8-2020

Social participation performance of wheelchair users using clustering and geolocational sensor's data

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Abstract— **For wheelchair users, social participation and physical mobility play a significant part in determining their mental health and quality of life outcomes. However, little is known about how wheelchair users move about and engage in social interactions within their life-spaces. In this project, we investigate the social participation performance of the wheelchair users based on a combination of geolocational and lifestyle survey data collected over a period of three months. This paper adopts a multi-variate approach combining geolocational travel patterns and various factors such as independence, willingness and self-perception to provide multi-faceted analysis to their lifestyles. We provide profiles of wheelchair users by combining these factors in an empirical analysis. With our users' geolocational data, we can demonstrate the influence of other factors on wheelchair users' social participation performance with regards to life-space mobility.**

I. INTRODUCTION

Improvements in Quality of Life (QOL) is a goal that many strive towards. It has been known that higher QOL has impact on a person's positive psychology [1]. For Wheelchair Users (WCUs), key established indicators of QOL are (1) physical mobility and (2) social participation, which have both been proven to be positively correlated with QOL [2].

The relationship between physical mobility and QOL of WCUs is an intuitive one - disability reduces one's mobility, resulting in lifestyle changes due to certain activities being no longer possible to perform. Subsequently, any factors that might help increase mobility allows them to re-establish their past livelihoods by empowering them to perform activities that might have brought meaning [3]. Thus, by simply having access to a wheelchair, WCUs can enjoy significant improvements in mobility, and can subsequently go about their lives with lesser difficulty.

The focus on this study, which is the concept of social participation, was first introduced in the World Health Organization's International Classification of Functioning, Disability, and Health (WHO-ICF) in 2001. The term has since become widely recognized as a measure of the standard of living for disabled or elderly persons, and thus a key goal of rehabilitation. However, there is no consensus on the definition of social participation. A previously conducted taxonomy found and analyzed 43 definitions of social participation and categorized it according to the following levels: (1) interacting with others without doing a specific activity with them, (2) doing an activity with others, (3) helping others, and (4) contributing to society. For the purposes of this study, we refer to social participation at the first level, where interactions are deemed to have taken place by virtue of proximity, in a public setting, to individuals who are otherwise not present in the WCU's household.

Given the many currently existing definitions of social participation, identifying key indicators of social participation has also proven to be a difficult task. Previous studies have identified many factors that are correlated with higher levels social participation. For example, social participation levels have been found to be: (1) correlated with levels of physical activity in WCUs [3][4], and (2) influenced by socio-economic attributes of individual WCUs [3][5]. Furthermore, a more recent meta-analysis of 35 peer-reviewed studies implied that social participation occurs mostly when the WCUs are not using their wheelchairs [6], giving rise to the possibility that there is more to the interactions between mobility and social participation than what is currently known. The same study went on to identify other factors such in categories such as body function, activity, participation in other aspects of life, environmental, and self-perceptual (personal) factors as shown in Table I.

TABLE I

FACTORS AFFECTING SOCIAL PARTICIPATION, BY CATEGORY

Category	Modifiable	Non-Modifiable
Body function	BMI, Confidence, Grip strength, Incontinence	Level of injury, Vision
Activity	Average speed travelled, Wheelchair skills	
Participation	Employment, Sports involvement	
Environmental	Caregiver concerns, Transportation, Wheelchair factors	Climate, Societal attitudes
Personal	Finances, Education level, Marital status	Age, Sex, Race, Years since injury, Num of Comorbidities

The WHO-ICF also presents performance as a complementary qualifier, which is used to identify actions, or the "lived experience" of a disabled individual in their environment, bearing in mind the social context. Limited efforts have been made in studying the social participation performance of WCUs alongside relevant studies on capacity. The first study to investigate both aspects combined the participants perceived community participation levels, represented by the Craig Handicap Assessment Recording Technique (CHART) scores, with actual mobility metrics (distance, speed, movement time) where they found significant correlations between

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WCU capacity and performance [4].

Much of the existing literature to date can be categorized by two approaches: (1) by focusing on technical aspects such as GPS tracking, or (2) by focusing on self-reported lifestyle measures gathered via human surveys. The former revealed the ground truth of participation, but lacked insight into individual preferences and capacity, while the latter exposes studies to accuracy issues, stemming from limitations in recall ability and possibilities of perception bias in WCUs.

