Quantifying Electric Powered Wheelchair Driving Ability

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Quantifying Electric Powered Wheelchair Driving Ability

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Electric Powered Wheelchairs (EPWs) are complex rehabilitation technology indispensable for independent mobility of people with disabilities. Clinical driving assessments are critical for the provision of EPWs and training EPW users to promote safe mobility. Multiple studies have illustrated that problems with driving EPWs are associated with impairments in motor, sensory and cognitive functions. Existing EPW driving assessment tools provide rehabilitation professionals little insight into the selection of specific training strategies for this key activity based on the users' impairments. The primary objective of this study is to develop clinical tools to quantify users' motor, sensory and cognitive impairments that are commonly evaluated during an EPW driving evaluation. The secondary objective is to develop an assistance based scoring system to evaluate EPW driving in the clinic and develop a set of clinically-relevant objective metrics that can serve as an outcome measure of EPW driving evaluation and training.

This motivated the development and content validation of two clinical tools, the Powered Mobility Screening Tool (PMST) and the Powered Mobility Clinical Driving Assessment (PMCDA). A set of objective variables termed Quantitative Driving Metrics (QDM) were developed as digital markers for user's driving ability. Preliminary psychometric evaluations of these movement-based variables in an EPW driving simulator revealed high stability and construct validity. Content validity of QDM was established through expert interviews. Real-world QDM computed using two modalities (passive motion capture and inertial measurement unit with 9 axis motion sensors) revealed high concurrent validity between the two modalities. A pilot study

demonstrated the feasibility of gathering data to compute QDM in a wheelchair clinic. Psychometric evaluation revealed that the PMCDA and QDM have acceptable measurement properties for use in a clinical setting.

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1.0 Introduction

Electric Powered Wheelchairs (EPWs) are key assistive devices that increase mobility and comfort while promoting social integration among people with disabilities (PwDs), thereby improving overall quality of life [1, 2]. Over the past few decades, the number of EPW users has been estimated to be 16 – 30% of all mobility device users in the United States, and this number is projected to increase significantly with the growing population [3-5]. Advances in medicine and rehabilitation that preserve and prolong the lives of PwDs, increase in the aging population of baby boomers, and increase in the number of veterans returning from conflict situations have contributed to the steady growth in the number of EPW users [6-8]. However, simultaneous increase in clinical workloads and limited insurance reimbursement for EPW driving training has limited clinicians' time and resources to train those PwDs who wish to gain the skill of independent powered mobility [9-12].

Lack of EPW driving training has been postulated as one of the contributory factors for an increasing number of accidents [13]. Lack of adequate training also results in injuries [13-18] and equipment abandonment [19, 20] thereby adversely affecting the quality of life of PwDs. To compound this critical issue, over 40% of individuals who receive EPWs continue to have problems with certain EPW driving skills that are necessary for activities of daily living [21]. It is estimated that the cost of EPW-related injuries could amount to $25,000 - $75,000 per accident [22]. Poor driving skills can also result in death of EPW users [22]. Hence, a continuing need exists to develop assessment tools and outcome measures that can help clinicians determine why individuals cannot drive an EPW and develop protocols to train them successfully [23, 24].

Clinical assessment tools, sometimes called rapid assessment instruments, are short and easy to use, have easily interpretable scores, and provide information that is useful to guide clinical decision making [25, 26]. When clinicians find that assessment tools have these qualities, they are much more likely to use them [27]. Various statistical methods have been employed to ensure standardization of clinical assessment tools to reduce their subjectivity and bias while increasing their reliability [27, 28]. Currently, only a few clinical EPW driving assessment tools are available to rehabilitation professionals for evaluating EPW driving in adults.

Outcome measures are assessment tools used to evaluate a patient's current status and ascertain whether or not a meaningful change in health status or a condition has occurred between the initial evaluation and a subsequent point in time [29, 30]. They may be collected through surveys or questionnaires and may be self-reported by the EPW user or completed by a parent, caregiver or someone who observes the user on a regular basis (observer-reported or clinician-reported). Outcome measures may require a clinician's assessment of the user's capacity to perform pre-specified tasks [28, 31]. Such task-based outcome measures can be based on either subjective assessment that is assigned a score (e.g., pass or fail for a given task) or objective measurements (e.g., time to complete a task) [24].

Based on the World Health Organization (WHO)'s International Classification of Functioning, Disability and Health (ICF), task-based assessments could be described as **capacity** or **performance** evaluations. Those assessments that record an individual's ability to complete a task in a *standardized* environment (e,g, clinic or in-patient facility at a hospital or a standardized obstacle course in a laboratory) are described as **capacity** evaluations, whereas **performance** evaluations describe what an individual does in his or her current or *natural* environment (e.g., user's home or nursing facility) [32].

The following section provides an overview of the clinical assessment tools, along with the subjective and objective outcome measures that have been discussed in the scientific literature to study EPW users' driving ability.

1.1 Clinical Powered Mobility Assessment Tools

Most of the existing clinical driving assessment tools are task-based assessments, developed to either be administered in the user's natural environment (i.e. EPW driving performance) or in the clinic (i.e. EPW driving capacity). The Power Mobility Indoor Driving Assessment (PIDA) and the Power Mobility Community Driving Assessment (PCDA) developed by Dawson et al [33] and Letts et al [23] are two clinical tools to assess indoor and outdoor EPW driving capacity. These were developed as screening tools administered in the clinic to help identify general areas where more training is needed (e.g. "parking under a table"), or where modifications to the EPW or environment are necessary. Scoring is subjective such that the evaluator rates how independently a driver can perform a given task such as "approaching a closet".

Kirby et al. published the Wheelchair Skills Test (WST) which has mainly been used to evaluate manual wheelchair mobility [34-37]. The WST has recently been validated to measure EPW driving [38-40]. The test has two versions, an observer-rated tool for rehabilitation professionals and caregivers to gather information regarding users' capacity (WST) and a self-reported questionnaire version (WST-Q) for the users to gauge their own driving performance in their own environment. Recent studies have demonstrated good measurement properties of both

WST and WST-Q [40, 41]. WST uses a simple scoring system for clinicians to evaluate EPW users based on whether the driver can or cannot accomplish a task.

Massengale et al developed the Power Mobility Road Test (PMRT) based on specific driving tasks from the WST to study the relationship between visual and cognitive impairments, personality traits and EPW driving [42]. The tool contains a comprehensive set of EPW driving tasks required for independent mobility in both stationary and dynamic environments. The 12 stationary tasks are predictable, while the 4 unstructured / dynamic tasks are unpredictable and require users to make decisions about interacting with the environment, such as avoiding a person walking down the hallway or avoiding a therapy ball in the way [42]. The PMRT is scored using a 4-point scale: 4: completed independently, 3: completed hesitantly requiring several trials and minor accidents, 2: committed serious accidents that could cause harm to driver or other people, 1: unable to complete a task [42]. The total score is calculated and expressed as a percentage, termed “total composite score”. A total composite score on the PMRT of ≥95% indicates safe driving. The assessment typically requires less than 15 minutes to administer, has high internal consistency, inter-rater, and intra-rater reliability (ICC >.8) in both real world and virtual-reality based assessments [43, 44]. However, this assessment tool is limited by the ceiling effect noted with many ordinal scoring systems and also by its inability to identify differences in driving capacity between users with novice, marginal and expert driving skills [43, 44].

Routheir et al established a framework for EPW driving assessments in 2003 [45], developed the Obstacle Course Assessment Of Wheelchair User Capacity (OCAWUC) in 2004 [46], and established reliability for the assessment tool in 2005 [47]. The Community Mobility Skills Course (CMSC) for people who use mobility devices was developed to demonstrate the need for increased training for higher level skills necessary for safe navigation in the community

[48]. These tools are limited by the time and resources required for their administration, and require further psychometric evaluation.

The Assessment of Learning Powered Mobility (ALP) was developed using the principles of grounded theory by Nilsson et al [49-51]. The tool adopts a user-led approach to train children with disabilities of all skill levels from novice to experienced and has recently been tested for use among adults with disabilities as well [51]. ALP has demonstrated high inter-rater reliability, however further psychometric evaluations are yet to be conducted [49, 50]. In addition to these assessment tools, two pediatric powered mobility assessment tools [52], the Powered Mobility Program and the Functional Evaluation Rating Scale [53] have not been discussed in this review to limit the focus of this discussion to powered mobility assessment tools for adults with disabilities.

In addition to the existing EPW driving assessment tools discussed above, there is growing evidence that demonstrates specific impairments in body functions negatively impact EPW driving skills [42, 45, 54, 55]. Cullen and Evans linked self-reported functional performance of driving an EPW with verbal recall, visual construction ability, and global cognition [54]. Anecdotal evidence from Mendoza et al note increased accidents among EPW users in a nursing home if they had executive dysfunction [56]. Routhier et al suggested that a variety of psychological factors influence EPW use: cognitive function, motivation, analytical capacity and problem-solving [45]. Batavia et al noted the negative impact of cognitive impairment on EPW driving in users with traumatic brain injury [57]. Those with visual problems and lower overall functional status have also been found to have worse outcomes in developing EPW driving skills [42], emphasizing the need for an individualized approach in training, based on the individuals' impairments and their functional ability.

1.1.1 Scientific Gaps in Existing Clinical EPW Driving Assessment Tools

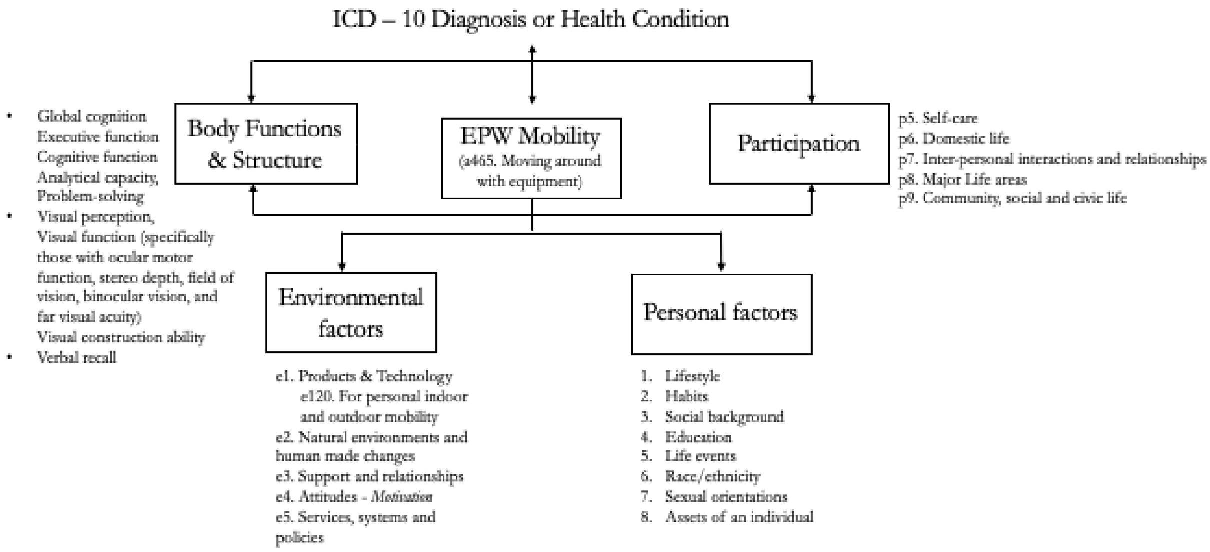

Figure 1: ICF based conceptual organization of factors that affect EPW driving

To better understand the concepts of motor, sensory and cognitive impairments as they relate to the activity of EPW driving (Fig.1), Mortenson and colleagues evaluated wheelchair related outcome measures based on the constructs of ICF [32, 58-60]. In the context of health, ICF defines body functions as the physiological functions of body systems (including psychological functions), activity as the execution of a task or action by an individual, and participation as the involvement in a life situation [32]. Problems in body functions are described as impairments. Difficulties an individual may have in executing activities are described as limitations in functional ability, and problems an individual may experience with involvement in life situations or participation are described as restrictions [32]. The terms capacity and performance are used to provide more context to the activity or funactional ability domains. Capacity describes an individual's ability to execute a task or an action, whereas, performance describes what an individual does in his or her current environment [32]. A summary of the psychometric properties of the existing tools including the constructs of ICF pertinent to EPW driving they address are shown in Table 1.

Table 1: Psychometric Properties Of Existing EPW Driving Assessment Tools

		PIDA	PCDA	WST	PMRT	OCAWUC	CMSC	ALP	PMST	PMCDA
Measurement Properties	Inter-rater reliability			✓	✓	✓	✓		✓	✓
	Intra-rater reliability			✓	✓	✓	✓	✓	✓	✓
	Test-retest reliability			✓						
	Face validity	✓	✓	✓	✓			✓	✓	✓
	Content validity			✓					✓	✓
	Concurrent validity			✓						✓
Constructs	Body Functions							✓	✓	
	Capacity vs. Performance	C	C	C&P	C	C	C	P	C	C

Mortenson et al concluded that all of the currently available EPW driving assessment tools have been focused on evaluating wheeled mobility capacity, or performance, or both, to assess activity and participation of a wheelchair user [59]. However, none of the tools assess how the driver's motor, sensory and cognitive impairments affect wheeled mobility [59]; in other words, none of the currently available tools quantify specific impairments in body functions that impact EPW driving in adults. Hence, **the first objective of this work is to develop a screening tool that can quantify the extent or degree of users' impairments that are commonly known to affect an EPW user's driving ability**.

1.2 Outcome Measures to Evaluate Powered Mobility

1.2.1 Subjective Outcome Measures

Task-based subjective outcome measures span a wide variety, ranging from those used as clinical assessment tools such as WST and PIDA, to ones developed by researchers for specific purposes such as the OCAWUC [24]. The WST-Q is the only assessment tool that has demonstrated good psychometric properties to measure users' EPW driving performance in the environment where they use their device [61]. Caregivers and rehabilitation professionals use this on-field evaluation tool to intervene and provide the skills training necessary to improve usage of the EPW. Unfortunately, like other user (or patient) reported outcome measures, WST-Q is limited by the subjectivity and biases inherent to self-report surveys [62]. Further, existing subjective measures are unable to differentiate between the two key contextual factors of speed and accuracy that constitute good EPW driving ability [24, 63, 64].

1.2.2 Objective Outcome Measures

Over the last three decades, technology-based strategies have been employed to overcome the limitations of subjective outcome measures [63-74]. EPW driving simulators enabled by virtual reality and sensors have demonstrated a distinct advantage over subjective clinical assessments by enabling the computation of metrics that objectively measure speed and accuracy [63, 64, 75]. Reliability, safety and the ease-of-use to conduct evaluations in various virtual environments with diverse tasks have been highlighted as some of the major advantages of virtual reality based strategies to measure outcomes [44, 63].

There have been other approaches to overcome the subjectivity in clinical EPW driving assessments as well. Sorrento et al demonstrated that joystick movements could be used as a measure to differentiate driving performance between experienced and novice EPW users [76]. Kumar et al showed that EPWs equipped with data loggers can be used to study driving behavior of EPW users during EPW soccer games [77]. Miro et al used an accelerometer based sensor package mounted on the EPW in an attempt to provide additional information for therapists during EPW driving assessments [78]. Recently, Fu et al employed accelerometers and gyroscopes in mobile phones to develop a machine-learning based cloud-computing framework to aid EPW driving assessments and study EPW maneuverability in the community [79-81]. However, despite the availability of such novel methodologies, translation of such technology-based assessments to everyday clinical practice has been a challenge. The major hurdle faced by rehabilitation scientists is the lack of scientifically rigorous clinically meaningful objective metrics that can be employed as part of EPW driving training programs [24]. Further the technical resources to compute such metrics overwhelm assistive technology providers, limiting clinical adoption.

In comparison to clinical assessment tools, far fewer training programs exist for EPW driving. Kirby et al developed the Wheelchair Skills Training Program (WSTP) for adults, which provide instructions for clinicians to train users using a common set of EPW driving tasks based on their capacity to execute these tasks [35, 41, 82, 83]. Providing this structured training for a period of 1-2 times per week resulted in a demonstrable increase in the users' confidence in driving an EPW, and the users were able to attain the self-selected goals for their rehabilitation program [38]. In addition to the WSTP, other training strategies have been reported for specific populations of individuals [49, 83-87]. However, due to the wide variability in impairments and EPW driving skills (functional ability) of the users, standardizing the selection of specific training strategies using existing clinical EPW driving assessment tools has been challenging. This selection process has been left to the discretion of individual rehabilitation professionals, making it difficult to document, and evaluate the comparative effectiveness of various EPW driving training strategies. Hence, the **second objective of this work is to develop a set of clinically-relevant objective EPW driving metrics** to quantify EPW users' driving ability that can enable the development of more targeted driving training programs.

1.3 Preliminary Work

Prior work at the Human Engineering Research Laboratories (HERL) conducted by Dicianno, Kamaraj, et al [43, 44, 88-91] lead to the development and validation of a Virtual Reality based driving Simulator (VRSim) [75]. This work demonstrated that virtual reality-based assessment can be a reliable and valid measure of EPW driving, similar to the real-world PMRT [44, 91]. Preliminary studies with VRSim was instrumental in identifying key limitations of existing powered mobility driving assessment tools and highlighted the need to develop objective outcome measures for EPW training programs.

1.3.1 Powered Wheelchair Driving Assessment in Virtual Reality

The VRSim incorporated common EPW driving tasks from the PMRT [42]. The PMRT was adopted as a part of VRSim since this tool was commonly used for clinical EPW driving assessment, had acceptable psychometric properties and correlated well with neuro-psychological measures important for safe EPW driving [42]. Twenty experienced EPW users (with over three years of experience driving an EPW) and eleven novice EPW users (with less than three months of EPW driving experience) participated in the study.

Figure 2: A picture illustrating the real-world office lounge, and the virtual office lounge in VRSIM

This study was instrumental in demonstrating that computer-based assessments are a reliable and valid means of evaluating powered mobility when compared to the PMRT. The virtual PMRT modeled within the EPW driving simulator showed high intra rater and inter-rater reliabilities for all the virtual driving tasks [44].

The study also highlighted several limitations of the PMRT that were similar to the limitations of other existing clinical EPW driving assessment tools. First, the tasks and scoring system used for the assessments in VRSim were inadequate to capture the wide range of EPW driving tasks executed by EPW users in the real-world [92]. Boucher et al, reported similar findings in their study to demonstrate the usability of an intelligent wheelchair system using a modified version of the Wheelchair Skills Test [93].

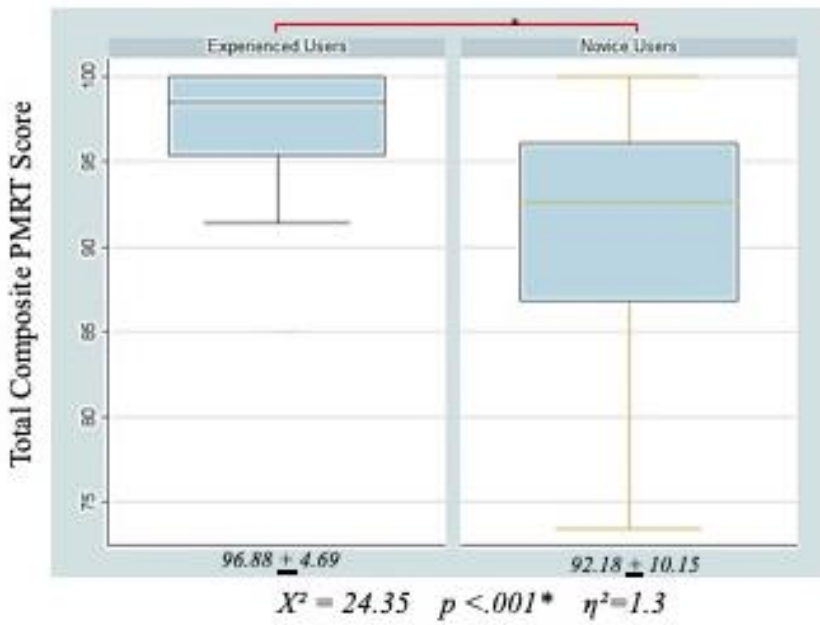

Figure 3: PMRT scores demonstrating ceiling effect in both novice and experienced users

Second, the PMRT was limited by the ceiling effect observed with the scores [44, 92] in both novice and experienced EPW users (Fig. 3) [89]. Hence, those with both moderate and high-level driving skills have similar scores. For example, a driver who completes a task but requires verbal cueing for assistance could score similarly to a person who completes the task independently. Third, the PMRT does not evaluate high level outdoor driving skills. Thus, individuals with mild impairments who are unable to perform these high level commonly encountered skills may be deemed adequate drivers when more training is needed to avoid injuries or accidents [13, 94]. Lastly, the differences between the scores within the PMRT are difficult for raters to distinguish due to the subjective nature of their description. For example, reduced clarity in the difference between a score of 2 and 3 in the PMRT can lead to a lack of consensus among raters on what constitutes serious and minor accidents [44, 92]. Thus, scores may not differentiate those with severe impairments who may never learn to drive from those with severe impairments who may ultimately drive with further rehabilitation. This may lead to PwDs not achieving their outdoor mobility or community re-integration goals if they receive falsely low scores. The current project aims to develop tools that will address these limitations.

1.4 Conclusion

Multiple studies have illustrated that difficulty in driving EPWs is associated with impairments in motor, sensory and cognitive functions. Although existing tools are able to provide a quantitative measure of the users' overall EPW driving ability in the clinic and the community, they are subjective and limited in their capability to identify how specific driving problems related to users' functional motor, sensory, or cognitive impairments can be addressed during training. Further, the relationship between these clinical assessment tools and the objective driving metrics that have been developed for specific research studies are unclear. The purpose of this work is to understand the relationship between clinical assessment tools and objective outcome measures in order to establish the clinical relevance of objective driving metrics. This will pave the way to the development of real-time objective metircs to develop individualized EPW driving training programs based on the users' impairments.

