Robotics: Science and Systems 2026
Sydney, Australia, July 13–17, 2026

A Minimal, Deterministic Approach to Shared Control for Safe Powered Wheelchair Driving

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***Abstract*—Powered wheelchairs provide essential mobility and independence for individuals with motor impairments, yet the skills required for driving and prevalence of safety risks, such as collisions and drop-offs, limit access for users with high levels of disability. Robotic driver assistance systems have the potential to mitigate these risks, unlocking access to powered wheelchairs for a broader population of users. This paper presents REACT, a shared control algorithm for powered wheelchairs built atop the LUCI driver assistance system, that performs minimal, deterministic control arbitration and action selection under safety constraints, and is robust to user, environment, and task variability. Additionally, we introduce a novel evaluation protocol designed to capture longitudinal, task-dependent, and user-specific effects of shared control. We implement REACT on a LUCI-equipped commercial powered wheelchair and conduct case studies using our proposed evaluation method. We find that the effects of REACT assistance vary substantially across participant impairment types, control interfaces, tasks, and timescales, and in many evaluated scenarios, lead to improved driving control input behavior. Users also consistently report positive perceptions of using the system. Our findings underscore the importance of analyzing not only task performance but also user–assistance interaction when evaluating shared control for powered wheelchairs, and additionally motivate longitudinal, multi-task assessment frameworks for assistive mobility systems.**

I. Introduction

Powered wheelchairs (PW) are an essential assistive technology that enables independent mobility for individuals with mobility impairments. Independent mobility is closely linked with improved quality of life, sense of autonomy, and participation in social and daily activities [6, 35]. However, the combined demands of environment perception, dynamic obstacles, reactive navigation, path planning, and control interface operation pose significant operational challenges. As a result, not all who would benefit from a PW possess the requisite cognitive and physical abilities to operate one safely.

PW-related accidents are dominated by tips, falls, and collisions [5, 12], and clinicians report difficulty with steering and navigation, particularly in confined spaces [39]. Visual, motor, or cognitive impairments may prevent individuals from safely operating a PW at all [13, 26]. As a result, individuals with higher levels of disability—arguably those who stand to benefit most from independent mobility—are often excluded due to safety concerns.

Robotic wheelchairs (RWs) augment PWs with sensing, computation, and intelligence to provide driving assistance and enhance safety. Prior work has demonstrated that shared control and semi-autonomous assistance can reduce collisions and improve driving performance relative to unassisted teleoperation [8, 14, 21, 32]. These approaches highlight the promise of driver assistance for improving both safety and accessibility.

Despite extensive research and the commercialization of driver assistance within other domains, robotic technologies have seen limited adoption in wheelchairs. Effective evaluation of how driver assistance affects user interaction and driving behavior also remains a challenge. Many studies emphasize task completion or system-level performance, offering limited insight into how assistance affects user-system interaction or control behaviors [1, 28]. Meanwhile, clinical assessments for powered mobility are designed for conventional powered wheelchair use and may not capture the dynamics introduced by shared control or robotics autonomy [28, 42]. Furthermore, existing driver-assistance systems are typically evaluated based on performance outcomes in controlled laboratory settings with obstacle courses and standardized driving tasks [1, 15]. While useful for benchmarking, such evaluations are unlikely to capture behavioral variability over time, context-dependent performance changes, or the navigation challenges users face in everyday environments [16, 43].

These challenges highlight a broader gap in assistive mobility research: despite growing technical capability, there is demand for shared-control approaches that accommodate uncertain user intent and context variability. There also is a lack of methods to capture how autonomy assistance reshapes driving behavior across tasks, interfaces, and time.

We present a shared control strategy for wheelchair driving that operates under minimal assumptions about the user, task, or environment, as well as an evaluation protocol that aims to move beyond one-shot benchmarks toward longitudinal, user-centered analysis. The contributions of this work are threefold:

1) REACT: A minimal, deterministic, and reactive shared-control algorithm, built on a commercially-available powered wheelchair safety system and designed to support navigation across diverse users, control interfaces, tasks, and environments without explicit inference of task, policy, or user intent.

2) A multi-session evaluation protocol for powered wheelchair driving that enables comparisons of driving behavior, safety, performance, and user experience across different types of driver assistance in minimally-controlled, real-world scenarios.
3) Case study evaluations with four diverse end-user drivers, where findings demonstrate the feasibility of the evaluation protocol and reveal longitudinal, task-dependent, and user-specific effects of driver assistance.

The rest of the paper is organized as follows. Section II provides an overview of related literature. Section III presents our reactive driver assistance algorithm. Section IV details our proposed evaluation protocol and metrics used to analyze user-RW interaction. Case study results and discussion are presented in Section V. Conclusions are presented in Section VII.

II. Related Work

In this section, we provide a summary of related research on smart wheelchair systems, shared control for assisted PW driving, and evaluations of smart wheelchair technology.

A. Smart Wheelchair Systems

Research on smart wheelchairs has focused largely on collision avoidance [14, 18, 22, 27, 33, 44], assisted navigation [9], autonomous driving [31], or some combination of the above [44]; with comprehensive surveys provided in [34] and [20]. Smart wheelchair systems fall into one of two categories of operation: fully autonomous or semi-autonomous [34]. The latter *share control* with the user, and often are preferred due to a desire to preserve driving autonomy and agency in mobility [19].

Shared control for powered wheelchairs must balance user agency with safety while remaining responsive under uncertainty in the user intent, environment, and control interface input. Prior work in shared control has shown that arbitration schemes that blend user and autonomy actions can deadlock or behave unpredictably when intent inference is ambiguous or confidence is low, particularly in safety-critical scenarios [40]. Minimal-intervention principles have therefore been proposed to preserve user control while ensuring progress and safety [3]. However, many shared control approaches in powered wheelchairs operate at the trajectory level, relying on prediction, optimization, or probabilistic blending over future states [4, 29, 38, 48]. These methods require assumptions about user goals, control consistency, or system dynamics that may not hold across tasks, days, or control interfaces.

PW driving is unique in the variety of interfaces that are available, from traditional joysticks to alternate drive interfaces such as sip/puff, head arrays, and switches. Differences in physical actuation of control interfaces and their mapping to PW control fundamentally shape user behavior and the system's ability to infer intent, with proportional joysticks and discrete interfaces like sip/puff devices exhibiting qualitatively different control patterns and preferences [11]. As a result, intent prediction and trajectory optimization may not generalize across users and interfaces.

Current shared control methods and "smart" systems possess certain limitations given their required assumptions about the user or control interface. Therefore, we design REACT—a minimal, task-agnostic, and deterministic shared control paradigm that takes action only when safety constraints are violated, otherwise preserving user control.

Lastly, the commercial deployment of driver assistance in PWs remains limited due to added complexities of the domain, such as strict regulatory standards, advanced seating and positioning requirements, and support for diverse accessible control interfaces. Furthermore, there is high cost and difficulty in operating robustly outside of controlled laboratory settings, especially for systems that require permanent environment modifications [20]. To date, there exist two commercial products that provide assistive PW controls without the requirement of any environment modification, Smile Smart System [37] and LUCI Driver Assistance [24]; only the latter handles both positive (collision risks; e.g., walls, doors, human obstacles) and negative obstacles (fall or tipping risks; e.g., curbs, drop-offs). We build our simple, reactive shared-control paradigm on top of the LUCI system, and our algorithm requires only the dramatically simplified, robust representation of the environment that results from the LUCI system's aggressive sensor processing.