From a technological standpoint, we can find various interesting uses of technology in past studies. The works of Malu and Findlater [7] relied on electronic health and fitness trackers to understand the topics of travel and immobility in patients. The work done by Grillion et al. [8] employed wireless sensors for manual wheelchair users to recognize activities of varying levels of intensity, allowing self-tracking of movement. In similar fashion. The SmartBFA (Smart Mobility and Accessibility for Barrier-Free Access) [9] project designed a scalable and sustainable system that automated the collection of routes used by WCUs. The work aimed to classify and determine accessible point-to-point routes to address interconnection gaps in first- and last-mile BFA paths for persons requiring barrier-free access (such as wheelchair users), then plot the barrier-free routes onto a map to be used by the WCUs.

Recognizing the limitation that the reliability of these self-reported lifestyle measures cannot be tested in the overwhelming majority of previous studies due to the lack of supporting behavioral data, we combined both the lifestyle measures and geolocational data from the sensors to better understand the behaviour and travel patterns of the wheelchair users. In addition, we also used the self-reported data as the participants' perceived capacity (the ability to execute a task or an action) to engage in social participation.

The key contribution of the paper is our methodology of combining both lifestyle measures and geolocation data (as the ground truth) to identify the characteristics of the WCUs who were not satisfied with their levels of social participation. This may lead to impactful real-world intervention by social workers to address the needs of these WCUs to create positive influence on their lifestyles and mental health.

II. OBJECTIVE

Given our access to a combination of geolocational data pertaining to the WCUs actual movements within their life-spaces and self-reported data, this study seeks to expand on the then unprecedented approach by Oyster et al. [4] in comparing capacity and performance. Thus, this study will present a comparison between the WCUs perceived social participation capacity, defined by self-reported information, and their actual social participation performance, as reflected by their geolocational information. We seek to determine, if any, distinctive patterns of performance in WCUs across different contributory factors ranging from social-economic to self-perceptual. This study expects to find no significant deviations between self-reported capacity and performance values and recorded performance values.

III. HYPOTHESIS

Bearing in mind the data that we have been given access to, which includes features such as: (1) tech-enablement score, (2) self-reported participation, (3) self-rated opportunity to participate, (4) self-reported willingness to participate, and (5) non-reliability on assistance in daily living (independence), this study puts forth the following hypotheses.

Hypothesis 1: WCUs who self-report higher performance levels will exhibit similarly higher actual performance.

Hypothesis 2: WCUs who self-report higher capacity levels will exhibit higher actual performance levels.

Hypothesis 3: WCUs which have higher levels of self-reported willingness to participate will also exhibit higher levels of physical activity.

IV. DATA ANALYSIS

A. Data Collection

The data of the project was derived from the SmartBFA (Smart Mobility and Accessibility for Barrier-Free Access) [9]. Sensors were mounted on wheelchairs to facilitate the collection of geolocational data. The sensors data allowed us to study how WCUs move and travel. The data was collected from 70 volunteers (WCUs) referred to participate by various community organizations across Singapore. We used a set of anonymized data which comprises the following two parts:

1) Self-reported lifestyle measures: The data comes from a 53-question face-to-face survey requiring responses related to lifestyle and access to technology (e.g., internet access, smart phone). The data columns and the categories are as shown in Table II.

TABLE II

DATA DICTIONARY OF THE SURVEY

Type	Data Columns
Demographic	gender age ethnicity language education google map usage employment smartphone ownership internet access
Travel	frequency distance mode planning habits factors discouraging travel wheelchair type weight items carried obstacles faced reasons for obstacles faced
Enabling Lives	reliance on support degree of social participation degree of family participation degree of community participation degree of economic participation opportunity to participate in social life opportunity to participate in community life opportunity to participate in family life opportunity to participate in economic life