2.0 Development of The Powered Mobility Screening Tool and The Powered Mobility Clinical Driving Assessment

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2.1 Background

Independent mobility is one of the most important determinants of quality of life for individuals with disabilities [95, 96]. Electric powered wheelchairs (EPW) are key assistive devices that promote independent mobility [1, 2]. However, there is a growing cohort of people who desire and deserve EPWs for mobility, but who have not been able to acquire a device because of severe impairments in motor, sensory, or cognitive function that have precluded them from passing a clinical assessment or because of inadequate resources to allow them to practice driving [33, 45, 55]. However, there are no clinical tools to quantify the degree of specific impairments in motor, sensory or cognitive function in the context of EPW driving to inform training programs [23, 42, 45, 54, 55].

There are multiple ways to approach this problem. Adopting previously established techniques used in adaptive vehicle driving is one such approach [97-101]. Driving rehabilitation specialists employ a series of tests that help identify major functional (motor, or sensory, or cognitive) impairments that affect driving ability [98, 102-105]. If a driver has an impairment in one functional domain, targeted training programs to teach compensatory mechanisms relevant to that specific domain can improve improve driving performance [106-109]. Such an evidence-based approach toward driving assessment and training has led to the development of comprehensive clinical practice guidelines which have been effective in targeted training and counseling drivers, such as the elderly [110].

Secondly, learning strategies and techniques that have been employed in training children with cognitive impairments could provide valuable insights to the development of newer assessment and training tools for potential adult EPW users. Tefft et al reported that problem solving, and spatial relations had a direct impact on the variance of EPW driving skills among children [111]. Furumasu et al adopted these principles to develop the Pediatric Powered Wheelchair Skills Test, which used a five-point scale to quantify a child's driving capacity in a developmentally appropriate way [52]. In 2011, Nilsson et al reported several strategies that have been applied to teach EPW driving skills for children with cognitive impairments based on their level of attention and social skills [49, 50, 112]. These studies have demonstrated the strong association of novel training strategies based on cognitive, sensory and motor impairments with improvements in EPW driving. Such associations highlight the need for standardized adult EPW driving rehabilitation programs that can be individualized based on the users' impairments and EPW driving ability.

In this study, we adopted the principles used in adaptive vehicle driving to screen for impairments, pooled them with the neuropsychiatric measures that have been used to measure capacity for EPW driving skills among adults, along with strategies and principles that have worked well with children to develop two new tools. We employed participatory design [113-115], and qualitative ethnographic methods [116, 117] to develop the Power Mobility Screening Tool (PMST) comprising a list of simple tests to quantify motor, sensory and cognitive impairments, and the Power Mobility Driving Assessment (PMCDA) to assess EPW driving capacity. The specific aim of this study was to establish content validity of both the PMST and the PMCDA.

2.2 Methods

2.2.1 Participants

Participants were approached by word of mouth, phone calls or via email to participate in the surveys and focus group phase of the study. The inclusion criteria were: being a professional expert (Physician, Occupational therapist, Physical therapist, Rehabilitation engineer or a scientist) in the field of Assistive Technology with at least five years of professional experience with the wheelchair delivery process or an expert EPW user who has been using an EPW for a minimum of three years, and between the age of 18 to 80 years. There were no exclusion criteria. A brief abstract explaining the purpose of the focus group and objective of the discussion forum was given to all the attendees as a part of the registration package of the 29th International Seating Symposium held in Nashville, TN in 2013. Any attendee of the Symposium who was interested in partaking was invited to participate in the discussion forum. There were no specific inclusion or exclusion criteria.

2.2.2 Research Protocol

2.2.2.1 Surveys

Two separate surveys were sent to the professional experts and the EPW expert users via email: The Tools and Tasks survey (Appendix A) and the Users' survey (Appendix B). The purpose of these surveys was to generate a list of items that could be included in the PMST and the PMCDA, and rank these items based on the level of importance. The Tools and Tasks survey consisted of two sections. Section one was a list of tests commonly used to evaluate motor, sensory and cognitive impairments by adaptive vehicle driving rehabilitation specialists [98, 101, 105, 118], and section two consisted of a list of driver tasks pooled from existing EPW driving assessment tools [17, 23, 33, 37, 42, 46]. Participants were asked to rank each of the screening tests in order of importance within the motor, sensory, and cognitive sections. They were instructed to use ranks ranging from 1 (most important) to 3 (least important) (Appendix A). Similarly, for section two, a rank of 1 (most important) to 5 (least important) was requested (Appendix A). A rank of "0" was given if the test or task should not be included. The participants were also given an option to add more tests or tasks.

The Users' survey consisted of two questions (Appendix B). Question one asked the participants to list the top 5 skills that are important for a person to be a highly skilled driver in both indoor and outdoor environments, and question two asked them to list the top 5 skills that are important for a person to be a moderately skilled driver who drives only indoors. The users were also asked to rank these tasks in the order of their importance within each question. The surveys were sent to the participants two weeks before the scheduled date of the focus group and a follow up reminder email alert to return all the surveys was sent one week before the focus group.

2.2.2.2 Focus group

After all the surveys were returned, a teleconference was set up for the focus group. Two researchers acted as moderators, and the entire focus group was audio recorded. The moderators presented the overall median rankings of the items, and initiated a discussion using a structured set of questions [116, 117, 119] (Table 3). Following the focus group, the recording was transcribed and analyzed for common themes by each of the moderators individually. Then, the two moderators had a discussion to reach a consensus about predominant themes. Based on these themes and comments raised during the focus group, the first iteration of the PMST and PMCDA was established.

Table 2: Questions For The Focus Group & Discussion Forum

SCREENING TOOL What sections should it contain? What tests should be included under each section and how many? Can the tests be used in people with high-level motor impairment? How should this tool be scored? How long will it take to complete? What supplies are needed?
ASSESSMENT TOOL What sections should the tool have? What tasks should be in each section? How should it be scored? How should each task be defined or delineated? How long will it take to complete? What supplies are needed?

2.2.2.3 Discussion Forum

Three months following the focus group, one of the moderators (Kamaraj) presented the first iteration of both tools in the discussion forum during the International Seating Symposium. A brief introduction of currently existing EPW driving tools was presented followed by the first iteration of the PMST and the PMCDA. The PMST and the PMCDA were further discussed, based on the structured set of questions listed in Table 3. Based on the comments put forth by the participants during the discussion forum, the second iteration of the PMST and PMCDA was developed (Appendix C).

2.3 Results

2.3.1 Surveys

	Medical Diagnosis	**Number of Years of EPW Usage**
Surveys & Focus Group	Cerebral Palsy	17
	SCI	5
	Connective Tissue Disorders	4.5
Discussion Forum	Cerebral Palsy	21

Table 3: Medical Diagnosis And Years Of EPW Usage Of The Users Who Participated In The Study

Twenty-one experts were approached and invited to take the surveys, of which eight professional experts consented to participate. Of the ten expert EPW users approached, three consented to participate. All the eleven experts returned the surveys within two weeks (Response rate of 100%). The mean duration of clinical experience of the professional experts was 13.8 ($\pm$

6.9) years, and all of them had Assistive Technology Professional (ATP) certifications. Table 4 shows the demographic profile of the expert EPW users.

Table 5 and 6 demonstrates the professional backgrounds of the eight experts who took the surveys, and the 46 experts who participated in the Discussion Forum. It is important to note that the only expert EPW user, who participated in the discussion forum, was also a Rehabilitation Scientist.

Table 4: Demographics Of The Experts Who Took The Surveys And Participated In The Focus Group

Professional Background	*n*	Mean Years of Experience (Years $\pm$SD)	Min (Years)	Max (Years)
Physical Therapists	4	13.8 (9.4)	5	26
Occupational Therapists	3	14.7 (5.7)	10	21
Rehabilitation Scientist	1	11.0	-	-
Total	8	13.8 (6.9)	5	26

2.3.2 Focus group

All eight professional experts who took the surveys participated in the focus group. These experts defined essential criteria for the PMST and the PMCDA. The first criterion was that the tests should be easy to administer for raters with any level of training (novice vs. experienced), and with any professional background (Occupation therapist vs. Physical therapist). As one of the physical therapists pointed out, "All physical therapists may not be trained to administer complex cognitive assessments… besides performing the mini mental status. So, we have to be clear that under my certification I can administer whatever test we choose to include, if this has to be a globally useful tool." Secondly, the tests should be inexpensive and should not require the purchase of any supplies that are not commonly available in clinical settings. The same therapist also noted, "I do not have access to an accessible bathroom all the time. So, if we define a task like approaching or parking by a sink, I might not be able to administer it to all my clients… all the time." Third, the scoring system should be clearly defined without any room for subjectivity. Experts agreed that a common problem with currently available tests is that the scoring systems are too complicated or subjective. One of the occupational therapists indicated, "Either the 1 to 4 or 0 to 100 might provide a good system, but if it's not clearly defined, then the room for subjectivity is where it gets challenging." These criteria led to the common consensus that the list of five screening tests (Appendix D) would be sufficient to quantify common user impairments that affect EPW driving. Similarly, the list of ten indoor tasks (Appendix E) and ten outdoor tasks (Appendix F) should not only be sufficient to assess users' safety and EPW driving capacity but would also help therapists identify clearly what area would require more user training.

Analysis of the transcripts of the focus group led to the identification of important thematic concepts for the tools. The group suggested that separate sections are essential for assessing driving capacity in the indoor and outdoor environments, as driving under these two circumstances have different skill sets. Hence it was recommended that the PMCDA be designed to have two sections with tasks ordered by increasing level of complexity. The group agreed that the number of tasks in the PMCDA is sufficient to assess the baseline driving capacity and safety of the EPW user. Further, they felt most testers would require few supplies to conduct testing with either of the tools. The experts ranked eight tasks as "0," indicating these tasks could be excluded from the assessment tool. However, during the development of the first iteration of the PMCDA, two of these tasks from the Indoor section (Drives backward or reverse 10ft in a straight line, and turns 90° while moving backward), and two of these tasks from the Outdoor section (Ascends 10° incline and descends 10° incline) were added to the list, since the users had ranked these skills highly, and had indicated that these are essential skills necessary for a new EPW user.

Several themes emerged regarding the scoring system. The experts felt that the possible total scores on both tools must have a wide range to stratify drivers with common impairments and variable driving capacity. For example, a dichotomous pass or fail system should be avoided, since this system might not provide the sufficient variations in scores to include drivers with all skill levels. The possible total scores of 5-15 on the PMST and 23-69 on the PMCDA were felt to be sufficient for stratification. They also felt strongly that the scoring used for individual tasks should be clear, mutually exclusive and suggested that a score of "0" on the tools should be avoided. Based on these concerns, a three-point scoring system was proposed for individual tasks within both the PMST and PMCDA.

2.3.3 Discussion Forum

Among the 1300 attendees of ISS, 46 therapists, durable medical equipment suppliers, and rehabilitation technicians and one wheelchair user with cerebral palsy participated in the discussion forum (Table 6). The discussion forum followed the same protocol as the focus group. Several salient issues were identified following the analysis of the transcription from the audio-recorded discussion forum. Overall, the group confirmed that all the tasks listed in the PMCDA are essential for the assessment of EPW driving capacity. In addition to the tasks listed in the first iteration, three other tasks were suggested for the indoor section of the PMCDA. First, "turning 90° and entering a doorway" was added since the group suggested this task is essential for safe driving and is a frequent occurrence in the user's natural environment. Second, "stopping the chair on command" was added, since participants proposed that this task was not only an assessment of the user's EPW driving capacity, but also a gauge of the EPW users' ability to respond to dynamic changes in their environment, which in turn reflects their ability to use the EPW safely. Last, "parking an EPW parallel to a transfer surface," which could either be a bed or a chair was also added, since participants felt this is a vital task that every EPW user will have to perform at some point in time irrespective of his or her medical need for using an EPW. It was suggested this last task could be performed during the mat assessment typically performed during a routine examination for an EPW [120]. One task that was discussed extensively during the discussion forum was the ability of an EPW user "To get on and off an elevator". Users also indicated this as one of the tasks that should be performed by an EPW user with moderate skill. However, this task was not added to the list for two reasons. First, it may not be feasible to administer the task in all clinics. And second, experts felt that two other tasks included in the list, namely, "Can safely maneuver in-between 2 chairs spaced 32 inches apart" and "Turns 180° in place to the left/right" assess basic skills also necessary for elevator use. However, the group agreed that during training, the trainer should make this an essential task to practice and discuss with the driver.

Table 5: Demographics Of The Experts In The Discussion Forum

Table 6a: Professional Background		**Table 6b: Years of Experience**	
Professional Background	**n (%)**	**Years of Experience**	**n (%)**
Physical Therapist	20 (44)	0 - 2 Years	1 (2)
Occupational Therapists	10 (22)	3 - 5 Years	0
AT Supplier	14 (31)	6 - 10 Years	12 (26)
Others (Rehab Technicians & Rehab Engineers)	2 (3)	$\geq$ 10 years	12 (26)
Total	*46 (100)*	$\geq$ 20 years	13 (28)
		$\geq$ 30 years	7 (16)
		$\geq$ 40 years	1 (2)

The group noted that objective measures to quantify users' impairments were essential and performing clinical tests that provide more insights in to the users' functional ability rather than lengthy neuropsychiatric or motor measures were advisable and acceptable. However, the group suggested two changes in the PMST. First, under the sensory section, the group pointed out that the term "visually" may not be applicable to all EPW users and will have to be changed to accommodate individuals with all levels of sensory functioning. Second, under the cognitive assessment, it was suggested that estimated length of time should be changed to "the entire period of assessment". Finally, a change in the scoring system was also suggested. The criterion definition of scoring level 2 should be changed to include all kinds of cues (visual, verbal and tactile) to encompass users with all different kinds of sensory impairments. Based on these comments and suggestions, the second iteration of the PMCDA and the PMST were developed (Appendix C).

2.4 Discussion

Over the years, a growing need for testing and developing wheelchair-specific outcome measures that allow clinicians to justify their equipment recommendations and demonstrate effectiveness of specific interventions has continued to exist [59]. By adopting the principles of ICF, such outcome measures can delineate methods to assess body functions and tasks important for activities and participation [59], towards gauging the capacity and performance of the user [32, 59, 121]. Design of outcome measures for EPW driving should also follow few key principles that have been recognized as salient in scientific literature. First, the goal of the assessment should be explicitly targeted towards enhancing mobility and independence of the user rather than preventing access to EPWs for potentially unsafe drivers [23]. In other words, the measure should be used with the goal of assessing safety and identifying areas where training can help a potential driver improve skills, rather than simply determining whether he or she is capable of driving at one point in time. Second, the measure should be scored in such a way that it can demonstrate progress with training that reflect improvement in functional ability [45-47]. Third, the measure should be able to identify key areas where training could improve skill [42], not only by identifying what tasks are difficult for a driver but also what body functions are contributing to those specific difficult tasks. The experts and users in this study reinforced these principles, and the participatory approach that was adopted accommodated all three principles when developing the tools. The iterative approach, with inclusion of over 50 professional experts and expert EPW users, established good face and content validity for the PMST and the PMCDA.

Although we adopted concepts from adaptive vehicle driving literature to develop the content of the PMST, the tool that emerged is uniquely suited for EPW driving. Experts identified several concerns in administering many of the standardized neuropsychological tests commonly used for vehicle driving in a wheelchair clinic. First, the qualifications and training necessary to administer these tests might preclude use by many potential raters. Second, each of the tests would require the clinic to purchase a test kit, and if multiple tests were to be administered together, it would result in an expensive assessment process. Third, the process would become quite lengthy, which decreases the likelihood of a rater offering these tests in a busy wheelchair clinic. Most importantly, they excluded many of the tests because they did not feel that the tools were sensitive or specific enough to measure impairments that commonly affect EPW driving skill. However, the experts did agree that quantitative measures are necessary in each of the three domains (motor, sensory and cognitive) to measure a user's impairments . Hence, rather than using standardized neuropsychological tests, the experts proposed the use of functional clinical tests (Appendix D) for screening. If any major clinical concerns would be identified during screening, then the experts recommended use of the PMST as a basis for referral for further testing by a specialist such as a neuropsychologist, audiologist or an ophthalmologist.

The content of the PMCDA includes similar driving tasks as those identified by a focus group conducted by Torkia et al. [16]. In that study, researchers identified four specific wheelchair mobility tasks/ maneuvers that were difficult for EPW users, namely, controlling the EPW's joystick, avoiding obstacles, maneuvering backwards and going through narrow doorways. In addition, this study also reported that during outdoor mobility EPW users face difficulty in four major areas: using streets and sidewalks, navigating through crowds, using adapted modes of transportation and dealing with rain or snow conditions. Although our tool does not include measures of transportation or inclement weather for practical reasons, it is worthwhile to note the striking similarities in the other tasks identified in their study.

There are significant advantages to using the PMST and the PMCDA in combination as a tool kit to assess EPW driving capacity over the currently existing tools. Currently, no other validated methods of *quantifying* cognitive, motor and sensory impairments related to EPW driving exist. This is the first time a tool with functional tasks has been validated dually with an assessment for EPW driving. A validated tool to quantify impairments may help to standardize the evaluation process if adopted across centers. This, in turn, could facilitate better knowledge translation and lead to the development of training interventions customized for each type of impairment that affects various driving skills. Individuals with cognitive or sensory impairments may need extra training and should not be excluded from opportunities to learn to drive based on a sole screening or assessment. Rather this combination of tools can help to identify areas that would need customized training to make the user a better EPW driver. Another advantage to using the PMST and the PMCDA is that they are pure measures of driving capacity, that is, they include only tasks that are exclusively related to EPW driving, not other factors like wheelchair maintenance. Lastly, as reported by one of the participants during the discussion forum, a clearly defined scoring system is quick, easy to administer and reduces ambiguity among scoring levels.

2.4.1 Study Limitations

Because the experts were identified through a convenience sample of colleagues and acquaintances in the field of Assistive Technology, they may have been following similar clinical practices as the investigative team, which may have made it easier to reach consensus on content validity. However, participants were recruited from several locations across the country, and inclusion of many participants from the discussion forum who were voluntarily attending the session increased the diversity of the input. Still, the tool was developed solely using input from American and Canadian experts and is not validated for other cultures or languages. Offering the survey only via email limited the external validity because not all EPW users necessarily have computers. However, using email also provided the ability for some users to participate who might not otherwise been able to participate due to transportation barriers.

The large number of participants in the discussion forum could have hindered some participants from expressing their views. However, we allowed ample time for individual questions and comments after the discussion forum ended, which provided the moderator an opportunity to incorporate individual questions and concerns in the iterative revision of tools. In addition, both the professional experts and the expert users were included in one group for the focus group and the discussion forum. One benefit of having this structure was that participants were able to hear opinions that may be quite different from their own. On the other hand, diversity within a focus group can sometimes cause the group to stray from the topic or have trouble focusing in on specific ideas. However, the latter was not a problem in this study as the group was closely moderated using the structured set of questions and sufficient content was produced to be useful for tool development. Finally, this study included only four expert EPW users, in comparison to the fifty professional experts in the study. However, tasks pooled from the past literature combined with the Users' survey were helpful in identifying key tasks for the PMCDA, which have also been identified by users in another focus group study [16].

2.5 Conclusion

The scientific literature is sparse in measurements that can quantify a spectrum of driving skills among adult EPW users and previous to this study no clinical tool was available to quantify the impact of motor, sensory and cognitive impairments that could impact EPW driving in adults. This study used a participatory approach to establish content validity of the new clinical tools. Further work is necessary to establish the feasibility and reliability of these assessment instruments and to build and evaluate training protocols for EPW driving.

3.0 Quantitative Driving Metrics in Virtual Environments

3.1 Background

Electric powered wheelchairs (EPWs) are vital assistive mobility devices for people with disabilities. However, constraints on time and resources limit clinicians' ability to provide training for newer users. The Virtual Reality based SIMulator, version 2 (VRSIM-2) was developed to address this need by incorporating the tasks of a common EPW driving assessment tool (Power Mobility Road Test (PMRT)) within the simulator. The goal of VRSIM-2 was to be an effective EPW simulator useful in administering PMRT within a virtual environment using four different Human Machine Interfaces (HMIs). These HMIs were intended to provide the necessary customization of VRSIM-2 to be used in different settings, such as a busy wheelchair clinic (using the more immersive VR screens with rollers) or a user's home (with the user's personal computer and customized joystick). Preliminary psychometric evaluation of VRSIM-2 using PMRT illustrated that these four HMIs of VRSIM-2 have good stability and high inter-rater reliability [44, 91]. Raw data from two HMIs with highest reliability and stability (PC screen with no rollers (HMI-1) & VR screen with rollers (HMI-2)) were employed in this study.

VRSIM-2 was designed to provide a set of kinematic variables (Trial Time, Number of Collisions, Average Linear velocity, Average Angular Velocity, Root Mean Squared Deviation from the midline of a task), termed Quantitative Driving Metrics (QDM) calculated based on the time and position of the virtual EPW in the virtual environment. The purpose of QDM is to serve as a surrogate digital marker for driving capacity within the virtual environment [122]. The variables for QDM were derived from their equivalents in computer access technology that evaluate users' performance when moving a computer cursor along tasks within a graphical user interface [75]. The purpose of this study is to evaluate the psychometric properties of QDM in VRSIM-2. We hypothesized that QDM will have stable measurements between the two HMIs (hypothesis 1), and that each of kinematic variables will independently be able to discriminate between experienced and novice EPW users (hypothesis 2). Further, we postulated high convergent validity with the total PMRT score (hypothesis 3).

