Dimensions of GPS-derived Daily Mobility in Older Adults

Kim, Eun-Kyeong ; Fillekes, Michelle Pasquale ; Röcke, Christina ; Weibel, Robert

Dimensions of GPS-derived Daily Mobility in Older Adults

Eun-Kyeong Kim[1,2], Michelle P. Fillekes[3], Christina Röcke[2], Robert Weibel[1,2]

[1] Department of Geography, University of Zurich, Winterthurerstrasse 190, 8057 Zürich, Switzerland
Email: eun-kyeong.kim@uzh.ch

[2] University Research Priority Program 'Dynamics of Healthy Aging', University of Zurich, Andreasstrasse 15, 8050, Zürich, Switzerland

[3] The Mobility Cooperative, Suurstoffi 16, 6343 Risch-Rotkreuz, Switzerland

Abstract

Daily mobility is a multidimensional construct. Location sensing enables measuring an individual's daily mobility in various ways and this has prompted the issue of choosing appropriate mobility indicators for a given application, in particular in the health sciences, where the aim is to link mobility behavior to outcomes related to health and well-being. We previously proposed a classification framework for daily mobility indicators and discovered six latent factors underlying daily mobility, using GPS data of older adults collected in a study in Germany. To reassure the validity of our framework for selecting representative mobility indicators, we examined the generality and robustness of those six dimensions with another GPS dataset of older adults collected from the *MOASIS* project. First, we applied the same method to calculate 20 mobility indicators per participant and conduct an exploratory factor analysis (EFA). Second, we ran the EFAs on the mobility indicators of each subgroup of participants by gender, age, and mobility levels. The six dimensions reappeared with minor variations in the mobility indicators of both the entire group and all the subgroups of participants, which implies they are general and robust.

1. Introduction

Daily mobility is one of the fundamental predictors for health and well-being of older adults because being mobile allows more independent daily life, active social participation, better cognitive/emotional functioning, and eventually longevity (Cuignet et al., 2020; Gayman et al., 2008; Hirsch et al., 2014; Webber et al., 2010). Research on health and aging has recently benefited from location sensing technologies, particularly using GPS-equipped mobile devices, to measure individual-level daily mobility via relatively simple mobility indicators, such as *time spent out of home* or *number of visited places*. However, in research outside of the health domain, such as geography and transportation, personal mobility has been conceptualized as a compound and multidimensional construct and quantified through various geographic variables (e.g., convex or concave hull, entropy of time usage in different places). Recent interdisciplinary studies at the intersection of the health and GIScience/informatics domain contributed to enriching and diversifying mobility indicators for application in studies on health and aging. Meanwhile, it has become challenging for researchers to choose a concise set of suitable mobility indicators for their given study.

To help select the most representative mobility indicators embracing the diverse aspects of daily mobility, our own previous work (Fillekes et al., 2019) proposed a conceptual framework for the classification of mobility indicators, conducted an exploratory factor analysis (EFA) on 20 mobility indicators derived from real-life GPS data of each of 95 older adults residing in Cologne, Germany, and identified 6 latent factors of daily mobility: 1) *extent of life space*, 2) *quantity of out-of-home activities*, 3) *time spent in active transport modes*, 4) *stability of life space*, 5) *elongation of life space*, and 6) *timing of mobility* (corresponding to Factors 1~6 in Figure 3 in order) – see Appendix A for the list of mobility indicators used in this study.

However, in order to back the claim that such 6 latent factors of daily mobility behaviors are generalizable, further empirical replication studies with independently collected GPS data are inevitable.

1.1 Research Goal and Research Questions

In this study, we, first, examine the generality (RQ1) and robustness (RQ2) of those 6 dimensions of daily mobility in older adults by answering the following research questions, and further, provide a guideline on how to leverage the representative mobility indicators to analyze individual mobility and its association with individual's characteristics with a proof-of-concept analysis.