B. Evaluations of Smart Wheelchair Technology

Stakeholder feedback and evaluation play a critical role in the development of smart wheelchair systems. Numerous previous works rely on qualitative methods, such as interviews and focus group discussions to understand end-user needs and system limitations [30, 49], and the importance of including stakeholders, such as caregivers and clinicians, in addition to powered wheelchair users is shown [45]. Other works adopt quantitative (metrics-based) approaches, to evaluate specific performance or safety metrics of proposed smart wheelchairs [25]. Many user evaluations are conducted with individuals without motor impairments who are not end users, which may not yield realistic results and feedback [36].

Across robotic wheelchair studies, evaluation tasks vary widely, ranging from structured obstacle courses and doorway traversal to user-specific activities of daily living [10, 21, 47]. A recent scoping review found little consistency in tasks, metrics, or outcomes used to assess powered wheelchair driving ability [1]. Most studies emphasize outcome measures such as collision counts, task completion time, and trajectory quality, while user-input metrics remain underutilized [1, 7]. Although frameworks exist that explicitly separate user input from system output and quantify their divergence [42], such analyses are rarely adopted. As a result, evaluations often prioritize showcasing system performance over capturing user–assistance interaction, and task descriptions frequently lack sufficient detail for replication or comparison [1, 4].

In this work, we propose a multi-session evaluation protocol that facilitates comparison of user driving behavior, safety, performance, and experience across driver assistance modes in minimally controlled, close-to-real-world settings.

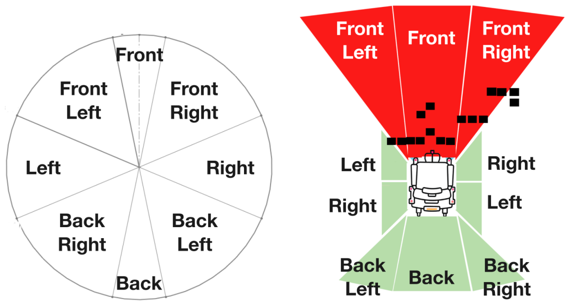

Fig. 1. Left: Scaling zones in the user input space. Right: Scaling zones in the immediate surroundings of the PW. Detected obstacles shown (black squares). Images adapted from the LUCI ROS 2 SDK Documentation [23].

III. REACT: Active Wheelchair Driver Assistance

In this section, we detail our REACT algorithm for powered wheelchair driver assistance, which is built upon LUCI smart wheelchair technology.

A. LUCI Smart Wheelchair Technology

LUCI is a hardware and software accessory that adds all-around sensor coverage to powered wheelchairs and on-board computation for collision and drop-off avoidance [24]. The primary method of driver assistance provided by LUCI is a thresholding of the driving control input from the user, based on environment obstacles and drop-offs detected from the on-board sensor data.

Control inputs, regardless of the control interface used, are modeled as linear and angular components of velocity control within a circular (2D) input space. To illustrate, consider a user operating a joystick to control the wheelchair. The user's input space is a circle in the X-Y plane, where joystick deflections radiate out from the center of the circle. The direction of the deflection represents the angular component of the velocity command, while the magnitude of the deflection represents the linear component.

LUCI partitions the control input space into eight ***zones*** (shown in Figure 1); it also partitions its sensor data, which represents the immediate surroundings of the powered wheelchair, into these zones. Each zone is assigned two *safety thresholds* (termed *scaling values* in the LUCI ROS 2 SDK), corresponding to the linear and angular components of the control command. The safety thresholds are the *maximum allowable* user input command that will be transmitted to the wheelchair control system. LUCI calculates the 16 safety thresholds at a rate of 10 Hz.

B. REACT Driver Assistance

In the design of our assistance algorithm, we aimed to circumvent assumptions about user goals, control consistency, and system dynamics that are present in shared-control approaches that operate at the trajectory level and may not hold across tasks, days, or control interfaces.

REACT is a minimal shared-control paradigm that builds upon LUCI's collision avoidance and drop-off protection system, taking action only when safety constraints are violated,

Algorithm 1 REACT Driver Assistance

1: **Given** User command $\vec{u}_t$, zone safety thresholds Γ_t and $\gamma_{[t-\kappa:t-1]}$, REACT threshold λ_t

2: $\langle u_t^\theta, u_t^m \rangle \leftarrow$ CartesianToPolar$(\vec{u}_t)$
3: $\gamma_t \leftarrow$ GetZoneThreshold(u_t^θ, Γ_t)
4: $\bar{\gamma} \leftarrow$ `average`$(\gamma_{[t-\kappa+1:t]})$ ▷ Smoothed γ threshold

5: **if** $u_t^m > \bar{\gamma}$ **and** $\lambda_t \geq \bar{\gamma}$ **then** ▷ Unsafe, below λ threshold
6:     $\Theta \leftarrow$ SampleCandidateHeadings(u_t^θ, Γ_t)
7:     $\mathcal{C} \leftarrow \{\}$
8:     **for all** $\theta \in \Theta$ **do**
9:         $\gamma \leftarrow$ GetZoneThreshold(θ, Γ_t)
10:         $s \leftarrow$ GetScore$(\gamma, \theta, u_t^\theta)$
11:         $\mathcal{C} \leftarrow \{\mathcal{C}, (\theta, \gamma, s)\}$
12:     $(\theta^*, \gamma^*, s^*) \leftarrow \arg\max_{(\theta,\gamma,s)\in\mathcal{C}} s$
13:     $r_t \leftarrow$ PolarToCartesian$(\theta^*, \mathtt{min}(u_t^m, \gamma^*))$
14: **else**
15:     $\vec{r}_t \leftarrow \vec{u}_t$ ▷ Pass through user input
16: **return** $\vec{r}_t$

and otherwise preserving user control. Rather than predicting or optimizing over future trajectories, REACT operates directly and deterministically on the instantaneous user command, selecting an alternate control action only as needed to avoid obstacles or drop-offs while remaining as close as possible to the user's intended direction and magnitude. As a result, REACT is task-agnostic, responsive to rapid changes in user input, and robust to the wide variety of conditions (user, environment, and task variability) under which powered wheelchairs must operate.

The core of the REACT algorithm is the computation of a *reactive autonomy command* $\vec{r}_t$ from the user input $\vec{u}_t$. Let Γ_t be the set of safety thresholds for all zones, from which we compute a smoothed safety threshold $\bar{\gamma}$ (described below). We further define a *REACT threshold* λ_t, such that a reactive autonomy command is issued whenever both the safe command threshold and user command fall below λ_t.[1] The idea is that above this threshold, the safety response is simply LUCI throttling of the issued command. REACT engages only when LUCI throttling is substantial.

Algorithm 1 describes the REACT algorithm. We first convert $\vec{u}_t$ to polar coordinates to get the magnitude u_t^m and heading u_t^θ components of the input command (line 2). We then extract a safety threshold γ_t, which is the magnitude component of the maximum allowable command according to Γ_t (converted to polar coordinates) within the zone corresponding to command heading u_t^θ (line 3).

To avoid spurious or oscillatory reactive assistance activation due to sensor noise and scaling zone discretization, we compute a temporally smoothed estimate $\bar{\gamma}$ of the safe command threshold by averaging over a sliding window of the κ most recent safety thresholds $\gamma_{[t-\kappa+1:t]}$ (line 4). (In our implementation, $\kappa = 10$). We use $\bar{\gamma}$ (rather than the

[1] We dynamically scale the REACT threshold λ_t based on the current PW speed (as approximated by the most recent executed control command), so that REACT engages sooner when speeds are higher. Changing the range of values for λ_t varies the aggressiveness of REACT assistance.

