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Neuroergonomic Assessment of Wheelchair Control Using Mobile fNIRS

Shawn Joshi, Roxana Ramirez Herrera, Daniella Nicole Springett, Benjamin David Weedon, Dafne Zuleima Morgado Ramirez, *PhD*, Catherine Holloway, *PhD*, Helen Dawes, *PhD,* and Hasan Ayaz, *PhD*

***Abstract*—For over two centuries, the wheelchair has been one of the most common assistive devices for individuals with locomotor impairments without many modifications. Wheelchair control is a complex motor task that increases both the physical and cognitive workload. New wheelchair interfaces, including Power Assisted devices, can further augment users by reducing the required physical effort, however little is known on the mental effort implications. In this study, we adopted a neuroergonomic approach utilizing mobile and wireless functional near infrared spectroscopy (fNIRS) based brain monitoring of physically active participants. 48 volunteers (30 novice and 18 experienced) self-propelled on a wheelchair with and without a PowerAssist interface in both simple and complex realistic environments. Results indicated that as expected, the complex more difficult environment led to lower task performance complemented by higher prefrontal cortex activity compared to the simple environment. The use of the PowerAssist feature had significantly lower brain activation compared to traditional manual control only for novices. Expertise led to a lower brain activation pattern within the middle frontal gyrus, complemented by performance metrics that involve lower cognitive workload. Results here confirm the potential of the Neuroergonomic approach and that direct neural activity measures can complement and enhance task performance metrics. We conclude that the cognitive workload benefits of PowerAssist are more directed to new users and difficult settings. The approach demonstrated here can be utilized in future studies to enable greater personalization and understanding of mobility interfaces within real-world dynamic environments.**

***Index Terms*—Neuroergonomics, Cognitive Workload, Functional Near Infrared Spectroscopy, Manual Wheelchair Control, Assistive Devices.**

I. Introduction

Wheelchairs have been one of the most common and widely accepted assistive devices for individuals with limitations in mobility for over two centuries [1, 2]. While typical manual wheelchairs can increase independence and allow users to better engage in their environment, information is lacking on the performance, both mentally and physically, of both traditional and emerging design interfaces particularly within realistic environments [3]. Furthermore, wheelchair control is a complicated motor task that increases both the cognitive and physical workload of an individual [4].

Cognitive load/workload (CL) embodies the limited information processing capacity of the brain demanded by a task or environment [5]. As environmental or task demands increase, a subsequent increase in CL is generated – if these demands exceed the brain's maximum processing capacity task performance inevitably declines [6]. Accidents, injuries, and errors are a result of poor task performance and high CL [7]. CL incorporates the interplay between the environmental demands (input), human characteristics (capacities), and task performance (output) on the operator [8, 9].

New or difficult tasks require increased attention and executive control leading to recruitment of the frontal lobes. The prefrontal cortex (PFC) is often monitored for CL due to its functional relationship with working memory [10, 11], decision making [12, 13] and executive control [14, 15]. The PFC also regulates motor coordination, acquisition, and timing based on environmental feedback [16]. Understanding the factors in reducing/optimizing CL in the effort of improving task performance is important, particularly within the context of operating complex machinery, as improper handling can lead to serious injuries, economic burden, and other maladies to and from the user [17, 18]. This is aligned with the field of Neuroergonomics – the study of the brain in natural environments and real-world tasks as opposed to artificial lab environments with simplified tasks [19-25].

Manual wheelchair control can be likened to operating heavy machinery. The dangers of having excessive CL while operating a wheelchair are numerous and can lead to serious injuries or property damage (to wheelchair or environment). Poor control can even lead to fatal and non-fatal accidents further impacting mobility, resulting in activity restriction, less social participation, and a reduced quality of life [26]. Injury prevention during wheelchair control can involve reducing the CL impact, by reducing the physical load (demands of the environment) [27, 28], or increasing physical capacity (human characteristics) [29].

Electric wheelchairs can allow users to reduce the negative physical impact of wheelchair control by bypassing their individual power constraints. The use of electric wheelchairs

S. Joshi, and H. Ayaz are with the School of Biomedical Engineering, Science and Health Systems at Drexel University, Philadelphia, PA 19104 USA. (e-mail: sj633@drexel.edu).
R. Ramirez Herrera, D. Z. Morgado Ramirez, and C. Holloway are with the Computer Science Department at University College London, London, WC1E 6BT England.
D. N. Springett, B. D. Weedon, and H. Dawes are with the Oxford Institute of Nursing, Midwifery, and Allied Health Research at Oxford Brookes University. Oxford, OX3 0BP England.

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can reduce both strain injuries and metabolic demand, allowing users to travel further and in more difficult terrain than traditional manual control [30]. However, electric wheelchairs can predispose users to a less active lifestyle, leading to lifelong health complications related to inactivity (obesity, cardiovascular disease, etc.) [31, 32].

