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How is our mobility affected as we age? Findings from a 934 users field study of older adults conducted in an urban Asian city

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Citation

TAN, Yi Zhen; TRAN, Ngoc Doan Thu; LIN, Sapphire; ZHAO, Fang; NG, Yee Sien; MA, Dong; KO, JeongGil; and BALAN, Rajesh Krishna. How is our mobility affected as we age? Findings from a 934 users field study of older adults conducted in an urban Asian city. (2024). *BTIW '24: Proceedings of the Behavior Transformation by IoT International Workshop, Minato-ku, Tokyo, June 3-7*. 27-32.

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ABSTRACT

In this paper, we analyze the results of a large study involving 934 older adults living in an urban Asian city that collected their mobility patterns, in the form of logged GPS data, along with a multitude of demographic and health data. We show that mobility, in terms of average distance travelled per day, is greatly affected by age and by employment status. In addition, other factors such as type of day, household size, physical and financial conditions and the onset of retirement also play a significant role in determining the mobility of an individual. These results will have high value to any researcher understanding and attempting to transform the lifestyle of older adults.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in collaborative and social computing**; • **Applied computing** → Law, social and behavioral sciences.

ACM Reference Format:

Yi Zhen Tan, Thu Tran, Sapphire Lin, Fang Zhao, Yee Sien Ng, Dong Ma, Jeonggil Ko, and Rajesh Balan. 2024. How is our mobility affected as we age? Findings from a 934 users field study of older adults conducted in an

urban Asian city. In *Behavior Transformation by IoT International Workshop (BTIW '24)*, June 3–7, 2024, Minato-ku, Tokyo, Japan. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3662008.3662016>

1 INTRODUCTION

As projected in a World Health Organization (WHO) report [18], over 16% of the global population will be aged 60 or older by 2030. This demographic shift necessitates a reevaluation of infrastructure design.

There are needs to gain deeper insights into how an older adult population residing in urban settings adapt to diverse socio-economic factors and how these elements shape their daily mobility within their living environments. However, conventional census approaches may fall short in capturing the micro-level mobility patterns of the aging population. We propose that leveraging mobile platforms with their inherent sensing capabilities can serve as a viable solution to this challenge. Given the widespread adoption of mobile devices, these devices can effectively monitor user mobility and engage with users to compile detailed datasets regarding the how and why behind individual mobilization. This data holds the potential to furnish policymakers with valuable insights into evolving urban behaviors.

In this research, we conduct an analysis of data obtained from an extensive study involving more than 934 senior individuals aged 50 and above residing in an urban Asian metropolis. Study participants were requested to install a mobile application on their devices, which recorded their GPS locations over two weeks. We complemented this information with a large amount of demographic details and self-reported data.



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BTIW '24, June 3–7, 2024, Minato-ku, Tokyo, Japan

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ACM ISBN 979-8-4007-0665-3/24/06.

<https://doi.org/10.1145/3662008.3662016>

The main hypothesis of the paper is that the mobility patterns of older adults change, and in particular their mobility decreases, as they age. We reconfirm this well-known hypothesis and go deeper to understand the factors that affect the mobility of older adults. In particular, what are the factors that make older adults more or less sedentary compared to their peers? Our analysis suggests that older adults that have are younger, employed and married exhibit higher levels of mobility.

Beyond basic demographic factors, we also look at the impact of type of day, household size, retirement and physical and financial conditions as well as mode of transportation has on the mobility of older adults.

We strongly believe that the outcomes of this study can provide value to researchers engaged in the design of cities and living environments tailored to older populations [12]. Specifically, these findings will facilitate a nuanced understanding of the influence that diverse public transportation and housing choices have on the mobility patterns of seniors residing in those areas. Furthermore, these findings carry significant medical implications [12], as a substantial body of prior research has established a direct correlation between sedentary behavior and various medical conditions [10]. By pinpointing the determinants of mobility, our aim is to supply data evidence that can be harnessed to mitigate these factors. This may involve devising initiatives to incentivize retirees to engage in outdoor activities, ultimately enhancing the overall mobility of the older population and, consequently, yielding improved medical outcomes.

2 RELATED WORK

2.1 Mobility patterns from GPS data

Many features of mobility patterns can be extracted from GPS data, including the locations of significance, modes of transport, trajectory patterns and location-based activities [4, 8, 11]. Our study makes use of the average GPS distance travelled as well as modes of transport.

