *assessment profile*. In practice, a healthcare provider could use their clinical expertise to determine a suitable profile befitting their client's individual differences. In this study, four basic profiles were used (Fig. 3) as a preliminary test of the system:

1) unimpaired (1% left and 1% right variability),
2) bilateral (5% left an 5% right variability),
3) unilateral-left (9% left and 1% right variability), and
4) unilateral-right (1% left and 9% right variability).

For each profile, an optimal policy was computed numerically via backward induction [21].

For each optimal policy, a RIDE risk score was formulated under the rationale that suboptimal decisions are not inherently risky and do not necessarily preclude functional driving. Mathematically, a deviation simply means that the driver can no longer achieve the highest possible utility. Functionally, the impact could range from trivial to substantial. The severity of a deviation can be quantified in terms of the expected utility difference. Thus, at the root node of each graph, the observed actions and computed actions were compared by their respective expected utilities. RIDE risk Γ was defined as the inverse hyperbolic sine (IHS) [22] of the relative error,

$$\Gamma(t) = \sinh^{-1}\left(\frac{\hat{U}(t) - U(t)}{U(t)}\right) \tag{4}$$

where $\hat{U}(t)$ and $U(t)$ were the observed and computed utilities, respectively, at time t. Thus, when the observed action matched the computed action at a given time t, the RIDE risk evaluated to zero; otherwise, riskier mismatches evaluated to higher values. The IHS transformation was chosen to dampen the effect of runaway scores (e.g., 2,000% risk is not pragmatically different from 200% risk).

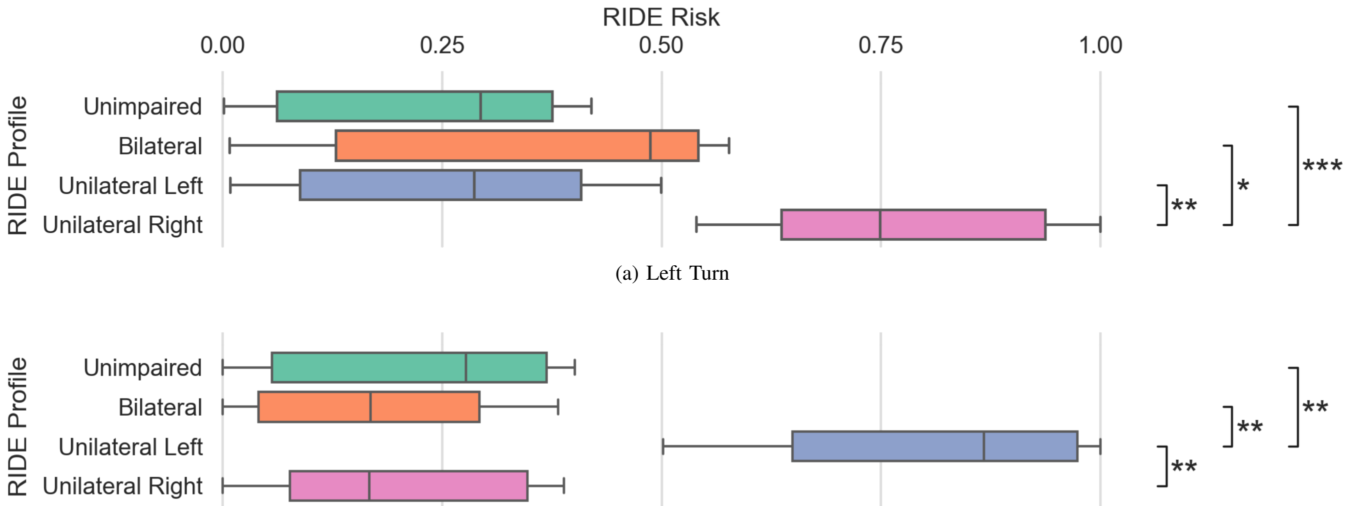
Data analysis was performed in GNU Octave.

C. Statistical Analysis

RIDE risk was normalized to the interval $[0, 1]$. Based on the Shapiro-Wilk test and quantile-quantile visualization, it was determined that the data were not normally distributed. Thus, nonparametric comparisons were used. All tests were conducted using $\alpha = .05$.

1) Within Tasks: RIDE risk was compared between the four assessment profiles using the Kruskal-Wallis one-way analysis of variance. Given a significant difference across profiles, the Conover-Iman test with Holm-Bonferroni correction was used for post hoc pairwise comparisons.

2) Between Tasks: RIDE risk, driving durations, and joystick variabilities were compared using the Wilcoxon signed-rank test.



