Diagnosis, Assessment & Disease Monitoring

RESEARCH ARTICLE

Outdoor life in dementia: How predictable are people with dementia in their mobility?

Sayeh Bayat[1,2] | Alex Mihailidis[1,2,3]

[1] Institute of Biomedical Engineering, University of Toronto, Toronto, Ontario, Canada

[2] KITE Research Institute, Toronto Rehabilitation Institute, Toronto, Ontario, Canada

[3] Department of Occupational Science & Occupational Therapy, University of Toronto, Toronto, Ontario, Canada

Correspondence
Sayeh Bayat, Institute of Biomedical Engineering, University of Toronto, 550 University Avenue, Toronto, ON M5G 1X5, Canada.
E-mail: sayeh.bayat@mail.utoronto.ca

Abstract

Introduction: People with dementia (PWD) often become disoriented, which increases their risk of getting lost. This article explores the extent to which we can predict future whereabouts of PWD by learning from their past mobility patterns using Global Positioning System (GPS) tracking devices.

Methods: Seven older adults with dementia and eight healthy older adults completed 8 weeks of GPS data collection. We computed the probability that an appropriate algorithm can correctly predict the participant's future destinations using spatial and temporal patterns in each participant's GPS trajectories.

Results: Relying on both spatial and temporal patterns, our results suggest that a 4-week record of mobility patterns displays 95% potential predictability across the dementia group, which is significantly higher than 92% potential predictability among the controls, $t(13) = -3.39$, $P < .01$, $d = -1.75$. That is, we can hope to be able to predict destinations of PWD about 95% of the time and destinations of controls about 92% of the time.

Discussions: Our findings on predictability of mobility patterns among PWD offer new perspectives on predictive mobility models that can be used to locate missing persons with dementia.

KEYWORDS
assistive technology, cognitive decline, disorientation, Global Positioning System, life-space, machine learning, mobility

1 | INTRODUCTION

Globally the population of older adults is increasing rapidly.[1] More importantly, older adults prefer to continue living in their own homes and avoid moving to care settings for as long as possible.[2] Although most older adults can live independently, some may need support to maintain their independence. A major threat to maintaining an independent lifestyle in older age is dementia, particularly Alzheimer's disease (AD). Dementia impairs cognitive and functional abilities required for everyday functioning.[3] Spatial navigation, the ability to determine and maintain a trajectory from one place to another place, is a complex cognitive ability that when impaired is among the earliest indicators of dementia.[4] Due to impairments in navigational skills, people with dementia (PWD) may become lost and go missing in familiar or unfamiliar environments,[5] placing them at higher risk of injuries, falls, and mortality.[6–8] Considering these risks, there is an increased need for solutions that can support outdoor mobility of PWD.

In recent years, we have witnessed the increasing popularity of information and communication technologies (ICTs), ranging from Global Positioning System (GPS) devices to activity trackers. This

emerging state of ICTs provides a host of new opportunities for the development of assistive technology devices (ATDs) that support independent living and autonomous outdoor mobility for PWD.[9] The available solutions include various sensors such as GPS and allow for continuous monitoring by caregivers.[10–12] These systems often set a safe zone for an individual with dementia to navigate through. If the user exits the safe zone, the system sends a notification to the designated contact.[13] Although these monitoring solutions are able to increase the safety of PWD and provide peace of mind for the caregivers, their restrictive "one size fits all" framework does not meet the needs of PWD for autonomy and independence.[9,14] Furthermore, some other reliability- and usability-related limitations of these devices include low battery capacity and removal of the device by PWD.[15]

Recent advances in machine learning (ML) provide a vast set of tools to address these challenge areas and improve safety and care for PWD. Particularly, these advanced methods can be used to predict the future destinations of PWD based on their past mobility patterns.[16] The predictive mobility models can enable safe and autonomous outdoor mobility for PWD in two ways. First, by predicting the user's next destination, the system can detect when the user is deviating from a predefined target destination and select the most appropriate intervention, if necessary. Second, if the user removes the tracking device or the device's battery dies during an outdoor excursion, the system can still predict the user's location and help caregivers locate the user safely. However, despite its various benefits, little research has been conducted to study the applications of ML in the development of personalized and intelligent monitoring systems to support outdoor mobility needs of PWD. In a related study, Lin et al.[17] developed a data mining method to construct a personalized safe zone for PWD using their GPS trajectories. Although compared to the previous solutions this personalized approach can better address the needs of PWD for autonomy, it cannot ensure safety if the PWD removes the tracking device. Furthermore, this approach investigated mobility patterns of PWD at macro scale and is not suitable for the development of personalized navigational assistance devices that require micro-level analysis of mobility patterns. In another study, Wojtusiak and Mogharab Nia[18] developed a model for predicting locations of PWD that reached an accuracy of 0.66. However, for the predictive models to be incorporated in the design of outdoor mobility ATDs, performance has to be improved significantly.