3.2 Methods

The institutional review boards of the Veterans Affairs Pittsburgh Healthcare system and the University of Pittsburgh approved this research study. Age-matched convenience sample of 10 novice (<3 months) and 10 experienced (>3 years) EPW users were recruited. Recruitments were conducted at the 31st National Veterans Wheelchair Games in Pittsburgh, Pennsylvania, and from local rehabilitation facilities, outpatient facilities, and disability organizations in Pittsburgh. The inclusion criteria were as follows: (1) age between 18 and 80 years; (2) user of an EPW (with standard proportional joystick) for >3 years; (3) having basic cognitive, visual, and motor skills to interact with an interface; and (4) able to provide informed consent. The exclusion criteria were (1) active pressure ulcers or open wounds, and (2) a history of motion sickness.

3.2.1 Experimental Set-up

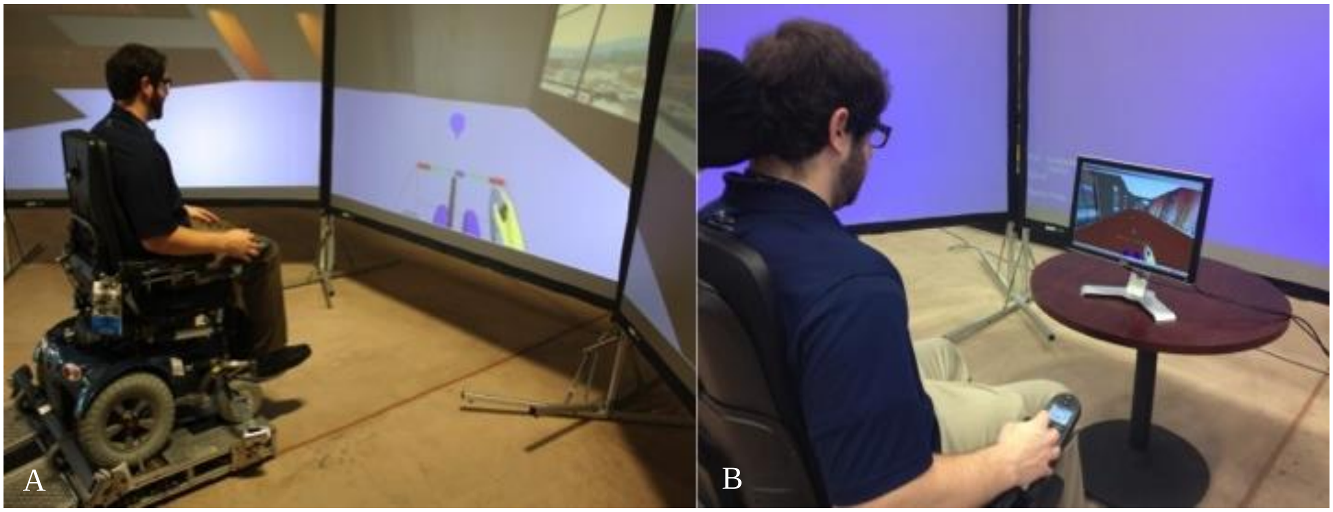

Figure 4: A picture illustrating the two display screens, VR and Computer screens, and the two driving modes, with rollers and with joystick.

VRSIM-2 had two first person display options, VR screens (Fig. 4.A) and a single PC screen (Fig. 4.B). Participants interacted with VRSIM-2 either using the dual roller system (Fig. 4.A) or an instrumented wheelchair joystick through custom software (Fig. 4.B). The custom software used a proportional derivative mathematical model to simulate the real-world motion of the EPW within the virtual environment [44]. The virtual environment consisted of a simulation of an indoor office space with a kitchen, a lounge area (Fig. 2), set of hallways lined by offices, and incorporated the tasks of the PMRT [42]. Participants were instructed to complete every task as quickly and accurately as possible. Participants were expected to drive along the course indicated by arrows, touching or passing through preset milestone markers signified by semi-transparent balloons. These sequentially displayed milestones defined the tasks of PMRT. An equivalent driving course was charted out in an open space for real-world PMRT [42].

3.2.2 Data Collection

After informed consent, participants performed up to 2 practice sessions in VRSIM-2. They selected a preprogrammed driving profile on their EPW (e.g., “indoor” profile) similar to their everyday driving profile to obtain adequate driving speed. For every HMI, participants drove through the complete driving course in VRSIM-2 and the real-world driving course. A balanced randomization scheme was used to set the order of the HMIs and the real-world driving evaluation. Optional breaks for 5 to 10 minutes were provided between driving sessions.

Two raters were randomly selected to be the evaluation team for each participant, from a group of five clinicians (1 occupational therapist, 3 physical therapists, 1 physician). Individual assessments were performed by each of the raters simultaneously for every trial using 2 separate PMRT scoring sheets. The team always consisted of at least 1 expert clinician who was a certified Assistive Technology Professional with >5 years of experience in EPW driving evaluations.

3.2.3 Data Processing

The software program that ran the simulation program for the virtual environment recorded the time along with the coordinates of the tasks and the virtual EPW. These coordinates were post processed using a MATLAB program to compute QDM. The median of the two measurements from each of the HMIs was computed to evaluate discriminative ability of the kinematic variables.

3.2.4 Statistical Analysis

Statistical analysis was performed using the STATA (version 16) statistical software package. This study employed repeated-measures design using VRSIM-2 with two different HMIs. The Total Composite score (T-PMRT) from the Power Mobility Road Test, and QDM computed using the movement data for the virtual EPW in the VRSIM-2 were the two main outcome measures. To evaluate the stability between the two HMIs (hypothesis 1), ICCs were calculated using each of the kinematic variables from both the HMIs. Since participants and HMIs were chosen randomly, a 2-way random-effects model assessing absolute agreement was used to compute $ICC_{2,2}$. The ICCs were interpreted as low (ICC≤50), moderate (>.50 - <.75), and high (>.75). Due to the violations of the normality assumptions, the non-parametric Median test with Bonferroni correction (p-value =.05/5 =.01) was used to assess discriminative ability of the QDM. A post-hoc η^2 was employed to compute effect size. An η^2 of <.1 was interpreted as low, 0.1 - 0.4 as moderate and >.4 as high. Multiple linear regression analysis was performed to evaluate construct validity with T-PMRT as the dependent variable and QDM as the independent variables Only variables that were stable between the two interfaces and able to discriminate between experienced and novice users will be used for the concurrent validity analysis.

3.3 Results

The demographics of the participants in the study are summarized in Table 6. The experienced users were all recruited at the National Veterans Wheelchair Games. The five clinicians who evaluated the driving sessions consisted of 4 women and 1 man, and had an average of 6.2 $\pm$ 4.1 years of clinical experience with EPW provision.

Table 6: Demographics of the Participants

	Experienced *(> 3Yrs of driving experience)*	**Novice** *(<3 months of driving experience)*
Number of Participants	10	10
Age (y)	54.6 $\pm$ 11.7	54.6 $\pm$ 13.3
Women	2	3
Race		
African American	3	6
Caucasian	7	4
Primary cause of disability		
Spinal cord injury	5	1
Traumatic brain injury	0	0
Multiple sclerosis	1	0
Amputation	0	2
Others (Cardiac conditions, Debility, Diabetes Mellitus)	4	7
Veterans	10	4

All the kinematic variables had high stability ($ICC_{2,2}$ >.75) between the two HMIs. Table 7 lists the ICC for each of the kinematic variables.

Table 7: Stability of QDM In Virtual Environment

		95% Confidence Intervals		
	$ICC_{2,2}$	**Lower Bound**	**Upper Bound**	***p-value***
Total composite PMRT	.91	.89	.95	<0.01*
Trial Time	.89	.8	.95	<0.01*
Collisions	.79	.69	.95	0.04*
Avg. Linear velocity	.79	.66	.95	0.02*
Avg. Angular velocity	.74	.59	.95	0.14
RMSD	.88	.81	.95	0.02*

*Statistically significant, $p<.05$

The median T-PMRT score and the medians for each of the kinematic variables are listed in Table 8.

Table 8: Discriminative Ability Of The PMRT And QDM In Virtual Environment

*Statistically significant, *p<.01*

	Experienced (n=10)		**Novice (n=10)**		X^2	***p-value***	**Effect size** η^2
	Median	Range	Median	Range			
Total composite PMRT	96.88	4.69	92.18	10.15	24.35	<0.001*	1.28
Trial Time	7.04	2.61	11.38	9.73	14.91	<0.001*	0.78
Collisions	8	14	54	92	26.09	<0.001*	1.37
Avg. Linear velocity	0.36	0.12	0.22	0.17	19.82	<0.001*	1.04
Avg. Angular velocity	0.05	.00	0.02	0.00	4.3	0.038	0.21
RMSD	0.32	0.16	0.46	0.38	9.18	0.002*	0.48

Overall, four predictor variables (Trial time, Collisions, Average Linear velocity and RMSD) explained 64% of the variance of the Composite PMRT scores with good model fit (R^2 = 0.64, F (4,90) =40.29, $p<0.001$). Each of the predictor variables had significant ($p<.001$) partial effects in the full model: trial time ($\beta=.004$), RMSE ($\beta=-4.8$), Collisions ($\beta=-.04$), and average speed ($\beta=18.63$).

3.4 Discussion

This preliminary evaluation of QDM's measurement properties in VRSIM-2 identified three key findings supporting the three hypotheses. First, there is little variation in QDM between the two HMIs as indicated by the high stability. This demonstrates the strength of the software algorithm that is computing the QDM and the adoption of such algorithm can be useful to deliver

EPW driving training using different interfaces with different levels of immersion in the virtual environment.

Second, the four variables explained 62% of the variance in the total composite PMRT scores, and each of the predictor variables had significant partial effects illustrating the high concurrent validity of the QDM. This demonstrates that the four variables are crucial factors being evaluated as part of EPW driving assessment and training. However, it is important to note that there are additional factors that clinicians consider during the evaluation which are not captured by these variables. This finding also provides strength to the conceptual framework described by Routhier et al that describes the multitude of factors that impact EPW driving ability.

Last, all four variables were able to independently discriminate between experienced and novice EPW users with high effect sizes. This was comparable to the discriminative ability of the clinical assessment tool measured by the total composite PMRT scores. This demonstrated that QDM and PMRT have similar capability to differentiate driving capacity between novice and experienced EPW users. Recruiting athletes with disabilities who were experienced EPW users and PwDs who had never driven an EPW from wheelchair clinics provided a diverse cohort of participants, offering support to the generalizability of these findings to other modalities of computing QDM.

3.4.1 Study Limitations

Several limitations of this study have to be further explored and evaluated. Although, the preliminary evaluation by Mahajan et al and this study provide strong statistical evidence for further development of QDM, the content validity of these variables needs further inquiry. This exploration will be required to establish clinical relevance for these variables and help define the limits of clinically meaningful change in these variables. One of the major limitations for QDMs computed in this study is the need for a virtual reality simulator to compute such variables. These simulators are not yet commercially available and even if they were, the cost and accessibility to such technology could be a major limiting factor for scalable adoption of such technology for EPW driving training. Nevertheless, this study lays the foundation for further investigation to develop technology that can compute such objective variables in the clinic.

3.5 Conclusions

This study examined the measurement properties of QDM computed from the movement of a virtual EPW in a virtual environment of EPW driving simulator. The findings demonstrate that QDM has high stability and construct validity in an EPW driving simulator. Future work will focus on incorporating QDM with the next generation of VRSIM to develop automated scores and develop an evidence-based EPW driving rehabilitation program. Further studies will explore the feasibility to compute objective performance-based metrics in the real-world to assist EPW driving training programs in the clinic.

4.0 Quantitative Driving Metrics in a Controlled Laboratory Environment

4.1 Background

Advances in robotic and sensor technology have boosted the design and development of novel intelligent personalized mobility systems [123]. Over the recent years, these advances have led to a gradual yet steady improvement in rehabilitation technology development [124]. Pertinent to powered mobility, there is an increase in the number of studies designing novel smart wheelchairs and robotic mobility systems that can assist people with disabilities (PwDs) to navigate everyday environmental barriers [64, 125, 126]. However, there is a lack of standardized tools and outcome measures that can compare the driving performance of EPW users while using such novel powered mobility devices [127].

Developing a set of clinically-relevant objective metrics that can be computed using sensors in the EPWs can provide real-time measurements of EPW users' driving ability [9]. Such real-time objective metrics aid two purposes. First, they serve as an objective alternative to the subjective user (or patient) reported and clinician or observer reported measures of EPW driving capacity and performance [24]. Second, they act as an objective benchmark to compare efficiencies between novel intelligent wheelchairs to navigate environmental barriers [127].

Different approaches using data logging systems attached to electric powered wheelchairs (EPWs) have been used to gather objective information about wheelchair movement. Moghaddam et al used an inertial measurement unit (triaxial accelerometer, a triaxial gyroscope and a triaxial magnetometer, to compute pitch, yaw and roll angles of the module) with a global positioning system receiver and a microprocessor to automatically recognize events and driving activities during use of an EPW [128]. Similarly, Miro et al used an accelerometer-based sensor package mounted on the EPW to compute degree of alignment with beds, proximity to doors, linear and angular velocities to define a driving profile for the EPW user [78]. Fu et al employed machine learning techniques to decrease the noise in the data from accelerometers and classify wheelchair maneuvering data into a series of EPW maneuvers [81]. The ongoing evolution of such approaches highlights the need for objective measurements of EPW driving ability. However, current metrics and variables described in scientific literature are difficult to gather, interpret and are not standardized to allow for comparison of metrics between different research studies [24]. They are unable to provide any meaningful relevance to the two key contextual factors, accuracy and speed that have been described as essential parameters for EPW driving training programs [24]. These challenges limit their adoption for clinical use by rehabilitation professionals as part of any EPW driving training programs.

The Quantitative Driving Metrics (QDM) was initially developed to serve as a digital marker for EPW users' driving capacity in an EPW driving simulator while using two different kinds of joysticks [71]. QDM was computed using the time and positional data of the virtual EPW in the driving simulator. Preliminary psychometric evaluation of these variables demonstrated high stability, discriminative ability and concurrent validity with clinical EPW driving assessment [Chapter 3]. In order to evaluate the feasibility to compute these previously validated variables in the real-world, a passive motion analysis system (VICON) was employed in this study. Since VICON could provide the coordinates information of the EPW in the real-world, similar to the data gathered from movement of the virtual EPW, this study employed the passive motion analysis system as the gold standard measure of real-world movement data capture. However, recognizing such passive motion capture systems limit clinical usability, a low-cost sensor package that could be used in a clinic to gather movement data from the EPW was designed.

The objective of this study is to further evaluate the measurement properties of QDM by establishing content and concurrent validity of the QDM computed in the real-world. We hypothesized QDM will have good content validity (hypothesis 1). Further, we expect that the QDM computed using two different modalities, a passive motion capture system and a low-cost sensor package will have high concurrent validity (hypothesis 2).

4.2 Methods

The institutional review boards of the University of Pittsburgh and the VA Pittsburgh Healthcare System approved this research study. A convenience sample of four rehabilitation professionals were invited to participate in the study. They were recruited through personal contacts of the investigators and were specifically identified as individuals who are experts in the field of power wheelchair provision.

A convenience sample of three researchers from the Human Engineering Research Laboratories who were expert EPW users were invited to participate in the study. EPW users were invited if they were (1) over 18; (2) have been an EPW user for over 5 years; and (3) able to provide informed consent. Individuals with active pressure ulcers or open wounds were excluded from the study.

4.2.1 Semi-structured Interviews

Four one-on-one semi-structured interviews were conducted in the wheelchair clinic with expert rehabilitation professionals. The goal of these interviews was to understand the process of EPW driving assessment and training commonly followed for EPW delivery. The primary focus was to define the contextual parameters that can be quantified using variables computed using a passive motion analysis system in a research laboratory.

4.2.2 Passive Motion Capture

The system comprised of twenty 3D infrared cameras, 14mm reflective markers, and the Vicon nexus 1.8 software package (Vicon motion systems, Los Angeles, CA). A driving course was constructed in the laboratory consisting of 14 different driving tasks (see Figure 4a). The dimensions of each task were defined according to the Standards for Accessible Design by the American Disability Act [129]. The obstacles required for each task, such as ramps and doorways, were designed to be modular and lightweight. Such a design aided quick restructuring of the tasks to provide different layouts of the driving course. The 14 tasks were randomly organized to generate three different layouts, one for each trial.

Twenty-five reflective markers were placed on the EPW to delineate the dimensions of the EPW as follows: two on the foot plate, three for each of the 2 rear casters, two on each main drive wheel (one on each side), two to define the boundaries of the joystick, five to define the boundaries of the arm rest, two for the attendant handle (to define the rear edge of the chair), two on the head rest, and six along the corners of seat pan and backrest (Fig.4b). To minimize motion artifact, these reflective markers on the EPW were considered secondary markers and referenced to a set of four primary markers above the head level of the EPW user. The primary markers were mounted on a custom orthogonal attachment designed to define a reference point above the EPW (Fig.4c). This custom attachment with the four primary markers remained attached to the EPW during all the trials, above the head level of the power wheelchair driver. The twenty cameras were adjusted to maximize the visibility of these primary markers. This setup minimized artifacts such as ghost markers and marker dropouts, since secondary markers if not removed could be obscured from the line of sight of the cameras. This setup was recorded in VICON as a static trial of the EPW to define the dimensions of the EPW along with the relationship between the primary and secondary markers. The secondary markers were removed from the EPW after the static trial, and the participants were instructed not to change the angle of the seat after the static trial had been completed. The positional data of the primary markers while the EPW moved through the driving course were recorded as dynamic trials. Three dynamic trials were recorded (one for each layout) following the static trial.

The set up was calibrated in a three-step process. First, the Vicon motion capture system was calibrated using a standard T-frame calibration wand ensuring camera error below 0.1mm for all cameras. Second, to define the dimensions of the EPW, a static calibration with both the primary and secondary markers was performed. These secondary markers defined the boundaries of the wheelchair in relation to the primary markers. Third, a static calibration of all the obstacles with reflective markers attached to them defined the physical dimensions of each task. The latter calibration was performed after the tasks were randomized for each trial.

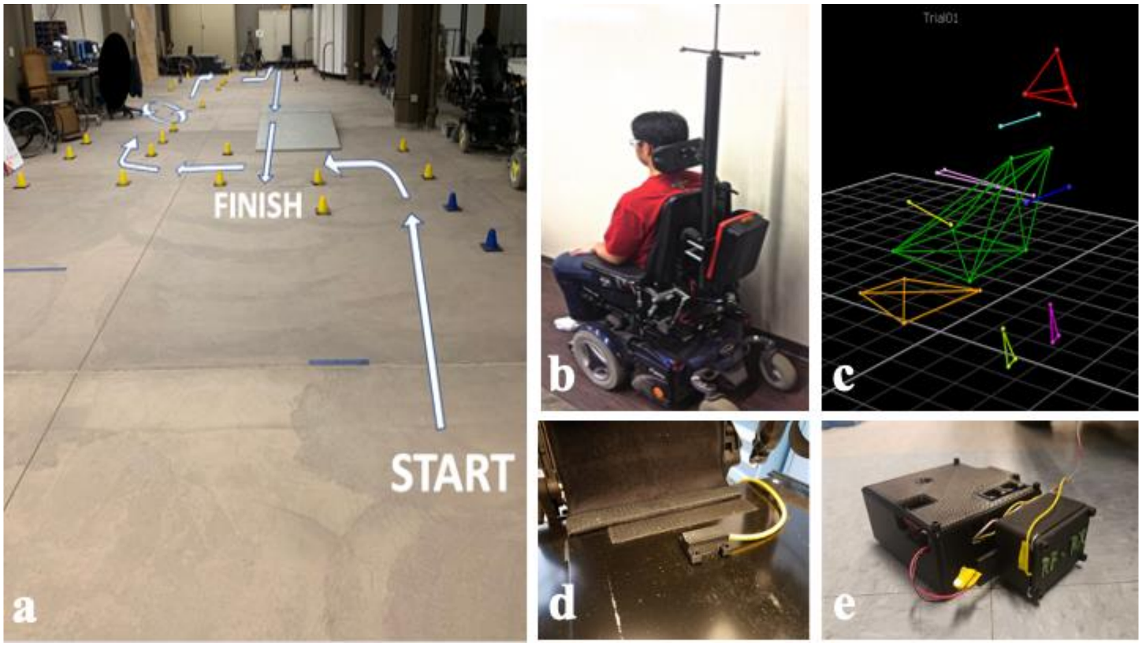

Figure 5: Experimental Setup: a. An image illustrating the EPW driving course in the laboratory; b. An image demonstarting the location of the primary markers; c. Model of an EPW in VICON; d. Image demonstrating the location of the IMU sensor and e. the Data Acquistion board attached to the EPW

4.2.3 Sensor-based Motion Capture

The Data Acquisition (DAC) Board was a low-cost modular sensor package that communicated with a single board computer to provide the quantitative metrics of the EPW. It consisted of an inertial measurement unit (IMU) sensor stick 9-DOF (SparkFun, CO) (Figure 5) to obtain angular velocity and linear acceleration in three axes, a SD card reader to record data (for independent use of the DAC board), an Arduino UNO (Arduino, Ivrea, Italy) microcontroller with a printed circuit board shield to connect with each mentioned component, and a radio-frequency transmitter unit used for synchronization with external systems (i.e., VICON motion capture cameras). The DAC board was powered with a 9V battery.

4.2.4 Data Collection & Processing

Three expert EPW users drove their power wheel chair (3 trials each) through the course with reflective markers as mentioned above. Data were collected at 120 Hz and processed using Vicon Nexus 1.8 software. The static and dynamic trials were used to collect positional data of the driving course and the EPW. Data were processed using the Nexus software package and exported to MATLAB (MathWorks Inc., Natick, Massachusetts, 2015) for further analysis. The data from the static and the dynamic trials were combined using a MATLAB program to calculate QDM for each task. Metrics for a task were computed from the timeframe the drive wheels crossed the beginning of the task (indicated by markers) and ended when rear wheels crossed the end of the task. For the purpose of these computations, each task was further divided into multiple segments with straight boundaries. For example, in the task of driving through a door, the 'approach' segment consisted of a corridor 36" wide, the 'passing' segment consisted of a doorframe, and the 'leaving' segment consisted of a second 36" corridor. Defining tasks by segments was necessary to avoid oddly shaped geometries, such as gradually widening or narrowing corridors. Further, this segmented analysis allowed for easy comparison of quantitative metrics of a task irrespective of its position in the course.