Power Assisted Devices (PADs) can provide a user with the extra physical capacity of electric wheelchairs, while continuing to promote the beneficial physical activity that a traditional manual wheelchair propulsion extends [29]. PowerAssisted Wheelchairs are controlled similarly to a traditional manual wheelchair but are fitted with small electric motors to augment the user's physical capacity. While PADs have inherent design problems, they are being increasingly adopted among manual Wheelchair Users (WU) [33]. However, information is lacking regarding the CL implications of PADs, as research has been limited towards the user's physical aspects of this novel interface [29, 34, 35].

Until recently, it has been extraordinarily challenging to monitor CL in active environments including wheelchair propulsion. CL has been measured using increasingly direct, precise and objective methodology, from subjective self-reports [23], performance-based measures [36], to more direct physiological, or neurophysiological measures [37]. Furthermore, the literature emphasizes the importance of direct neurophysiological measures, as they can evaluate brain activity/CL continuously, and with more precise spatial and temporal acuity [38, 39].

fNIRS is a non-invasive optical neuroimaging technique that can be used to monitor the cortical hemodynamic response relatively similar to the functional Magnetic Resonance Imaging (fMRI) but using a wearable sensor. fNIRS is portable, user-friendly, relatively inexpensive, with rapid application times and resistant to motion artifacts posing it as a good candidate for neuroimaging on the go during physical activity and within natural environments [9, 40]. It uses near infrared light between 650nm and 950nm range [41] to measure brain activity via cortical oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) concentration changes evoked by motor and cognitive tasks [42, 43]. Improvements in fNIRS has led to miniaturized, wireless, and battery-operated hardware, and improved signal quality and motion artifact rejection signal processing techniques, to allow for minimally-intrusive investigations of cortical activity in physically active tasks and environments [9, 19, 44-48].

Wheelchair control is a complex motor task conducted within natural environments where over-recruitment of the PFC can lead to decreased performance and safety. Furthermore, the PFC is an important part of the indirect locomotor pathway, which is activated when the automatic execution of a motor task is impaired (e.g. in complex and challenging environments)[49, 50]. Therefore, it is imperative that new clinical strategies to objectively assess assistive technologies are developed and must import neuroergonomic considerations in the development of new wheelchair/mobility devices. The objective of this study was to determine the operator-environmental-machine interactions on CL and evaluate how the intervention/augmentation of PADs influence wheelchair operator behavior and brain activity. This paper set out to assess a new generation assistive mobility device and its effects on CL between two user groups – novice and experienced – out of laboratory settings through task performance metrics and neural hemodynamic monitoring.

II. Methods

Forty eight participants (22 males) were recruited and were either novice (n = 30; 31.8 ± 9.0 yrs) or experienced (n = 18; 33.4 ± 13.5 yrs). Only those physically capable of controlling a manual wheelchair for over an hour, and without mental impairment or recent physical injury were recruited. All participants completed a Physical Activity Readiness Questionnaire (PAR-Q) [51] and were determined to be eligible for participation. All participants reported normal or corrected-to-normal vision. Experienced WU are those whose primary means of locomotion involves the use of a manual wheelchair. Novice wheelchair users were abled-bodied participants who had no previous experience propelling a wheelchair.

The study was conducted at the Oxford Brookes Sports Hall in Oxford, UK with approval obtained from the University Research Ethics Committee.

A. Measurements and Devices

The manual wheelchair frame (QUICKIE LIFE R), weighing 10.5kg, was fitted to each participant to traverse two environments (see section B). The wheelchair accommodated a 45cm seat width (all participants were comfortably adjusted) and used the M24 Alber Twion (Alber GmbH, Albstadt, Germany) PowerAssist wheels (6kg each). The PowerAssist offers two maximum speed settings: 6km/h and 10km/h. The last one was chosen as the 6km/hr setting could impact/cap an individual's speed and affect results even given that the average manual wheelchair user propels at a speed of 4km/hr. From the three modes that the device had (eco, sport, and auto), we chose the eco mode. This was preferred as it required more physical effort than the sport mode (meant for outdoor activity) and over the auto mode that switches between sport and eco modes at an inconsistent frequency.

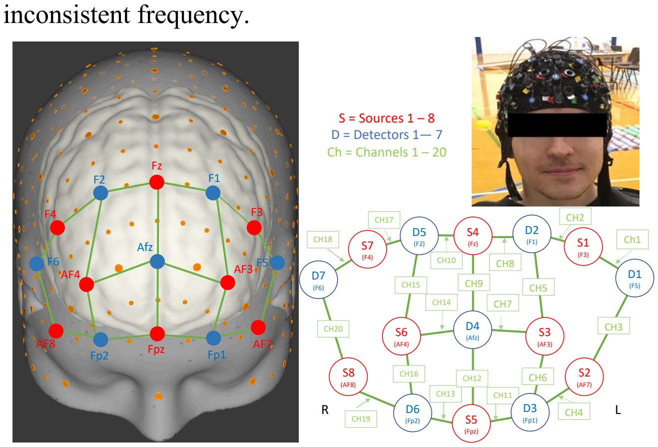

Fig. 1. fNIRS Sources (Red) and Detectors (Blue) form 20 channels (green) overlaid on a human scalp (left). The Source (S1-S8) and Detectors (D1-D7) montage that creates the layout for visualizing the results (bottom right). The experimental fNIRS set up photo is also displayed (top right).