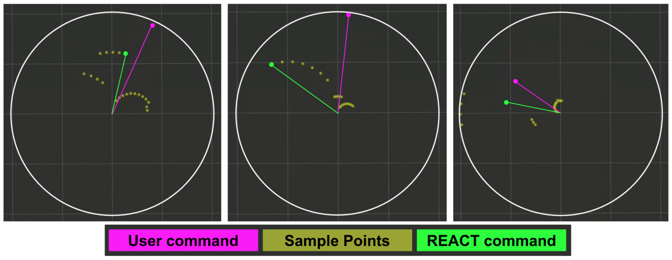

Fig. 2. Examples of REACT algorithm output. The user command vector (magenta) and reactive command vector (green) are shown, along with sampled candidate control commands (dark yellow points, $N = 21$), where a point's distance from the circle center corresponds to its control magnitude, according to the zone safety threshold.

instantaneous γ_t) to reason about whether a command is unsafe ($u_t^m > \bar{\gamma}$) and whether the amount of safety scaling falls below the REACT threshold for engagement ($\bar{\gamma} \leq \lambda_t$, line 5). If either is false, the command is either safe and/or above threshold, and the user command is passed through unchanged (line 15).

Otherwise, reactive assistance kicks in. In this case, the system first uniformly samples N alternative candidate command headings in a cone of size ϕ centered on the user's input heading (line 6). (In our implementation, $N = 21$ and $\phi = 120°$.) For each candidate command heading, we extract the safety threshold, again as the magnitude component of the (polar-coordinates converted) maximum allowable command (according to Γ_t) in the corresponding safety zone (line 9). We then score each candidate based on safety (i.e., higher safety threshold) and alignment with the user's original input (i.e., closer to u_t^θ) (line 10). We compute a weighted sum of the angular difference between θ and u_t^θ (encompassing *alignment*), and the safety threshold γ (encompassing *safety*). The scoring function we use is $s{=}\alpha|\theta{-}u_t^\theta|{+}\beta\gamma$, with alignment weight $\alpha{=}50$ and safety weight $\beta{=}1.25$.[2]

Finally, we generate a *reactive autonomy command* $\vec{r}_t$ using the highest scoring candidate command heading θ^* (line 12) and either the user's input magnitude or the candidate command magnitude, whichever is lower (i.e., $\mathtt{min}(u_t^m, \gamma^*)$, line 13). Discussion of sensitivity of REACT behavior to algorithm parameters can be found in Appendix A.

Figure 2 illustrates the result of REACT driver assistance. This approach aims to preserve the general directional intent of the user while redirecting motion toward safer regions of the control space. We run REACT at 40 Hz.

IV. Evaluation Methodology

In this section, we describe the study protocol and metrics of our evaluation methodology. Our user study design strives for a close-to-real-world evaluation of PW driving across a variety of driving tasks requiring different driving skills, and under multiple driving assistance conditions: (1) No Assistance,

[2]Accounting for the order of magnitude difference in scale between $|\theta{-}u_t^\theta|{\in}[0, 0.33\pi]$ and $\gamma{\in}[0, 100]$, our parameters give a higher weight to safety than alignment, meaning our implementation favors candidates that prioritize safety (implicitly maintaining input magnitude) over similarity to the user's input. This can lead to more aggressive redirection of the chair when REACT is actively engaged.

Fig. 3. Our robotic wheelchair—a LUCI Dev Kit, additionally outfitted with a tablet interface and multiple control interfaces (back and side views).

(2) LUCI, and (3) LUCI+REACT. Assessment is performed within a case-study framing, where the four participants are selected to cover a range of impairment presentations and user interfaces for driving a PW.

A. Hardware and Materials

We build our robotic wheelchair on top of a LUCI Dev Kit—a Sunrise Quickie Q500M PW (Malsch, Germany) outfitted with a LUCI unit (Figure 3). Sensors that are provided by the LUCI Dev Kit include *mm*-wave radar, ultrasonics, active stereo depth cameras, and wheel encoders. We further augment the system with a tablet interface and multiple control interfaces and switches (described next).

LUCI can be temporarily overridden by users through a single button on the LUCI dashboard. If REACT is running, turning off LUCI will also turn off REACT. Note that is impossible to run REACT without LUCI since REACT is built atop the LUCI system. The user can turn off REACT (but not LUCI) using the REACT GUI (described below).

REACT is implemented in C++ within ROS 2. ROS 2 nodes are run on a remote laptop and communicate with the PW through the LUCI ROS 2 SDK [23] over a dedicated Wi-Fi network. Data is recorded through a ROS 2 tool (rosbag2) on the remote laptop as well as on a Raspberry Pi with an NVMe, which provides backup data recording and storage. An experimenter has a tablet that is used to label the datastream during recording, indicating different tasks as they are being performed by the participant.

Control Interfaces. Within the study, the following interfaces are available for users to control the PW:

- Joystick: 2-axis, proportional, operated via hand deflection, left- or right-handed, 2-D.
- Head array: 3 switches, proportional, operated via head taps on the headrest, nominally 1-D, 2-D if 2 headrest pads can be activated simultaneously.
- Sip/Puff: Non-proportional, operated via respiration with custom thresholds that map to 4 control commands, nominally 1-D, 2-D under latch control.

A *proportional* interface is one for which the magnitude of the control response scales with the magnitude of the interface actuation (e.g., joystick deflection). By contrast, a non-proportional interface operates as a switch to activate a fixed-value control response. *Latch* control, commonly employed clinically with sip/puff interfaces, allows a user to latch translational motion (always-on) while issuing rotational control commands.

GUI Interface. We use a tablet interface mounted on the PW to provide users with visual feedback on the state of REACT (on/off and current direction of the reactive autonomy command; see Appendix B). The on/off GUI also serves as a REACT engagement button, allowing the user to turn REACT on or off at their discretion. There are two possible REACT engagement paradigms:

- Manual toggle: REACT remains in its current mode (on or off) until the user explicitly toggles a change. Pressing the button once toggles REACT on or off, depending on the current state.
- Opt-out: REACT is **on** by default. Pressing the button temporarily overrides REACT for 30 seconds before automatically turning REACT back on.

Participants select, according to their preference, a single engagement paradigm for the duration of their study sessions.

To meet the various positioning and seating needs of users, the LUCI override and REACT button functionalities can alternatively be mapped to external switches. The LUCI alternate switch override is supported directly via the LUCI Dashboard interface. The REACT alternate switch button is achieved through the Microsoft Xbox Adaptive Controller and Logitech G Adaptive Gaming Kit. These kits provide a breakout of game controller buttons and a variety of accessible switches, which can be positioned for ease and comfort of activation for each user, and can be plugged directly into the LUCI Dev Kit to receive input.

B. User Study Design

The study is carried out over 5 sessions, which include participant fitting and adjustment to our RW, training and familiarization on the use of our RW and the LUCI and LUCI+REACT systems, assessing driving both qualitatively and quantitatively through a battery of functional wheelchair maneuvering tasks, and semi-structured interviews on user perceptions of LUCI and LUCI+REACT.