The IMU collected linear acceleration (m/s^2) and angular velocity (rads/s) at a sampling frequency of 120 Hz. Post processing was conducted in MATLAB to compute QDM from the IMU output. A low pass filter was employed to eliminate high frequency noise from the accelerometer data. Four variables (Time for each task (seconds), linear velocity (m/s) along the driving direction (y-axis), Root mean square error (RMSE) of the Angular velocity around the vertical axis (z-axis), and jerk (m/s^3) along the path of the EPW) were computed as QDM. The computation of these metrics is further detailed in Appendix G.

4.2.5 Statistical Analysis

Averages of each of the variables were computed across the three trials for each of the EPW users. Pearson's correlation, r was used to evaluate concurrent validity between the movement data gathered from the two modalities, if the data were normally distributed. If the variables were not normally distributed, the non-parametric spearman's rho, r_s was employed as the correlation coefficient to evaluate concurrent validity. All statistical comparisons were performed using the STATA statistical package (Version 14). A Bonferroni corrected alpha level was used for statistical significance. A correlation coefficient above 0.75 was interpreted as good to excellent validity, 0.5 to 0.75 as moderate to good validity, between 0.5 and 0.25 as fair validity and less than 0.25 as little or no validity [130].

4.3 Results

4.3.1 Semi-structured Interviews

One an average, the interviewees had 28 $\pm$ 3.8 years of experience in powered wheelchair provision. They were two occupational therapists, one physical therapist and an Assistive Technology Professional.

Rehabilitation professionals usually had the EPW users drive through an obstacle course in and around the clinic as part of the EPW driving assessment. Practioners often select tasks based on the user's environment, living conditions and the support an individual might receive in their natural environment, be it their home or community. Based on the one-on-one interviews, two contextual domains of evaluation were identified.

1) Assessment of safety - Safety of the driver and safety of others around the driver are both important. Clinicians stressed that it was not the number of collisions that gives the measure of safety, rather the number of possible or impending collisions that a driver might encounter. They emphasized that it is in the best interest of a novice user for the practioner to intervene before a collision occurs, since collisions have significant impact on the users' confidence and hinder the users' ability to acquire skills. Although there are no established numbers of collisions to classify a driver as safe or unsafe, collisions and collision avoidance behavior provide a good measure of the driver's ability to control the EPW. Particularly, an individual's ability to avoid an impending collision provides the evaluator a good insight of the driver's safety and learning behavior during training.

Practioners assess the users' response to dynamic changes in the environment as a gauge of user's impulsivity. As a therapist pointed out "if a new driver is impulsive, meaning they are quick, almost bump in to things and are constantly trying to changing paths to get to where they have to get to, I see that as they might have issues in smaller spaces like elevators. Such situations will further exaggerate their anxiety with driving and makes me question their safety". In contrast, clinicians noted individuals who are cautious and have a slow progression tend to improve their driving ability within a short period of time, provided they are able to drive their EPW every day. Clinicians noted that impulsive driving addressed early on during training help change driving behavior in the community and promotes safe driving. However, teaching new drivers to be mindful of impulsive driving behavior is a major challenge.

2) <u>Accuracy of executing a driving task</u> was described as the driver's ability to control the position of the chair in a pre-defined space. Practioners recommended assessing the driver's ability to volitionally make corrections to complete a task as a measure of accuracy. Depending on the users' needs, the practioners also evaluate drivers' ability to navigate dynamic challenges a user might encounter by having the drivers' steer through a busy side walk. They observe the number of times a driver has to make directional changes or corrections to maintain a steady progression in the direction he or she intends to be driving or is asked to drive. This ability to make corrections in the course along with the overall deviations from driving direction when asked to complete a task were viewed as good measures of an individual's ability to accurately execute a task.

Further, the amount of time required to complete a task was one of the key factors that were highlighted. However, practioners stressed that similar to the number of collisions, speed of the EPW and time to complete a task alone are not to be employed as direct measures of driver safety or accuracy. Rather, they suggested using these measures as key metrics to demonstrate change in driving behavior with a training program. One clinician explained the relevance of speed and time in the context of everyday functional mobility as follows, "before he came to see me for a wheelchair, he was dependent on his caregiver to get out of bed and do things around the house. But now, he can move around inside the house and get to the kitchen whenever he wanted to. With him, I am not worried he takes fifteen minutes to get to the kitchen from the living room now. I am fairly certain within the next months he should be able to do that in less than 5 minutes." Such scenarios point to the need for measures that can quantify change in driving ability over time.

4.3.2 Computation of QDM in real-world

Based on the semi-structured interviews, four variables were identified as QDM for this study. Three of these variables -- task completion time, linear velocity of the EPW, and root mean squared error of the angular velocity of the EPW have been used previously as digital markers of EPW driving ability in virtual reality. Number of collisions was not included as one of the variables of QDM based on the feedback from the practioners. Further, since clinicians invariably intervened to avoid the occurrence of collisions, counting the number of collisions could introduce a possibility of bias and was therefore excluded. In order to address the need to quantify the smoothness of the EPW's trajectory, the third derivative of position, jerk was computed using the positional data from the motion capture system and the IMU sensor. Computation of normalized jerk is detailed in Appendix G.

This study demonstrated the feasibility to compute QDM in real-world using two modalities of movement data capture. Table shows the correlations between the two modalities. Time, linear velocity, and jerk were not normally distributed. Hence, spearman's rho was employed to compute the correlation coefficients for these variables.

Table 9: Concurrent validity between the two modalities of movement capature employed to compute QDM

QDM	Correlation Coefficients	*p-value*
Time (sec)	0.8471	<.001*
Linear Velocity (m/s)	0.8577	<.001*
Angular Velocity RMSE	0.8718	<.001*
Y-axis Jerk (m/s^3)	0.8772	<.001*
Y-axis Peaks in Jerk	0.8984	<.001*

*Bonferroni corrected statistical significance (.05/5), *p<.01*

4.4 Discussion

This study assessed the content and concurrent validity of the QDM. Overall, there was consensus among the clinicians that objectively measuring movement during EPW driving evaluation will be a useful tool for everyday implementation in the clinic, highlighting good content validity for QDM. In addition to the contextual domains (speed and accuracy) identified by Bigras et al in their scoping review, this study identified safety as a key factor that will have to be evaluated and addressed during training [24].

Practitioners highlighted three potential areas of applications for use of QDM in the clinic. One, with objective metrics, the justification submitted to payers could be strengthened and potentially reduce the probability of payment denials. As one of the clinicians pointed out, “there have been instances when insurance payments for new users have been denied on the basis that they might not be able to use the device adequately. If there is to be an instrument that gave us measurements, just like the a speedometer of the car that demonstrates that the individual can control the device within safe parameters, it would be very helpful to document, especially for some of our clients with severe disabilities, who need these devices the most.” Second, objective metrics could provide the much-needed visual feedback during wheelchair training. Currently, during wheelchair training, most of the feedback provided to the user are through vocal commands or demonstrations by the rehabilitation professional, particularly for using the joystick. Clinicians occasionally use mirrors to illustrate the movement of the EPW in response to the movement of the joystick. This was commonly done to show the users’ the extent to which certain portions of their device could extend beyond the foot print of the EPW, and demonstrate jerk in the EPW during sudden movements. “Offering a visual of a number that users could follow during training could be a great motivating factor for some of our newer drivers”, noted one of the clinicians.

Lastly, experts also noted that objective quantitative measures could be a useful tool for training young rehabilitation professionals who are beginning their career in providing wheelchair services.

The correlation coefficients showed good concurrent validity between the two modalities of gathering movement data of the EPW. Based on the insights from the semi-structured interviews, RMSE, and jerk of the EPW's trajectory could be good measures of an individual's ability to accurately execute a task. Task completion time and velocity of the EPW could be good measures of agility with which an individual can execute a task.

In contrast to the four variables that can deduced solely from the movement data of the EPW, as the practioners pointed out, safety will have to be assessed within the context of environmental factors that varies with every task. Hence, identifying surrogate digital markers of safe driving poses a unique challenge. Evaluating two metrics of EPW movement while gathering information about the environment where the movement occurs could help to address this challenge. First, measuring the distance to a potential barrier along with the time required by an individual to respond to such a barrier would reflect the impulsivity in a driver's behavior and could serve as a surrogate marker of safety of the user and the others around the user. Second, gathering data regarding directional changes in trajectory of the EPW changes while approaching a possible barrier will reflect the attempts by the user to avoid an impending collision. It is crucial that this information will have to be gathered at multiple different locations to gather data regarding the various possible scenarios that arise from the variations in the environment around the EPW.

4.4.1 Study Limitations

The study does have a few limitations. The variables calculated in this study were based on four one-on-one interviews with clinicians from one wheelchair clinic. Considering the variety of factors that influence powered mobility [45] and the tools available to evaluate them [131], it is essential to acknowledge that QDM is not representative of all the factors that impact powered mobility. To address this issue and arrive at a consensus, we intend to conduct more interviews and focus groups at multiple centers targeted to identify other clinical parameters, and further evaluate validity of any newly identified variables.

Second, calculating RMSE for a broad array of tasks could be challenging. In calculating the RMSE of a task, this study adopted the center between the task boundaries as the ideal path for our tasks. However, all tasks may not have an "ideal" path, such as the center of a hallway. Adopting such a current approach would falsely elevate the RMSE. Hence, for interactive and dynamic tasks such as the driving between two chairs or other architectural barriers, future studies should employ other methods to deduce the line of ideal fit, and calculate the RMSE from such a line. Assessing the RMSE in such a way along with the position of the dynamic obstacle would provide a much more precise estimate of EPW movement and the environmental context around the movement.

Lastly, this study employs linear analytical approaches to describe trends in the movement data. Being a pilot study, this preliminary analysis served as a proof of concept to this novel approach. However, employing non-linear analytical methods [132, 133] that have been useful in identifying patterns of variability within continuous data will help identify patterns that may not be captured by the linear approaches that focus on the averages of these quantitative metrics.

4.5 Conclusion

The preliminary results from this pilot study employing qualitative and quantitative methods demonstrate content and concurrent validity of the QDM. Further validation of these results along with evaluation of additional measurement properties like stability, convergent validity and minimal detectable change of these variables can establish clinical relevance of these variables with training programs. Future studies should aim to develop large datasets that can employ non-linear computational techniques [134] and machine learning algorithms [135] using QDM to identify patterns in driving behavior.

5.0 Measurement Properties of Power Mobility Screening Tool, Power Mobility Clinical Driving Assessment and the Quantitative Driving Metrics in the Clinic

5.1 Background

Clinical assessment tools that can be easily administered, scored and interpreted are crucial to developing and implementing novel interventions [26, 27]. Psychometric evaluations of newly developed tools help reduce biases during administration and improve external validity or generalizability of the findings [136]. The Powered Mobility Screening Tool (PMST) and Powered Mobility Clinical Driving Assessment (PMCDA) were developed to achieve two goals, (1) develop simple clinical assessment tools to quantify EPW users' motor, sensory and cognitive impairments and (2) quanitfy EPW driving capacity using a scoring system based on the level of the users' functional ability as defined by the cueing or assistance provided by the rater, while the user executes a series of EPW driving tasks [137]. In addition, a set of variables computed using data from Inertial Measurement Units (IMUs) known as the Quantitative Driving Metrics (QDM) were developed as digital markers of users' EPW driving ability [88].

Previous work demonstrated that these new tools have good content validity, and QDM has high concurrent validity between two modalities of gathering movement data from the EPW [Chapter 4]. Given that the Wheelchair Skills Test (WST) has been the most scientifically rigorous and commonly used clinical EPW driving assessment tool, this study aimed to use the WST scores as the gold standard measure to further evaluate the psychometric properties of the newly developed clinical tools (aim 1), and the objective outcome measures (aim 2).

We hypothesized that the total PMST and PMCDA scores will have high intra-rater reliability (ICC >.9) (hypothesis 1.1), and inter-rater reliability (ICC >.9) (hypothesis 1.2). Further, we postulated the PMCDA score will have good concurrent validity with the WST score (hypothesis 1.3). Similar, we expect the QDM will be highly stable (ICC >.9) across the three EPW driving trials performed by the same EPW user (hypothesis 2.1). We expect a statistically significant difference in variables of QDM between experienced and novice EPW users (hypothesis 2.2), and QDM will have high convergent validity with the WST score (hypothesis 2.3).

5.2 Methods

The institutional review board of the University of Pittsburgh approved this research study. A sample of 5 novice (<3 months) and 5 experienced (>3 years) EPW users were recruited. Recruitment was conducted at the University of Pittsburgh Medical Center's Center for Assistive Technology (CAT). Inclusion criteria were: age18 years and over, having a disability that prevents effective use of a manual or power assist wheelchair or scooter and necessitating an EPW, and able to provide informed consent. Individuals with active pressure ulcers or open wounds were excluded from the study.

Raters were recruited by word of mouth through clinicians and technicians associated with the Human Engineering Research Laboratories. A physical therapist, occupational therapist, rehabilitation technologist, an assistive technology professional, a student or any individual in training to receive certifications in the above specialties were invited to participate in the study as a rater. Any individual who might not be able to commit 6 hours to the study to view and score the driving trails was excluded from the study.

5.2.1 Experimental Setup

All the real-world EPW driving evaluations were conducted at CAT. A driving course comprised of twenty commonly performed EPW driving tasks was designed at CAT (Table.10). The dimensions of each task were defined according to the Standards for Accessible Design by the Americans with Disabilities Act. An image illustrating the driving course with the different tasks is shown in Fig. 6.

Table 10: List of the twenty tasks of the driving course at the Center for Assistive Technology

1. Drive forward 15’ 2. Drive backward 10’ 3. Pass through 36" doorway 4. Travel over 1" door threshold 5. Up slope (10 degrees) 6. Down slope (5 degrees) 7. Unpaved surface (6' long) 8. Cross slope (5 degrees)	9. Up slope (5 degrees) 10. Down slope (10 degrees) 11. Avoid therapy balls 12. Approach transfer surface 13. Approach accessible sink 14. Turn 90 degrees while moving forward 15. Turn 90 degrees while moving forward through a door	16. Stop on command 17. Turn 180 degrees in place 18. Drive forward (30' within 30 seconds) 19. Turn 90 degrees while moving backward 20. Maneuver between two chairs (32" apart)

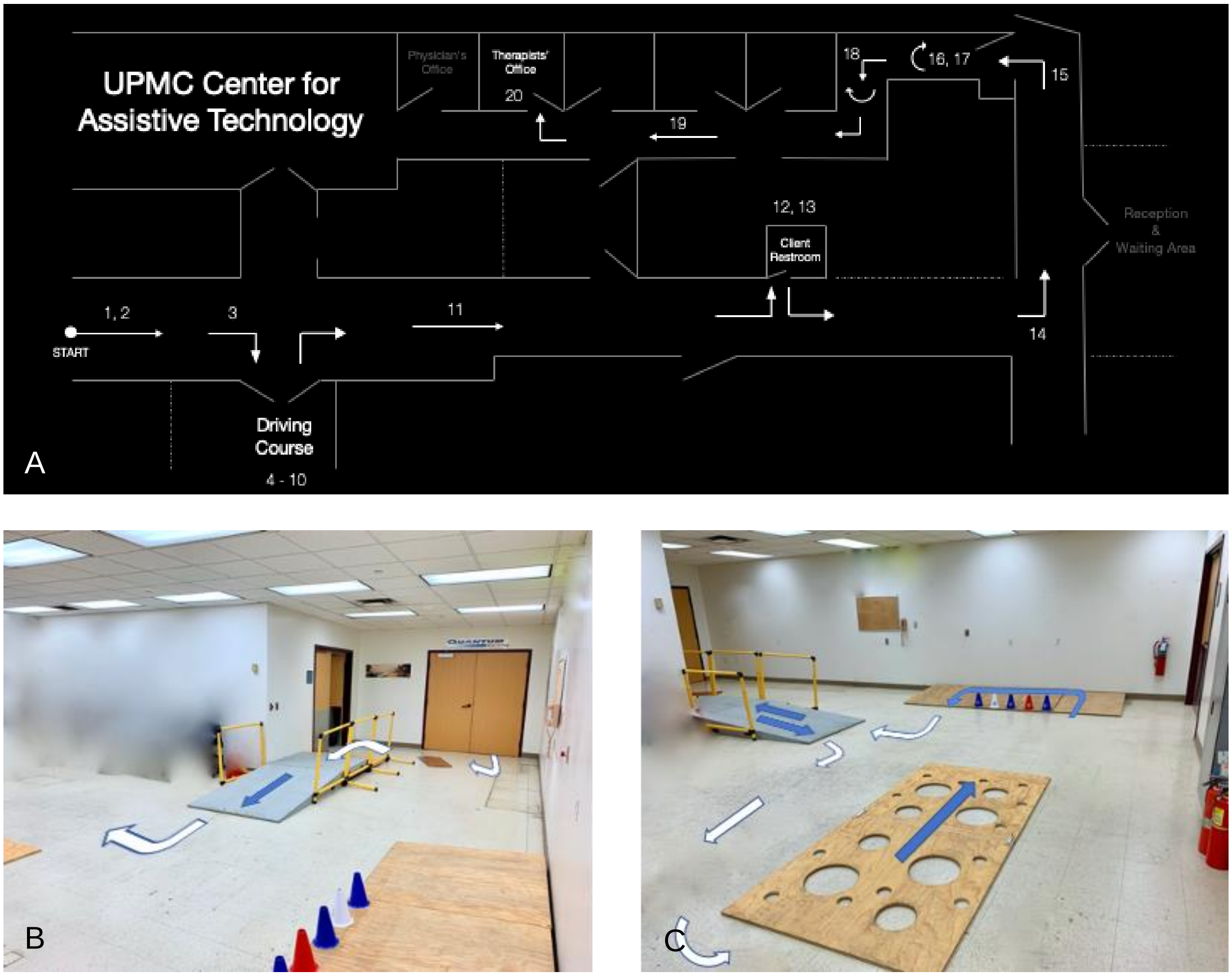

Figure 5: A. Illustration of the EPW driving course at the Center for Assistive Technology demonstrating the twenty different tasks performed by EPW users; B & C. Pictures of the ramps that were used as part of the driving course

5.2.2 Instrumentation

To capture the movements of the EPW objectively, a movement capture system (Fig.7A) comprised of an IMU embedded with 9-axes motion sensors (UDOO NEO Extended, Freescale®, USA) (Fig.7B) was placed on the frame of the EPW (Fig.7C) to collect acceleration and angular velocity data at a sampling frequency of 100Hz. A binary signal generated by a toggle switch was delivered to the UDOO board via Bluetooth from an application on an Android phone (Fig.7D) to indicate the beginning and end of each task, and the beginning of each trial in the raw data. The binary signal was delivered in-sync with the verbal commands from the experienced rater administering the driving evaluation. The IMU data was stored using an on-board SD card. The sensors were removed from the chair after completion of the driving evaluations. The software to execute this setup and instrumentation is listed in Appendix I.

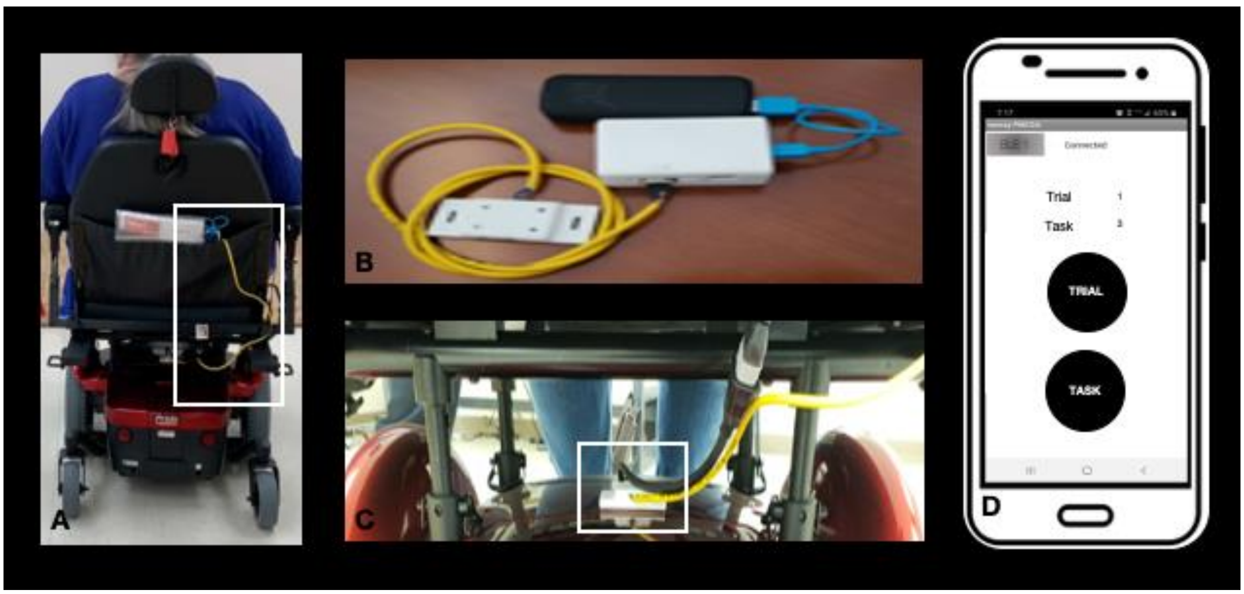

Figure 6: Instrumentation. A. An image showing the placement of sensors and the batteries in the EPW. B. An image of the UDOO board in a case; C. An image illustrating the placement of the IMU sensors on the base of the EPW, and D. A screenshot of the application on an Android phone.