Participants wore a portable fNIRS sensor (NIRSport from NIRx Medical Technologies LLC, NY, USA) positioned over the forehead. fNIRS channel placement was standardized according to the established international 10-20 system for the eight light source and eight detector placements (see Fig. 1)

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[52]. The inter-optode distance of approximately 3 cm formed 20 channels (measurement areas) sampled at 7.81Hz. Cortical regions with landmarks for the experimental configuration were generated using fNIRS Optodes Locator Decider (FOLD) toolbox [53, 54] with the Laboratory of Neuroimaging (LONI) Probabilistic Brain Atlas (LPBA40) [55]. Table 1 below shows the channel according to source detector pair EEG labelling with 'x-y-z' configuration coordinates and brain area/landmark specificity for improved comparability and reproducibility. All sessions were video recorded using a GoPro Hero Action Digital.

TABLE I
FNIRS POSITIONS AND BRAIN LOCATIONS

Channel: Source - Detector	Brain Area	Specificity (%)	D (mm)	X (mm)	Y (mm)	Z (mm)
1: F3 – F5	mFG$_L$	74.22	29	-45	35	23
2: F3 – F1	mFG$_L$	87.01	29	-30	38	39
3: AF7 – F5	iFG$_L$	87.56	34	-47	42	4
4: AF7 – Fp1	iFG$_L$	53.57	31	-34	56	-4
5: AF3 – F1	mFG$_L$	80.24	44	-24	50	30
6: AF3 – Fp1	mFG$_L$	90.79	30	-26	60	5
7: AF3 - Afz	mFG$_L$	55.88	39	-16	59	21
8: Fz – F1	sFG$_L$	74.89	30	-11	40	47
9: Fz - Afz	sFG$_L$	48.54	40	0	48	37
10: Fz – F2	sFG$_R$	75.09	28	11	40	48
11: Fpz – Fp1	mFG$_L$	50.16	31	-14	64	-3
12: Fpz - Afz	sFG$_L$	47.28	41	-1	61	11
13: Fpz – Fp2	mFG$_R$	51.58	30	14	65	-3
14: AF4 - Afz	mFG$_R$	52.67	37	15	59	22
15: AF4 – F2	mFG$_R$	75.53	43	23	51	31
16: AF4 – Fp2	mFG$_R$	91.67	30	26	61	6
17: F4 – F2	mFG$_R$	82.62	29	29	40	40
18: F4 – F6	mFG$_R$	87.56	28	46	38	24
19: AF8 – Fp2	iFG$_R$	52.77	30	34	58	-4
20: AF8 -F6	iFG$_R$	88.89	33	47	45	4

Column 1 represents the Channel: Source – Detector (i.e. 1: F3 – F5). Column 2 represents the Brain Areas, where i = Inferior, m = Middle, s = Superior, FG = Frontal Gyrus, L = Left, and R = Right. Column 3 represents the specificity to the primary brain area, where secondary brain areas have less specificity. Column 4 displays the distance between the source and detector, and Columns 5-7 represent the MNI coordinates.

Errors were recorded manually by two researchers during the experiment and additionally verified using the video-recorded from the experiment. It consisted on totaling the number of errors per obstacle for a final total error count. Higher error counts implied worse performance, and higher potential for injury. Additional task performance metrics include average speed and completion time per circuit.

B. Environmental Design

Two types of environment (simple and complex) were designed. The simple environment was a flat path that is free of obstacles. It formed the outer circuit of 13 m x 14 m for a total distance of 54 m, and the complex environment incorporated four separate obstacles and was the inner circuit of 36 m. Each obstacle (approximately 7 m) had 1 m of free space at both ends to provide sufficient buffer before the subsequent obstacle. Obstacles were built to represent real-world wheelchair conditions, two of which required more strength (Rough Terrain and Incline Ramp), and two which required more coordination (Uneven Slope/Side Slopes and Maneuvering/Weaving). The experimental setup is displayed in Figure 2 and described below. The environments were set with guiding lines for participants to follow.

All obstacles were designed in accordance to safety standards described within the wheelchair manual, as well as the American Disability Association (ADA) 2010 guidelines [56]. All errors were tabulated when the user shifted off the obstacle path, hesitated or abruptly stopped during transit, or bumped into obstacles, ignored obstacles, or crossed predetermined safety markings. The obstacles are detailed below 1-4 and depicted (see Fig. 2).