To design more accurate predictive models, we first need to characterize the dynamics of the outdoor mobility of PWD. At present, there are a number of research studies characterizing the outdoor mobility patterns of PWD using passively collected GPS data. For instance, Tung et al.[19] measured the life-space mobility of individuals with AD from GPS data. Later, Bayat et al.[20] provided a more inclusive characterization of PWDs' mobility patterns, by introducing a GPS-based framework that quantified temporal, spatial, and semantic dimensions of outdoor mobility. For predictive modeling, however, it is important to understand what percentage of PWD's outdoor mobility pattern is regular and thus predictable, and what percentage of their mobility patterns is random and thus unpredictable. Although a number of studies on human mobility modeling have explored the inherent randomness

RESEARCH IN CONTEXT

1. **Systematic Review**: With the advances in machine learning and availability of location data, one can predict the future destinations of people with dementia (PWD) based on their past mobility patterns. Although these predictive models show great potential for enabling safe outdoor mobility for PWD, little research has been conducted to study them.
2. **Interpretation**: These findings highlight that relying on both heterogeneous spatial patterns of the movements and temporal order of the visitations, a 4-week record of the daily mobility patterns, on average, exhibits 95% potential predictability across the dementia group, meaning that 95% of the time, we can hope to predict the destinations of PWD correctly.
3. **Future Directions**: This study provides means to advance not only our understanding of mobility patterns of PWD, but also our approach to support safe outdoor mobility of PWD, making this area particularly receptive for new developments.

and regularity in mobility patterns,[21,22] there are no studies, to date, to quantify the predictability and randomness of mobility patterns of PWD. However, regularity and rhythm are the themes that have been raised in a number of qualitative studies on the daily lives of PWD, suggesting that PWD have a more structured and routine everyday life.[23,24]

Aiming to better capture the essence of mobility of PWD, in this article, we study the randomness and predictability manifested in GPS trajectories of PWD and compare it to the randomness and predictability manifested in GPS trajectories of cognitively intact older adults. Given the importance of a structured daily life for PwD, we hypothesized that the randomness of mobility patterns derived from GPS data will be lower and the predictability of mobility patterns derived from GPS data will be higher in a cohort of community-dwelling older adults with dementia compared to a cohort of cognitively intact older adults.

2 | METHODS

2.1 | Participants

This study included seven community-dwelling individuals (three females, four males) who had a diagnosis of dementia by a specialist and lived with a care partner. A control (CTL) group was formed by eight (three females, five males) cognitively intact community-dwelling older adults. For inclusion in the CTL group, potential candidates were screened for cognitive impairments using the Montreal Cognitive Assessment (MoCA) and the recommended cut-off score of 26 was

adopted.[25] Participants were recruited through the Baycrest Health Sciences database of research volunteers as well as printed and electronic advertisements on flyers, magazines, and social media sites. All participants were 65 years or older, lived in their own homes, and were from the greater Toronto area. We obtained informed consent from all participants, which was approved by the Baycrest Health Sciences Ethics Committee and the University Health Network Research Ethics Board.

2.2 | Measures

Functional abilities of the participants to perform basic activities of daily living were assessed using Katz Activities of Daily Living (ADL).[26] ADL scores range from 0, indicating high dependence to 6, indicating independence.[26] The Katz ADL is shown to be a valid and reliable index to identify disability in basic activities of daily living in older adults.[27] Furthermore, the participants' abilities to perform instrumental activities of daily living were assessed using Lawton-Brody Instrumental Activities of Daily Living (I-ADL).[28] I-ADL scores range from 0, indicating low function and dependence to 8, indicating high function and independence.[28] Previous studies have displayed reliability and validity of I-ADL comparing across versions.[29] Finally, participants were also assessed for comorbid conditions that significantly influence mobility using the Charlson Comorbidity Index (CCI).[30] CCI's reliability and validity have been assessed in different ways, and overall, it has shown to be a valid and reliable test.[31]