Experimental Environment and Driving Tasks. The study driving tasks are designed to incorporate skills adapted from the clinical standard Wheelchair Skills Test (WST) [46] for powered wheelchairs (version 5.4.2) and presented in Table I. We group the driving tasks in our protocol into five categories based on primary task demand:

1) Dynamic: Navigating dynamic obstacles, which may require reactive adaptation.
2) Precision: Navigating environments with constrained geometry requiring fine control.
3) Incline: Navigating inclines.
4) Reverse: Driving primarily in reverse, which presents a distinct perceptual and PW control challenge.
5) General: General driving in relatively unconstrained environments, including simple turning maneuvers.

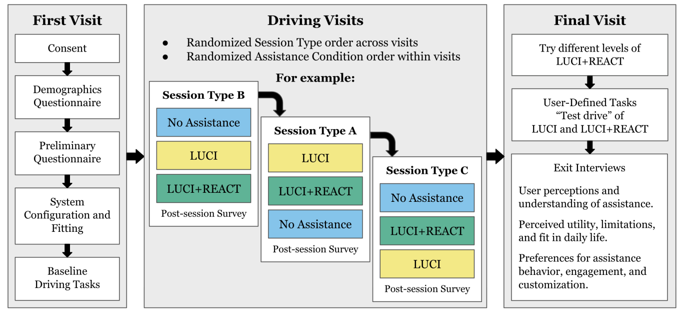

Fig. 4. Example session schedule for a single participant

Tasks are executed within a hospital setting in which physical therapy sessions occur concurrently within the same space. The environment is distracting, noisy, and uncontrolled.

Protocol. Each participant engages with three types of sessions: one "First Visit" session, three "Driving Visit" sessions, and one "Final Visit" session. An example schedule for a given participant is shown in Figure 4.

<u>First Visit.</u> After consent, participants complete a questionnaire on powered wheelchair experience and are fitted to the study wheelchair. Driving speed settings and assistance engagement interfaces are configured, and a single engagement paradigm is selected for all Driving Visits. Participants then complete baseline driving under *No Assistance* on four tasks: *Traverse sidewalk*, *Weave through stationary obstacles (forward & backward)*, and *Ascend and descend long, gentle ramp (forward)*, and *Turn around at top of ramp*. This first session lasts approximately 1-2 hours, depending on the complexity of the RW setup for a given participant.

<u>Driving Visits.</u> Each driving session consists of three phases with different assistance conditions: *No Assistance*, *LUCI*, and *LUCI+REACT*. There are three session *types* (*A*, *B*, and *C*) that differ in the tasks performed. A single type is assigned to each driving session, and each task is completed once per assistance condition. The presentation order of tasks, assistance conditions, and session types are randomized and counterbalanced across sessions and participants; with the exception of assistance condition presentation in the first Driving Visit, where conditions are presented in order of increasing assistance for familiarization. Every visit, participants repeat the *Traverse sidewalk* and *Weave through stationary obstacles (forward & backward)* tasks to facilitate cross-session comparison. Driving sessions last approximately 2-3 hours depending on the participant's driving speed.

<u>Final Visit.</u> Participants try LUCI+REACT with different sets of parameters that modulate how quickly REACT engages, followed by participant-defined tasks, where participants are encouraged to 'test drive' the RW with assistance to try tasks that resemble what they do on a daily basis. Participants then complete a semi-structured interview on their perceptions and preferences of the assistance conditions.

<u>Assessment.</u> Task performance is assessed after each task using the Wheelchair Skills Test (WST) Capacity scoring criteria, WST Questionnaire, completion time, and collision counts. At the end of each driving visit, participants additionally are

TABLE I
DRIVING TASKS FOR STUDY. SEE APPENDIX D FOR IMAGES OF TESTING SETUP.

Task Description	Session Type	Task Category	Corresponding WST Skill Description
Traverse sidewalk	First, A, B, C	General	Rolls forward
Weave through stationary obstacles (forward)	First, A, B, C	Precision	Turns while moving forward
Weave through stationary obstacles (backward)	First, A, B, C	Reverse	Turns while moving backward
Ascend and descend long, gentle ramp (forward)	First, A	Incline	Ascends and descends slight incline
Turn around at top of ramp, in elevator, in van simulator	First, A, B	Precision	Turns in place
Enter and exit accessible van simulator (forward)	A	Incline	Ascends and descends steep incline
Back into a tight space	A	Reverse	Turns while moving backward
Traverse wide long hallway (forward)	B	General	Rolls forward
Traverse doorway (wide, narrow)	B	Precision	Gets through hinged door
Dock beside a bed for transfer (“parallel parking”)	B	Precision	Maneuvers sideways
Ascend (forwards) and descend (backwards) steep ramp	B	Incline	Ascends and descends steep incline
Enter and exit elevator (forward)	B, C	General	Turns while moving forward
Exit elevator (backward)	C	Reverse	Rolls backward
Traverse narrow long hallway (Forward)	C	Precision	Rolls forward
Traverse narrow long hallway (Backward)	C	Reverse	Rolls backward
Avoid dynamic obstacles (other human, robot)	C	Dynamic	-

TABLE II
PARTICIPANT DEMOGRAPHICS

Case	Age Gender	Diagnosis	Interface	PW Use	Notes on PW Driving	Notes on Driving Visits
P1	65yo Male	ALS	Joystick, left-hand	Daily 25% of day	Reports difficulty in PW driving due to a lack of confidence in ability to consistently control their PW and in navigating their home environment, citing concerns with bumping into and damaging items.	Completed all session types, tasks and trials.
P2	64yo Male	cSCI (C4, complete)	Sip/Puff	Daily	Reports difficulty in PW driving due to sip/puff positioning and filter blockage, when navigating areas with people, and when driving in reverse.	Excluded *Avoid robot dynamic obstacle*, Reverse tasks (except *Descend steep ramp*), and *Enter, exit, turn around in van simulator*.
P3	29yo Male	Cerebral Palsy Vision, Hearing Impairments	Joystick, left-hand; Sight cane, right-hand	Daily All day	Reports difficulty in PW driving due to veering off course (especially when trying to go straight), and difficulty safely navigating around obstacles due to impaired vision.	
P4	54yo Male	cSCI (C4, complete)	Head Array	Daily	Reports difficulty in PW driving on difficult terrain, drop-offs such as sidewalks and curbs, mental fatigue when navigating safely in spaces with people and objects, and worry about hurting others.	Completed one Driving Visit; unable to complete subsequent visits due to seating needs that our PW could not meet.

asked to rate their *comfort* with controlling their PW under each of the three assistance conditions.

C. Evaluation Metrics

We use the following metrics to evaluate impact of each assistance condition on task performance and control input characteristics.

Total Safety Incident Counts. We report the total number of safety incidents across all tasks for each assistance type.[3]

Percentage of Safe Trials. We report the percentage of trials with zero safety incidents.

WST Capacity Score. The WST objectively assesses a PW user's *capacity* (i.e., what the person 'can do') to carry out the task. Clinical expert experimenters observe participants carry out tasks during visits and assign a score based on their performance, considering factors such as proficiency in which they carry out the task, adequacy of meeting task requirements, safety, and speed. Capacity scores for the No Assistance condition reflect a user's baseline capacity for completing the task in our RW. Changes in the score under the LUCI and LUCI+REACT conditions are thus indicative of the impact of the assisted driving conditions, as determined by a clinician.

WST Questionnaire. The WST questionnaire aims to assess users' subjective (self-reported) capacity to carry out tasks in their own setting based on their self-ratings for *performance*, *confidence*, and *frequency*. Users provide their scores at the end of each task.