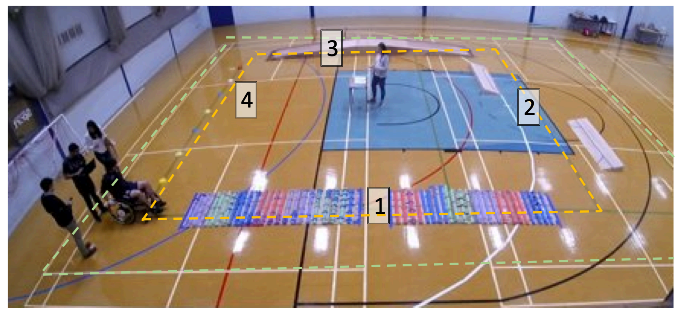

Fig. 2. Experimental setup, including outer simple environment (green) and inner complex environment (yellow) with the 4 obstacles (numbered within the figure, and described below) in the Oxford Brooks Sports Hall, numbered in order.

1) *Rough Terrain*
Required control over a high friction surface, mimicking carpet, grass, or unsmooth flooring.

2) *Side Slopes/Uneven Slope*
Required balancing during transit of two angled slopes, each 2.4 m and 0.70 m apart, with a gradient of 10° and set at 20 cm high (safety tested for balance). One slope was approached with the left wheel while the other with the right to give an unbalanced sensation mimicking approaches to curb ramps.

3) *Incline Ramp*
Required ascending and descending a 5° slope to a flat platform. This was to mimic accessible standard ramps in public buildings.

4) *Maneuvering/Weaving*
Required weaving or maneuvering in between 7 cones set 0.92 m apart, mimicking the minimum acceptable accessible door width, and or situations with many fixed objects within the path.

C. Experimental Setup

Participants navigated each circuit in both clockwise and counterclockwise directions alternating every 4 circuits during the experiment to avoid asymmetrical strain/exhaustion. A pseudorandomized predetermined circuit order per participant was conducted to reduce a repetitive learning effect. The study design employed a 2x2 within subject design (environment x interface). Ultimately, participants completed 8 repetitions of both the simple (free of obstacles) and complex environments (with obstacles), with four repetitions of the PAD, and four repetitions of traditional manual control totaling 16 circuits.

Participants completed each circuit at a self-selected pace, allowing environments to be comparable by completion time.

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Participant's pace was determined to be within ±5s of their initial circuit time (complex environment without PowerAssist) and instructed to make the fewest errors. This was an unobtrusive way to control for effort, and account for both fatigue and learning. Rest period prior to each circuit (30-50s) facilitated a more stable physiological baseline of fNIRS signals. Each individual circuit completion time was recorded.

C. Signal Processing and Statistical Analyses

NIRS data was recorded via NIRStar (v15.0) and processed via NIRS AnalyzIR toolbox [57, 58]. One participant (from the Novice User Type) was removed as the data had significant motion contamination. Therefore 47 participants' data were used within this study (29 novices and 18 experienced). The data were pre-whitened to resolve high frequency noise, cardiovascular effects, and signal drift using an autoregressive model [57]. The differential path length factor was calculated per subject [59]. Attenuation changes in the wavelengths (760nm and 850nm) were transformed to concentration changes of HbO and HbR respectively using the modified Beer-Lambert approach [40]. Wavelet filter was applied to HbO and HbR data to remove motion artifacts with a threshold of 5 standard deviations, and a wavelet basis function of sym8 [60]. Beta values calculated from HbO/HbR amplitudes for each block with local baseline (paired t-test: rest vs. circuit) per source-detector pair or channel for each task condition through subject-level autoregressive iteratively reweighted least squares General Linear Modeling. The parameter estimates were derived using a canonical HRF, as previous evidence suggests that tasks of duration longer than ten seconds, such as within this experiment, have better performance for testing hypothesis of difference response amplitudes [61]. The parameters of the canonical (double gamma function) HRF employed included: 1s as the dispersion time constants for the peak and undershoot period, 4s and 16s as the peak and undershoot time respectively, 1:6 as the ratio of main peak height to the undershoot, and 32s as the duration.

Statistical analysis of task performance metrics during the experimental procedure employed the use of GLM implemented in NCSS (NCSS, LLC. Kaysville, Utah, USA). The dependent measures (errors, speed, completion time), were assessed and parameter estimates derived. Bonferroni p-value adjustments were calculated to indicate significance for interaction effects. Cohen's d values were also calculated to indicate the observed effect size.

Group analysis employed mixed effects with repeated measures across the entire sample allowing for a population inference of both biometric and task performance measures. The subject factor was treated as a random effect drawn from a larger population, while the fixed effects were conditions of environment (simple vs. complex), interface (manual vs. PowerAssist) and user type (experienced vs. novices). Type I Errors were controlled using false detection rate (FDR) Benjamini-Hochberg adjustments [62, 63].

III. RESULTS

A. Task Performance Metrics

All 48 participants reported similar responses within the PAR-Q (no fatigue, sickness, alcohol intake, etc.) and were hence eligible for study participation. All 48-participant task performance metrics (number of errors, speed, time) were evaluated using GLM and presented in Table II. For the error and speed dependent variables, the fixed factors in GLM were interface type with 2 levels (PowerAssist and Manual), and user type with 2 levels (Experienced and Novice). For the error dependent variable, there were no statistically significant results ($p>0.05$) for any of the interactions or main effects. For the speed dependent variable, there were statistically significant results for the main effect of user type ($F_{1,764} = 70.11$ $p<0.001$, $d = 0.6241$), where the experienced group was 0.164 m/s faster than the novice group. However, there were no significant interactions with interface type.