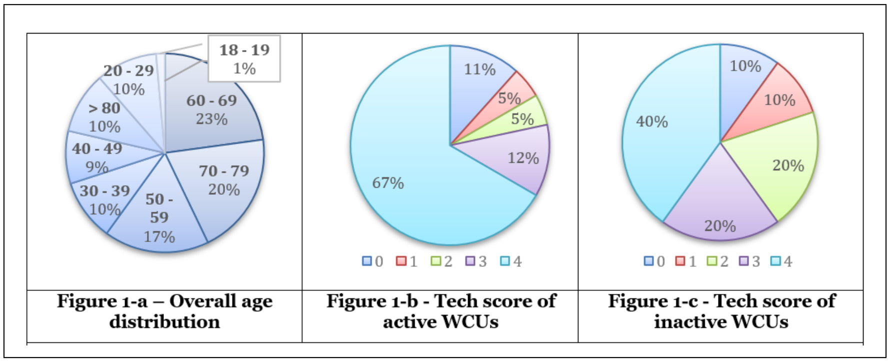


Fig. 1. Demographic and Tech Scores of the participants

2) Geolocational data tracked by sensors: The data is collected from each WCU via a wheelchair-mounted device, consisting of a GPS and a set of sensors. When switched on, it collects data such as GPS coordiantes, date, and velocity at 100 millisecond intervals. The information is uploaded online whenever it has access to local area network such as when the WCU reaches home.

Geolocational data is stored on a private repository in the AWS S3 service in the form of compressed GPS logs in minute intervals. We extract the information pertaining to the location and distances travelled by the 70 volunteers and merge the minute-long logs into an overall comma separated table (CSV) per volunteer. Data retrieval, extraction and preprocessing are done using the Python. Of the data from 70 volunteers available to our study, due to technical challenges in extraction and cleaning, we selected the GPS data of 22 of the volunteers based on criteria such as data completeness for our geolocational analysis.

B. Exploratory Analysis on Self-Reported Lifestyle Measures

The respondents comprised 54% males. 31% of the WCUs are employed, with the other 69% either gainfully unemployed, or currently seeking jobs. Chinese WCUs account for most of the participants at 67%, followed by 17% Indian, 12% Malay, 3% Eurasian and 1% of other ethnicities. 85% of the participants go out of the house more than 4 times a week, with the remainder going out 3 times or less, or barely at all. Furthermore, Elderly WCUs make up the main bulk of the volunteers, with 60% being 50 and above (Figure 1-a). By categorizing the 70 volunteers by their physical activity levels, with, (1) active WCUs going out of the house for more than 3 times a week on average and (2) inactive WCUs leaving their houses on an average of 3 days a week or less, we see that active users are more likely to have higher tech-enablement scores than the inactive ones (see Figure 1-b, Figure 1-c). Tech-enablement score is a reflection of the WCU having access to smartphones, mobile broadband, home broadband and navigation apps such as google maps. We also compare the self-reported capacity and performance levels of our volunteers. Participation is reflected by the survey questions regarding current participation levels in community, economic, family and social life (see Table II), while opportunity is reflected by the questions pertaining to the WCUs opportunity to participate in said areas. In Table III, we provided exploratory comparisons of the participation and opportunity scores for active and inactive users.

For the purposes of the study, we will use participation scores as a self-reported performance measure and opportunity scores as a self-reported capacity measure. The actual participation performance is derived from the geolocational data analysis, by considering the travel patterns and distances.

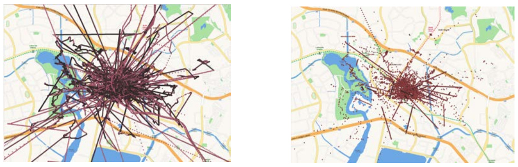
TABLE III
PARTICIPATION (PART) AND OPPORTUNITY (OPP) SCORES FOR ACTIVE AND INACTIVE USERS

	Active		Inactive	
	PART	**OPP**	**PART**	**OPP**
Family	3.00	3.10	3.72	3.73
Social	2.50	2.70	3.32	3.32
Community	2.00	2.70	3.05	3.15

Further analysis of the survey data was done based on the self-reported measures. Our analysis were performed using (1) the Waikato Environment for Knowledge Analysis (WEKA) suite of machine learning algorithms, and (2) SciKit-Learn in Python. We first performed cluster analysis to determine the distinctive features of the WCU clusters, then followed by statistical tests for analysing significant differences between the means of self-reported measures and the actual performance levels of the volunteers.