Joystick Bout. A control input *bout* is defined as a distinct period in which the user actively engages the interface above a threshold until returned to its neutral state [17]. The duration of bouts is a measure of sustained control. The number of bouts is a proxy for the number of distinct inputs given by a user, and fewer bouts may indicate fewer large corrections during motion and thus better path planning.

Human-Autonomy Disagreement. We use human-autonomy disagreement to quantify periods of user-system conflict. We define human-autonomy disagreement as the difference—in both heading and magnitude—between the user's input and the assistance-modified output prior to wheelchair execution.

Heading disagreement is computed as the angular dot prod-

[3] Safety incidents would include collisions, drop-offs which may potentially result in dangerous tipping, or 'emergency stop' activations by experimenters. Emergency stops are activated when experimenters determine the continued motion of the chair to pose a safety hazard to the participant, such as continued motion towards a drop-off or continued motion despite collision.

TABLE III
PERCENTAGE OF SAFE TRIALS

Case	% Safe Trials		
	NO	LUCI	LUCI+ REACT
P1	94	94	94
P2	72	83	92
P3	55	85	80

TABLE IV
TOTAL SAFETY INCIDENT COUNTS

Case	Safety Incident Counts		
	NO	LUCI	LUCI+ REACT
P1	3	3	2
P2	16	9	3
P3	33	4	7

TABLE V
OBJECTIVE CAPACITY SCORE FOR ALL TASKS OVER ALL SESSIONS

Case	Capacity Score		
	NO	LUCI	LUCI+ REACT
P1	91.3	92.4	90.2
P2	84.0	88.9	96.0
P3	49.3	84.0	78.7

uct between the two command vectors. Magnitude disagreement is computed as the percentage of magnitude difference between the two command vectors. Software and hardware characteristics of systems result in an inherent baseline disagreement between user input and system output (typically 8–10% [41]). We characterize our system's baseline by computing the disagreement between the user input and the executed control command under the *No Assistance* condition, averaged over all participants and reported as baseline $\pm$ standard deviation (SD). (Angular disagreement: $3.34\% \pm 2.27\%$ or $6.02° \pm 4.08°$; Magnitude disagreement: $11.2\% \pm 6.3\%$.)

D. Participant Demographics

Case studies are conducted with four current powered wheelchair users, whose demographics are summarized in Table II. All participants report having never used any type of smart wheelchair technology. All participants gave their informed consent to participate in the experiment, which was approved by Northwestern University's Institutional Review Board (STU00220498).

V. RESULTS AND DISCUSSION

In this section, we examine results from the four case study participants. We find the impact of assistance on user input commands to vary by participant and task, and our observations highlight the importance of task variety and multi-session variability.

Note: Participant P4 was able to complete only one driving session (Table II). We accordingly exclude them from all analyses by and over driving sessions (Tables III-VII, Figure 6) but do include them in by-task analyses (Figure 5).

A. Effects of Assistance on Task Performance

We discuss the effects of assistance on the task performance outcomes of safety and driving skill.

1) Assisted Driving Impact on Safety: From Table III, assisted driving conditions improve the percentage of safe trials for P2 and P3, with minimal effect for P1 (who has close to 100% safe trials in unassisted driving). From Table IV, assisted driving conditions are effective across the board at reducing the number of safety incidents from the unassisted driving baseline, with LUCI+REACT being more effective for P2, and LUCI alone being more effective for P3.

2) Assisted Driving Impact on Objective Capacity: We report in Table V the percentage score (out of 100) across all tasks that were successfully administered for a given participant, across all assistance conditions.

We see that P1 is a skilled PW driver, with minimal variance in scores between assistance conditions. Both assisted driving conditions improve P2's driving performance, with LUCI+REACT yielding the largest improvement. P3 is the least skilled driver, and their scores dramatically improved under assistance, with both LUCI and LUCI+REACT improving driving performance by $\sim 30\%$ from unassisted driving. In general, these results indicate that both assisted driving conditions do not degrade (P1) and, in fact, often improve (P2 and P3) PW driving capacity for users performing the evaluated tasks.

3) Assisted Driving Impact on Self-reported Capacity: We report in Table VI the average percentage score (out of 100) given by participants for each of *performance*, *confidence*, and *frequency* across all tasks that were successfully administered for a given participant, across all assistance conditions.

We see that across the board, both assisted driving conditions improve self-ratings of task *performance* and *confidence*. P1 appears to rate their driving with LUCI and LUCI+REACT similarly; P2 gave themselves a score of 100% when driving with LUCI; P3 rates themselves driving with no assistance, LUCI, and LUCI+REACT in increasing order.

It is interesting to note that, despite rating their performance and confidence with LUCI+REACT as the highest, P3 rated their *frequency* as lowest. This indicates that despite the improvements, they thought that they would be less likely to use LUCI+REACT in their own setting. This could be attributed to unexpected changes in PW heading due to the redirective nature of LUCI+REACT, coupled with P3's vision impairment, leading to disorientation when redirection occurred frequently. This was corroborated by their preference for a 'less aggressive' level of REACT during their Final Visit, where they cited that the smaller amount of redirection made it easier to use.

B. Effects of Assistance on Driving Input

Assistance does not uniformly affect driving; instead, it changes control behavior in task- and user-specific ways. Moreover, there are some user-task instances when LUCI+REACT improves input characteristics, others when LUCI alone improves them, and instances when both do. What we do see is that for *no combination* of user and task do both forms of assistance uniformly degrade input characteristics (i.e., choppier input with more bouts and shorter bout durations).

Figure 5 reports bout characteristics, aggregated across trials for each task category. We see that for P1, LUCI+REACT improves bout characteristics (lower count and higher duration) on only one task category (*precision*). P4, by contrast, has the same result but for *incline* tasks. P2 and P3 see improvements on a majority of task categories.

TABLE VI
SUBJECTIVE PERFORMANCE, CONFIDENCE, AND FREQUENCY RATINGS FOR ALL TASKS OVER ALL SESSIONS

Case	Performance			Confidence			Frequency		
	NO	LUCI	LUCI+ REACT	NO	LUCI	LUCI+ REACT	NO	LUCI	LUCI+ REACT
P1	95.2	96.2	97.1	95.2	95.2	95.1	97.1	97.1	98.0
P2	93.3	100.0	97.3	92.0	98.6	96.0	93.3	100.0	94.7
P3	74.7	89.3	92.0	81.3	92.0	93.3	41.3	41.3	34.7