Previous research involved providing participants with a dedicated wearable GPS device to track their mobility patterns during travel [2, 15, 23]. However, this approach encounters challenges related to device management and usage, such as charging or alteration of participants' routines [7, 13]. In comparison, leveraging on smartphone GPS data proves advantageous as most participants habitually charge and carry their smartphones, thereby mitigating the effort and errors associated with data collection challenges [6, 13]. Our study was conducted in a urban setting with dense public transportation coverage and a high rate of smartphone usage, even among older adults. This setting facilitated the non-intrusive collection of comprehensive GPS mobility traces of older adults.

2.2 Mobility of older adults

Research on the mobility of older adults has gained significant attention, leading to the formulation of theoretical and empirical assessment frameworks that reveal its complexity and interdisciplinary nature [14, 16].

Among various travel modes, active travel, such as walking and cycling, has been of special interest due to its direct relevance to the physical activity of older adults. Notably, a robust relationship

Index	Variable	Value	No. of participants (n)	Percentage
1	Gender	Female	621	66.5%
		Male	313	33.5%
2	Age	<60	482	51.6%
		60-70	340	36.4%
		>70	112	12.0%
3	Marital Status	Married	648	69.4%
		Not Married	286	30.6%
4	Employment Status	Full-time/Part-time	501	53.6%
		Not working/retired	433	46.4%
5	Income Adequacy	Some/Much difficulty	413	44.2%
		Just enough	395	42.3%
		Enough with leftover	99	10.6%
		Did not indicate	27	2.9%
6	Frail by any test	None	691	74.0%
		At least 1	243	26.0%
7	Household Members	1	120	12.8%
		2	253	27.1%
		3	214	22.9%
		4	212	22.7%
		>=5	135	14.5%

Table 1: Demographics Information

has been identified between the active travel of older adults and the physical environment of their neighborhoods [1, 17].

Hirsch et al. analyzed GPS data from 95 older adults in Canada, investigating how environmental and demographic variables influenced geographical mobility [5]. Larger-scale studies examining the mobility patterns of older adults commonly rely on survey data, such as telephone interviews [9, 19–21]. However, data collected on daily trips using a recall survey method can have limitations due to self-report bias.

Our study leverages the ubiquitous nature of mobile phones and their integrated GPS tracking capabilities to amass a notably large dataset from a diverse population of urban older adults, contributing further empirical evidence to the understanding of previously investigated mobility patterns in older adults.

3 DATASET

The data used in this extensive study combined a range of baseline survey evaluations covering aspects related to health, social and environmental interactions with geo-spatial data collected over a 14-day time period via a mobile GPS tracking application named X-ING [22], installed on the participants' mobile phones – a commercial app that supported both Android and iOS devices. The study was approved by a medical IRB panel run by a large hospital group located in the Asian city the study was conducted in.

3.1 Participants

A non-random sample of community-dwelling adults aged above 50 (N = 934) were recruited through a combination of physical and digital posters distributed across various community locations serving older adults. The demographics and percentage breakdown of the participants is presented in Table 1. We use these attributes in the analysis presented in Section 4.

3.2 Data Collection

Our data collection took place at four community sites across the Asian city from April to September 2022. Participants were asked to engage in a series of three activities, which included answering a questionnaire, performing a series of tests to evaluate their physical

condition and given instructions to install and use the X-ING GPS logging application on their mobile phones.

After the session was done, the participants continued with their daily routines while keeping track of their travels for the subsequent 14 days. The attrition rate was less than 1%, with 934 out of the 942 recruited participants successfully completing the study (and their data being used for this paper).

3.3 Travel Diaries

The travel logs captured by the X-ING app recorded the start time, end time, and GPS distance traveled for every trip taken by our participants. In addition, the mode of transport and reason for each trip was also logged. The available options for travel mode are included in Table 2.

Index	Transport Mode	Description
1	Foot	Walk by foot
2	PV Driver	Travel in private vehicle (car or motorcycle) as the driver
3	PV Passenger	Travel in private vehicle (car or motorcycle) as the passenger
4	Taxi/Car Service	Travel in paid taxi or private car hire service
5	Bus	Travel on bus
6	Train	Travel on the railway system
7	Bicycles	Ride with traditional bicycle
8	E-Bike	Ride with electric bicycle. This will be considered "Other" in the analysis due to the small sample size.
9	Wheelchair	Travel with Personal Mobility Device (WheelChair). This will be considered "Other" in the analysis due to the small sample size.
10	E-Scooter	Travel with Personal Mobility Device (E-Scooter). This will be considered "Other" in the analysis due to the small sample size.
11	Other	Any travel that does not match all of the above modes.