TABLE II
Behavioral Results per User Type, Environment, and Interface

Factors	Conditions	Errors	Speed (m/s)	Time (s)
A	1: Novices	1.671±0.121	**0.663±0.012**	**71.937±0.963**
	2: Experienced	1.757±0.156	**0.826±0.015**	**62.767±1.243**
B	1: Simple	NA	NA	65.47±1.077
	2: Complex	NA	NA	69.234±1.077
C	1: Manual	1.786±0.135	0.739±0.013	68.329±1.077
	2: PowerAssist	1.642±0.135	0.75±0.013	66.375±1.077
A*B	1,1	NA	NA	71.685±1.362
	1,2	NA	NA	72.188±1.362
	2,1	NA	NA	59.253±1.759
	2,2	NA	NA	66.281±1.759
C*A	1,1	1.641±0.171	0.661±0.017	72.543±1.362
	1,2	1.93±0.222	0.817±0.022	64.115±1.759
	2,1	1.7±0.171	0.665±0.017	71.33±1.362
	2,2	1.583±0.22	0.836±0.022	61.42±1.759
C*B	1,1	NA	NA	65.026±1.523
	1,2	NA	NA	71.633±1.523
	2,1	NA	NA	65.914±1.523
	2,2	NA	NA	66.836±1.523

A represents the User Type, B represents the Environment, and C represents the Interface. Data displayed includes the mean ± standard error. Shaded boxes represent significant results *($p<0.05$). **Bold** represents significant results at higher significance *$p<0.001$.

For the circuit completion time dependent variable, the fixed factors in GLM were with two levels (PowerAssist and Manual), and user type with two levels (Experienced and Novice), and environment with two levels (Complex and Simple). As expected, there was a significant difference for user type ($F_{1,768} = 33.99$ $p<0.001$, $d = 0.4345$), where the experienced group completed their circuits on average of 9.17 s faster than novices, and a significant effect for environment ($F_{1,768} = 5.73$ $p=0.0169$, $d = 0.1784$), with the complex

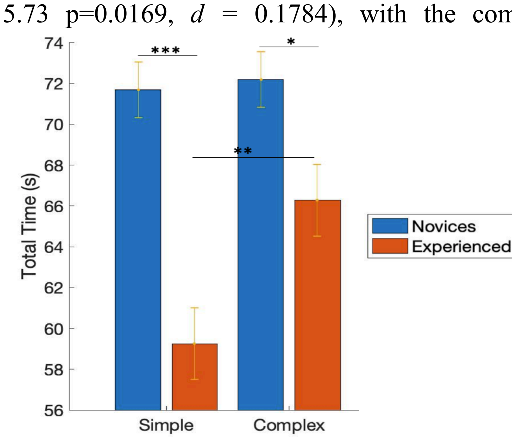

Fig 3. Circuit Completion Time between user type (novice and experienced) per environment (*$p<0.05$; **$p<0.01$; ***$p<0.001$). Novices were slower than experienced and found both environments equally difficult.

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environment taking an average of 3.76 s longer to be completed than the simple one. A significant interaction between user type and environment ($F_{1,768} = 4.30$ p=0.038, d = 0.1464) is depicted in Figure 3.

Novices had longer circuit completion times than Experienced WU regardless of environment, but similar circuit completion times between the two environments, whereas Experienced WU had higher completion times for the complex environment when compared to the simple one.

B. Functional Near Infrared Spectroscopy

Increased HbO (decreased HbR) is often associated with increased cortical activity, while decreased HbO (increased HbR) is often associated with decreased activity [64]. Within Figures 4-8, solid bars depict the regions of significantly increased or decreased PFC activity after FDR correction (q<0.05). According to the color-bar on the right-side of figures 4-8, red regions indicate increased HbO amplitudes via positive beta-values, while blue regions indicate decreased HbO amplitudes via negative beta-values.

All 47-participant fNIRS (per channel) were evaluated using GLM, with environment, interface type, and user type as fixed factors with subject as a random factor.

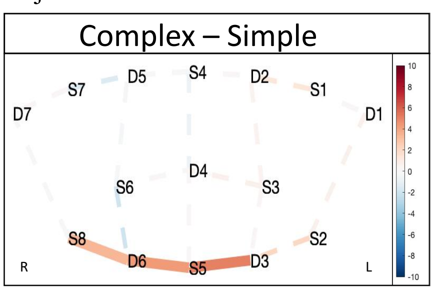

Fig 4. fNIRS results of 47 subjects, displaying PFC HbO comparing differences between Complex and Simple Environments. Environmental Complexity increased HbO within the middle frontal, and right inferior frontal gyrus. (FDR corrected, q<0.05)

Figure 4 depicts the brain activation difference between complex and simple environments for all 47 participants. Both the mFG and the right iFG of the PFC experienced significantly elevated HbO for the complex environment as to the simple, regardless of interface or user type. HbR was significantly increased in the same channels of the mFG as in Figure 4.