5.2.3 Research Protocol

After obtaining informed consent, participants were requested to complete a demographic questionnaire, providing information such as age, gender, primary clinical diagnosis and assistive technology usage information. If the participant did not have his/her own chair, they were provided a test EPW to complete the study. The test chair was adjusted to the appropriate height, weight and comfort level of the participant.

5.2.3.1 Real-world Driving Assessments

After the participant was fitted with the EPW and the instrumentation, they were given time to familiarize themselves with the EPW until they were comfortable with controlling the chair. They then drove through the driving course three times (3 trials), depending on their level of fatigue and comfort. During these driving trials, an experienced occupational therapist familiar with process of power wheelchair provision performed a driving evaluation. This rater used the most recent version of the Wheelchair Skills Test (V5.0) to rate the participants' capacity on a 4-point scale. The scores were recorded electronically using RedCap, and the three driving trials were video recorded for review by other raters.

5.2.3.2 Video Based Driving Assessments

The video recorded driving trials were hosted on a secure server at the University of Pittsburgh and streamed through Redcap for review by raters. Raters were invited to participate through an online consent form on RedCap. After an electronic consent, the raters responded to a brief online questionnaire to provide demographic information and viewed video recorded educational material about the use of PMST and PMCDA. They then viewed the EPW driving trials and electronically recorded their scores on Redcap. Subsequent to the first review, the raters reviewed the video recordings for a second instance after a period of two weeks.

For the purpose of the reliability assessments, each driving trial of the EPW user was considered a separate assessment. The recorded videos were presented to the raters in a randomized order for scoring to reduce rater induced biases between the three trials.

5.2.4 Data Processing

The four-point scores from each of the individual driving tasks were used to compute the WST Percent score. Similarly, a total score and percent score were computed for the PMST and the PMCDA.

The IMU data was processed in MATLAB using a low-pass filter to plot graphs and compute variables that describe the various movements of an EPW during a driving task. The orientation of the accelerometers and gyroscopes in relation to the front of the EPW are shown in Fig. 8.

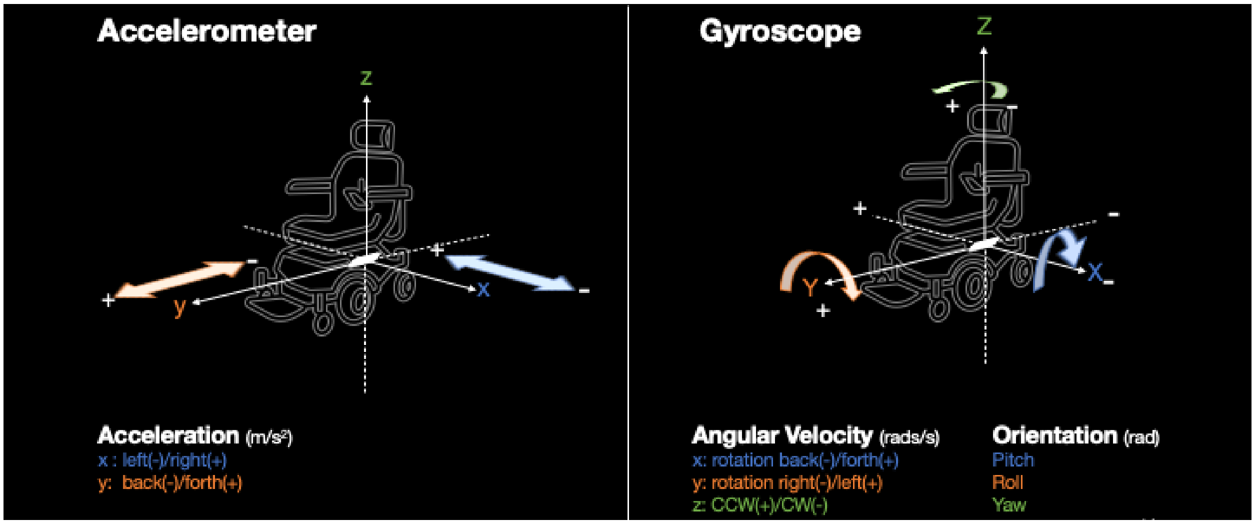

Figure 7: Orientation of sensor axes in relation to the front of the EPW

Acceleration, angular velocity and orientation were used to compute sixteen different variables that could be used to describe the motion of an EPW (Table. 11). The formulae for computing these variables are described in Appendix G.

Table 11: A list of the all variables computed from the IMU data

Accelerometer	Gyroscope	Orientation
1. Time per task 2. Linear velocity 3. # of Peaks in x Axis Jerks 4. Average Jerk in the x axis 5. # of Peaks in y Axis Jerks 6. Average Jerk in the y axis 7. Normalized Jerk	8. Angular velocity around the Z axis 9. Ave. (Abs.) angular velocity 10. RMS of Ave. angular velocity 11. # of Peaks in angular velocity 12. Area Under the Curve (AUC) 13. Number of Z axis crossings	14. RMS of Pitch 15. RMS of Roll 16. RMS of Yaw

The twenty EPW driving tasks (Table 10) were grouped in to three categories based on the expected trajectory an EPW will travel during a task. Tasks that have a straight forward or backward path were grouped as tasks with linear trajectories. Tasks that were expected to transverse an arch or a semi-circular path were categorized as tasks with circular trajectory, and tasks that were expected to have bidirectional changes in the orientation of EPW were grouped as tasks with rotational trajectories.

Based on the expected maximum variation of data along the EPW's trajectories, eight variables were chosen as QDM (Table 12) to describe the motion of the EPW for each of the three categories of tasks. For example, in the case of the twelve tasks with linear trajectories, maximum variation of data was expected in the back and forth direction. Hence, jerks in x and y axis computed using the acceleration data from the accelerometer were included as QDM. However, in order to evaluate the overall smoothness in tasks execution, normalized jerk was also computed in addition to time taken to complete the tasks and linear velocity.

Similarly, for tasks with curved and rotational trajectories maximum variation of data was expected from the gyroscope data. Hence, as a measure of efficiency of tasks execution, variables that were predominantly derivates of angular velocity were included as QDM for the rotational and curved trajectories.

Table 12: QDM to describe the motion of Linear, Curved and Rotational Trajectories

Tasks	QDM
Linear Trajectories 1. Drive forward 15' 2. Drive backward 10' 3. Travel over 1" door threshold 4. Up slope (10 degrees) 5. Down slope (5 degrees) 6. Unpaved surface (6' long) 7. Cross slope (5 degrees) 8. Up slope (5 degrees) 9. Down slope (10 degrees) 10. Avoid therapy balls 11. Stop on command 12. Drive forward (30' within 30 seconds)	i. Total time ii. Linear velocity iii. # of Peaks in x Axis Jerks iv. Average Jerk in the X axis v. # of Peaks in y Axis Jerks vi. Average Jerk in the y axis vii. Normalized Jerk viii. Number of Z axis crossings
Curved Trajectories 13. Pass through 36" doorway 14. Turn 90 degrees while moving forward 15. Turn 90 degrees while moving forward through a door 16. Turn 90 degrees while moving backward 17. Maneuver between two chairs (32" apart	i. Total time ii. Ave (Abs.) angular velocity iii. RMS of Ave. angular velocity iv. # peaks in angular velocity v. Pitch RMS vi. Roll RMS vii. Yaw RMS viii. Normalized Jerk
Rotational Trajectories 18. Approach transfer surface 19. Approach accessible sink 20. Turn 180 degrees in place	i. Total time ii. Ave (Abs.) angular velocity iii. Ave. angular velocity Area Under the Curve iv. # peaks in angular velocity v. Pitch RMS vi. Roll RMS vii. Yaw RMS viii. Normalized Jerk

5.2.5 Statistical Analysis

Descriptive statistics including mean and standard deviation were calculated for the total scores of WST, PMST, PMCDA, and the continuous variables computed as QDM for each group of tasks. Normality of all the variables were assessed using graphs (histogram, kernel density plot) and objectively using the Shapiro-Wilk test (SWilk).

To evaluate the intra-rater reliability and inter-rater reliability, Intraclass Correlation Coefficients (ICCs) were calculated using the PMST and PMCDA scores. Since participants and raters for each trial were chosen randomly, a 2-way random-effects model assessing absolute agreement was used to compute $ICC_{2,2}$. The ICCs were interpreted as low ($ICC \leq 50$), moderate (>.50 - <.75), high (>.75 - .9) and greater than 0.9 as excellent reliability [130]. Since the tools evaluated in this study are meant for clinical use, a higher ICC (>.9) was expected. Similarly, ICCs was also employed to evaluate the stability of the variables that constitute QDM across the three driving trials.

A power analysis for the inter-rater reliability analysis with a hypothesized value of 0.9, a null value of 0.7, alpha level of 0.05 and power of 0.8 for 6 raters estimated a sample size of 10 participants. Similarly, a power analysis for intra-rater reliability analysis revealed an estimated a sample size of 19 assessments. Hence, the goal was to recruit 10 participants who will perform three driving trials each for a total of 30 assessments for inter-rater and intra-rater reliability.

A Student T-test was used to evaluate the discriminative ability of the clinical assessment scores and the QDM. When normality assumptions were violated, the non-parametric Mann Whitney U-test with Bonferroni correction was used to assess discriminative ability. Variables that had a statistically significant difference between experienced and novice users were considered for the regression analysis to evaluate concurrent validity of QDM with the WST scores.

Pearson's correlation, r was used to evaluate concurrent validity between the PMCDA scores and the WST scores, if the data were normally distributed. If the variables were asymmetrically distributed, the non-parametric spearman's rho, r_s was employed. Simple linear regression was used to establish concurrent validity between the independent QDM variables and the WST Percent score. Scatter plots were used to check for non-linear patterns. A variable was considered to significantly predict WST percent score, if the overall F test was high and the p-value was less than 0.05. The coefficient of determination (R^2) was used to assess the fit of each model. Jackknife residuals for each model were calculated and were plotted against the fitted values for each model to look for non-normal patterns.

Multiple linear regression was used to determine a final model for the prediction of WST Percent score, establishing convergent validity. For each model the R^2, the Mean Square Error, F Test-value, and Variance Inflation Factor (VIF) were assessed to determine the best model. Correlation between the independent variables was examined to determine multicollinearity. Residuals for the final model were then calculated to assess normality. The HETTEST was performed to assess heterogeneity. All significance tests were two-sided and STATA version 16 was used for all analysis.

5.3 Results

There were ten individuals with disabilities who participated in this study. The five experienced EPW users have been driving their powered wheelchair for over three years, in comparison to the five novice users who have not driven a powered mobility device. The five novice users were prescribed an EPW for their everyday mobility needs and were waiting for the delivery of their device. Table 13 provides an overview of the demographics of the ten participants.

Table 13: Demographics: EPW Users

	Experienced (> 3Yrs of driving experience)	**Novice** (<3 months of driving experience)

	Number of Participants	5	5
	Age (y)	51.4 ± 15.1	67.1 ± 14.4
	Women	4	5
Race	African American	2	1
	Caucasian	2	4
	Hispanic	1	-
Diagnosis	Spinal cord injury	2	-
	Traumatic brain injury	0	-
	Multiple sclerosis	1	-
	Amputation	0	-
	Others	2	5
>40 Hrs. Wheelchair Use	Electric Powered	5	-
	Manual	-	3
	None	-	1
Mobility Aids	Non ambulatory	-	2
	Walker	1	3
	Quad Cane	-	2
	Crutches	1	-

There were six raters who reviewed the videos of the EPW driving. An overview of their experience with EPW provision is shown in Table 14.

Table 14: Demographics: EPW Users

	n	**ATPs**	**Years of Experience** (Years)		
			0 - 2	3 - 5	6 - 10
Physical Therapists	2	2		1	1
Wheelchair Distributor / Vendor	2	2		2	
Students (Rehabilitation Technology Graduate students)	2	-	2		
Total	6		2	3	1

A summary of the WST, PMST, PMCDA scores and the QDM computed for each trial are shown in Appendix H. Three novice participants were able to complete only two trials due to fatigue, and lack of time. The PMST had moderate internal consistency, whereas the PMCDA has high internal consistency as demonstrated by the Cronbach's alpha of 0.48 and 0.86, respectively.

5.3.1 Reliability & Stability Analysis

The PMCDA had high inter-rater reliability between the raters, and high intra-rater reliability between the two time points of the same rater (Table 15). The ICC for the inter-rater reliability estimation of PMST was not statistically significant. However, the PMST had high intr-rater reliability between the two time points of the same rater.

Table 15: Reliability analysis of the PMST and the PMCDA

Variables	Inter-rater Reliability		Intra-rater Reliability	
	ICC (95% CI)	*p-value*	ICC (95% CI)	*p-value*
n	6		5	
PMST Total Score	0.83 (0.13 – 0.98)	0.1	0.84	0.012*
PMCDA Total Score	0.79 (0.43 – 0.94)	0.03*	0.91	<0.001*

**Statistical Significance with p-value < 0.05*

Table 16: Stability analysis of the QDM

	Variables	Experts	Novice	$ICC_{2,2}$ (95% CI)	*p-value*
1	Total Task time (mins)	3.3 (+ 0.36)	8.5 (+ 1.28)	0.94 (0.78 – 0.99)	0.03*
Accelerometer based variables					
2	Ave. linear velocity (m/s)	1.2 (+ 0.17)	0.7 (+ 0.17)	0.94 (0.78 – 0.99)	0.03*
3	Ave. y jerks (m/s3)	56.2 (+ 5)	104.9 (+ 7.2)	0.94 (0.78 – 0.99)	0.03*
4	Total y jerk peaks	1123.3 (+ 99.3)	2099 (+ 143.3)	0.94 (0.74 – 0.99)	0.04*
5	Ave. x jerks (m/s3)	7.9 (+ 1.9)	2.9 (+ 0.62)	0.97 (0.88 – 0.99)	<.01*
6	Total x jerk peaks	1188 (+ 85.9)	1959 (+ 243.7)	0.93 (0.75 – 0.99)	0.04*
7	Ave. Normalized Jerk	914.6 (+ 112.9)	1229 (+ 133.2)	0.95 (0.88 – 0.99)	0.01*
Gyroscope based variables					

8	Ave. angular velocity	10.8 (+ 1.07)	6.4 (+ 0.87)	0.96 (0.85 – 0.99)	0.01*
9	Ave. angular velocity RMS	14.4 (+ 1.5)	9.5 (+ 0.17)	0.97 (0.9 – 0.99)	<.01*
10	Total angular velocity peaks	63.3 (+ 8.7)	134.6 (+ 15.9)	0.98 (0.95 – 0.99)	<.01*
11	Area Under the Curve (AUC)	54.8 (+ 3)	59.3 (+ 3.8)	0.83 (0.33 – 0.97)	0.35
12	Number of Z axis crossings	1080.5 (+ 624.1)	6969.6 (+ 1371.5)	0.43 (-1.0 - 0.99)	0.87
13	Pitch RMS	0.6 (+ 0.04)	0.35 (+ 0.13)	0.9 (0.62 – 0.98)	0.13
14	Roll RMS	0.56 (+ 0.2)	0.5 (+ 0.1)	0.97 (0.9 – 0.99)	<.01*
15	Yaw RMS	10.42 (+ 0.8)	9.2 (+ 0.5)	0.77 (.01 – 0.96)	0.52

**Statistical Significance with p-value < 0.05*

All variables computed using the data from accelerometer had high stability. However, only four of the eight variables computed using data from the gyroscope were stable across the three trials (Table 16).

Due to non-normal distribution, the non-parametric spearman's rho was employed to determine concurrent validity between PMCDA and the WST scores. The PMCDA had high concurrent validity with the WST for tasks with linear and curved trajectories. However, the two scores were not correlated for tasks with rotational trajectories (Table 16).

Table 17: Concurrent Validity between WST and PMCDA

Spearman's Rho (p-value)	**WST – Linear**	**WST – Curved**	**WST – Rotational**	**WST – Percent**
PMCDA – Linear	0.8816 (<0.0001*)	-	-	-
PMCDA - Curved	-	0.9250 (<0.0001*)	-	-
PMCDA - Rotational	-	-	0.3038 (0.1235)	-
PMCDA Percent	-	-	-	0.8954 (<0.0001*)

**p-value with Bonferroni correction (0.05/4)* $\leq$ *0.01*

5.3.2 Tasks with Linear Trajectories

The twelve tasks with linear trajectories were analyzed as a group. Since there were nine individual tests performed to evaluate the difference in driving ability between novice and experienced users, a Bonferroni corrected *p-value* of <.005 was considered significant. Similar to the WST Percent Score, four variables (Total Task time, Average Linear Velocity, Total peaks in the y axis jerk, and the total number of Z axis crossings) were statistically different between the experienced and the novice users.

Table 18: Discriminative Ability of the WST and QDM for Tasks with Linear Trajectories

	Variables	**Swilk** *(p-value)*	**Test**	**Experienced**	**Novice**	***p-value***
1	WST (Percent Score)	0.0003	MWU	100 (± 0)	92.5 (± 0.1)	<0.0001*
2	PMCDA (Percent Score)	<0.001	MWU	99.7 (± 0.22)	92.8 (± 0.85)	<0.0001*
3	Total Task time (mins)	0.0418	MWU	2.06 (+ 0.14)	4.31 (+ 0.27)	<0.0001*
4	Ave. linear velocity (m/s)	0.0054	MWU	0.97 (+ 0.1)	0.57 (+ 0.14)	0.0033*
5	Ave. y jerks (m/s3)	0.0004	MWU	8.53 (+ 1.53)	3.99 (+ 0.43)	0.0057
6	Total y jerk peaks	0.2006	Ttest	644.44 (+ 50.47)	1023 (+ 72.77)	0.0002*
7	Ave. x jerks (m/s3)	0.0014	MWU	7.92 (+ 1.59)	3.59 (+ 0.46)	0.0047
8	Total x jerk peaks	0.0368	MWU	701.66 (+ 53)	977. 8 (+ 96.36)	0.022
9	Ave. Normalized Jerk	0.0151	MWU	1113.42 (+ 78.29)	1397.47 (+ 153.1)	0.1823
10	# of Z axis crossings	0.0249	MWU	621.44 (+ 148.87)	1693 (+ 283.17)	0.003*

**p-value with Bonferroni correction (0.05/10) ≤ 0.005*

A simple linear regression (Table 18) revealed that three variables (Task times, Total peaks in the y axis jerk, and the total number of Z crossings) independently were able to explain the variance in the WST Percent score.

Table 19: Concurrent Validity between WST and QDM for Tasks with Linear Trajectories

	Variables	R^2	MSE	F - Statistic	p-value
1	Total Task time	50.71	0.0015	17.49	0.0006*
2	Ave. linear velocity	1.2	0.003	0.22	0.6471
4	Total y jerk peaks	27.52	0.002	6.45	0.0111*
5	# of Z axis crossings	50.61	0.001	4.81	0.0006*

**p-value with Bonferroni correction (0.05/5) $\leq$ 0.01*

Based on Table 19, Model 2 was chosen as the final since all the variables made a significant contribution to the model and has similar R^2 compared to Model 3. VIF and tolerance, demonstrated that the model does not have an issue with collinearity. Heterogeneity showed no pattern and was confirmed with an insignificant HETTEST. Residuals were also assessed for leverage and influential points using leverage values and cook's distance, and showed no outlier.

Table 20: Convergent Validity between WST and QDM for Tasks with Linear Trajectories

Model	Variables	R^2	F – Statistic	p-value	VIF
1	Total y jerk peaks	27.52	6.45	0.0211*	1
2	Total y jerk peaks*, # of Z axis crossings*	61.39	12.72	0.0005	1.1
3	Total y jerk peaks, # of Z axis crossings, Total Task time	61.4	7.95	0.0021	4

**Statistical Significance with p-value < 0.05*

5.3.3 Tasks with Curved Trajectories

Among the eight variables computed as QDM for tasks with curved trajectories, five variables (Table 20) were statistically different between the experienced and novice users.

Table 21: Discriminative Ability of the WST and QDM for Tasks with Curved Trajectories

	Variables	Swilk *(p-value)*	Test	Experts	Novice	p-value
1	WST (Percent Score)	0.0004	MWU	100 (± 0)	80 (± 1.65)	<0.0001*
2	PMCDA (Percent Score)	<0.0001	MWU	99.6 (± 0.4)	87.7 (± 1.5)	<0.0001*
3	Total Task time (mins)	0.0144	MWU	1.04 (± 0.09)	2.01 (± 1.2)	<0.0001*
4	Ave. Angular velocity	0.2931	Ttest	14.42 (± 0.95)	7.34 (± 0.81)	<0.0001*
5	Ave. Ang. Vel. RMS	0.5416	Ttest	18.18 (± 1.08)	10.2 (± 1.1)	<0.0001*
6	Total Ang. Vel. Peaks	0.0006	MWU	10.15 (± 161.79)	31.15 (±13.3)	<0.0001*
7	Ave. Pitch RMS	0.0006	MWU	0.23 (± 0.13)	0.14 (± 0.05)	0.035
8	Ave. Roll RMS	0.0001	MWU	0.51 (± 0.52)	0.37 (± 0.28)	0.8421
9	Ave. Yaw RMS	0.7121	Ttest	7.23 (± 0.31)	7.17 (± 0.25)	0.561
10	Ave. Normalized Jerk	0.0001	MWU	600.72 (±129.9)	996.34 (± 425.24)	0.0003*

**p-value with Bonferroni correction (0.05/10) ≤ 0.005*

The five variables demonstrated good concurrent validity (Table 21) with the WST Percent score as indicated by the statistically significant high R^2 and F-statistic. Evaluation of assumptions revealed high correlation between angular velocity and angular velocity RMS. Hence, angular velocity RMS was eliminated for further analysis, and average absolute angular velocity of a curved task was retained due to the ease of interpretability.