Table 2: Travel mode options and description

4 FACTORS AFFECTING MOBILITY

In this section, we analyse the effect that various factors has on the mobility of older adults. These results reinforce conventional wisdom with additional insights provided by our large dataset.

4.1 Base Results

Our base hypothesis is that mobility decreases as age increases. Here we define mobility as the average recorded distance (in kilometers) traveled per day. The left plot in Figure 1 reveals a declining trend in mobility as individuals age. We also observe that those who are not employed exhibit shorter travel distances in comparison to their employed counterparts. These findings align with our initial expectations, as the natural aging process tends to reduce an individual’s physical capability, and the absence of regular employment reduces the financial input and eliminates a significant source of daily mobility. In the right plot of Figure 1, we present these two factors combined, corroborating the validity of both age and employment status as distinct factors affecting mobility.

4.2 Weekday mobility vs. Weekend mobility

An individual’s mobility frequently follows a weekly pattern, given the common 5-day weekday and 2-day weekend structure. To examine the effect of such a weekly pattern, in Figure 2, we present the average daily GPS distance traveled separated by weekdays and weekends/public holidays, considering the participants’ employment status. This distinction is important as employed participants typically have regular work-related travel on weekdays, as opposed

to non-employed participants. As depicted in the plots, the disparities in mobility between employed and non-employed participants are more pronounced on weekdays compared to weekends. We observe a slight reduction in mobility during weekends (and public holidays) for the employed group, and not for the non-employed group. Furthermore, an important observation is that even on weekends, the employed population exhibits higher mobility, suggesting that maintaining employment for older adults can serve as an effective strategy to sustain their mobility.

4.3 Household size

We delve deeper into the data using Figure 3, where we depict the average GPS mobility for various age groups, differentiating between weekdays/weekends, and the number of household members.

The plots in Figure 3 reveal that larger households display an increasing trend in mobility, with this effect being more pronounced in the age group below 60. We believe that this is an effect of this group consisting of households with younger members, tending to be more active as a family. Secondly, as participants age, along with a higher likelihood of household members aging correspondingly, the overall travel distance patterns exhibit a gradual decline. Except for some cases with only a small number of samples to analyze (age group >70), we see a common trend in mobility patterns of increased mobility with more household members.

4.4 Marital status

Next, we investigate the effect of marital status and gender on GPS mobility by categorizing participants into different marital status groups, as depicted in Figure 4. The “Not Married” category encompassing individuals who are single, separated, or divorced. Interestingly, the data suggests that, on average, married participants exhibit higher levels of mobility compared to those who are not married.

4.5 Physical and financial conditions

The financial and physical well-being of older individuals can exert a significant influence on their mobility, as activities outside home often entail financial expenses and physical exertion. We looked at the average daily GPS distance traveled with respect to different age groups and their self-reported income adequacy levels, categorized into three levels: some/much difficulty, just enough, and enough with left over. We observed a positive relationship between mobility and income adequacy, indicating that greater financial stability is associated with increased mobility.

Physical motor abilities decreases as people age. We carried out four different frailty tests, Fried, FRAIL, HGS, and GS [3], classifying participants as “frail” if they exhibited frailty in at least one of these tests. The results shown in Figure 5 affirm that physical frailty significantly diminishes participants’ mobility, and the degree of decline tends to escalate in higher age groups. This offers strong confirmation that supporting the physical condition of the older population can be highly effective in preserving and promoting the mobility of older individuals in our society.

Another aspect that indirectly influences expected income is the number of years since retirement. In Figure 6 we present the average GPS travel distance with respect to the number of years