RQ1. Are the 6 latent factors of daily mobility proposed by Fillekes et al. (2019) also found in another daily GPS data set of older adults?
RQ2. Are the latent dimensions of daily mobility similar between participant groups with different demographic and mobility characteristics? — specifically, this includes the subgroups:
RQ2-1. *Gender*: similarity between male and female older adults;
RQ2-2. *Age*: similarity between young-old and oldest-old adults;
RQ2-3. *Mobility level*: similarity between more mobile and less mobile older adults (i.e., higher vs. lower number of visited locations).

2. Data and Methods

2.1 Data

This study adopted GPS data of healthy older adults (n=152) living in the German-speaking area of Switzerland, collected from the *Mobility, Activity and Social Interaction Study (MOASIS)* project conducted by the *University Research Priority Program 'Dynamics of Health Aging'* of the University Zurich. The goal of the MOASIS project is to investigate how daily mobility, activity, and social interaction of healthy older adults relate to their daily psychological functioning and well-being (Roecke et al., 2018).

During the 30-day data collection phase with two real-life sessions (2 weeks each), participants wore on their waist the customized wearable multi-sensor device, *uTrail*, containing GPS, accelerometer, and microphone. GPS signals were recorded with the sampling rate of 1 Hz (Bereuter et al., 2016).

2.2 Methods

To answer RQ1 and RQ2, we analyzed the data and mobility indicators in largely four steps. First, we preprocessed GPS data of valid participants. Second, 20 daily mobility indicators were calculated using the same methods used in our previous study (Fillekes et al., 2019). Third, to examine the generality (RQ1), we ran the EFA on the daily mobility indicators for all the valid participants and checked if the 6 factors were still identified. Fourth, to investigate the robustness (RQ2), we extracted various subsets of participants in terms of three control variables (i.e., *gender*, *age,* and *mobility level*), and then ran the EFA for each subset.

GPS data (pre)processing

The (pre)processing of the MOASIS uTrail GPS data included several procedures, same as our former analysis on the data collected in Cologne, Germany (Fillekes et al., 2019): data filtering, participant validation, speed outlier removal, home detection, and stop-move detection. The participant validation analysis determined the valid participants (n=111) with at least 8-

hour/day GPS recordings as well as at least one segment of each stop and move per day for at least 3 days of 2 weekdays and 1 weekend day.

Mobility Indicator Calculation with Random Sampling

To minimize the study day selection bias in measuring individual-based daily/global mobility, we randomly sampled 3 valid study days (2 weekdays plus 1 weekend day per participant) for each participant 10 times. Then, 10 sets of the 20 different mobility indicators were computed for each participant.

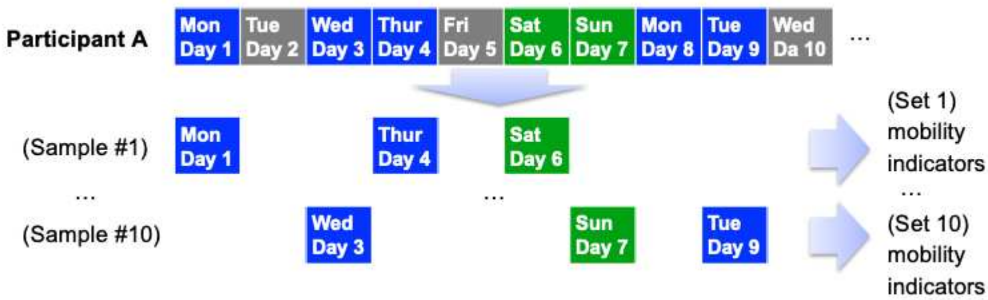


Figure 1. Mobility indicator calculation with random sampling of three valid study days (blue-coloured days - valid weekdays; green-coloured days – valid weekend days; grey-coloured days - invalid days).

Exploratory Factor Analysis (EFA) and Pair Matrix Visualization

EFA was conducted for each of those 10 sets of mobility indicators, resulting in 10 EFA results. To effectively summarize the 10 results, the pair matrix visualization method was applied (Fillekes et al., 2019). If two indicators belong to the same factor, it increases the counting number in the pair matrix as shown in Figure 2.