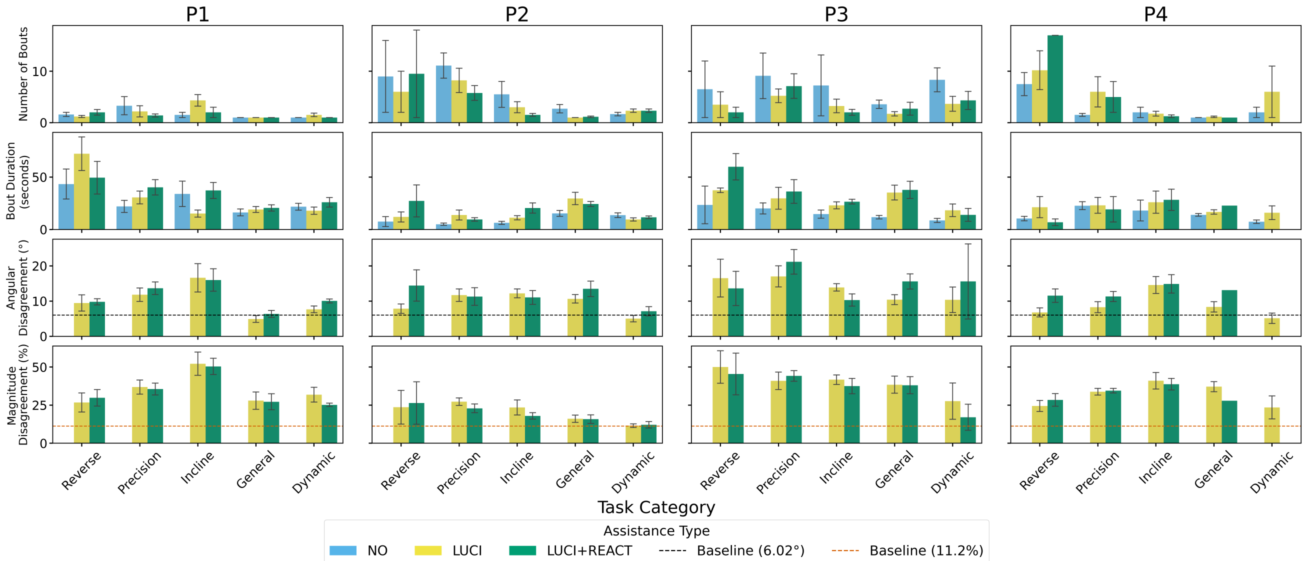

Fig. 5. Bout characteristics and control input disagreement for each Case, grouped by task category. 1st row: Mean number of bouts for all trials per category. 2nd row: Mean bout duration for all trials per category. 3rd row: Mean angular disagreement for all trials per category. 4th row: Mean magnitude disagreement for all trials per category. All means reported with standard error.

TABLE VII
SELF-REPORTED COMFORT UNDER EACH ASSISTANCE CONDITION, ACROSS DRIVING SESSIONS 1-3 (VISITS 2-4). SCALE: 1='NOT COMFORTABLE', 7='VERY COMFORTABLE'.

Case	NO			LUCI			LUCI+REACT		
	1	2	3	1	2	3	1	2	3
P1	7	7	7	6	7	7	6	7	7
P2	6	6	7	6	7	7	6	7	7
P3	3	2	2	5	6	6	6	7	7

C. Disagreement and User Perception

Both assisted driving conditions generally result in human-autonomy disagreement above the characterized baselines, for all participants (Figure 5, bottom two rows). LUCI+REACT demonstrates slightly higher angular disagreement than LUCI, which is consistent with the redirective nature of LUCI+REACT in comparison to LUCI's speed-thresholding only. By contrast, the average magnitude disagreements of both assisted driving conditions are generally comparable, suggesting that both conditions similarly reduce a user's speed, despite different intervention strategies.

Notably, while higher disagreement might result in user frustration [41], in many cases users perceive the command modifications from driving assistance to be helpful. Contextualizing human-autonomy disagreement with subjective user experience and changes in their control is critical for interpretation. For example, assisted driving conditions for both P2 and P3 showed reduced bout counts compared to unassisted driving in the majority of task categories (Figure 5, top two rows), suggesting that they needed fewer corrective movements when assistance was active, despite higher disagreement values. This also aligns with reports from participants of high levels of comfort when driving under assisted conditions (Table VII).

D. Importance of Task Variety

Driving behavior varies substantially across task categories, likely because different tasks typically require different skills to complete (Figure 5). This is most prominent in *reverse* and *precision* tasks, where dense obstacles and obstructed view present more opportunities for assistance intervention, which may result in more user-autonomy conflict. Conversely, straight navigation tasks require simpler, linear trajectories. Different participants also struggle to varying extents on different task categories, and thus the opportunities for autonomy to assist vary between participants. This highlights the importance of evaluating assistance across diverse driving tasks to understand its impact for different users in varied driving scenarios

E. Multi-session Variability and User-Defined Tasks

Both P2 and P3 reported that they had come to better understand both the PW hardware and the underlying assistance conditions with increased interaction with the system, and were beginning to alter their driving strategies to leverage assistance. This is reflected in all of P1, P2, and P3's self-reported comfort scores with controlling the PW, with assistance increasing with repeat sessions, as seen in Table VII.

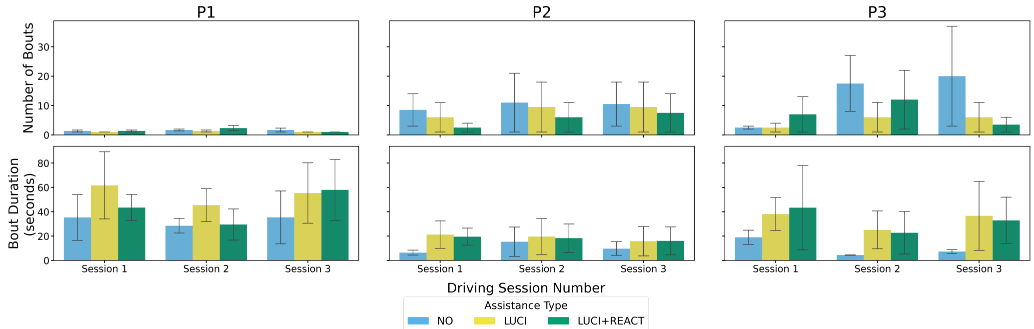

Fig. 6. Bout characteristics for each Case, for tasks repeated over all driving sessions (visits 2-4). Mean number (top row) and duration (bottom row) of bouts over all trials per driving session.

We further see in Figure 6, for P1 and P3, notable variability in driving input characteristics between sessions, both within and across assistance conditions.

This variability suggests an inherent limitation in single session evaluations, where the interaction being evaluated is often novel to the user. Here the same user performing the same tasks under the same assistance condition exhibits different effects across visits, reflecting user learning and adaptation, as well as the variability users experience day-to-day, which our multi-session study protocol aims to capture.

Lastly, a portion of the Final Visit session involved user-defined tasks. The observed tasks can be grouped into three categories: (1) established daily tasks, (2) exploration of an unknown area, and (3) caregiver-assisted tasks. Of note, P2 chose to drive LUCI+REACT outdoors, and in doing so encountered dynamic obstacles (people and cars) and different ground surface features (5 cm sidewalk cracks and grates). P3 and P4 chose to navigate a van ramp, a task their caregivers normally execute for them—both cite being confident to do so only under LUCI and LUCI+REACT assistance.

F. Generalization to Novice Users

While we are unable to provide statistical data as yet, we are able to identify suggestions from our case study results. We expect novice users could benefit from REACT as a training tool, allowing users to gain confidence and guidance (as reported by P3) and help with fatigue when initially learning to drive. Additionally, we anticipate experienced users (P2 and P3) to adapt their driving style to leverage, and thus benefit from, driver assistance. This suggests even experienced users may find benefit in having the driver assistance system. We also do expect that if a user is very skilled with their PW, the change in task performance and driving behavior metrics could be limited (P1).

VI. Limitations

Our study is limited by a small sample size due to the difficulty of recruiting PW users with mobility impairments for a 5-session protocol. Due to time constraints and emphasis on participant safety and comfort, we were unable to obtain complete datasets for all participants. Additionally, some tasks were not reasonable with certain interfaces (e.g., sustained reverse driving with a sip/puff) and were skipped.

Although our sample size is limited, small sample size studies play a role as exploratory studies with trends that can later be confirmed with larger sample sizes [2]. Future work will include larger cohorts with more diverse input modalities to better understand the impact of control interface on assistance effects, particularly for discrete versus continuous interfaces.