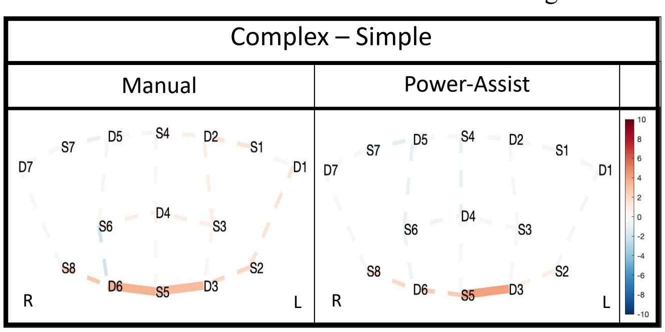

Fig 5. fNIRS results of 47 subjects, displaying PFC HbO differences between the Complex and Simple Environments for the Manual and PowerAssist Interfaces. The use of the PowerAssist interface led to fewer activated regions of the middle frontal gyrus. (FDR corrected, q<0.05)

Upon further evaluation, when exploring the effect of interface within the environmental differences, the use of the PowerAssist feature was more effective than traditional manual control, resulting in fewer regions of increased HbO (see Fig. 5). HbR only significantly increased in a similar channel under manual control as in Figure 5 left.

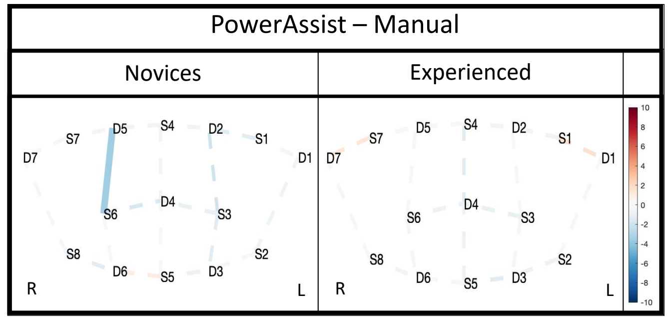

Fig 6. fNIRS results of 29 novices and 18 experienced WU, displaying PFC HbO comparing interface effect (PowerAssist – Manual). The PowerAssist Interface decreased HbO for novices (left) and played no role in differing activation patterns for experienced users (right). (FDR corrected, q<0.05)

No overall significant differences between the manual and PowerAssist interface were found, however upon further evaluation of user type within the interface differences, the PowerAssist feature was more effective in reducing HbO (Right mFG) for novices, and had no significant effect for experienced WU (See Fig. 6) (t(188) = -4.3185, p = 0.002, d = -0.6299). HbR only showed a significant increase in HbR within the mFG for experienced WU. Furthermore, this CL reduction due to the PowerAssist interface was consistent for novices within the complex environment, but not within a simple flat environment (see Fig. 7). HbR results were complimentary to the results displayed in Figure 7 right, with an increased HbR in the same channel.

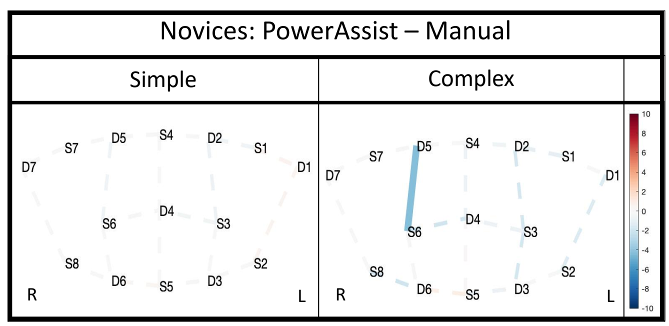

Fig 7. fNIRS results of 29 novices and displaying PFC HbO comparing interface effect (PowerAssist – Manual). The PowerAssist Interface decreased HbO for novices within the complex environment only (right) and played no role in differing activation patterns in the simple environment (left). (FDR corrected, q<0.05)

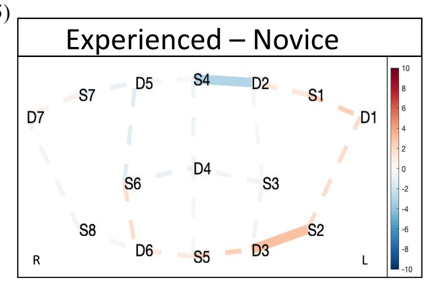

Fig 8. fNIRS results of 47 subjects, displaying PFC HbO comparing differences between Experienced and Novice WU. Wheelchair Experience increased HbO within the right dorsal middle frontal gyrus, and decreased HbO within the right ventral middle frontal gyrus. (FDR corrected, q<0.05)

Figure 8 depicts the brain activation differences between experienced and novice WU for 47 participants. The left

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inferior frontal gyrus had significantly increased HbO (t(188) = 3.0611, p = 0.0337, *d* = 0.4465), and the left superior frontal gyrus had significantly decreased HbO (t(188) = -3.0675, p = 0.0337, *d* = *-0.4474*) for experienced WU. HbR results showed significant decreases for experienced WU compared to novices within the mFG and sFG.