2.3 | GPS data collection

Location data were collected every 60 seconds using the SafeTracks Prime Mobile GPS device (SafeTracks GPS Canada). The SafeTracks Prime Mobile GPS device is proven to be reliable and valid for capturing outdoor mobility behaviors.[32] The participants were asked to place the GPS device in their pocket, purse, or bag and carry it with them when traveling outside their homes during the 8-week study period. Verbal and written instructions on how to wear, use, and charge the GPS device were given to the participants by the research team. Care partners of the PWD were also instructed on how to work with the device so that they could support their partners throughout the study. The GPS device was not worn overnight and during indoor activities. To increase compliance, the participants received reminder e-mails and phone calls every week.

2.4 | GPS data preprocessing

Because the standardized approaches for assessing older adults' outdoor mobility such as the life-space assessments examine movements in a 4-week period,[33] for each participant, we extracted 4 weeks of continuous GPS data recordings. Each participant's GPS recordings had at most 1 day of missing data. The trajectory segmentation method

described in Bayat et al.[32] was applied to extract the destinations visited by each participant. If GPS data went missing and the last known location of the user was in close proximity of a subway station, an underground transit trip was detected. Next, the extracted destinations were clustered using the method described in Bayat et al.,[32] and each destination was assigned a cluster ID. Finally, a time series of each participant's locations was built by segmenting the 4-week period into hour-long intervals and assigning a cluster ID to each interval.

## 2.5 | Measuring randomness of mobility patterns

To quantify how random (i.e., unforeseeable) the mobility patterns of each participant are, we look at three different entropy measures presented in Song et al.[21] First, we evaluate random spatial entropy, capturing the randomness present in the spatial distribution of participants' destinations. For an individual who has visited N destinations, random spatial entropy captures the randomness of their locations if each destination is visited with equal probability. Next, we compute heterogeneous spatial entropy to capture heterogeneity of visitations and consider the probability that a particular destination was visited by the participant in the past. Finally, we compute spatiotemporal entropy, which captures the heterogeneity of visitations, the sequence of destinations, and the time spent at each destination. Thus, spatiotemporal entropy provides the full spatial and temporal characteristics present in a person's mobility pattern.

2.6 | Measuring the maximum predictability of mobility patterns

To understand the predictability present in mobility patterns of a participant, we measure the probability that an appropriate predictive model can accurately predict their future destinations. Song et al.[21] showed that this quantity has an upper bound; meaning, if a participant with entropy S moved within N distinct locations, then the predictability of her mobility patterns has a maximum Π_{max}. To understand the predictability power of mobility patterns, we find the maximum predictability corresponding to each of the three entropy measures by solving $S = H(\Pi_{max}) + (1 - \Pi_{max})\log_2(N - 1)$ for Π_{max}. In this equation, $H(\Pi_{max})$ is the binary entropy function ($H(\Pi_{max}) = -\Pi_{max}\log_2(\Pi_{max}) - (1 - \Pi_{max})\log_2(1 - \Pi_{max})$).[21]

2.7 | Statistical analysis

All data are expressed as mean (M) ± standard deviation (SD). To assess the differences between PWD and cognitively intact CTLs, first, the Shapiro-Wilk test was performed to check the normality of the data in each group. If the data was normally distributed in both groups, a Levene's test was performed to assess homogeneity of variances. If there was not enough evidence to suggest that the variances are different between the groups, then Student's t-test was performed to examine
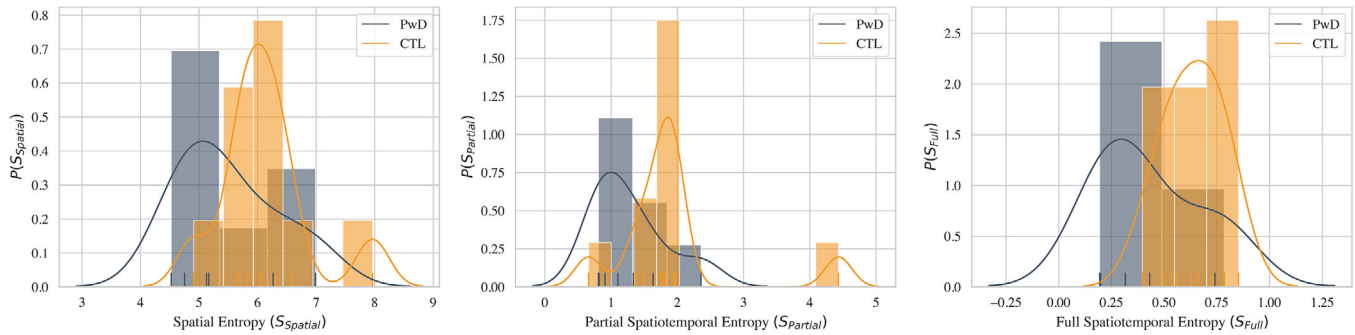
FIGURE 1 Group comparison results for the three randomness measures. CTL, control; PWD, people with dementia