Table 22: Concurrent Validity of WST and QDM for Tasks with Curved Trajectories

	Variables	R^2	MSE	F – Statistic	*p-value*
1	Total Task time	46.02	0.016	14.49	0.0014*
2	Ave. Angular velocity	45.66	0.016	14.28	0.0015*
3	Ave. Ang. Vel. RMS	45.38	0.014	14.13	0.0016*
4	Total Ang. Vel. peaks	39.43	0.018	11.07	0.004*
5	Ave. Normalized Jerk	44.64	0.016	13.71	0.0018*

**p-value with Bonferroni correction (0.05/5) ≤ 0.01*

Based on Table 22, Model 5 was chosen as the final since all the variables made significant contributions to the model with R^2 that is comparable to Model 3 and 4, with VIF less than 2. No assumptions of multiple regression were violated supporting generalizability of this model to other data samples.

Table 23: Convergent Validity of WST and QDM for Tasks with Curved Trajectories

Model	Variables	R^2	F - Statistic	*p-value*	VIF
1	Ave. Angular velocity	45.66	14.28	0.0015*	1
2	Ave. Angular velocity#, Total Ang. Vel. peaks	49.88	7.96	0.004*	2.06
3	Ave. Angular velocity#, Total Ang. Vel. Peaks, Ave. Normalized Jerk#	67.42	10.34	0.0006*	3.25
4	Ave. Angular velocity#, Total Ang. Vel. Peaks, Ave. Normalized Jerk#, Total Task time	67.49	7.27	0.0022*	4.98
5	Ave. Angular velocity#, Ave. Normalized Jerk#	64.25	14.38	0.0003*	1.2

**Statistical Significance with p-value < 0.05*

5.3.4 Tasks with Rotational Trajectories

The PMCDA scores were significantly different between the experienced and novice EPW users, whereas the WST scores did not reveal any difference. Similar to tasks with curved trajectories, Total task time, Ave. Angular velocity, Total angular velocity peaks and normalized jerk were significantly different between experienced and novice users (Table 24). No significant concurrent validity between WST and QDM was identified for tasks with rotational trajectories. Due to the lack of significant associations between WST scores and QDM, convergent validity evaluation was not performed for tasks with rotational trajectories.

Table 24: Discriminative Ability of the WST and QDM for Tasks with Rotational Trajectories

		Swilk *(p-value)*	Test	Experienced	Novice	*p-value*
1	WST (Percent Score)	<0.001	MWU	100 ($\pm$ 0)	96.66 ($\pm$ 0.02)	0.2477
2	PMCDA (Percent Score)	<0.001	MWU	98.6 ($\pm$ 0.6)	92.4 ($\pm$ 1.5)	<0.001*
3	Total Task time	0.0002	MWU	0.58 (+ 0.1)	1.4 (+ 0.2)	0.0003*
4	Ave. Angular velocity	0.2898	Ttest	20.82 (+ 3.71)	12.22 (+ 4.8)	0.0002*
5	Total Ang. Vel. peaks	0.1761	Ttest	6.44 (+ 1.53)	15.4 (+ 1.2)	0.0001*
6	Ave. Ang. Vel. AUC	0.1329	Ttest	120.52 (+ 11.8)	129.39 (+ 5.8)	0.744
7	Ave. Pitch RMS	0.0054	MWU	0.25 (+ 0.12)	0.12 (+ 0.05)	0.0172
8	Ave. Roll RMS	0.0005	MWU	0.62 (+ 0.56)	0.40 (+ 0.28)	0.2428
9	Ave. Yaw RMS	0.0507	Ttest	11.13 (+ 0.88)	8.58 (+ 0.56)	0.0137
10	Ave. Normalized Jerk	0.0003	MWU	534.88 (+ 50.17)	974.77 (+ 151.97)	0.0030*

**p-value with Bonferroni correction (0.05/10) $\leq$ 0.005*

Table 25: Concurrent Validity of WST and QDM for Tasks with Rotational Trajectories

	Variables	R^2	MSE	F - Statistic	p-value
1	Total Task time (mins)	0.7	0.001	0.12	0.7337
2	Ave. Angular velocity (rads/s)	0.2	0.001	0.03	0.8542
3	Total Ang. Vel. peaks	4.18	0.001	0.74	0.4012
4	Ave. Normalized Jerk	23.41	0.001	5.2	0.0358

**p-value with Bonferroni correction (0.05/4) $\leq$ 0.01*

5.4 Discussion

This study employed a multi-level approach to evaluate the measurement properties of two clinical tools and objective digital markers of EPW driving capacity by adopting the principles of item response theory [136]. The results demonstrate that both PMST and PMCDA have high intra-rater, but only the PMCDA has high inter-rater reliability. The PMST has poor inter-rater reliability, refuting 1.2 partially. To determine whether inexperience of the students could have contributed to poor inter-rater reliability of the PMRT, a secondary analysis was conducted excluding the student raters. However, the secondary analysis demonstrated a higher inter-rater reliability of the PMCDA, but no changes in the PMST. Two potential reasons for poor reliability of the PMST could be the small number of items within the tool which render it incapable of capturing the impairments, or because the small sample of novice EPW users did not have the variability in impairments that could be measured by the tool [136].

The PMCDA scores have high correlation with the WST scores for tasks with linear and curved trajectories indicating good concurrent validity between the tools, supporting hypothesis 1.3. The variations among EPW users in executing the rotational tasks could have led to the low concurrent validity between the two scores. This finding is also noted in the discriminative validity evaluations. Both the WST and PMCDA scores are different between novice and experienced users for tasks with linear and curved trajectories. However, only the PMCDA scores demonstrate statistically significant difference between novice and experienced users for tasks with rotational trajectories. This indicates that scoring the task based on the feedback or cueing provided by the rater, rather than evaluating the ideal or safe method of execution could be a more effective strategy for evaluation of tasks with variable methods of execution.

The high Cronbach's alpha of the PMCDA indicates that the individual tasks have shared covariance and measure the same underlying construct of EPW driving ability. On the other hand, Cronbach's alpha of less than 0.5 for PMST suggest that the items of PMST have to be revised in order to gather appropriate information pertinent to the users' motor, sensory and cognitive impairments.

The multistep approach in demonstrating the psychometric properties of the QDM enabled the identification of one or two variables for each group of tasks that could be generalizable to other data samples. Among the fifteen potential variables that were computed from the raw IMU data, eleven variables revealed stable measurements across the three trials, supporting hypothesis 2.1. Grouping together data from multidirectional EPW movement to compute variables like Area Under the Curve that changes in both positive and negative direction could have affected the stability of the four measures that had low ICCs.

At least four of the eight variables computed for each of the three groups of tasks were significantly different between experienced and novice users demonstrating good discriminative validity of QDM, supporting hypothesis 2.2. Selecting appropriate variables based on the direction of movement of the EPW demonstrated high concurrent validity between the WST score and QDM of tasks with linear and curved trajectories. However, there were no variables that demonstrated concurrent validity for tasks with rotational trajectories. One potential cause for this finding could be the lack of variance in the outcome variable (WST scores) for rotational trajectories.

Multiple regression identified two variables for each of the two models as QDM – total number of peaks in jerk along the forward axis, total number of vertical (Z) axis crossings for tasks with linear trajectories, average angular velocity around the vertical axis and average of the normalized jerk demonstrating high convergent validity, supporting hypothesis 2.3. Both these models are well fit and meet the assumptions of the regression, indicating good generalizability of these findings. These variables can be considered to be good digital markers of accuracy of task execution. Similar objective technology-based variables have been successfully employed in various other medical specialties to demonstrate motor skill learning using different digital signals or markers gathered during human movement. The review conducted by Brueckner et al, provides a broad overview of studies that employed Root Mean Square to quantify variations in EMG data reflective of changes in motor performance as result of practice [138]. Balasubramanian et al reviewed different technical measure of smoothness described in neurorehabilitation and motor control literature for diverse kinds of movements [139]. Ghasemloonia et al employed normalized jerk as a quantifiable metric for surgical trainee assessment and proficiency in robotic and virtual training simulators [140]. Bloomer et al demonstrated that normalized jerk can be effectively employed to assess prosthesis training using a within-subject paradigm compared across two training time points [141].

Based on the literature review conducted as a part of this work, this is the first study to demonstrate feasibility and evaluate measurement properties of objective movement measurement in an outpatient clinic setting to evaluate EPW driving ability. The simplicity of this approach using IMUs and a mobile app to quantify EPW driving could aid better clinical adoption of this technology-based outcome measurement.

5.4.1 Limitations

The small sample of novice EPW users with limited variability in impairments is a major limitation. This could have impacted the reliability analysis of PMST and the validity of QDM for tasks with rotational trajectories. Adopting a statistical analysis that could accommodate for the small sample was one way to address this limitation. However, the findings pertinent to PMST and rotational trajectories will have to be further explored in a larger study sample with patients who have a broader range of impairments.

Further, the experimental protocol comparing driving performance between experienced and novice users could have maximized the effect of the results. The lack of test-retest comparisons as a part of this protocol limits the internal validity of the findings. Future studies will aim to address these limitations to further validate the results by employing a more stringent repeated measures study design to evalute the psychometric properties of the quantitive driving metrics.

5.5 Conclusion

This study demonstrates that the PMCDA using a feedback-based scoring system has high reliability and validity for clinical use. The QDM computed using the objective measurement of the movement of EPW could serve as digital marker of a user's EPW driving capacity. Future work should evaluate the responsiveness of these measures in a larger sample size along with further iteration and revision of the PMST to quantify the user's impairments. Identifying key motor learning strategies that can influence change in the QDM could enable the development of evidence-based personalized EPW driving training strategies that could be readily used in clinics.

6.0 Conclusions

Powered mobility driving assessment tools are critical to the development and delivery of novel interventions that can improve an EPW user's driving ability and promote safe mobility. The review of literature identified two key scientific gaps, the lack of measures to quantify users' impairments and the lack of an approach to document the feedback received by users' during assessment and training. Using participatory design, the first study developed the Powered Mobility Screening Tool (PMST) and the Powered Mobility Clinical Driving Assessment (PMCDA) to address these scientific gaps.

In study two, Virtual EPW driving assessments conducted in an EPW driving simulator demonstrated stability and construct validity of Quantitative Driving Metrics (QDM) in virtual environment. These objective movement measurements of the EPW demonstrated that they could be used as digital markers of EPW driving ability. The third study conducted a robust evaluation to demonstrate the feasibility and concurrent validity of computing objective measures in the real-world using two passive movement analysis systems in the laboratory.

The last study evaluated measurement properties of the newly developed clinical assessment tools and objective outcomes measures in an outpatient assistive technology clinic using a portable sensor package and a mobile app. The ease of sensors setup along with the stability and validity of the four variables computed from the data gathered demonstrate that valuable information can be gathered for clinicians and wheelchair vendors.

Availability of such objective information in the clinic could be helpful in multiple ways, (1) QDM could eliminate subjectivity and enable standardizing driving assessments, and (2) promote adoption of better training strategies in the clinic. Combining QDM with objective measures to quantify attention and cognition [142-144] could help develop a spectrum of digital biomarkers that can identify driving patterns of EPW users. Such an array of digital biomarkers can pave the way to the development of training programs targeted to modulate individual factors that influence a user's driving behavior. Combining these digital markers of driving ability with scientifically proven methods to improve cognition and motor control strategies could aid the development of novel methods of EPW driving training.

6.1 Challenges

This dissertation project includes multiple studies supported by grants with varying timeline and funding. This posed a unique challenge in coordinating the data collection efforts for each of the studies. Particulary, the funding constraints of study one and study four limited the sample size for these pilot efforts.

In addition to the funding constraints, unique technical challenges occurred as the project progressed. For example, in study three, the instrumentation required to sync signals from the VICON motion capture system and the inertial sensor based system attached to the EPW required designing and manufacturing trigger switches that prolonged the timeline of the project. Further, the continually evolving quality of the inertial sensors necessitated that multiple sensors had to be tested before designing the final on-board sensor system that was required in study four.

The varying timeline and funding constraints posed challenges with study design as well. For example, during study four, the limited funding meant test-retest reliability could not be evaluated due to the lack of time and resources to have participants come back for a second visit.

6.2 Key Lessons

The different studies that employed different technologies such as virtual reality, the VICON passive motion capture system and the intertial sensor system enabled the evalution of QDM within different systems that could have different applications. The experience of working with these different technologies made it possible to develop processes to evaluate objective metrics in the clinic. This work can inform design of future research protocols to evaluate validity and reliability of the metrics.

The execution of study four in the Center for Assistive Technology was very useful in understanding clinical workflows, and learning about the limited time available for clinicians to perform clinical EPW driving evalutions. This protocol validated the design recommendations from the focus froups in study one. For example, a driving protocol needs to be intuitive for the clinicians and they should be able to deliver the assessment with no additional materials that will have to be purchased. This ability to be flexible with order of tasks in PMST and PMCDA was appreciated by all the raters and indicated that such options could promote better adoption of the tools in the clinic.

In addition, one of the key lessons of conducting study four in the clinic was the immediate qualitative feedback from clinicains about the protocol and the willingness or acceptance to use a phone based digital application as part of the EPW driving evalution. This aspect further validated the technical feasibility to conduct evaluations using digital aids in the clinic.

6.3 Recommendations

6.3.1 Study Protocols

Planning to conduct future studies in the outpatient clinic or in other clinical settings as part of everyday clinical workflows could serve as a true litmus test for the adoption of the technology or the instrumnents' capability for adoption by clinicians or assistive technology professionals who will be using the tools. Further, given the wide variations of users' impairments, functional ability and EPW driving capacity, future studies should be conducted as mutli-center trials to validate the preliminary findings that were indentified as part of this dissertation project. Conducting trials in clinical settings could decrease burden on study participants for a second visit and could enable gathering repeated measures for assessments to further evaluate the psychometric properties of the clinical assessments such as test-retest reliability, while reducing attrition.

6.3.2 Mobile App

Further improvements in the user interface of the current android app that was used to demarcate different tasks in the clinic could promote the use of such apps in the users' living environment to measure EPW driving performance in the community. Particularly, designing the interface that can enable a caregiver to follow simple instructions guiding them through steps that they could perform to complete an assessment could enable better adoption of the app in both clinical and non-clinical settings.

In addition to the interial sensors data, gathering data from the users' EPW joystick could enable the development to more reliable objective metrics.Such an integration process could also inform the development of better control systems for novel robotic wheelchairs such as the Mobility Enhancement Robotic Wheelchair [145] that are being developed.

Future work should employ these digital tools to gather data from a larger population of EPW users with diverse impairments to identify trends in QDM to describe EPW driving patterns, analogous to the propulsion patterns of a manual wheelchair, paving the way for evidence-based individualized training programs.

Appendix A The Tools and Tasks Survey

Appendix A.1 Screening Tools

Please choose 3 items in each section that are the most important components of a screening for power mobility. Rank them in order from 1 (most important) to 3 (least important) and leave the rest blank. You may choose a combination of existing items or write in your own, but please list only a total of 3 items in each section.

Appendix A.1.1 Motor tests

<u>Choose 3 here</u>

1. Range of motion of the upper limbs
2. Range of motion of the head, neck and trunk
3. Motor coordination
    a. Purdue pegboard − Measures two types of activities: gross movements of hands, fingers and arms, and "fingertip" dexterity in an assembly task. Involves sequential insertion of pegs and assembly of pegs.
    b. Grooved peg board/ fine motor speed- manipulative dexterity test using holes with randomly positioned slots and pegs, which have a key along one side.
4. Others:

Appendix A.1.2 Sensory tests

<u>**Choose 3 here**</u>

1. Visual
   a. <u>Ocular Movement</u>: The *NSUCO/Maples Oculomotor Test* is a standardized method of scoring standard eye movement testing.
   b. <u>Visual Field</u> (*By confrontation testing*)
   c. <u>Visual acuity</u>
      i. *Snellen's chart* (for far vision)
      ii. *Near vision acuity charts*: Charts that can assess vision within 1m distance.
   d. <u>Depth perception (Stereopsis)</u>: *Random Dot Steroacuity test:* Designed to rapidly test for amblyopia and strabismus in early and non-readers and non-verbal children and adults.
   e. <u>Color vision</u>: *Color Vision Testing Made Easy*: Intended use is for screening color vision of young children beginning at age 3 and individuals with developmental delays.
   f. <u>Visual Perception</u>
      i. *Motor-Free Visual Perception Test (MVPT-3)* − assesses an individual's visual perceptual ability -- with no motor involvement needed to make a response
      ii. *Developmental Test of Visual Perception Adolescent and Adult (DTVP-A)* − A measure of visual perception that reliably differentiates visual-perceptual problems from visual-motor integration deficits.
   g. Others:

2. Auditory
   a. Calibrated finger rub auditory screening test (CALFRAST) – confrontational testing using fingers to make audible sound
   b. Portable Audiometer
   c. Others:

Appendix A.1.3 Cognitive Tests

<u>Choose 3 here</u>

1. <u>Cognition and memory skills</u>

   a.Trail making A & B: Specifically assesses working memory, visual processing, visuo-spatial skills, selective and divided attention, and psychomotor coordination.

   b.Clock drawing test: Assess a patient's long-term memory, short-term memory, visual perception, visuospatial skills, selective attention, abstract thinking, and executive skills. Preliminary research indicates an association between specific scoring elements of the clock drawing test and poor driving performance.
2. Porteus maze − set of paper forms on which the subject is required to trace a path, tests problem solving
3. Digit span (WSIR) − tests speed of information processing, longest list of letters or numbers that a person can repeat back in correct order
4. Continuous performance test by Connors (CPT) – tests Visual attention; task-oriented computerized assessment of attention disorders. Clients are presented with a repetitive, "boring" task and must maintain their focus
5. Others:

Appendix A.2 Driving Tasks

Please choose 5 items in each section that are the most important components of a driving skills assessment. Rank them in order from 1 (most important) to 5 (least important) and leave the rest blank. You may choose a combination of existing items or write in your own, but please list only a total of 5 items in each section.

Appendix A.2.1 Indoor Tasks

1. Drives forward (15ft) (in a straight line) in narrow corridor without hitting walls
2. Drives backward (or reverse) 10ft, in a straight line
3. Turns 90° while moving forward
    a. Left
    b. Right
4. Turns 90° while moving backward
    a. Left
    b. Right
5. Turns 180°in place
    a. Left
    b. Right
6. Passes through doorways without hitting walls (36” doorways)
7. Avoids “Wet floor” sign (within a 5ft wide corridor)
8. Avoids one person coming towards participant in hallway
9. Can safely maneuver in-between objects and tight spaces
    a. Drive between a couch and coffee table, in a living room setup
    b. Can enter an elevator
    c. Adjust within an elevator
    d. Exit the elevator
10. Approaches furniture without bumping into them
    a. Parking under table
    b. Parking beside table
11. Other:
12. Other:
13. Other:

Appendix A.2.2 Outdoor Tasks

1. Drives forward 30ft in 30s
2. Crossing Street without lights
3. Avoids moving obstacles approaching from both sides − Left &Right
    a. Avoids two or more moving obstacles (person coming towards participant) in sidewalk
    b. Avoid an unexpected ball
4. Ascends 5° incline
5. Descends 5° incline
6. Ascends 10° incline
7. Descends 10° incline
8. Rolls 10ft across 5° side-slope
    a. Left
    b. Right
9. Is able to drive over 15cm pothole
10. Other:
11. Other:
12. Other:
13. Other:
14. Other:

Appendices contain supplementary or illustrative material or explanatory data too lengthy to be included in the text or not immediately essential to the reader's understanding of the text.

When using the Appendix Style, type the title of the Appendix section after the inserted heading.

Appendix B Users' Survey

Years of experience driving a power chair ____

Main disability ____

Question 1: List the top 5 skills that you think are important for a person to be a highly skilled driver in both indoor and outdoor environments. Please rank them in order of importance from most important to least important.

Indoor skills

1.

2.

3.

4.

5.

Outdoor skills

1.

2.

3.

4.

5.

Question 2: List the top 5 skills that you think are important for a person to be a moderately skilled driver who drives only indoors. Please rank them in order of importance from most important to least important.

Indoor skills

1.
2.
3.
4.
5.

Please include any additional comments below:

Appendix C Clinical Driving Assessment Tools

Appendix C.1 The Power Mobility Screening Tool (PMST)

MOTOR	
Driver can functionally control an interface (joystick, head control, etc) with appropriate body part to drive the chair	1-3
Driver controls chair with sufficient endurance (ability to tolerate sitting and operating the interface)	1-3
SENSORY	
Driver can identify an object (e.g therapy ball) 2 meters away with clinic in background, in left, center, and right visual fields	1-3
COGNITIVE	
Driver displays ability to understand cause and effect (action on the control interface will move the chair)	1-3
Driver has ability to focus, concentrate, attend to task and shift focus within the task during screening	1-3
TOTAL	**5-15**

Instructions:

- Ask client to drive the EPW in an open space free from obstacles.
- You may provide visual or auditory clues along with verbal instructions to complete tasks.
- Tasks can be completed in any order and also as part of a routine physical examination or mat assessment.
- Client may identify objects by any means (verbally, gestures, etc) and may use visual aids.
- Control interface settings should be adjusted for safety and at discretion of the trainer and driver.

Scoring System for the screening tool:

Score of 1: If the driver requires physical assistance, lacks the skill, or cannot complete the task

Score of 2: If the driver requires verbal or auditory hints or cues but no physical assistance, has partial skill (e.g. can identify an object in 2 of 3 visual fields or can partially move a joystick)

Score of 3: If the driver completes the task without help or has adequate skill, even if additional time is needed for the task.