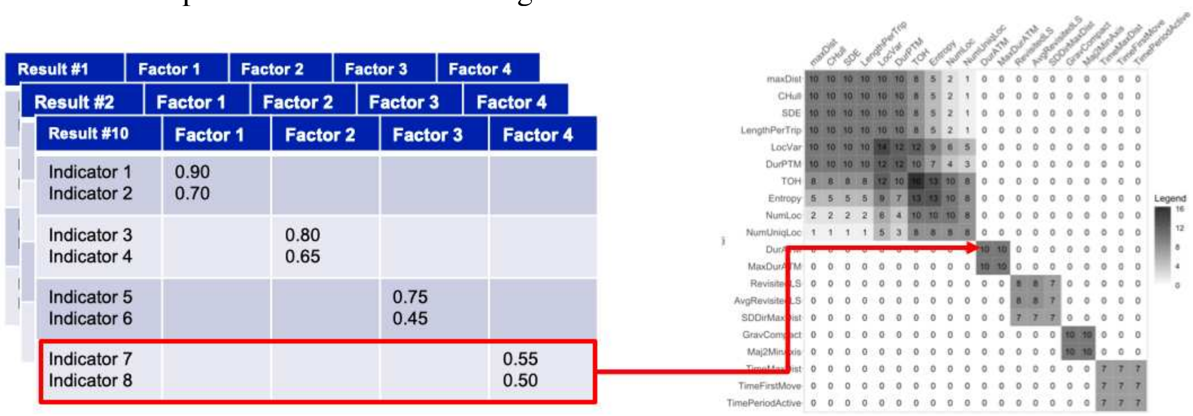


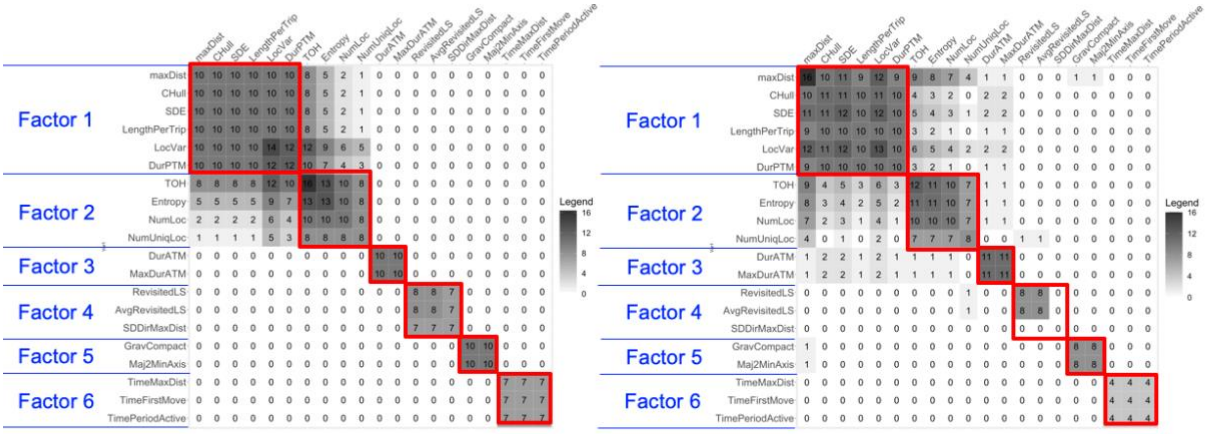
Figure 2. Pair matrix visualization for summarizing 10 result sets of exploratory factor analysis.

One pair matrix was generated for the entire group of participants as well as for each of the 6 subgroups, respectively. This resulted in a total of 7 pair matrices (Figure 3, Figure 4). To divide the participants into subgroups by gender, age, and mobility level, we considered the statistical distribution of participants over each control variable as well as cognitively simpler values as follows:

- Gender: male (n=56) vs. female (n=53); no label for gender (n=2);
- Age: $65 \leq$ age < 75 (n=69) vs. age ≥ 75 (n=40); no label for age (n=2);
- Mobility level: the median number of out-of-home locations ≤ 3 (n=69) vs. > 3 (n=42).