(a) Left Turn

(b) Right Turn

Fig. 4. Intra-task comparisons of driving risk across assessment profiles. (a) For the left turn task, risk from the unilateral-right profile was significantly higher than that of the unimpaired, bilateral, and unilateral-left profiles. Other differences were not significant. (b) For the right turn task, risk from the unilateral-left profile was significantly higher than that of the unimpaired, bilateral, and unilateral-right profiles. Other differences were not significant. Abbreviations: * ($p < .05$), ** ($p < .01$), *** ($p < .001$), RIDE (Robotic Individualized Driving Evaluation)

Statistical analysis was performed in Python using the `pandas`, `scipy`, and `scikit-posthocs` libraries.

IV. RESULTS

A. Intra-Task

1) Left Turn: There was a significant difference in RIDE risk across the four assessment profiles ($p = .003$). Post hoc comparisons (Fig. 4a) indicated that the RIDE risk from the unilateral-right assessment profile (median[IQR], $0.75[0.64 - 0.94]$) was significantly higher than that of the unimpaired profile ($0.29[0.06 - 0.38]$, $p < .001$), bilateral profile ($0.49[0.13 - 0.54]$, $p = .021$), and unilateral-left profile ($0.29[0.09 - 0.41]$, $p = .002$). Other differences were not significant.

2) Right Turn: There was a significant difference in RIDE risk across the four assessment profiles ($p = .008$). Post hoc comparisons (Fig. 4b) indicated that the RIDE risk from the unilateral-left assessment profile ($0.87[0.65 - 0.97]$) was significantly higher than that of the unimpaired profile ($0.28[0.06 - 0.37]$, $p = .003$), bilateral profile ($0.17[0.04 - 0.29]$, $p = .001$), and unilateral-right profile ($0.17[0.08 - 0.35]$, $p = .003$). Other differences were not significant.

B. Inter-Task

1) Stochastic: For the unilateral-left assessment profile, there was a significant difference in RIDE risk between the left turn task ($0.29[0.09 - 0.41]$) and right turn task ($0.87[0.65 - 0.97]$, $p = .031$). For the unilateral-right assessment profile, there was a significant difference in RIDE risk between the left turn task ($0.75[0.64 - 0.94]$) and right turn task ($0.17[0.08 - 0.35]$, $p = .031$). For the unimpaired and bilateral assessment profiles, there were no significant differences in RIDE risk between tasks (Table II).

2) Deterministic: There were no significant differences in either driving duration or joystick variability between tasks (Table II).

V. DISCUSSION

In this paper, the design and preliminary results of RIDE are presented. RIDE uses a robotic wheelchair to assess PWC driving stochastically. In integrating context from the driver and environment, this stochastic approach complements deterministic assessments by providing a more standardized method for personalization. Individual differences are configurable via the model's assessment profiles.

Clinical profiles are routinely used for diagnosis, prognosis, and treatment throughout the healthcare industry, from internal medicine [23] to sports medicine [24] to rehabilitation medicine [25]. Clinical decisions are made with a breadth of information, including client demographics, biomedical measurements, clinical ratings, etc. Healthcare providers develop clinical recommendations through the lens of the client's profile. In this study, the profile-based design mirrors this approach. RIDE computes risk through the lens of a given assessment profile. It was hypothesized that PWC driving actions would yield significantly different RIDE risk scores as viewed through different assessment profiles.

Within tasks, experimental testing indeed revealed significant differences between certain profiles. For a given directional task, significantly higher RIDE risk was observed under the contradirectional profile but not the ipsidirectional profile. This result was likely due to the turning strategy adopted by the participants (Fig. 5). In preparing for a turn, they tended to anticipate the turn by executing a wider arc—bringing themselves closer to the contradirectional wall—prior to executing the turn. Under most circumstances (i.e., bilateral, ipsidirectional, or no impairment), this would be a reasonable driving plan and would not cause significant

TABLE II

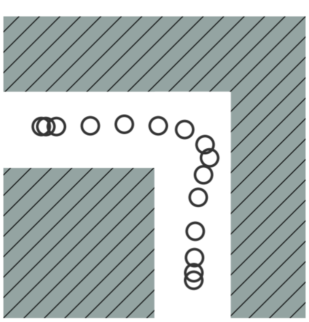
INTER-TASK COMPARISONS FOR STOCHASTIC AND DETERMINISTIC METRICS

	Metric	Profile	Left Turn Task		Right Turn Task		
			Mdn	(IQR)	Mdn	(IQR)	p
Stochastic	RIDE Risk	Unimpaired	0.29	(0.06–0.38)	0.28	(0.06–0.37)	.844
		Bilateral	0.49	(0.13–0.54)	0.17	(0.04–0.29)	.219
		Unilateral Left	0.29	(0.09–0.41)	0.87	(0.65–0.97)	**.031***
		Unilateral Right	0.75	(0.64–0.94)	0.17	(0.08–0.35)	**.031***
Deterministic	Driving Duration (s)	N/A	9.00	(8.25–10.50)	9.50	(9.00–10.00)	.655
	Joystick Variability (°)	N/A	7.02	(6.79–8.62)	7.11	(5.28–9.08)	.844