Upon further evaluation, when exploring the effect of environment within user type differences, only the complex environment led to increased HbO in the right inferior frontal gyrus (see Fig. 9) (t(188) = 3.6967, p = 0.0229, *d* = 0.5392). HbR results were complimentary to the results displayed in Figure 9, with a decrease specifically for the complex environment in the iFG.

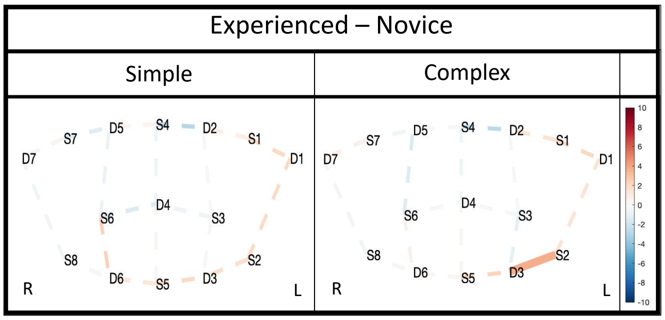

Fig 9. fNIRS results comparing 29 novices and 18 experienced WU, displaying PFC HbO between environments (Simple and Complex). The Complex Environment lead to increased HbO for experienced WU (right) and the Simple Environment (left) played no role in differing activation patterns between Experience Groups. (FDR corrected, q<0.05)

Furthermore, upon exploring the effect of wheelchair interface within user type differences, the manual interface led to increased HbO of the left inferior frontal gyrus (t(188) = 3.1056, p = 0.0409, *d* = 0.453) (see Fig. 10 left) while the PowerAssist interface led to decreased HbO within the left superior frontal gyrus (t(188) = -3.0793, p = 0.0409, *d* = -0.44916) (see Fig. 10 right). HbR results were complimentary in the mFG with a decrease during manual control, and a decrease in the mFG during PowerAssist.

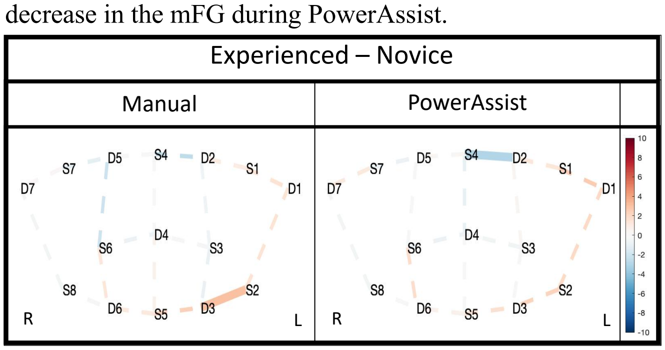

Fig 10. fNIRS results comparing Experience Groups interaction with different Interfaces, displaying PFC HbO. The manual interface lead to increased HbO for experienced WU (left) and the PowerAssist interface decreased HbO for those with more experience. (FDR corrected, q<0.05)

IV. Discussion

Excessive workload can lead to serious injuries, increased economic burden, and other maladies to and from the user [18, 65]. This can further impact mobility, resulting in activity restriction, affecting social participation, health and wellbeing and quality of life [26]. Wheelchair control is a more complicated, and physically demanding activity compared to walking and any effort to lessen and investigate these factors during real-world navigation can lead to newer devices that may further independence, and equality for these marginalized populations [66].

This study set out to apply the Neuroergonomics approach [67] to explore the effects of environment, user type and interface for wheelchair control. We designed environments with everyday scenarios WU navigate. Additionally, experienced WU (whose main means of locomotion involves daily use of a wheelchair) were recruited as well as people new to wheelchair use (novices), in order to gain an understanding of how experience of wheelchair control may interplay with other factors and impact dependent variables.

A. Cognitive Workload Impact of Environmental Conditions

Environmental complexity as related to task demands, are correlated with increased CL [68], and within this study, both task performance metrics and brain measures yielded complementary information, giving strong evidence that a complex environment can lead to increased CL within wheelchair control. Specifically, the complex environment led to increased time (see Table I) and increased HbO within the mFG and iFG (see Fig. 4). The mFG plays a critical role within reorienting attentional control to behaviorally relevant environmental information [69], as well as motor inhibition [70]. The iFG is important in attentional, and inhibitory control of motor skills [71, 72]. The mFG, and iFG are involved within dual-task performance involving motor tasks [73].