C. Geolocational Analysis

GPS data is cleaned using Python and analyzed on QGIS. We first perform aggregation to reduce the granularity of our GPS data from 100 millisecond intervals to 1-minute intervals by obtaining the mean coordinate of each minute. Figure 2(a) and Figure 2(b) depict an example of the before and after of a volunteer. We trim GPS data that was logged when the volunteer was travelling above 5km/h to omit instances where the volunteer was likely to be in transit i.e., not interacting with his environment. Lastly, we conduct filtering to remove occurrences of the straight-line phenomena in our GPS data. These lines of GPS data spans across various impassable terrain and is not an accurate representation of WCU activity; travelling in a straight line is



(a) Geolocational Data Before Averaging

(b) Geolocational Data After Averaging

Fig. 2. Using averaging to handle Geolocation noises

extremely difficult over long durations given the obstructions from urban structures. One plausible explanation for said phenomena is interpolated data being automatically logged by the GPS device between points of time where GPS signal was lost and then regained. Further data processing steps were taken to filter the data for our analysis.

V. CLUSTERING ANALYSIS

A k-means cluster analysis was performed using data of all 70 volunteers to identify distinct groups of WCUs using their self-reported participation levels in likert scale of 1 to 5 on the following factors: (1) social, (2) family, (3) economic, (4) community life, (5) independence in daily living and (6) willingness to participate in out-of-home activities. Figure 3 shows the plot of k (number of clusters) vs inertia (i.e., sum of squared errors) which we use to determine an appropriate number of clusters. k is selected as 4 for our study. Upon clustering the WCUs, we found four cluster profiles with their characteristics as summarized in Table IV and cluster centroids are shown in Table V.

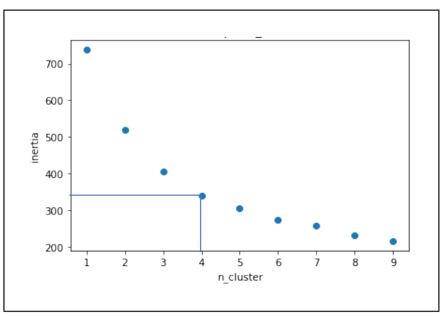


Fig. 3. Clustering inertia graph

TABLE IV
WCU CLUSTER PROFILES

Cluster No.	Characteristics
1	Able, Willing, Not Satisfied
2	Dependent, Less Willing
3	Able, Not Willing
4	Able, Willing, Satisfied

The decision tree (Figure 4) is generated using the j48 algorithm (c=0.25, min-obj=8) on all 53 attributes, after each WCU has been assigned a cluster number. We derive certain characteristics of each profile: The first group of WCUs (Cluster 1) are fairly independent, i.e., able to move around without assistance, and willing to participate in social activities. However, their self-rated performance levels are slightly lower than average, possibly because they are unsatisfied with their current amount of participation. This might be due to influencing factors such lack of opportunity to participate in social activities.

The second group of WCUs (Cluster 2) are highly reliant on support from caregivers to go about activities in their daily life. They are somewhat less willing to participate in social activities, perhaps being aware of the limits imposed upon them by virtue of their dependence on others. This group had a notably high self-rated participation in family life, indicating they felt able to participate in social activities in the family setting, most likely at home.

The third group of WCUs (Cluster 3) are also independent but unwilling to participate in social activities. This group demonstrated low self-reported ratings across all areas of social participation, likely because they simply do not venture outside the home to participate in such activities.

The last group of WCUs (Cluster 4), like the first, are also able and willing. For this group, their self-rated participation levels were also high across all areas, indicating satisfactions with their current levels of social participation, as well as their perceived ability to participate in family life. Notably, a significant number of WCUs in this category were holding jobs or could identify other kinds of tangible contributions they made to society.

VI. RESULTS

The results show below were generated based on data extracted from 22 out of the 70 participants, totaling an equivalent of 1043 manhours in GPS data. The analysis on the remainder 48 participants was not completed for this study due to challenges in the quality of data and the computational time required to process it. For example, some users did not consistently turn on the sensor equipment for tracking. The preliminary exploratory data analysis found that WCUs who self-report higher performance levels do not necessarily exhibit higher actual performance levels (Hypotheis H1). WCUs who self-report higher capacity levels did not neccesarily exhibit higher actual performance level (Hypothesis H2) compared to those who reported lower capacity levels. WCUs with higher levels of self-reported willingness to participate did exhibit higher levels of physical activity (Hypothesis H3).