We collected data in a clinical setting with uncontrolled noise and distractions, in an effort to create a realistic but reproducible environment for data collection. However, there may have been more or fewer distractions for different users and/or over visits, which may have affected driving. There is also variance in the gaps between and the duration of visits for participants, which may impact system and environment familiarity, and thus driving behavior. Furthermore, since our setting, chair, and some tasks are unfamiliar to most users, trials may not fully capture how users would drive in their own settings, but rather a single session interaction between the participant and system characterized by the participant's given output on that particular day.

VII. Conclusion

We introduced REACT, a minimal, deterministic shared-control algorithm for powered wheelchairs that intervenes only under safety constraints, and demonstrated its deployment on a LUCI Dev Kit commercial platform. We also introduced a multi-task, multi-session evaluation protocol that revealed interaction effects that would have been missed by a single-session laboratory study. Case study evaluations under this protocol with four end-users with diverse diagnoses and interfaces showed assistance to reshape driving behavior in user- and task-dependent ways. Together, these results motivate lightweight, minimal-intervention, safety-driven wheelchair assistance, paired with an evaluation protocol in minimally controlled, close-to-real-world settings.

Acknowledgments

We thank Rachel Kalvakota, OTR/L, OTD, Devon Butts, PT, DPT, and Sarah Van Dyck, OTR/L for their contributions to study protocol refinement and for serving as clinician leads during study sessions, and Kalvakota and Corinne Fischer, OTR/L for their assistance with participant recruitment and scheduling. We thank Breanna Lu and Luke Meyer for their assistance with conducting study sessions. This material is based upon work supported by the National Science Foundation under Grant ITE-2345174. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] Catherine Bigras, Dolapo D. Owonuwa, William C. Miller, and Philippe S. Archambault. A scoping review of powered wheelchair driving tasks and performance-based outcomes. *Disability and Rehabilitation: Assistive Technology*, 15(1):76–91, 2020.

[2] Bastiaan R. Bloem, Mariana H. G. Monje, and Jose A. Obeso. Understanding motor control in health and disease: classic single (n=1) observations. *Experimental Brain Research*, 238(7):1593–1600, 2020.

[3] Alexander Broad, Todd Murphey, and Brenna Argall. Highly Parallelized Data-Driven MPC for Minimal Intervention Shared Control. In *Proceedings of the Robotics: Science and Systems Conference*, 2019.

[4] T. Carlson and Y. Demiris. Collaborative Control for a Robotic Wheelchair: Evaluation of Performance, Attention, and Workload. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 42(3):876–888, 2012.

[5] Anna Carlsson and Jörgen Lundälv. Acute injuries resulting from accidents involving powered mobility devices (PMDs)—development and outcomes of PMD-related accidents in Sweden. *Traffic Injury Prevention*, 20(5): 484–491, 2019.

[6] Rory A Cooper, Rosemarie Cooper, and Michael L Boninger. Trends and Issues in Wheelchair Technologies. *Assistive Technology*, 20(2):61–72, 2008.

[7] Angela A. R. De Sá, Yann Morère, and Eduardo L. M. Naves. Skills assessment metrics of electric powered wheelchair driving in a virtual environment: a survey. *Medical & Biological Engineering & Computing*, 60(2): 323–335, 2022.

[8] Louise Devigne, Marco Aggravi, Morgane Bivaud, Nathan Balix, Catalin Stefan Teodorescu, Tom Carlson, Tom Spreters, Claudio Pacchierotti, and Marie Babel. Power Wheelchair Navigation Assistance Using Wearable Vibrotactile Haptics. *IEEE Transactions on Haptics*, 13(1), 2020.

[9] E. B. Vander Poorten, E. Demeester, E. Reekmans, J. Philips, A. Hüntemann, and J. De Schutter. Powered wheelchair navigation assistance through kinematically correct environmental haptic feedback. In *Proceedings of the IEEE International Conference on Robotics and Automation*, 2012.

[10] Mohamad A. Eid, Nikolas Giakoumidis, and Abdulmotaleb El Saddik. A Novel Eye-Gaze-Controlled Wheelchair System for Navigating Unknown Environments: Case Study With a Person With ALS. *IEEE Access*, 4:558–573, 2016.

[11] Ahmetcan Erdogan and Brenna D. Argall. The effect of robotic wheelchair control paradigm and interface on user performance, effort and preference: An experimental assessment. *Robotics and Autonomous Systems*, 94:282–297, 2017.

[12] Brett Erickson, Masih A Hosseini, Parry Singh Mudhar, Maryam Soleimani, Arina Aboonabi, Siamak Arzanpour, and Carolyn J Sparrey. The dynamics of electric powered wheelchair sideways tips and falls: experimental and computational analysis of impact forces and injury. *Journal of NeuroEngineering and Rehabilitation*, 13:1–10, 2016.

[13] Linda Fehr, W Edwin Langbein, and Steven B Skaar. Adequacy of power wheelchair control interfaces for persons with severe disabilities: a clinical survey. *Journal of Rehabilitation Research & Development*, 37(1-3):353–360, 2000.

[14] Bastien Fraudet, Emilie Leblong, Patrice Piette, Benoît Nicolas, Louise Devigne, Marie Babel, François Pasteau, François Routhier, and Philippe Gallien. Swadapt2: benefits of a collision avoidance assistance for powered wheelchair users in driving difficulty. *Disability and Rehabilitation: Assistive Technology*, 19(5):1907–1915, 2024.

[15] Amina Gacem, Eric Monacelli, Ting Wang, Olivier Rabreau, and Tarik Al-Ani. Assessment of wheelchair skills based on analysis of driving style. *Cognition, Technology & Work*, 22, 2020.

[16] Michael Gillham, Matthew Pepper, Steve Kelly, and Gareth Howells. Feature determination from powered wheelchair user joystick input characteristics for adapting driving assistance. *Wellcome Open Research*, 2:93, 2018.

[17] Kimberly A. Ingraham, Nicole L. Zaino, Claire Feddema, Mia E. Hoffman, Liesbeth Gijbels, Alexis Sinclair, Andrew N. Meltzoff, Patricia K. Kuhl, Heather A. Feldner, and Katherine M. Steele. Quantifying Joystick Interactions and Movement Patterns of Toddlers With Disabilities Using Powered Mobility With an Instrumented Explorer Mini. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 33:431–440, 2025.

[18] Takuma Ito and Minoru Kamata. Interactive Collision Avoidance Based On Surrounding Mobility Type for an Intelligent Powered Wheelchair. *International Journal of Advanced Robotic Systems*, 10(5):241, 2013.

[19] William D Kearns, Adam J Becker, John P Condon, Victor Molinari, Ardis Hanson, William Conover, and James L Fozard. A Comprehensive Review of Smart Wheelchairs: Past, Present, and Future. *IEEE Transactions on Human-Machine Systems*, 34(1):64–76, 2022.

[20] Jesse Leaman and Hung Manh La. A Comprehensive Review of Smart Wheelchairs: Past, Present, and Future. 47(4):486–499.

[21] Emilie Leblong, Bastien Fraudet, Louise Devigne, Marie Babel, François Pasteau, Benoit Nicolas, and Philippe Gallien. SWADAPT1: assessment of an electric wheelchair-driving robotic module in standardized circuits: a prospective, controlled repeated measure design

pilot study. *Journal of NeuroEngineering and Rehabilitation*, 18(1):140, 2021.