B. Cognitive Workload Impact of Interface Conditions

The results (see Table I) indicated that the PowerAssist and manual interface had equal (no significant difference) error performance within a complex environment. Additionally, the PowerAssist interface did not significantly increase speed or decrease completion time as hypothesized. These suggest that the PowerAssist interface may be behaviorally similar to a typical manual wheelchair interface, with less physical effort, but with no improvement to function/safety consistent with a recent survey [33]. Furthermore, the overall use of the PowerAssist interface did not lead to different, or decreased CL within either the inferior, middle, or superior frontal gyri.

However, it is of noticeable importance that different user types experienced the interfaces differently (see Fig. 10). The manual interface increased CL within the iFG more for experienced WU than novices. This is further supported by Woods et. al, where it was found that the iFG had greater activation for experienced individuals during familiar conditions [74] (i.e. manual wheelchair control). This gives evidence that those with expertise are more attuned to familiar motor tasks and have greater activation in brain areas regarding motor planning. Additionally, the left sFG had decreased HbO (see Fig. 10 right) in line with research demonstrating that it is often deactivated during cognitive-related processing [75]. This deactivation was more pronounced for experienced WU than novices when using the PowerAssist interface, implying that WU during PowerAssist may activate the default mode network (DMN) or task-negative mode, a large scale brain network that is considered to be involved with involuntary actions, because their tasks became or perceived to be significantly more simple [75, 76].

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C. Cognitive Workload Impact of Expertise

Overall user type was not associated with any particular decrease in error reduction, however, did lead users to be significantly faster and therefore more efficient. Increased expertise can lead to decreased CL (determined via evaluation of speed/timing [36]) and is supported within this study's task performance metrics which offer an indirect insight in CL. This information is further validated by the brain measures (see Fig. 8) where the difference of user type led to a different pattern of activation (increased HbO within the iFG, and decreased within the sFG) [74-76]. sFG is known to contribute to higher cognitive functions particularly working memory, with particular regard to spatial cognition [77]. Furthermore, previous studies suggest that the supplementary motor areas may extend into parts of the sFG, playing a role in higher cognitive processing within motor control [78].

Furthermore, similar information between the performance and brain measures were found when exploring the interaction effects of environment on expertise. In Figure 3, the complex environment led to an increased completion time only for experts when compared to the simple environment. Novices had the same completion time for both environmental conditions, and both were significantly higher compared to experienced individuals. Similarly, the complex environment showed an increase in HbO within the iFG (see Fig. 9, right). In the simple environment, no brain activity difference (see Fig. 9, left). On the contrary, completion time showed a significant difference between user types (increased time and hence CL for novices). This may represent that at the same brain activity level, those with expertise are able to achieve better performance (and therefore more efficient) as suggested by neural efficiency concept [79-81].

D. Holistic Outlook

In summary, the neuroergonomic approach within this study highlights the importance of a comprehensive evaluation opportunity in identifying the CL impact of wheelchair interfaces and dynamics environments by combining brain and behavioral performance measures. As new generation assistive devices emerge, it becomes more important to investigate their mental workload implications within ecologically valid settings. While there are no current study publications that these results can be similarly compared to, a recent clinical trial evaluating the physical workload between three different PADs suggest similar findings of increased performance with the use of each PAD over traditional manual control [82] which are similar to our own findings involving ECG before [83].

E. Limitations and Future Work

In this study, we applied a new generation of mobile and wearable neuroimaging to measure prefrontal function of physically active participants. We were only able to monitor the prefrontal cortex due to the limitations of the available sensors, however other brain areas including the motor and parietal cortices could be informative in future studies. Additionally, no short-separation channels were used which could have been useful to reduce the influence of systemic physiological artefacts arising from superficial blood flow [84]. Furthermore, we conducted the experiment in an indoor controlled facility. However, wheelchair studies involving even more realistic conditions and actual everyday settings can offer more insights. Future work may involve the assessment of cognitive decline for wheelchair control, as many WUs experience cognitive impairment, and the use of power assistive wheelchairs may play an important role.

V. Conclusions

In summary, this is the first study to our knowledge, using a comprehensive neuroergonomic approach to monitor CL implications of environmental complexity, different wheelchair interfaces, and user experience levels with mobile fNIRS in a real-world setting with actual experienced WU. Our findings support the importance of a comprehensive assessment methodology, using integrated task performance and neurocognitive metrics. Across all subjects, environmental difficulty reduced wheelchair performance and increased brain activity. Secondly, the augmentation of PowerAssist did reduce the mental effort burden specifically for novices, and even more specifically for novices within the more difficult environment. This is important because it could provide better conditions for motor learning of safe maneuvering especially in more complex environments. Finally, brain activity differences between experienced and novices only emerged again only during the more difficult complex environment.

Ultimately, real-world mobile brain imaging can offer unique insights for the personalization of mobility devices, and assessing the effectiveness of newer mobility interfaces, or their interaction with different environmental difficulties in wheelchair control for both new and experienced users. Understanding the factors in reducing/optimizing the cognitive workload within disability interfaces and motor tasks like wheelchair control is vital to improve daily life.

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