A. Hypothesis 1: Self-reported performance levels and Actual performance levels

We show our analysis and results in Figure 5. Overall, there was a mean difference of 0.68 between self-reported performance (M=3.45) and actual performance (M=2.77) levels. A Wilcoxon signed-rank test showed that self-reported performance was significantly higher than actual performance at the 0.05 significance level (T = 14.0, p = 0.0029). Non-parametric test has been used for this analysis as the initial data exploratory analysis indicates that the differences

TABLE V
CLUSTER CENTROIDS

Cluster	Family participation	Economic Participation	Community participation	Social participation	Willingness	Degree of Independence
1	3.5769	2.3077	2.8846	3.2692	4.2692	4.6538
2	4.0833	1.4167	2.5833	2.9167	3.6667	1.25
3	2.25	1.5	2.0625	1.8750	1.6250	4.0625
4	4.6875	3.75	4.125	4.6250	4.4375	4.4375

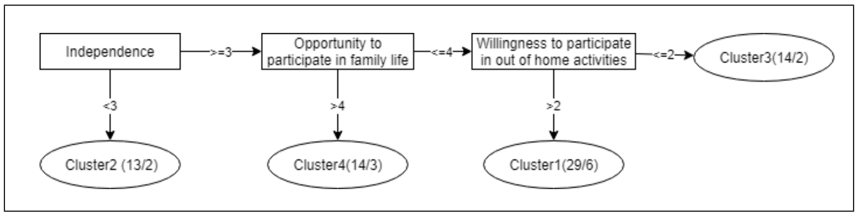


Fig. 4. Decision tree explaining the cluster characteristics

for the matched-pairs cannot be assumed to be normally distributed.

Further statistical tests conducted for the specific profiles enabled us to derive the following: (1) WCUs in cluster 1 had higher self-reported performance (M=3.45) compared to actual performance (M=2.77) levels. A Wilcoxon signed-rank test showed that the difference was significant at the 0.05 significance level (T = 0.0, p = 0.0114). (2) WCUs in cluster 2 displayed no difference between self-reported performance (M=3.33) and actual performance (M=3.33) levels. However, the cluster size was too small to perform any statistical tests, hence the overall interpretation remains inconclusive for this group. (3) WCUs in cluster 3 had slightly higher self-reported performance (M=2.8) compared to actual performance (M=2.6) levels. A Wilcoxon signed-rank test indicated that this difference was not significant at the 0.05 significance level (T = 2.0, p = 0.5637). Lastly, (4) WCUs in cluster 4 had the highest difference in terms of self-rated performance (M=3.67) and actual performance (M=2.67) levels. A Wilcoxon signed-rank test showed that self-reported performance was significantly higher than actual performance at the 0.1 significance level.

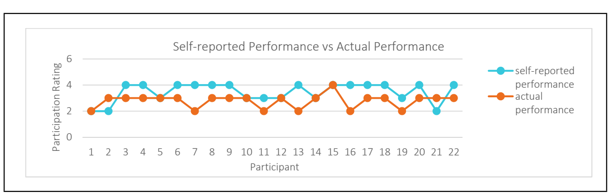


Fig. 5. Self-reported vs actual performance levels per participant

Therefore, when we examine the results in the context of the self-reported performance levels, we form two distinct groups: WCUs who self-report higher performance levels (cluster 1 and 4) and WCUs who self-report lower performance levels (cluster 2 and 3). The analysis found that the former does not actually exhibit similarly high actual performance levels, which does not support Hypothesis H1. On the other hand, self-reported and actual performance values seem to be similar for the latter. However, the results remain inconclusive on account of cluster 2. This is the group of people who are potentially feeling inadequate and dissatisfied with their quality of life. We recommend potential intervention from social worker to address any psychological and/or mental health concerns for the WCUs.