the differences between the two groups. Otherwise, the group differences were examined using the Welch two-sample t-test. $P < 0.05$ between groups was considered statistically significant. To determine the effect size, Cohen's d coefficient was computed for t-tests.

3 | RESULTS

3.1 | Group characteristics

PWD were older compared to the CTLs (PWD vs. CTL: 79.3 ± 6.3 vs. 71.5 ± 5.2 years). Both groups had similar education level (PWD vs. CTL: 14.1 ± 3.4 vs. 16.5 ± 2.5 years), proportion of females (PWD vs. CTL: 43% vs. 44% females), and number of comorbidities (PWD vs. CTL: 2.14 ± 1.6 vs. 1.43 ± 1.2). The MoCA scores demonstrated cognitive impairment in PWD and normal cognitive function in the CTLs (MoCA scores: 15.3 ± 7.5 vs. 27.4 ± 1.4). PWD displayed lower levels of ability to perform I-ADLs (4.71 ± 1.70 vs. 8.0 ± 0.0) and physical ADLs (5.57 ± 2.99 vs. 6.0 ± 0.0). Finally, for each participant, GPS data from 27 to 28 days is included in the analyses (PWD vs. CTL: 27.4 ± 0.49 vs. 27.8 ± 0.43 days). According to the travel diary recordings, the most common reasons for missing GPS data were devices running out of charge and participants forgetting to take the device with them.

3.2 | Group comparisons in randomness measures

On average, PWD visited 16.0 ± 5.08 and cognitively intact CTLs visited 22.4 ± 9.37 unique destinations. Although PWD displayed a trend toward visiting fewer number of unique destinations compared to CTLs, this trend did not reach statistical significance, $t(13) = 1.45$, $P = 0.17$; d = 0.751. Furthermore, this trend is also displayed by spatial entropy. In fact, while there was a trend toward reduced spatial randomness in the mobility patterns of the dementia group (5.50 ± 0.874) compared to the CTL group (6.06 ± 0.327), the two-sample Student's t-test did not reach statistical significance, $t(13) = 1.69$, $P = 0.115$; d = 0.875. However, heterogeneous spatial entropy for the two groups differed significantly according to Student's t-test, $t(13) = 2.25$, $P < .05$; d = 1.16. The effect size for this analysis (d = 1.16) was found to exceed Cohen's large effect (d = .80). These results indicate that individuals

in the dementia group (1.28 ± 0.561) displayed lower heterogeneous spatial randomness in their mobility patterns than did individuals in the CTL group (1.77 ± 0.227). The 95% confidence interval (CI) of the difference is 0.019 to 0.95. Furthermore, spatiotemporal entropy also differed significantly between the two groups according to Student's t-test, $t(13) = 2.35$, $P < .05$; d = 1.21. The effect size (d = 1.21) exceeded Cohen's large effect. These results indicate that individuals in the dementia group (0.426 ± 0.224) displayed lower spatiotemporal randomness in their mobility patterns compared to the controls (0.657 ± 0.125). The 95% CI of the difference is 0.018 to 0.44. The group comparison results for the randomness measures are plotted in Figure 1.

3.3 | Group comparisons in predictability measures

The maximum predictability values extracted from the spatial entropy measures for all participants were zero. The group comparison results for the heterogeneous and spatiotemporal predictability measures are plotted in Figure 2. While there was a trend toward increased heterogeneous spatial predictability in the mobility patterns of the dementia group (0.833 ± 0.085) compared to the CTL group (0.768 ± 0.029), the two-sample Student's t-test did not reach statistical significance, $t(13) = -2.06$, $P = 0.06$; d = -1.07. Maximum spatiotemporal predictability for the two groups differed significantly according to Student's t-test, $t(13) = -3.39$, $P < .01$; d = -1.75. The effect size for this analysis (d = -1.75) was found to exceed Cohen's convention for a large effect. These results indicate that individuals in the dementia group (0.945 ± 0.02) displayed higher maximum spatiotemporal predictability in their mobility patterns compared to the CTL group (0.918 ± 0.011). The 95% CI of the difference is −0.045 to −0.009.