[22] Edmund F LoPresti, Vinod Sharma, Richard C Simpson, and L Casimir Mostowy. Performance testing of collision-avoidance system for power wheelchairs. *Journal of Rehabilitation Research & Development*, 48(5): 529–44, 2011.

[23] LUCI. SDK Documentation — LUCI SDK. URL https://lucimobility.github.io/luci-sdk-docs/.

[24] LUCI. Luci mobility, 2023. URL https://luci.com/.

[25] S.P. Parikh, R. Rao, Sang-Hack Jung, Vijay Kumar, J.P. Ostrowski, and C.J. Taylor. Human Robot Interaction and Usability Studies for a Smart Wheelchair. In *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2003.

[26] Alice Pellichero, Krista Best, Jean Leblond, Pauline Coignard, Éric Sorita, and François Routhier. Relationships between cognitive functioning and power wheelchair performance, confidence and life-space mobility among experienced power wheelchair users: An exploratory study. *Journal of Rehabilitation Medicine*, 53(9):jrm00226, 2021.

[27] Jacek Pieniazek and Wieslaw Szaj. Augmented wheelchair control for collision avoidance. *Mechatronics*, 96:103082, 2023.

[28] Joelle Pineau, Robert West, Amin Atrash, Julien Villemure, and François Routhier. Towards a Standardized Test for Intelligent Wheelchairs. In *Proceedings of the 10th Performance Metrics for Intelligent Systems Workshop*, 2010.

[29] Qiang Zeng, Etienne Burdet, and Chee Leong Teo. Evaluation of a Collaborative Wheelchair System in Cerebral Palsy and Traumatic Brain Injury Users. *Neurorehabilitation and Neural Repair*, 23(5):494–504, 2009.

[30] Paula W. Rushton, Dahlia Kairy, Philippe Archambault, Evelina Pituch, Caryne Torkia, Anas El Fathi, Paula Stone, François Routhier, Robert Forget, Joelle Pineau, Richard Gourdeau, and Louise Demers. The potential impact of intelligent power wheelchair use on social participation: perspectives of users, caregivers and clinicians. *Disability and Rehabilitation: Assistive Technology*, 10 (3):191–197, 2015.

[31] Hye-Yeon Ryu, Je-Seong Kwon, Jeong-Hak Lim, A-Hyeon Kim, Su-Jin Baek, and Jong-Wook Kim. Development of an Autonomous Driving Smart Wheelchair for the Physically Weak. *Applied Sciences*, 12(1):377, 2021.

[32] David Adrian Sanders, Benjamin John Sanders, Alexander Gegov, and David Ndzi. Results from investigating powered wheelchair users learning to drive with varying levels of sensor support. In *Proceedings of the 2017 Intelligent Systems Conference (IntelliSys)*, 2017.

[33] Richard Simpson, Edmund LoPresti, Steve Hayashi, Songfeng Guo, Dan Ding, William Ammer, Vinod Sharma, and Rory Cooper. A prototype power assist wheelchair that provides for obstacle detection and avoidance for those with visual impairments. *Journal of NeuroEngineering and Rehabilitation*, 2:1–11, 2005.

[34] Richard C. Simpson. Smart wheelchairs: A literature review. *Journal of Rehabilitation Research & Development*, 42(4):423.

[35] Richard C Simpson, Edmund F LoPresti, and Rory A Cooper. How many people would benefit from a smart wheelchair? *Journal of Rehabilitation Research & Development*, 45(1), 2008.

[36] Sivashankar Sivakanthan, Jorge L. Candiotti, S. Andrea Sundaram, Jonathan A. Duvall, James Joseph Gunnery Sergeant, Rosemarie Cooper, Shantanu Satpute, Rose L. Turner, and Rory A. Cooper. Mini-review: Robotic wheelchair taxonomy and readiness. *Neuroscience Letters*, 772:136482, 2022.

[37] Smile Smart Technology. Smilesmartsystem for powerchairs, 2024. URL https://www.smilesmart-tech.com/product/smilesmartsystem-powerchairs/.

[38] Catalin Stefan Teodorescu, Bingqing Zhang, and Tom Carlson. Probabilistic Shared Control for a Smart Wheelchair: A Stochastic Model-Based Framework. In *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 2019.

[39] Caryne Torkia, Denise Reid, Nicol Korner-Bitensky, Dahlia Kairy, Paula W Rushton, Louise Demers, and Philippe S Archambault. Power wheelchair driving challenges in the community: a users' perspective. *Disability and Rehabilitation: Assistive Technology*, 10(3):211–215, 2015.

[40] Peter Trautman. Breaking the Human-Robot Deadlock: Surpassing Shared Control Performance Limits with Sparse Human-Robot Interaction. In *Proceedings of the Robotics: Science and Systems*, 2017.

[41] C Urdiales, M Fdez-Carmona, G Peinado, and F Sandoval. Metrics and benchmarking for assisted wheelchair navigation. In *Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR)*, 2013.

[42] Cristina Urdiales, Jose M. Peula, Ulises Cortés, Christian Barrué, Blanca Fernández-Espejo, Roberta Annichiaricco, Francisco Sandoval, and Carlo Caltagirone. A Metrics Review for Performance Evaluation on Assisted Wheelchair Navigation. In *Proceedings of the Bio-Inspired Systems: Computational and Ambient Intelligence*, 2009.

[43] Pooja Viswanathan, Ellen P. Zambalde, Geneviève Foley, Julianne L. Graham, Rosalie H. Wang, Bikram Adhikari, Alan K. Mackworth, Alex Mihailidis, William C. Miller, and Ian M. Mitchell. Intelligent wheelchair control strategies for older adults with cognitive impairment: user attitudes, needs, and preferences. *Autonomous Robots*, 41 (3):539–554, 2017.

[44] Chao Wang, Alexey S Matveev, Andrey V Savkin, Tuan Nghia Nguyen, and Hung T Nguyen. A collision avoidance strategy for safe autonomous navigation of an intelligent electric-powered wheelchair in dynamic uncertain environments with moving obstacles. In *Proceedings of 2013 European Control Conference (ECC)*,

pages 4382–4387, 2013.

[45] Rosalie H. Wang, Alexandra Korotchenko, Laura Hurd Clarke, W. Ben Mortenson, and Alex Mihailidis. Power Mobility with Collision Avoidance for Older Adults: User, Caregiver, and Prescriber Perspectives. *Journal of Rehabilitation Research & Development*, 50(9):1287–1300, 2013.

[46] Wheelchair Skills Program. Wheelchair skills program, 2024. URL https://wheelchairskillsprogram.ca/en/.

[47] Erik Wästlund, Kay Sponseller, Ola Pettersson, and Anders Bared. Evaluating gaze-driven power wheelchair with navigation support for persons with disabilities. *Journal of Rehabilitation Research & Development*, 52 (7):815–826, 2015.

[48] Yifan Xu, Qianwei Wang, Jordan Lillie, Vineet Kamat, Carol Menassa, and Clive D'Souza. CoNav Chair: Development and Evaluation of a Shared Control based Wheelchair for the Built Environment, 2025. URL http://arxiv.org/abs/2507.11716. arXiv:2507.11716 [cs].

[49] Bingqing Zhang, Giulia Barbareschi, Roxana Ramirez Herrera, Tom Carlson, and Catherine Holloway. Understanding Interactions for Smart Wheelchair Navigation in Crowds. In *CHI Conference on Human Factors in Computing Systems*, 2022.