B. Hypothesis 2: actual performance levels of high capacity WCUs vs low capacity WCUs

We show our analysis and results in Figure 6. Given the self-reported opportunity to participate in social life, we are able to split our sample of WCUs into 2 group, namely one group which has high capacity WCUs who reported an opportunity score of > 3, and another group with low capacity group who reported an opportunity score of $<= 3$. The Mann Whitney-U test conducted (t=49.5, p=0.2430) showed no significant difference between the actual performance of the high capacity group (M=2.6667) against the actual performance of the low capacity group (M=2.8462).

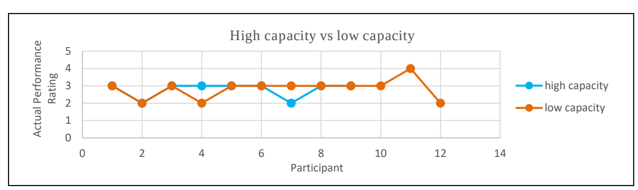


Fig. 6. Performance levels of high vs low capacity WCUs

C. Hypothesis 3: Self-reported Willingness to participate and Actual performance levels

To investigate our third hypothesis, participants were split into two groups: willing and unwilling, based on the mean value of participants' self-reported willingness scores. As seen in Figure 7, the average actual performance for the more willing group (M=2.82) was slightly higher than that of the less willing group (M=2.73). A Mann Whitney-U test conducted showed no significant difference in actual performance levels between the two groups (t=56.5, p=0.389).

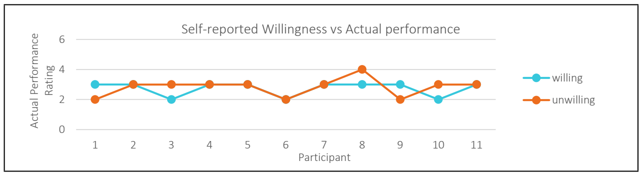


Fig. 7. Actual performance levels of willing vs unwilling WCUs

VII. CONCLUSION

This study found that self-reported performance levels taken from WCUs via surveys are often not representative of their actual performance level. WCUs who self-reported high levels of social participation performance had exhibited significantly lower levels of actual participation. Furthermore, social-participation capacity is not a perfect proxy indicator of actual social participation performance, as there was no significant difference between actual performance levels of WCUs with high capacity and low capacity. Thus, this study revealed that self-reported measures pertaining to levels of physical activity are not neccessarily accurate source of truth in the face of actual recorded performance as reported by the geolocational data from the sensors mounted on the wheelchairs. We hope that our study, and the insights it presented on the relationship between actual social participation performance vs performance capacity of WCUs, as shown through the gathered lifestyle and mobility data, can help welfare organizations in assisting WCUs in their efforts to attain better social participation, and contribute to their overall wellness.

VIII. FURTHER RESEARCH

The results from this study have highlighted several worthwhile areas for future interest. Further analysis on the data may reveal more insights, or allow exploration into an additional hypothesis regarding social participation of WCUs as compared to how tech-enabled they are. We hope further studies could enable insights into the movement patterns of WCUs, allowing analysis to be conducted on both the location, and duration of activity to derive meaningful results pertaining to the behaviors of WCUs belonging to the different profiles. We hope to derive solutions addressing societal issues (e.g., isolation of marginalized citizens in urban environment) from further investigations.

The insights presented in this paper may be subjected to the environmental context in which the data was collected. Further studies can be replicated in different geographical or cultural contexts to derive different sets of results. The study can also be replicated with a deeper focus on the different types of mobility devices that the WCUs may use (e.g., motorized scooters, manual wheelchairs). Furthermore, with increases in smartphone penetration, computer literacy, and social media usage, we cannot assume that social participation remains strongly bound by physical constraints. With WCUs being more able, and willing, to achieve social participation through social media platforms and the larger internet, there exists a growing opportunity for further research in these areas. Studies can be conducted to adequately measure and determine the impact of such platforms on the social participation of WCUs or people with disabilities in general.

We recognize that the study is limited by several factors. The insights were derived from a small sample size, as collected from a limited number of participants. The sample is also limited in geographical scope, with all participants being residents of Singapore. Further studies can be explored for a more varied geographical scope.

ACKNOWLEDGMENT

We thank the members of SmartBFA(Smart Mobility and Accessibility for Barrier-Free Access) for the data for analysis. The SmartBFA project is funded by Tote Board Enabling Lives Initiative Grant and supported by SG Enable.

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