4 | DISCUSSION

The current article is a first attempt at understanding the predictability and randomness manifested in outdoor mobility patterns of community-dwelling older adults with dementia and cognitively intact older adults. Among the key findings of the study are the lower randomness in the spatial and temporal mobility patterns of PWD compared to cognitively intact CTLs. Taking a closer look at the
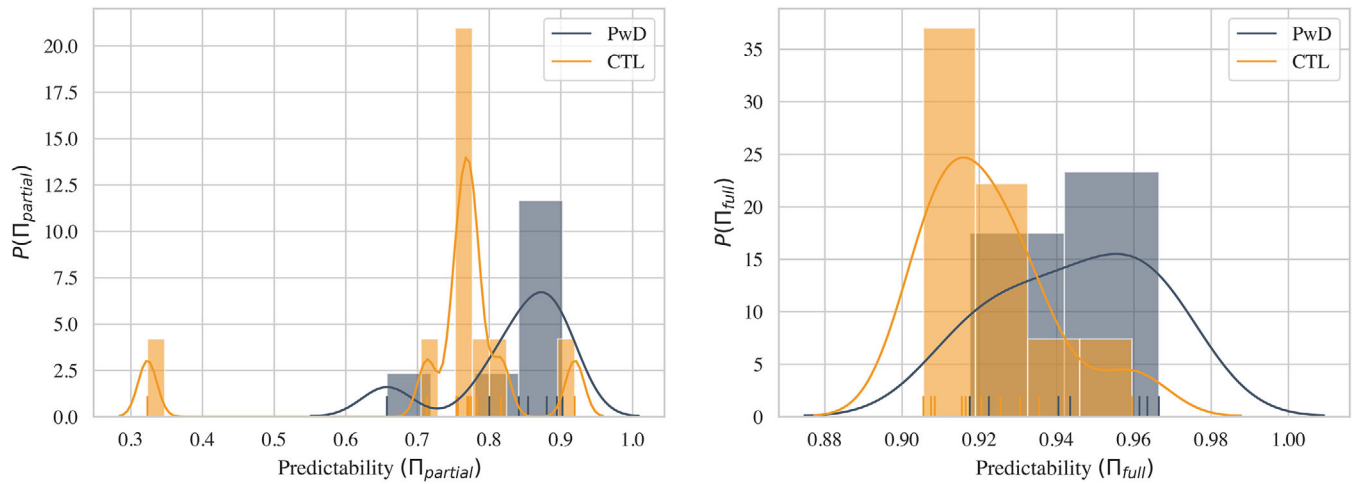
FIGURE 2 Group comparison results for the heterogeneous spatial and spatiotemporal predictability. CTL, control; PWD, people with dementia

randomness measures, we can observe that the distribution of random entropy peaked at about 6 in the dementia group and at about 5 in the CTL group. This indicates that each control participant who chose his or her next location randomly could be found, on average, in any of the $2^6 = 64$ locations, whereas each participant with dementia who chose his or her location randomly could be found, on average, in any of the $2^5 = 32$ locations. This difference, consistent with previous studies on life-space mobility and driving space,[19,34] confirms that people at various stages of dementia display lower levels of spatial mobility compared to cognitively intact controls. In addition, people often do not choose places to visit randomly.[35] The fact that the spatiotemporal entropy peaked at about 0.4 for the dementia group and at about 0.7 for the CTL group confirms this by showing that the true uncertainty in participants' locations is about $2^{0.4} = 1.3$ and $2^{0.7} = 1.6$ for PWD and cognitively intact CTLs, respectively. That is, considering the heterogeneity of visitations, both PWD and CTLs are likely to be found on average in fewer than two locations, with PWD displaying less uncertainty in their whereabouts and being more likely to be found at one location compared to CTLs ($P < 0.05$).