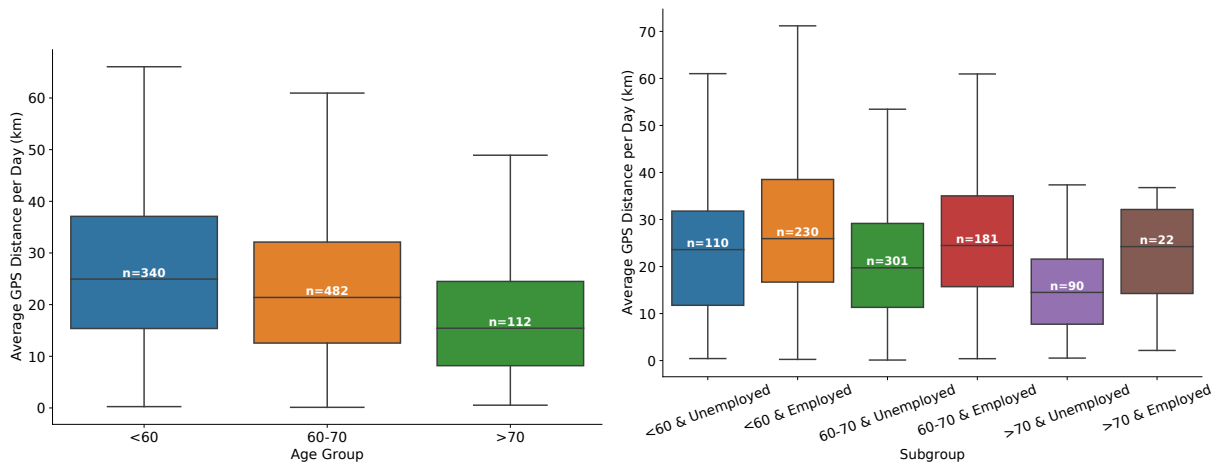


Figure 1: Relationship of Average GPS Distance with Age and Employment

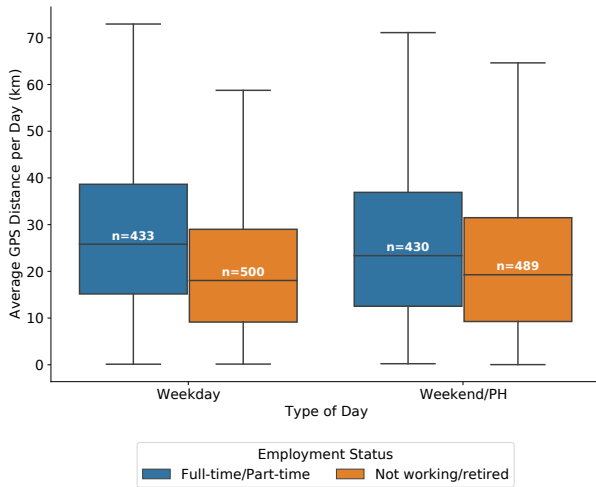


Figure 2: Effect of Type of Day on Average GPS Distance, separated by employment status

since their retirement, only including participants that indicated that they were "retired" (363 subjects). We notice that while the first four years after retirement exhibit similar mobility distances, after passing five years of retirement, there is a noticeable decline in the distance traveled. This suggests that long-retired elders might be less likely to engage in longer travels and this should be taken into consideration by planners.

4.6 Mode of Transport

In a typical urban environment, numerous public transportation methods such as buses and subways coexist with private vehicles and hiring services. The city in this study offers a densely connected bus and subway system where the buses are used for both long distance trips and to connect small neighborhoods with nearby subway stations. The city also offers numerous hired car and taxi services and has a very well deployed road infrastructure.

We found that walking was the most commonly employed mode of transport, with one of the shortest average travel distances. While bicycle trips had longer distances, they were still fairly short compared to other modalities such as the use of personal vehicles or other transportation services. Surprisingly, the average distance traveled by bus was also relatively modest. This might be because buses were frequently used to reach the nearest subway station for longer-distance journeys.

An intriguing finding is that, although the average travel distance is similar for personal vehicles, taxi/car hiring services, and subways/trains, having access to a personal vehicle significantly boosts the number of trips taken by a participant. On average, each of the 283 drivers engaged in 42 driving-based journeys, while subways/trains were only used approximately 11.4 times per participant. Furthermore, it is noteworthy that passengers (not driver) of personal vehicle, despite having access to a personal vehicle, undertook an average of 11.2 journeys, nearly a quarter of the number observed for drivers.

5 CONCLUSION

Mobility patterns, encompassing both transportation modes and distances traveled by individuals, serve as important indicators that reflect people’s lifestyles and travel behaviours. Nevertheless, accurately capturing these patterns is challenging, demanding extensive, large-scale, and multi-dimensional data collection.

In this study, we compiled a comprehensive dataset using a mobile application, incorporating GPS tracking information and self-reported trip diaries from 934 seniors residing in an urban Asian metropolis. Through accounting for various factors that related to the senior’s living conditions, we unveiled several intriguing findings. Notably, we observed a decline in mobility and a shift in preference towards public transportation among aging individuals, being influenced by various societal and financial factors. These insights provide valuable guidance for potential societal interventions aimed at fostering increased mobility among the elderly.