Appendix C.2 The Power Mobility Clinical Driving Assessment Tool (PMCDA)

INDOOR	**Score**
Drives forward (15ft) (in a straight line) in 36” hallway	1-3
Drives backward 10ft in a straight line in 36” hallway	1-3
Passes through 36" doorway	1-3
Avoids therapy balls approaching from left and right	1-3
Turns 90° while moving forward	1-3
Turns 90° and enters a doorway	1-3
Turns 90° while moving backward	1-3
Turns 180° in place to the left	1-3
Can safely maneuver in-between 2 chairs 32 in apart	1-3
Approaches an accessible sink	1-3
Approaches a transfer surface (bed or chair)	1-3
Negotiates over 1 in door / mock threshold (piece of wood)	1-3
Stops on command (emergency stop)	1-3
OUTDOOR	
Drives forward 30ft in 30s	1-3
Drives over an unpaved surface	1-3
Ascends 5° incline	1-3
Descends 5° incline	1-3

Ascends 10° incline	1-3
Descends 10° incline	1-3
Crosses a street	1-3
Rolls 10ft across 5° side-slope	1-3
Ascends an ADA curb cut	1-3
Descends an ADA curb cut	1-3
TOTAL	**23-69**

Instructions:

- You may provide visual or auditory clues along with verbal instructions to complete tasks.
- Tasks can be completed in any order.
- Control interface settings should be adjusted for safety and at discretion of the trainer and driver.

Scoring system for the driving assessment tool:

Score of 1: If the driver requires physical assistance or cannot complete the task

Score of 2: If the driver requires verbal or auditory hints or cues but no physical assistance

Score of 3: If the driver completes the task without help

Appendix D Successive iterations of the screening tests

<table>
<tr><td colspan="4"></td></tr>
<tr><th colspan="2">Ranked Screening Tests
(From the Survey)</th><th rowspan="2">List Of Screening Tests In The First Iteration Of The PMCDA
(After The Focus Group)</th><th rowspan="2">Specific Changes Suggested During The Discussion Forum</th></tr>
<tr><th>Professional Experts' Ranks</th><th>Screening Tests</th></tr>
<tr><td>1</td><td>• Range of motion of the head, neck and trunk [146, 147]
Others:
• Knowledge of cause and effect
• Motor planning/problem solving ability e.g. maneuvering out of a tight spot
• Basic Cognition: Orientation to person, place, situation</td><td rowspan="2">MOTOR
• Driver can functionally control an interface (joystick, head control, etc) with appropriate body part to drive the chair
• Driver controls chair with sufficient endurance (ability to tolerate sitting and operating the control interface) during the screening

SENSORY</td><td rowspan="2">SENSORY
• Driver can identify an object (e.g therapy ball) 2 meters away with clinic in background, in left, center, and right visual fields

COGNITIVE</td></tr>
<tr><td>1.5</td><td>• Confrontation testing [148, 149]
• Snellen's chart (for far vision) [150]
• Random Dot Steroacuity test [151]
Others:
• Strength of the body part that will be controlling chair
• Ability to use control interface e.g. switch, joystick, etc</td></tr>
</table>

<table>
<tr>
<td>2</td>
<td>• Range of motion of the upper limbs [152, 153]
• Near vision acuity charts [154]
• Proteus Maze [155]
• Continuous performance test [156]
Others:
• Mini mental exam</td>
<td rowspan="3">• Driver can visually identify an object (e.g therapy ball) 2 meters away with clinic in background, in left, center, and right visual fields

COGNITIVE
• Driver displays ability to understand cause and effect (action on the control interface will move the chair)
• Driver has ability to focus, concentrate, attend to task and shift focus within the task</td>
<td rowspan="3">• Driver has ability to focus, concentrate, attend to task and shift focus within the task during the entire period of assessment</td>
</tr>
<tr>
<td>2.5</td>
<td>• The NSUCO/ Maples Oculomotor Test [157]
• Motor – Free Visual Perception Test (MVPT) [158]
• Digit span [159, 160]</td>
</tr>
<tr>
<td>3</td>
<td>• Motor coordination [161, 162]
• Trail making A & B [163]
Others:
• Functional vision – visual scanning, visual conflict
• Endurance with use of trial equipment with driving obstacles
• Reliability of use the control interface (non-fatigable, consistent)</td>
</tr>
</table>

Appendix E List of indoor driver tasks

<table>
<tr><th colspan="2">Ranked Indoor Driver Tasks From the Survey</th><th>List Of Indoor Tasks In The First Iteration Of The PMCDA After The Focus Group</th><th>Specific Changes Suggested During The Discussion Forum</th></tr>
<tr><th>Professional Experts’ Ranks</th><th>Indoor Driver Tasks</th><th></th><th></th></tr>
<tr><td>1</td><td>• Drives forward (15ft) (in a straight line) in narrow corridor without hitting walls
• Avoids one person coming towards participant in hallway</td><td rowspan="6">• Drives forward (15ft) (in a straight line) in 36” hallway
• Drives backward 10ft in a straight line in 36” hallway
• Passes through 36" doorway
• Avoids therapy balls approaching from left and right
• Turns 90° while moving forward
• Turns 90° while moving backward
• Turns 180° in place to the left
• Can safely maneuver in-between 2 chairs spaced 32 in apart
• Approaches an accessible sink
• Negotiates over a 1 in door threshold or mock threshold (piece of wood)</td><td rowspan="6">These tasks were added to the list:
• Turns 90° and enters a doorway
• Approaches a transfer surface (bed or chair)
• Stops on command (emergency stop)</td></tr>
<tr><td>2</td><td>• Turns 90° while moving forward
• Passes through doorways without hitting walls (36” doorways)</td></tr>
<tr><td>3</td><td>• Turns 180°in place - Left</td></tr>
<tr><td>4</td><td>• Can safely maneuver in-between objects and tight spaces</td></tr>
<tr><td>5</td><td>• Approaches furniture without bumping into them</td></tr>
<tr><td>0</td><td>• Drives backward (or reverse) 10ft, in a straight line
• Turns 90° while moving backward
• Avoids “Wet floor” sign (within a 5ft wide corridor)
• Parking under table
• Parking beside table</td></tr>
</table>

Appendix F List of Outdoor driver tasks

<table>
<tr><th colspan="2">Ranked Outdoor Driver Tasks From the Survey</th><th rowspan="2">List Of Outdoor Tasks In The First Iteration Of The PMCDA After The Focus Group</th><th rowspan="2">Specific Changes Suggested During The Discussion Forum</th></tr>
<tr><th>Professional Experts' Ranks</th><th>Outdoor Driver Tasks</th></tr>
<tr><td>1</td><td>• Avoids moving obstacles approaching from both sides - Left &Right
• Drives forward 30ft in 30s</td><td rowspan="5">• Drives forward 30ft in 30s
• Drives over an unpaved surface
• Ascends 5° incline
• Descends 5° incline
• Ascends 10° incline
• Descends 10° incline
• Crosses a street
• Rolls 10ft across 5° side-slope
• Ascends an ADA[1] curb cut
• Descends an ADA[1] curb cut</td><td rowspan="5">• No additional tasks suggested</td></tr>
<tr><td>2</td><td>• Ascends 5° incline</td></tr>
<tr><td>3</td><td>• Descends 5° incline</td></tr>
<tr><td>4</td><td>• Crossing Street without lights
• Rolls 10ft across 5° side-slope</td></tr>
<tr><td>0</td><td>• Ascends 10° incline
• Descends 10° incline
• Is able to drive over 15cm pot-hole</td></tr>
<tr><td colspan="4">[1]American Disabilities Act</td></tr>
</table>

Appendix G Computation of Quantitative Driving Metrics (QDM)

1. **Task Time:** Found by subtracting the time at the beginning of the task from the time at the end of the task.
2. **Linear Velocity:** Calculated by dividing the distance for a task by the time it took to complete the task.
3. **Root Mean Square of Angular Velocity around Z axis:** The root mean square value of the z-axis angular velocity data for a given task, calculated by $\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$ where x_i is the angular velocity values and n is the number of values in the task.
4. **Number of Peaks in Angular Velocity around Z axis:** Number of local minima and maxima in the z-axis angular velocity data, calculated using the ‘findpeaks’ function in matlab with parameters:
    a. MinPeakHeight: 2 + the rms of the z-axis angular velocity data for the task
    b. MinPeakProminence: ¼ * rms of the z-axis angular velocity data for the task
5. **Area Under Curve of Angular Velocity around Z axis:** The approximated integral of the z-axis angular velocity data, calculated using ‘trapz’ function in MATLAB.
6. **Number of Peaks in Jerk of y axis:** Number of local minima and maxima in the y-axis jerk data (found using the derivative of linear acceleration data), calculated using the ‘findpeaks’ function in MATLAB with parameters:
    a. MinPeakHeight: 2 + the rms of the y-axis jerk data for the task
    b. MinPeakProminence: ¼ * rms of the y-axis jerk data for the task

7. **Average Jerk along y axis:** Average of the y-axis jerk data for a given task.
8. **Number of Peaks in Jerk of x axis:** Number of local minima and maxima in the x-axis jerk data (found using the derivative of linear acceleration data), calculated using the 'findpeaks' function in matlab with parameters:
    a. MinPeakHeight: 2 + the rms of the x-axis jerk data for the task
    b. MinPeakProminence: ¼ * rms of the x-axis jerk data for the task
9. **Average Jerk along x axis:** Average of the x-axis jerk data for a given task.
10. **Normalized Jerk:** A value derived from the jerk values of all 3 axes. First, the jerk data from all 3 axes was combined into one vector using: $jerk_{xyz} = \sqrt{{jerk_x}^2 + {jerk_y}^2 + {jerk_z}^2}$. This vector was fed into the formula $\sqrt{.5 * (\sum_{i=1}^{n} jerk_{xyz}(i)^2) * time}$, where *n* is the total number of data points for the task and *time* is the time taken to complete the task.
11. **Number of Axis Crossings in Angular velocity around Z axis:** Calculated by finding the number of times the z-axis angular velocity data reaches 0.

Appendix H Summary of Clinical Assessment Scores and QDM

Variables	Trial 1		Trial 2		Trial 3	
	Experienced	Novice	Experienced	Novice	Experienced	Novice
n	5	5	5	5	5	2
Wheelchair Skills Test (Percent Score)	100 (± 0)	91.02 (± 0.07)	100 (± 0)	90.3 (± 0.02)	100 (± 0)	98.33 (± 0.01)
PMST Total Score						
PMCDA Total Score						
Trial times (mins)	3.3 (+ 0.36)	8.5 (+ 1.28)	3.3 (+ 0.29)	7.1 (+ 0.43)	3.4 (+ 1.18)	5.3 (+ 1.14)
Ave. linear velocity (m/s)	1.2 (+ 0.17)	0.7 (+ 0.17)	1.1 (+ 0.11)	0.6 (+ 0.07)	1.1 (+ 0.12)	0.8 (+ 0.14)
Ave. y jerks (m/s3)	56.2 (+ 5)	104.9 (+ 7.2)	53.7 (+ 4.05)	85.5 (+ 7)	60.6 (+ 6)	72.8 (+ 11.9)
Total y jerk peaks	1123.3 (+ 99.3)	2099 (+ 143.3)	1074 (+ 81)	1701.2 (+ 139.9)	1211.75 (+ 120.8)	1455.3 (+ 238.2)
Ave. x jerks (m/s3)	7.9 (+ 1.9)	2.9 (+ 0.62)	6.3 (+ 1.2)	3 (+ 0.5)	7.1 (+ 1.3)	3.6 (+ 1.1)
Total x jerk peaks	1188 (+ 85.9)	1959 (+ 243.7)	1244.2 (+ 81.6)	1608.6 (+ 238.9)	1409.25 (+ 133.4)	1492.7 (+ 231.4)
Ave. Normalized Jerk	914.6 (+ 112.9)	1229 (+ 133.2)	887.7 (+ 58.7)	1290.8 (+ 192.7)	1010.85 (+ 63.5)	1140.2 (+ 399.3)
Ave. angular velocity	10.8 (+ 1.07)	6.4 (+ 0.87)	10.6 (+ 0.67)	7.34 (+ 0.9)	10.9 (+ 1.3)	8.6 (+ 1.54)
Ave. angular velocity RMS	14.4 (+ 1.5)	9.5 (+ 0.17)	14 (+ 1.02)	10.4 (+ 1.3)	14.3 (+ 1.6)	11.6 (+ 2.1)
Total angular velocity peaks	63.3 (+ 8.7)	134.6 (+ 15.9)	67 (+ 8.06)	122 (+ 16.2)	74.5 (+ 9.2)	117 (+ 35.5)
Area Under the Curve (AUC)	54.8 (+ 3)	59.3 (+ 3.8)	55.3 (+ 1.76)	61.6 (+ 2.7)	55.7 (+ 3.9)	64.8 (+ 8.5)
Number of Z axis crossings	1080.5 (+ 624.1)	6969.6 (+ 1371.5)	1055.4 (+ 203.7)	2098 (+ 491.3)	2521 (+ 1588.3)	1973.3 (+ 355.3)
Pitch RMS	0.6 (+ 0.04)	0.35 (+ 0.13)	0.58 (+ 0.04)	0.38 (+ 0.03)	0.56 (+ 0.23)	0.48 (+ 0.02)
Roll RMS	0.56 (+ 0.2)	0.5 (+ 0.1)	0.58 (+ 0.1)	0.53 (+ 0.13)	0.61 (+ 0.2)	0.34 (+ 0.03)
Yaw RMS	10.42 (+ 0.8)	9.2 (+ 0.5)	10.28 (+ 0.9)	9.13 (+ 0.39)	9.12 (+ 0.35)	9.62 (+ 0.88)

Appendix I Software

Appendix I.1 Data Logger Code

Datalogger code for PMCDA tasks

```
#include <SPI.h>

#include <Wire.h>

#include <SD.h>

#include <Adafruit_Sensor.h>

#include <Adafruit_BNO055.h>

#include <utility/imumaths.h>


/* Set the delay between fresh samples */

#define BNO055_SAMPLERATE_DELAY_MS (100)

Adafruit_BNO055 bno = Adafruit_BNO055();


/*Variables to record data*/

float times =0.0;

const int chipSelect = BUILTIN_SDCARD;

char filename [16];

String dataString="";
```

```
void setup () {
 Serial.begin (9600);// Serial com for data output
 Serial1.begin (9600);
 if(!bno.begin()) {
  /* There was a problem detecting the BNO055 ... check your connections */
  Serial.print("Ooops, no BNO055 detected ... Check your wiring or I2C ADDR!");
  While (1);
 }
 bno.setExtCrystalUse(true);                    // Use the crystal on the development board

 Serial.print("Initializing SD card...");
 // make sure that the default chip select pin is set to output, even if you don't use it:
 pinMode(chipSelect , OUTPUT);

 // see if the card is present and can be initialized:
 if (!SD.begin(chipSelect)) {
  Serial.println("Card failed, or not present");
  // don't do anything more:
  return;
 }
 Serial.println("card initialized.");
 int n = 0;
```

```
  snprintf(filename, sizeof(filename), "data%03d.txt", n); // includes a three-digit sequence number
in
                                                                   the file name
  while(SD.exists(filename)) {
    n++;
    snprintf(filename, sizeof(filename), "data%03d.txt", n);
  }
  File dataFile = SD.open(filename,FILE_READ);
  Serial.println(n);
  Serial.println(filename);
  dataFile.close();
  //now filename [] contains the name of a file that doesn't exist
  Delay (20);
}

void loop (){
  times = (float) millis()/1000;
  // Possible vector values available in IMU BNO055 are:
  // - VECTOR_ACCELEROMETER - m/s^2
  // - VECTOR_MAGNETOMETER  - uT
  // - VECTOR_GYROSCOPE     - rad/s
  // - VECTOR_EULER         - degrees
  // - VECTOR_LINEARACCEL   - m/s^2
```

```
// - VECTOR_GRAVITY       - m/s^2
//Read Euler angles and acceleration in 3 axes
imu::Vector<3> euler = bno.getVector(Adafruit_BNO055::VECTOR_EULER);
imu::Vector<3> acc = bno.getVector(Adafruit_BNO055::VECTOR_ACCELEROMETER);

dataString += String(times); dataString += String("\t");
dataString += String(euler.x());  dataString += String("\t");
dataString += String(euler.y());  dataString += String("\t");
dataString += String(euler.z());  dataString += String("\t");
dataString += String(acc.x());  dataString += String("\t");
dataString += String(acc.y());  dataString += String("\t");
dataString += String(acc.z());  dataString += String("\t");

//Receive values from PMCDA app:
while (Serial1.available()>0){
  dataString += Serial1.readStringUntil('>');
}

//Save values into the SD card:
File dataFile = SD.open(filename, FILE_WRITE);
// if the file is available, write to it:
if (dataFile) {
  dataFile.println(dataString); dataFile.close();Serial.println(dataString);  }
```

// if the file isn't open, pop up an error:

```
else {    Serial.println("error opening datalog.txt");  } }
```

Appendix I.2 Mobile Application Code (Android)

Set Bluetooth connection node between the App and the datalogger:

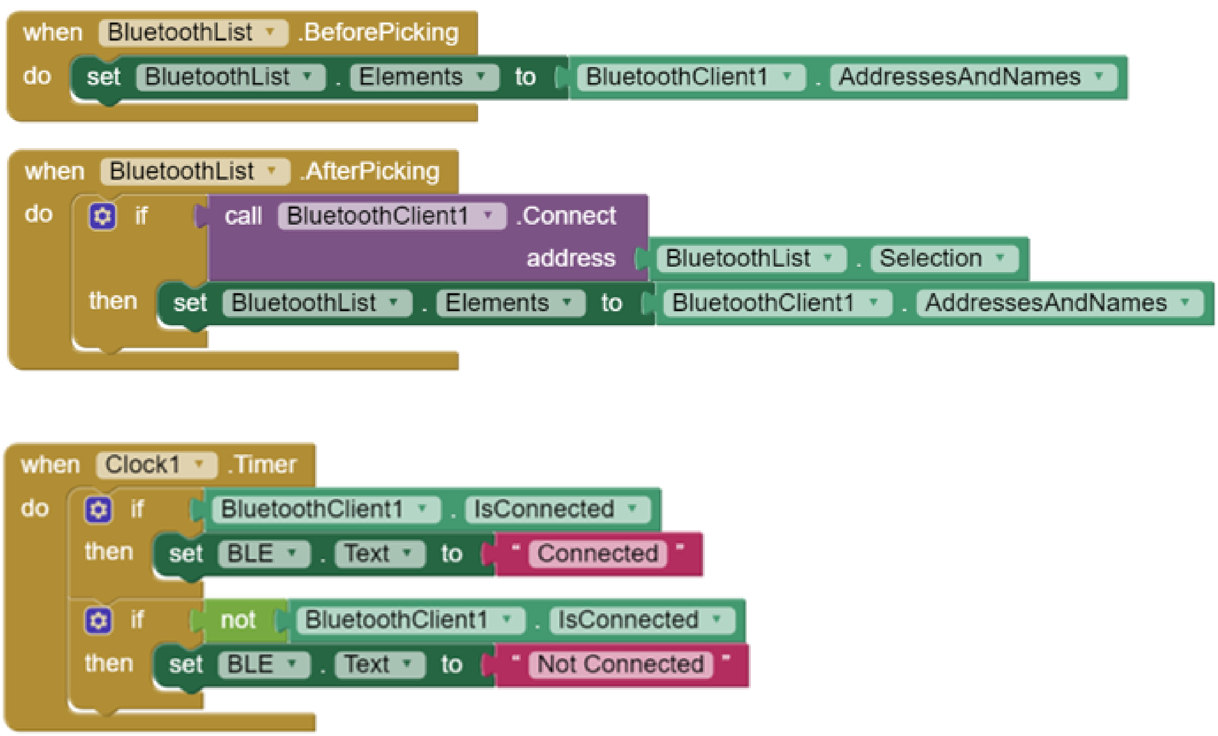

Figure 8: An image of node connections that enables communication between the app and the datalogger.

Save task and trial in a string package to send to the Datalogger:

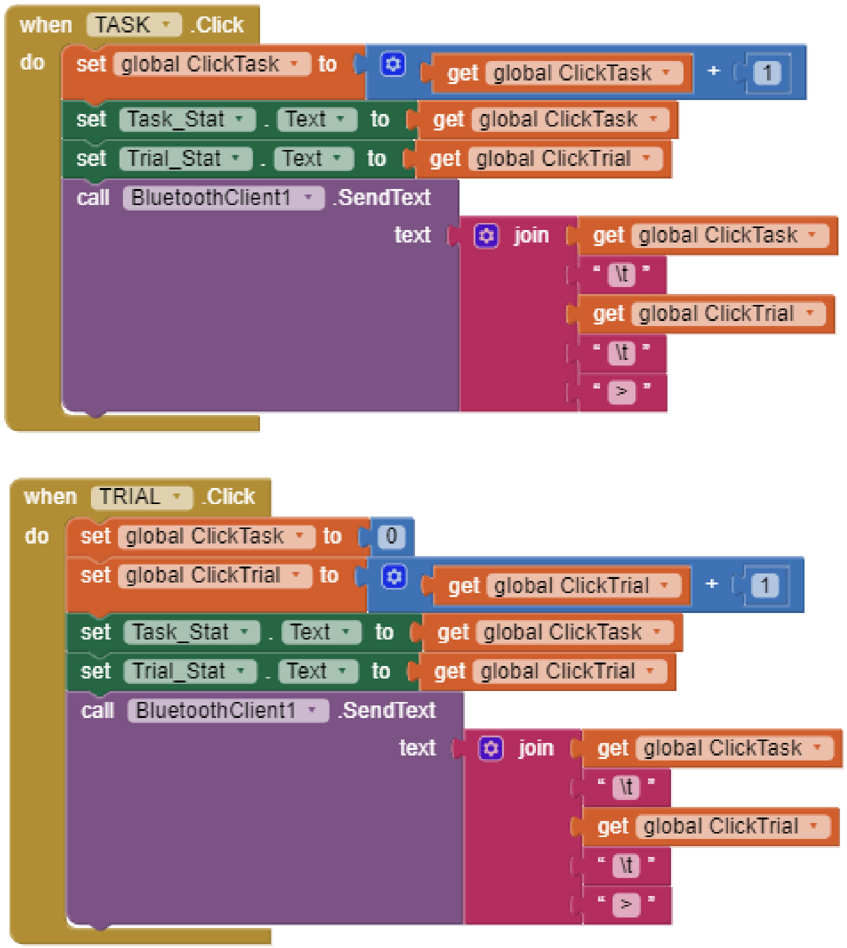

Figure 9: An image illustrating the setup to capture data in the application.