3. Preliminary Results

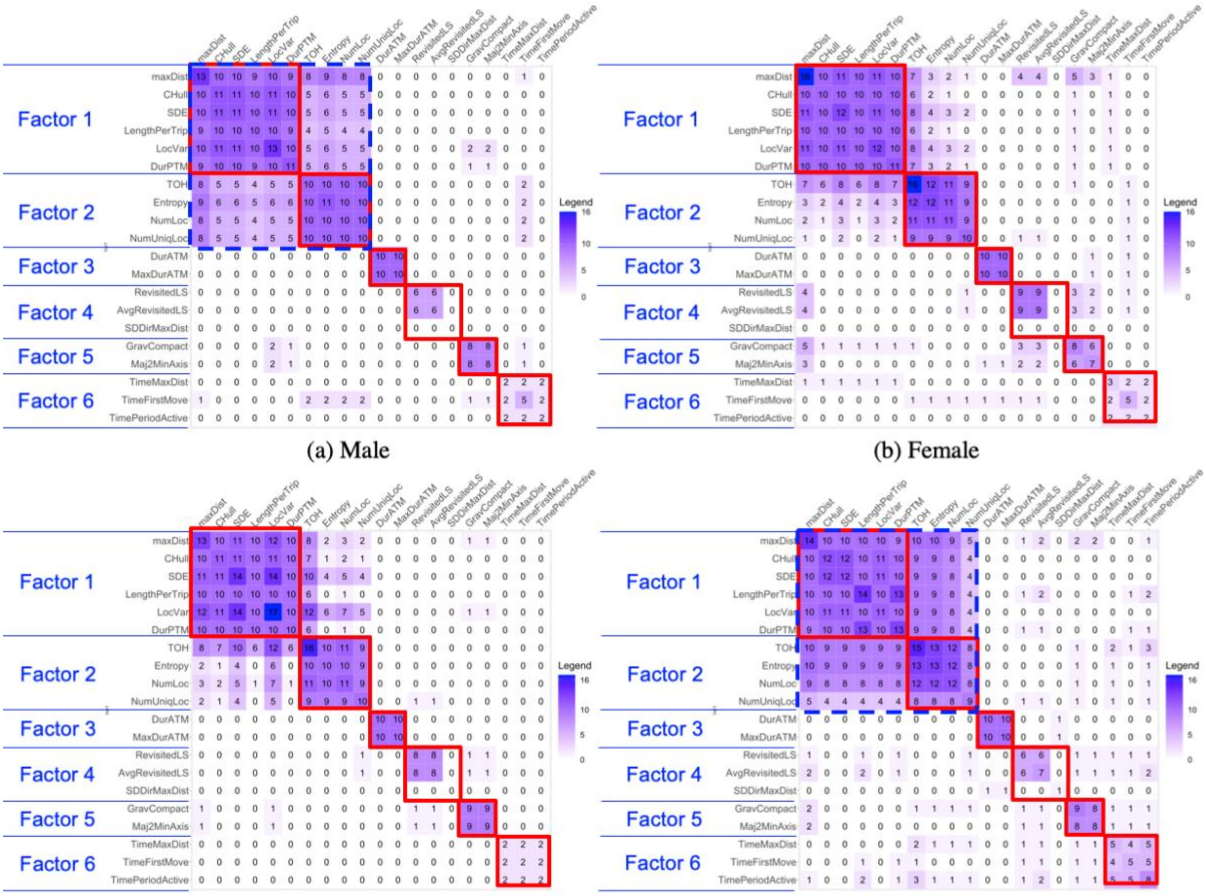
Regarding RQ1 and RQ2, the previously found 6 latent factors again appeared in the entire group and subsets of the participants from another independently conducted MOASIS project, which shows clear replication evidence for the 6 dimensions of mobility measures (see Figure 3 and Figure 4).



German Cologne Data (n=95)
(Fillekes et al. 2019)

MOASIS Data (n=111)

Figure 3. Six latent factors of daily mobility found in the entire sample of participants of different GPS datasets from the 'German Cologne' (left) and 'MOASIS' (right) studies.