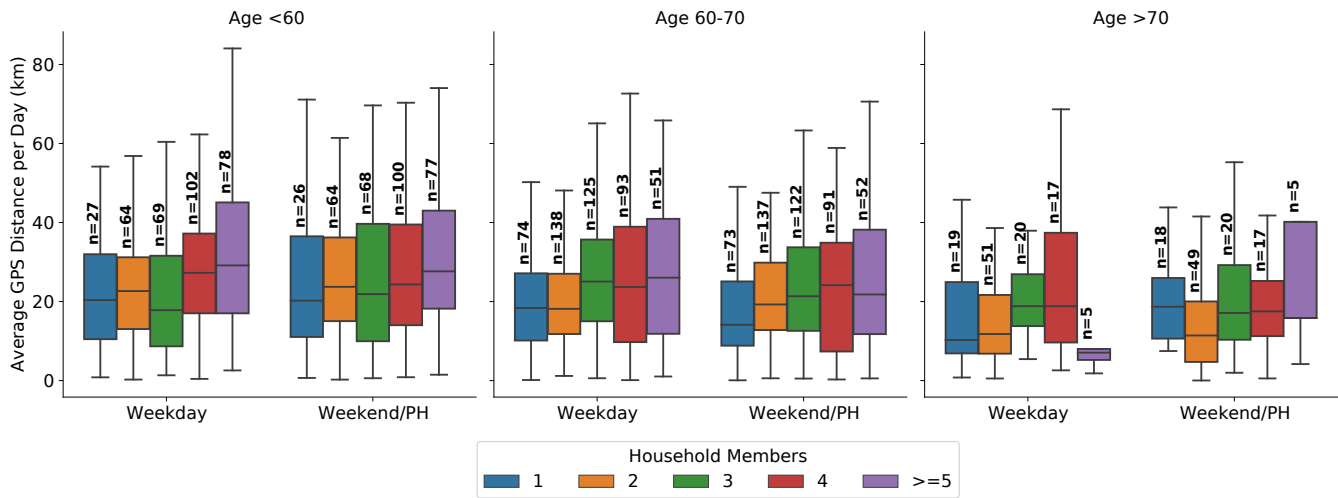


Figure 3: Effect of Type of Day on Average GPS Distance for different number of household members

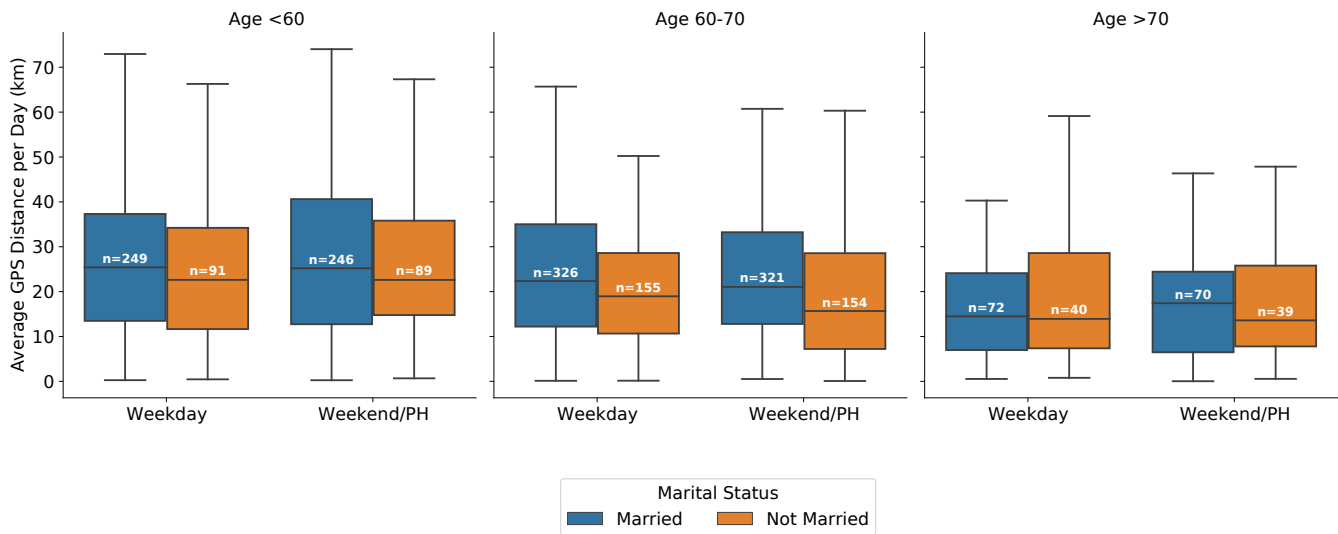


Figure 4: Effect of Type of Day on Average GPS Distance for different marital status

ACKNOWLEDGEMENTS

This research/project is supported by the National Research Foundation, Singapore, and Ministry of National Development, Singapore under its Cities of Tomorrow R&D Programme (CoT Award COT-H1-2020-1).

Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of National Research Foundation, Singapore and Ministry of National Development, Singapore.

This research was supported by the Singapore Ministry of Education (MOE) Academic Research Fund (AcRF) Tier 1 grant.

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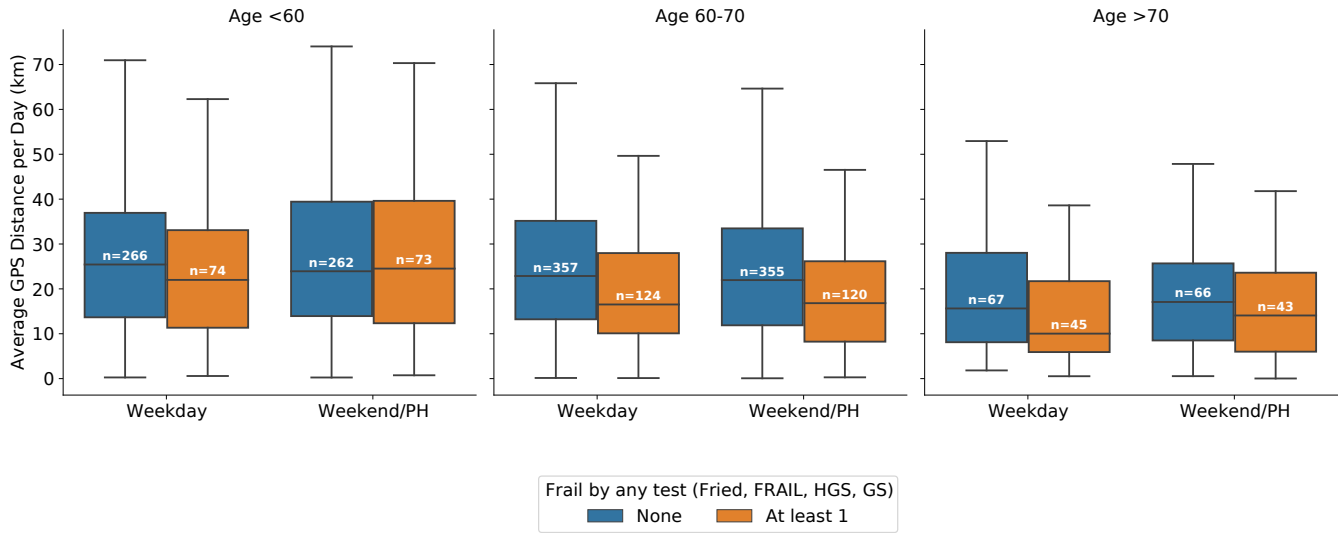


Figure 5: Effect of physical frailty on average GPS distance for different age groups.

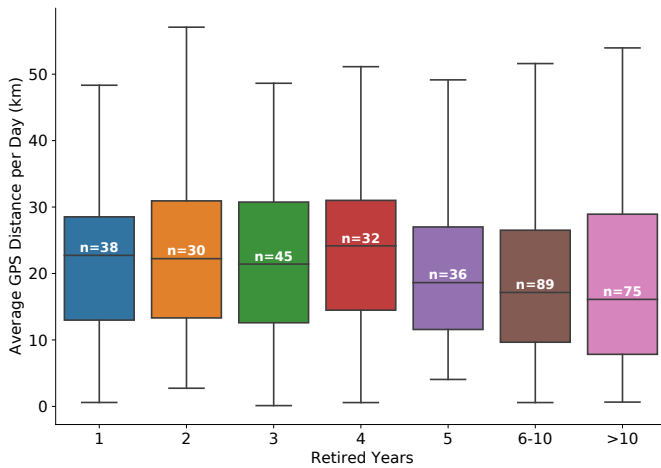


Figure 6: Effect of number of retired years (duration) on average GPS travel distance.

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