Appendix I.3 Matlab Code for computing Quantitative Driving Metrics

```
clear

clc

%cd /Users/matthewsivaprakasam/Desktop/MATLAB/HERLIMU/Fall2019
```

```
foldersp = dir('IMU_*');
folders = {};
for i = 1:length(foldersp)
    folders = horzcat(folders,['IMU_',num2str(i)]);
end
MAX_TRIALS = 3;


subjectzg = {};
subjectza = {};
subjectzp = {};
subjecttime = {};
subjectvelo = {};
subjectyp = {};
subjectya = {};
subjectxp = {};
subjectxa = {};
subjectnj = {}; %normalized jerk
subjectzac = {}; %axis crossings
subjectzav = {}; %z gyro average of absolute value
subjectxo = {}; %XYZ orientations
subjectyo = {};
subjectzo = {};
```

```
for i = 1:length(folders)
   %cd(folders(i).name);
   cd(folders{i});
   files = dir('DATA00*');
   trialszg = [];
   trialsza = [];
   trialszp = [];
   trialstime = [];
   trialsvelo = [];
   trialsyp = [];
   trialsya = [];
   trialsxp = [];
   trialsxa = [];
   trialsxa = [];
   trialsnj = [];
   trialszac = [];
   trialszav = [];
   trialsxo = [];
   trialsyo = [];
   trialszo = [];
```

```
for j = 1:length(files)
    filename = files(j).name
     data = dlmread([filename]);
     mkdir(['Data00' num2str(j) ' files']);
     cd(['Data00' num2str(j) ' files']);

     fidrms = fopen([filename,'RMSTable','.xls'],'w');
     %fidturn = fopen([filename,'TurnTable','.xls'],'w');

     %filter out values with same time stamp
     [~,idx, ~] = unique(data(:,1),'stable');
     data = data(idx,:);

     %% Clear temporary variables
     time = data(:,1);
     ax = data(:,2); %left(-)/right(+) (blue)
     ay = data(:,3); %back(-)/forth(+) (red)
     az = data(:,4)-9.8; %(yellow)
     gx= data(:,5);  %back(-)/forth(+) (blue)
     gy= data(:,6);  %rotation right(-)/left(+) (red)
     gz= data(:,7);  %CCW(+)/CW(-) (yellow)
     task = data(:,8);
```

```
trialnumber= data(:,9);
distances = [15 15 1000 8 1000 1000 8 10 1000 1000 8 1000 1000 1000 1000 1000
1000 1000 1000 1000 1000 1000 30 1000 1000];

%"Calibrate" data
ax = ax - mean(ax(1:50));
ay = ay - mean(ay(1:50));
az = az - mean(az(1:50));
gx = gx - mean(gx(1:50));
gy = gy - mean(gy(1:50));
gz = gz - mean(gz(1:50));

zgyrorms = [];
zpeaks = [];
zarea = [];
times = [];
velocities = [];
yjerkpeak = [];
yjerkavg = [];
xjerkpeak = [];
xjerkavg = [];
normjerk = [];
zaxiscross = [];
```

```
zav = [];
xo = [];
yo = [];
zo = [];
% figure (1)
% subplot(3,1,1)
% plot(time,ax,time,ay,time,az)
% legend('ax','ay','az')
% subplot(3,1,2)
% plot(time,gx,time,gy,time,gz)
% legend('gx','gy','gz')
% subplot(3,1,3)
% plot(time,task)

for x=1:(max(task)/2)
    tasknumber = 2*x-1;
    taskstart = find(task==tasknumber,1,'first');
    taskend = find(task==tasknumber,1,'last');
    m = taskend-taskstart;
    timetask = zeros(m,1);
    axtask = zeros(m,1);
    aytask = zeros(m,1);
    aztask = zeros(m,1);
```

```
gxtask = zeros(m,1);
gytask = zeros(m,1);
gztask = zeros(m,1);

for n=taskstart:taskend
    timetask(n+1-taskstart) = time(n);
    axtask(n+1-taskstart) = ax(n);
    aytask(n+1-taskstart) = ay(n);
    aztask(n+1-taskstart) = az(n);
    gxtask(n+1-taskstart) = gx(n);
    gytask(n+1-taskstart) = gy(n);
    gztask(n+1-taskstart) = gz(n);
end

if x == 17
    xlswrite([filename,'TurnTable','.csv'],[axtask, aytask, aztask, gxtask, gytask,
gztask]);
end

[b,a] = butter(4,.6,'high') ;
dyaccel = gradient(aytask(:)) ./ gradient(timetask(:));
dxaccel = gradient(axtask(:)) ./ gradient(timetask(:));
dzaccel = gradient(axtask(:)) ./ gradient(timetask(:));
```

```
%peaks
ylocs = [];
xlocs = [];
zlocs = [];
ztrapz = 0;
if length(dyaccel) > 3
   [pks, ylocs] = findpeaks(abs(dyaccel),'MinPeakHeight', rms(dyaccel)+2, 'MinPeakProminence', rms(dyaccel)/4);
   [pks, xlocs] = findpeaks(abs(dxaccel),'MinPeakHeight', rms(dxaccel)+2, 'MinPeakProminence', rms(dxaccel)/4);
   [pks, zlocs] = findpeaks(abs(gztask),'MinPeakHeight', rms(gztask)+2, 'MinPeakProminence', rms(gztask)/4);
   ztrapz = trapz(timetask,gztask);
end

%normalized jerk
combined = sqrt(dxaccel.^2 + dyaccel.^2 + dzaccel.^2);
normalized = sqrt(.5*sum(combined.^2)*(timetask(end)-timetask(1)));

times = vertcat(times, timetask(end) - timetask(1));
velocities = vertcat(velocities, distances(x)/(timetask(end) - timetask(1)));
zgyrorms = vertcat(zgyrorms, rms(gztask));
```

```
zpeaks = vertcat(zpeaks, length(zlocs));
zarea = vertcat(zarea, ztrapz);
yjerkpeak = vertcat(yjerkpeak, length(ylocs));
yjerkavg = vertcat(yjerkavg, mean(abs(dyaccel)));
xjerkpeak = vertcat(xjerkpeak, length(xlocs));
xjerkavg = vertcat(xjerkavg, mean(abs(dxaccel)));
normjerk = vertcat(normjerk, normalized);
%zaxiscross = vertcat(zaxiscross, length(find(gztask == 0)));
zaxiscross = vertcat(zaxiscross, length(gztask(gztask>-.1 & gztask<.1)));
zav = vertcat(zav, mean(abs(gztask)));

%calculate orientation
freq = 100;     %frequency: 150Hz
dt = 1/freq;     %seconds

pitch_gyro = zeros(length(axtask),1); roll_gyro = zeros(length(axtask),1);
pitch_com = zeros(length(axtask),1); roll_com = zeros(length(axtask),1);
yaw_gyro = zeros(length(axtask),1); yaw_com = zeros(length(axtask),1);

ax1 =zeros(length(axtask),1); ay1 = zeros(length(axtask),1); az1 =
zeros(length(axtask),1);

for i=2:length(axtask)
```

```
        ax1(i) = ax1(i-1) + 0.005*(axtask(i-1) - ax1(i-1));
        ay1(i) = ay1(i-1) + 0.005*(aytask(i-1) - ay1(i-1));
        az1(i) = az1(i-1) + 0.005*(aztask(i-1) - az1(i-1));
    end

    for i=2:length(axtask)
        pitch_gyro(i) = pitch_gyro(i-1) - gxtask(i-1)/(1/dt);
        roll_gyro(i) = roll_gyro(i-1) - gytask(i-1)/(1/dt);
        yaw_gyro(i) = yaw_gyro(i-1) - gztask(i-1)/(1/dt);
        %Complementary Filter
        pitch_com(i) = 0.98*(pitch_com(i-1) - gxtask(i-1)/(1/dt)) + 0.02*ax1(i-1);
        roll_com(i) = 0.98*(roll_com(i-1) - gytask(i-1)/(1/dt)) + 0.02*ay1(i-1);
        yaw_com(i) = 0.98*(yaw_com(i-1) - gztask(i-1)/(1/dt)) + 0.02*az1(i-1);
    end

    xo = vertcat(xo, rms(pitch_com));
    yo = vertcat(yo, rms(roll_com));
    zo = vertcat(zo, rms(yaw_com));
%     dyaccel = filter(b,a,dyaccel);
%     dxaccel = filter(b,a,dxaccel);

    %fprintf(fidrms, '%f\n', rms(gztask));
```

```
%    prexa = axtask;
%    preya = aytask;
%    for i =  2:length(prexa)
%        dxaccel(i) = dxaccel(i-1) + .1*(prexa(i-1)-dxaccel(i-1));
%        dyaccel(i) = dyaccel(i-1) + .1*(preya(i-1)-dyaccel(i-1));
%
%    end

%           figure(4)
%           subplot(5,5,x)
%           plot(timetask,dxaccel);
%           hold on;
%           plot(timetask(xlocs), dxaccel(xlocs), '*');

        if (x==1)
           title('Forth15','fontsize',8);
        end
        if (x==2)
           title('Back15','fontsize',8);
        end
        if (x==3)
           title('doorway','fontsize',8);
        end
```

```
if (x==4)
    title('1" threshold','fontsize',8);
end
if (x==5)
    title('10� up','fontsize',8);
end
if (x==6)
    title('6� down','fontsize',8);
end
if (x==7)
    title('potholes','fontsize',8);
end
if (x==8)
    title('cross','fontsize',8);
end
if (x==9)
    title('6� up','fontsize',8);
end
if (x==10)
    title('10� down','fontsize',8);
end
if (x==11)
    title('1" threshold','fontsize',8);
```

```
end
if (x==12)
    title('avoid ball','fontsize',8);
end
if (x==13)
    title('extra','fontsize',8);
end
if (x==14)
    title('transfer','fontsize',8);
end
if (x==15)
    title('sink','fontsize',8);
end
if (x==16)
    title('90� left','fontsize',8);
end
if (x==17)
    title('90� left door','fontsize',8);
end
if (x==18)
    title('stop','fontsize',8);
end
if (x==19)
```

```
    title('180�','fontsize',8);
end
if (x==20)
    title('90� reverse right','fontsize',8);
end
if (x==21)
    title('180�','fontsize',8);
end
if (x==22)
    title('90� right','fontsize',8);
end
if (x==23)
    title('30 straight','fontsize',8);
end
if (x==24)
    title('90�R door chairs','fontsize',8);
end
if (x==25)
    title('chairs 90�R door','fontsize',8);
end

%           figure(5)
%           subplot(5,5,x)
```

```
%          plot(timetask,dyaccel);
%          hold on;
%          plot(timetask(ylocs), dyaccel(ylocs), '*');


       if (x==1)
          title('Forth15','fontsize',8);
       end
       if (x==2)
          title('Back15','fontsize',8);
       end
       if (x==3)
          title('doorway','fontsize',8);
       end
       if (x==4)
          title('1" threshold','fontsize',8);
       end
       if (x==5)
          title('10� up','fontsize',8);
       end
       if (x==6)
          title('6� down','fontsize',8);
       end
       if (x==7)
```

```
    title('potholes','fontsize',8);
end
if (x==8)
    title('cross','fontsize',8);
end
if (x==9)
    title('6� up','fontsize',8);
end
if (x==10)
    title('10� down','fontsize',8);
end
if (x==11)
    title('1" threshold','fontsize',8);
end
if (x==12)
    title('avoid ball','fontsize',8);
end
if (x==13)
    title('extra','fontsize',8);
end
if (x==14)
    title('transfer','fontsize',8);
end
```

```
if (x==15)
    title('sink','fontsize',8);
end
if (x==16)
    title('90� left','fontsize',8);
end
if (x==17)
    title('90� left door','fontsize',8);
end
if (x==18)
    title('stop','fontsize',8);
end
if (x==19)
    title('180�','fontsize',8);
end
if (x==20)
    title('90� reverse right','fontsize',8);
end
if (x==21)
    title('180�','fontsize',8);
end
if (x==22)
    title('90� right','fontsize',8);
```

```
    end
    if (x==23)
      title('30 straight','fontsize',8);
    end
    if (x==24)
      title('90�R door chairs','fontsize',8);
    end
    if (x==25)
      title('chairs 90�R door','fontsize',8);
    end

%         figure(3);
%         subplot(5,5,x);
%         plot(timetask,gztask);
%         hold on;
%         plot(timetask(zlocs), gztask(zlocs),'*');

    if (x==1)
      title('Forth15','fontsize',8);
    end
    if (x==2)
      title('Back15','fontsize',8);
    end
```

```
if (x==3)
    title('doorway','fontsize',8);
end
if (x==4)
    title('1" threshold','fontsize',8);
end
if (x==5)
    title('10� up','fontsize',8);
end
if (x==6)
    title('6� down','fontsize',8);
end
if (x==7)
    title('potholes','fontsize',8);
end
if (x==8)
    title('cross','fontsize',8);
end
if (x==9)
    title('6� up','fontsize',8);
end
if (x==10)
    title('10� down','fontsize',8);
```

```
end
if (x==11)
   title('1" threshold','fontsize',8);
end
if (x==12)
   title('avoid ball','fontsize',8);
end
if (x==13)
   title('extra','fontsize',8);
end
if (x==14)
   title('transfer','fontsize',8);
end
if (x==15)
   title('sink','fontsize',8);
end
if (x==16)
   title('90� left','fontsize',8);
end
if (x==17)
   title('90� left door','fontsize',8);
end
if (x==18)
```

```
    title('stop','fontsize',8);
end
if (x==19)
    title('180�','fontsize',8);
end
if (x==20)
    title('90� reverse right','fontsize',8);
end
if (x==21)
    title('180�','fontsize',8);
end
if (x==22)
    title('90� right','fontsize',8);
end
if (x==23)
    title('30 straight','fontsize',8);
end
if (x==24)
    title('90�R door chairs','fontsize',8);
end
if (x==25)
    title('chairs 90�R door','fontsize',8);
end
```

```
        end
%
% %         figure(1); suptitle('Subject Data');

%         figure(5); suptitle('Y Jerk');
%         figure(4); suptitle('X Jerk');
%         figure(3); suptitle('Z Gyroscope');
%
%
%         saveas(figure(3), [filename,'ZgraphGyro.jpg']);
%         saveas(figure(5), [filename,'YgraphJerk.jpg']);
%         saveas(figure(4), [filename,'XgraphJerk.jpg']);
       close all;
       cd ..;

      trialszg = horzcat(trialszg, zgyrorms);
      trialszp = horzcat(trialszp, zpeaks);
      trialsza = horzcat(trialsza, zarea);
      trialstime = horzcat(trialstime, times);
      trialsvelo = horzcat(trialsvelo,velocities);
      trialsyp = horzcat(trialsyp, yjerkpeak);
      trialsya = horzcat(trialsya, yjerkavg);
      trialsxp = horzcat(trialsxp, xjerkpeak);
```

```
    trialsxa = horzcat(trialsxa, xjerkavg);

    trialsnj = horzcat(trialsnj, normjerk);

    trialszac = horzcat(trialszac, zaxiscross);

    trialszav = horzcat(trialszav, zav);

    trialsxo = horzcat(trialsxo, xo);

    trialsyo = horzcat(trialsyo, yo);

    trialszo = horzcat(trialszo, zo);


end

cd ..;


 subjectzg = horzcat(subjectzg, trialszg);

 subjectzp = horzcat(subjectzp, trialszp);

 subjectza = horzcat(subjectza, trialsza);

 subjecttime = horzcat(subjecttime, trialstime);

 subjectvelo = horzcat(subjectvelo, trialsvelo);

 subjectyp = horzcat(subjectyp, trialsyp);

 subjectya = horzcat(subjectya, trialsya);

 subjectxp = horzcat(subjectxp, trialsxp);

 subjectxa = horzcat(subjectxa, trialsxa);

 subjectnj = horzcat(subjectnj, trialsnj);

 subjectzac = horzcat(subjectzac, trialszac);

 subjectzav = horzcat(subjectzav, trialszav);
```

```
    subjectxo = horzcat(subjectxo, trialsxo);
    subjectyo = horzcat(subjectyo, trialsyo);
    subjectzo = horzcat(subjectzo, trialszo);
end
%
 alldata = {subjecttime,subjectvelo,subjectzg,subjectzp,subjectza,subjectyp, subjectya, subjectxp, subjectxa, subjectnj, subjectzac, subjectzav, subjectxo, subjectyo, subjectzo};
% titles = {'time','velocity','z gyro','z num peaks','z AUC','y num peaks', 'y avg', 'x num peaks', 'x avg'};
%
%
% %%plot each figure as a task, each figure containing subjects horizontally
% %%and variables as the horizontal graphs
%
% %for each task (figure), for each variable, for each patient, get data
% for i= 1:size(subjectzg{1},1)
%     figure(i+20);
%
%     for j = 1:length(alldata)
%         subplot(length(alldata), 1, j);
%
%         bardata = [];
%         subject = alldata{j};
```

```
%         for k = 1:length(subject)
%             dataset = subject{k};
%             dataelement = dataset(i,:);
%             while length(dataelement) ~= MAX_TRIALS
%                 dataelement = horzcat(dataelement,NaN);
%             end
%             if k == 7
%                 dataelement = [0 0 0];
%             end
%             bardata = vertcat(bardata,dataelement);
%         end
%         bar(bardata);
%         title(titles{j});
%     end
%     set(gcf, 'Position',  [100, 100, 1500, 1500])
%     suptitle(['Task ', num2str(i)]);
%     saveas(gcf,['Task ',num2str(i),'.jpg']);
% end


%%%%generate master table
%for each subject for each variable print its values for each trial
datatable = [];
subjcol = [];
```

```
trialcol = [];

for i = 1:length(subjectzg)

    subtable = [];
    for j = 1:length(alldata)
        variable = alldata{j};
        subject = variable{i};
        trialstable = [];
        for k = 1:size(subject,2)
            if j == 1
                subjcol = vertcat(subjcol,i);
                trialcol = vertcat(trialcol, k);
            end

            trialstable = vertcat(trialstable,subject(:,k)');
        end
        subtable = horzcat(subtable, trialstable);

    end
    datatable = vertcat(datatable, subtable);

end
```

```
datatable = horzcat(subjcol, trialcol, datatable);
xlswrite('MasterTableNew.xls', datatable);

% filename = 'newer';
% saveas(figure(23), [filename,'ZgraphGyro.jpg']);
% saveas(figure(21), [filename,'Times.jpg']);
% saveas(figure(22), [filename,'Velocities.jpg']);
% saveas(figure(24), [filename,'ZPeak.jpg']);
% saveas(figure(25), [filename,'ZAUC.jpg']);
% saveas(figure(26), [filename,'YPeak.jpg']);
% saveas(figure(27), [filename,'YAvg.jpg']);
% saveas(figure(28), [filename,'XPeak.jpg']);
% saveas(figure(29), [filename,'XAvg.jpg']);

%subjects are a cell of arrays, each containing the trial numbers for each
%variable

% for i = 1:length(subjectzg)
%
%     figure(9);
%     subplot(length(subjectzg),1,i);
%     subject = subjectzg{i}; %contains cells containing rows
```

```
%    bar(subject);
%
%    figure(10);
%    subplot(length(subjectzg),1,i);
%    subject = subjecttime{i}; %contains cells containing rows
%    bar(subject);
%
%    figure(11);
%    subplot(length(subjectzg),1,i);
%    subject = subjectvelo{i}; %contains cells containing rows
%    bar(subject);
%
%    figure(12);
%    subplot(length(subjectzg),1,i);
%    subject = subjectyp{i}; %contains cells containing rows
%    bar(subject);
%
%    figure(13);
%    subplot(length(subjectzg),1,i);
%    subject = subjectya{i}; %contains cells containing rows
%    bar(subject);
%
%    figure(14);
```

```
%     subplot(length(subjectzg),1,i);
%     subject = subjectxp{i}; %contains cells containing rows
%     bar(subject);
%
%     figure(15);
%     subplot(length(subjectzg),1,i);
%     subject = subjectxa{i}; %contains cells containing rows
%     bar(subject);
%
%     figure(16);
%     subplot(length(subjectzg),1,i);
%     subject = subjectzp{i};
%     bar(subject);
%
%     figure(17);
%     subplot(length(subjectzg),1,i);
%     subject = subjectza{i};
%     bar(subject);
%
% end
%
% figure(9);
% title('Z Gyro');
```

```
%
% figure(10);
% title('Time');
%
% figure(11);
% title('Velocities');
%
% figure(12);
% title('Y Num Peaks');
%
% figure(13);
% title('Y Average');
%
% figure(14);
% title('X Num Peaks');
%
% figure(15);
% title('X Avg');
%
% figure(16);
% title('Z Num Peaks');
%
% figure(17);
```

```
% title('Z Area');


% filename = 'Overall';

% saveas(figure(9), [filename,'ZgraphGyro.jpg']);

% saveas(figure(10), [filename,'Times.jpg']);

% saveas(figure(11), [filename,'Velocities.jpg']);

% saveas(figure(12), [filename,'YPeak.jpg']);

% saveas(figure(13), [filename,'YAvg.jpg']);

% saveas(figure(14), [filename,'XPeak.jpg']);

% saveas(figure(15), [filename,'XAvg.jpg']);
```

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