Other key findings of the study are that if we rely on both heterogeneous spatial patterns of the movements and temporal order of the visitations, a 4-week record of the daily mobility patterns, on average, exhibits 95% potential predictability across the dementia group. This finding suggests that only about 5% of the time a person with dementia chooses their location in a random manner, and in the remaining 95% of the time, we can hope to be able to predict their destination. While the observed spatiotemporal predictability in mobility patterns of the CTL group is comparable to the reported spatiotemporal predictability in mobility patterns of a sample of adults aged 65 or younger,[21] we observed that the mobility patterns of PWD trended toward a higher level of spatiotemporal predictability ($P = 0.06$) compared to a cohort of cognitively intact CTLs. Furthermore, the small standard deviation of spatiotemporal predictability in both groups indicates that the predictability distributions are highly bounded, and the predictability power does not vary widely from one person to another

in one group. These findings support the feasibility of accurate predictive models to support outdoor mobility for older adults with dementia.

Finally, comparing the three proposed predictability measures (i.e., random spatial predictability, heterogeneous spatial predictability, and spatiotemporal predictability), we determined that if we disregard the temporal order of the visitations and only consider the heterogeneous spatial patterns of movements, the predictability power declines, and its variability increases from person to person. Finally, if we consider destination visitations completely random (random spatial predictability), the predictability power in both groups becomes insignificant. These findings suggest that for both groups a significant share of predictability is hidden in the temporal characteristics of the mobility patterns and encourage incorporating both spatial and temporal mobility patterns in the design of predictive models.

5 | LIMITATIONS

There are several limitations to this study. The sample size was small (seven PWD and eight CTLs) and had a higher proportion of males. Furthermore, due to the small sample size, the effects of severity of dementia on randomness and predictability of mobility patterns were not analyzed. Thus, we inevitably introduced some sampling bias, the impacts of which are not yet fully understood. The study occurred in the greater Toronto area, Canada, and thus the findings may not be generalizable to suburban or rural regions, with different geographic characteristics. Future studies should consider matching participants for factors including sex, neighborhood characteristics, and methods of transportations. Finally, because our participants were at moderate to severe stages of dementia, to ensure safety, they were accompanied by their care partner during the out-of-home excursions. However, the trips made by two people require alignment of goals, which may lead to less variability in destinations and higher predictability in mobility patterns. Future studies with a larger sample should investigate the predictability of mobility patterns in people with mild cognitive

impairment or at early stages of dementia, who have higher levels of independence and autonomy, and use ecological momentary assessment to collect information about who accompanies the individuals on their trips.

6 | CONCLUSION AND FUTURE WORK

Recent advances on wearable tracking technologies and human mobility have raised a question: To what extent are mobility patterns of people with dementia predictable? In this work, by following daily GPS trajectories of seven older adults with a diagnosis of dementia and eight cognitively intact CTLs, we address this question for the first time. We find that the spatial and temporal patterns in PWD's GPS trajectories could indeed yield high predictive power. Furthermore, by comparing mobility patterns between PWD and CTLs, we show that the predictability power is significantly higher in PWD compared to CTLs.

Our findings on predictability and randomness of outdoor mobility patterns among PWD offer new perspectives on not only predictive mobility models that can be used to locate missing PWD but also dynamics of mobility of PWD that can be monitored during clinical trials and interventions throughout the progression of dementia. At the same time, our findings have privacy implications. In fact, the surprising power of spatiotemporal mobility patterns in predicting future mobility patterns can lead to potential information leakage about individuals' home address and whereabouts.

The findings of this study open up many interesting directions for further research in the field. The first direction is to search for improvement in intelligent assistive systems with predictive abilities that support outdoor mobility of PWD and minimize their risk of becoming lost. Although developing models to make predictions on participants' whereabouts was beyond the goal of this article, with appropriate machine learning algorithms, we could use the identified predictability to develop high-performance predictive models. Another interesting direction is to incorporate activity types and transportation modes into mobility models and understand their effects on the predictability power. Indeed, in light of the strong influence of spatial and temporal mobility patterns on predictability power, the question is if we can better understand and predict individuals' whereabouts by leveraging our knowledge of their patterns of activity types and transportation. In summary, with the increasing availability of trajectory data, we now have the power to revolutionize not only our understanding of mobility patterns of PWD but also our approach to support safe outdoor mobility of PWD, making this area particularly receptive for new developments.

CONFLICTS OF INTEREST
The authors have no conflicts of interest to declare.

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