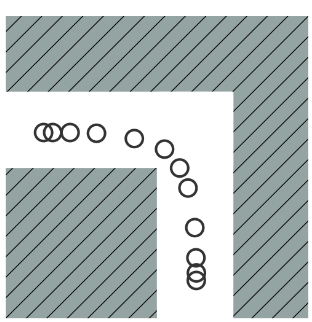
Abbreviations: * ($p < .05$), IQR (interquartile range), Mdn (median), N/A (not applicable), RIDE (Robotic Individualized Driving Evaluation)

risk. However, under a contradirectional assessment profile, this wider trajectory (Fig. 5a) represents a significantly increased risk of colliding with the contradirectional wall. The stochastic model developed in this study accounted for this context via the given assessment profile. If the driver had instead taken a more direct line to the corner (Fig. 5b), the ipsidirectional profile would instead have yielded the highest RIDE risk. This profile-based approach enables clinicians to perform standardized assessments that account for impairment context. Furthermore, the robotic assessment could be performed in clients' homes and communities to provide targeted risk assessments of their daily environments. Thus, RIDE could serve as a clinical decision support tool to assess clients' needs within individual and environmental contexts.

Stochastic models can leverage context to extract more meaning from deterministic metrics. However, stochastic assessment has yet to be used for power mobility, although it has been used in the related field of power seating [26]. In conventional wheelchair seating practice, seating pressures are measured to screen for pressure ulcer risk. Since conclusive thresholds for pressure ulcer formation have yet to be determined [27], stochastic gradient descent has been used to predict pressure ulcer risk by integrating interface pressure measurements with clinical context (i.e., pressure ulcer history) [26]. In the present study, stochastic modeling was also used to assess risk via contextual profiles. It was hypothesized that the deterministic metrics would not detect significant differences between PWC driving tasks, whereas the stochastic RIDE model—given context via assessment profiles—would detect significant differences.



(a) Representative



(b) Hypothetical

Fig. 5. Representative and hypothetical trajectories for the left turn task. (a) A representative trajectory from one driving trial, in which the participant anticipated the turn by executing a contradirectional arc. (b) A hypothetical trajectory, in which the driver takes a more direct path around the corner.

Between tasks, experimental testing indeed revealed significant differences in stochastic metrics but not deterministic ones. This result highlighted the contextless nature of traditional measurements. For example, a more direct turning trajectory (Fig. 5b) may not be ideal in all contexts, despite being superior by deterministic measurements (e.g., lower driving duration and joystick variability). Consider a PWC user, Alice, with advanced cervical dystonia. Her chin tends to point down toward her right shoulder, causing her field of vision to be rotated rightward. Even with seating adjustments and physical therapy, her postural condition will unlikely resolve in the near future. Thus, her reduced leftward perception constitutes a unilateral-left impairment. For Alice, the more direct trajectory (Fig. 5b) represents a significantly increased risk of collision with the corner. The more roundabout trajectory (Fig. 5a)—despite its higher driving duration and joystick variability—would represent a more optimal decision. The RIDE model would account for Alice's condition and could complement deterministic metrics to provide a more contextual, client-centered assessment.

Beyond assessment, training is needed to address identified barriers. For example, trainees of the Wheelchair Skills Training Program have seen improvements in PWC driving performance [28]. However, the improvements were modest and transient. To boost efficacy, robotics-based stochastic assessment may be able to identify personalized hotspots for more targeted training. This computational approach could also reveal hidden risks. For example, for wheelchair seating, stochastic modeling revealed potential underappreciation of the coccygeal region in predicting pressure ulcer risk [26]. For PWC driving, stochastic modeling could reveal analogous insights on previously underappreciated risks and barriers. Furthermore, because RIDE leverages a robotic wheelchair, the training could potentially occur remotely. Robotic assessment could allow PWC users to continue self-paced training at home so that skill improvements could be better retained over time.

There were limitations to this study. In terms of system design, all obstacles were treated equally. Future work should distinguish between different obstacle types and their respective threat levels. In terms of experiment design, the sample size was small. Future work should include more participants so that more diverse driving strategies and trajectories can be observed. Additionally, the study participants did not present with disabilities since this was a preliminary test of the robotic system and assessment profiles. Future work will assess the drivers, so the sample should include people with disabilities. Lastly, only two driving tasks were included. Future work should include a higher quantity and variety of tasks, especially to test the bilateral and ipsidirectional profiles.

VI. CONCLUSION

The RIDE model brings a personalized approach to power mobility clinical practice. It represents a novel use of robotic wheelchairs: stochastic assessment of PWC driving. In contrast to deterministic metrics, this stochastic approach accounts for individual and environmental differences. Clinicians can use configurable RIDE profiles to perform standardized assessments that account for impairment context and, in turn, provide more targeted training to enhance functional independence in PWC users.

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