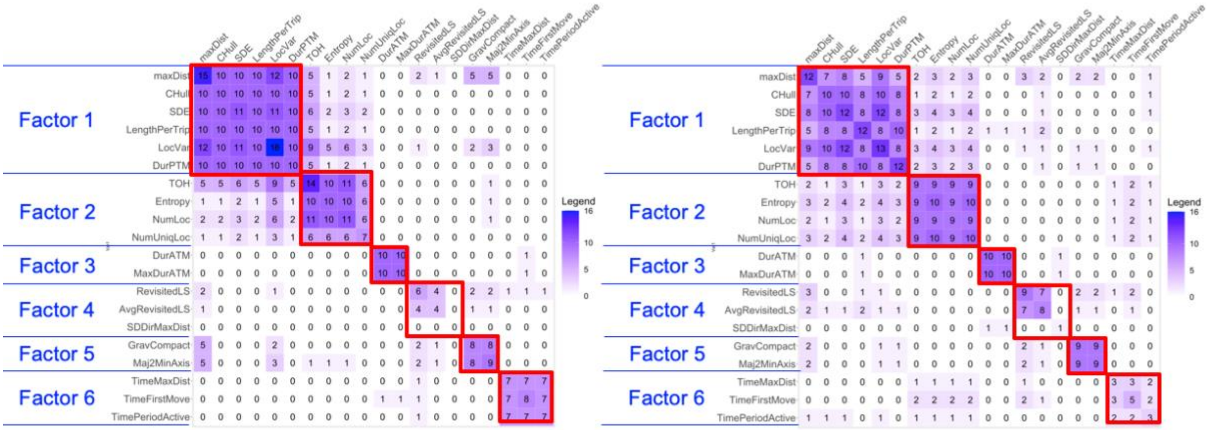
(a) Male

(b) Female

(c) 65 ~ 75 years old

(d) 75 ~ years old

(continue)



(e) Median # of Out-of-Home Locations <= 3 (f) Median # of Out-of-Home Locations > 3

Figure 4. Six latent factors of daily mobility found in the subgroups of the MOASIS study participants extracted by three control variables of gender, age, and mobility level: (a) male; (b) female; (c) 65 ≤ age < 75; (d) age ≥ 75; (e) median number of out-of-home locations ≤ 3; (f) median number of out-of-home locations > 3.

While the 6 factors were found again in most subsets, the two factors of ‘extent of life-space’ (Factor 1) and ‘quantity of out-of-home activities’ (Factor 2) were only moderately associated and merged together in the oldest old group (Figure 4d) and the male older adult group (Figure 4a). There is a possibility that the reduced mobility or high dependency on passive mode of transports of the older age group contribute to reduced differentiation of those two latent dimensions of mobility. As such, the correlation between the latent factors implies a further interesting relationship between latent factors to explore.

4. Future Work

In future work, we will quantify the similarity/difference of the EFA results between the two studies of Cologne, Germany and MOASIS with a matrix similarity measure. To further meet our research aim, we will conduct a proof-of-concept analysis to provide a guideline on how the latent dimensions can be used to select the mobility indicators, and such a generalized and robust set of key mobility measures can help explore the relationships between individuals’ mobility behaviors and their demographic or health traits. This research will potentially advocate a solid guide towards how to observe and measure individuals’ daily mobility for future health- and aging-related research.

Appendix A

Table 1. Description of the computation of the mobility indicators and six latent mobility dimensions, modified from Table 5 and Table 9 of Fillekes et al. (2019).

Factor	Indicator name	Definition of daily mobility indicator
1: Extent of life space	MaxDist	Length of straight line connecting the home with the GPS fix furthest away from home
	CHull	Area of convex hull enclosing all GPS fixes
	SDE	Ellipse defined at one 1 standard deviation (SD) containing approximately 68% of GPS fixes within the ellipse’s boundary
	LengthPerTrip	Average length of a move
	LocVar	Combined variance of X and Y coordinates (Saeb et al., 2016)
	DurPTM	Time spent in passive transport modes
2: Quantity of out-of-home activities	TOH	Duration between all out-of-home (OH) fixes, interpolating for up to 60-min gaps between consecutive GPS fixes if both fixes are OH
	Entropy	Entropy computed as in Saeb et al. (2016). Entropy measures how a participant’s time was distributed over the different stop locations: the

		higher the entropy, the more regularly time is distributed and/or the higher the number of unique locations
	NumLoc	Number of OH locations visited
	NumUniqLoc	Stops visited multiple times (referring to the same location cluster) during the included study days are only counted once
3: Time spent in active transport modes	DurATM	Time spent in active transport modes
	MaxDurATM	Duration of longest continuous trip using active transport modes
4: Stability of life space	RevisitedLS	Percentage of the daily convex hull that has overlap with any convex hulls of the other included study days
	AvgRevisitedLS	Average percentage overlap of the daily convex hull with the convex hulls of the other included study days
	SDDirMaxDist	Direction of most distant point from home. Weekly aggregation is done by circular SD: the larger the circular standard deviation, the more variability in day-to-day orientation of life space
5: Elongation of life space	GravCompact	K = P/(2$\sqrt{\pi A}$) (where P = perimeter of convex hull and A = area of convex hull. The higher the more elongated is the life space
	Maj2MinAxis	Ratio between major and minor axis of standard deviational ellipse
6: Timing of mobility	TimeMaxDist	Time of day starting at 3 AM [min] when most distant location from home is reached
	TimeFirstMove	Time of day starting at 3 AM [min] of the first move (approximation of first OH activity) of a day
	TimePeriodActive	Assignment of OH activities (moves and OH stops) based on start time to one of the three classes: morning (6 AM–12 noon), afternoon (12 noon–6 PM), or evening (6 PM–11 PM). A day is coded as 1 (morning day) if morning activities > evening activities; as 3 (evening day) if evening activities > morning activities; 2 (neutral timing day) in all other cases

Acknowledgements

This research was funded by Velux Stiftung and URPP "Dynamics of Healthy Aging." We thank two reviewers for their constructive comments on this study.

References

Bereuter, P., Fillekes, M., & Weibel, R. (2016). Analyzing GPS and Accelerometer Data in the Study of the Mobility, Activity and Social Interaction of Older Adults. *AGILE Workshop on Visually-Supported Computational Movement Analysis, 14 June 2016, Helsinki, Finland*, *June*.

Cuignet, T., Perchoux, C., Caruso, G., Klein, O., Klein, S., Chaix, B., Kestens, Y., & Gerber, P. (2020). Mobility among older adults: Deconstructing the effects of motility and movement on wellbeing. *Urban Studies*, *57*(2), 383–401. https://doi.org/10.1177/0042098019852033

Fillekes, M. P., Giannouli, E., Kim, E.-K., Zijlstra, W., & Weibel, R. (2019). Towards a comprehensive set of GPS-based indicators reflecting the multidimensional nature of daily mobility for applications in health and aging research. *International Journal of Health Geographics*, *18*(1), 17. https://doi.org/10.1186/s12942-019-0181-0

Gayman, M. D., Turner, R. J., & Cui, M. (2008). Physical Limitations and Depressive Symptoms: Exploring the Nature of the Association. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *63*(4), S219–S228. https://doi.org/10.1093/geronb/63.4.S219

Hirsch, J. A., Winters, M., Clarke, P., & McKay, H. (2014). Generating GPS activity spaces that shed light upon the mobility habits of older adults: a descriptive analysis. *International Journal of Health Geographics*, *13*(1), 51. https://doi.org/10.1186/1476-072X-13-51

Roecke, C., Katana, M., Fillekes, M., Martin, M., & Weibel, R. (2018). Mobility, physical activity and social interactions in the daily lives of healthy older adults: the MOASIS project. *Innovation in Aging*, *2*(suppl_1), 274–274. https://doi.org/10.1093/geroni/igy023.1014

Saeb, S., Lattie, E. G., Schueller, S. M., Kording, K. P., & Mohr, D. C. (2016). The relationship between mobile phone location sensor data and depressive symptom severity. *PeerJ*, *4*(9), e2537. https://doi.org/10.7717/peerj.2537

Webber, S. C., Porter, M. M., & Menec, V. H. (2010). Mobility in Older Adults: A Comprehensive Framework. *The Gerontologist*, *50*(4), 443–450. https://doi.org/10.1093/geront/gnq013