Comparative Analysis of Spatial Human Mobility Parameters in 15 Most Populous U.S. Metropolitan Statistical Areas

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Abstract*—This research paper presents the results of two studies investigating human mobility patterns in the 15 largest Metropolitan Statistical Areas (MSAs) in the United States. It studied 14 daily mobility parameters aggregated at the MSA level, derived from four primary mobility parameters: Number of Visited Locations (N_LOC), Number of Unique Visited Locations (N_ULOC), Radius of Gyration (R_GYR), and Distance Traveled (D_TRAV) over a 30-day period. The first study was conducted on data from two large MSAs, one coastal and one inland (Boston and Atlanta, respectively). The aim was to examine associations between daily values of mobility parameters aggregated at the MSA level and identify those carrying similar or identical information. Results of factor analysis showed that these could be adequately described by two independent factors, pointing to one or two of the mobility parameters as sufficient to represent the whole set in analyses based on associations. These could either be D_TRAV, as it had high loadings on both factors, or N_LOC and R_GYR due to their high loadings on the two extracted factors. The second study was conducted on daily mobility datasets from the 15 MSAs. The aim was to compare daily mobility patterns of these MSAs and group them based on their mobility pattern similarities. Factor analysis of the aggregated mean daily distances (D_TRAV) across different MSAs over the studied period classified them into two distinct groups: one predominantly composed of inland MSAs and the other primarily of coastal MSAs. Strong weekly cycle trends emerged in these groups. Specifically, individuals from the inland MSA group tended to travel the furthest on Fridays and the least on Sundays, whereas those from the coastal MSA group traveled the most on Saturdays and the least on Mondays. This weekly pattern was robust, with 7-day lag autocorrelations of mean daily parameter values ranging between 0.81 to 0.99, excluding the mean daily N_LOC. These findings offer a foundational understanding of MSA mobility patterns, paving the way for more detailed studies on the nuances of these patterns.

***Index Terms*—Big data analytics, cellular network data, human mobility, spatial parameters.**

I. Introduction

Characterizing people's mobility patterns is a fundamental aspect of understanding human behavior [1] [2]. This understanding has significantly evolved due to advancements in digital technologies, providing more detailed insights into movement patterns [3].

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Although human mobility and overall behavior are often complex, analyzing mobility during daily activities such as work commutes, shopping, socializing, or weekend trips to other cities reveals distinct patterns. This enables somewhat reliable predictions about future mobility [4], [5].

Traditional approaches to collecting data on human movement, like surveys, are limited by their restrictive nature, high costs, and time-consuming processes [6], [7]. However, the advent and widespread adoption of mobile devices have revolutionized data collection methods [1], [2]. These devices capture intricate details about individuals' daily travel routines, especially in urban areas [3]. Consequently, this rich dataset has proven invaluable for developing predictive models and analyzing mobility patterns [8], [9].

The study of broad mobility patterns of large groups using mobile device location data is increasingly significant. It can directly aid various aspects of municipal management and government, such as urban planning, traffic management, disease control, environmental impact assessment, and service provision by public and private entities [9], [10]. The study of these patterns is based on the analysis of mobility indicators derived from aggregated mobility data of large groups. The quality of these studies depends on the quality of these mobility parameters and their correct interpretation. It is, therefore, crucial to study and understand the characteristics and interrelationships of these mobility indicators.

This paper presents two studies of human mobility. The first study aims to examine associations between different aggregate mobility parameters and identify those carrying similar or identical information. It was conducted using aggregated daily mobility data for October 2020 from two large U.S. metropolitan statistical areas (MSAs) – Atlanta-Sandy Springs-Roswell, GA and Boston-Cambridge-Newton, MA-NH. These areas were chosen for their distinct geographies, which could affect mobility patterns. Atlanta is an inland city with a metropolitan area road network converging on the central area from all sides. In contrast, Boston is a coastal city with its eastern side occupied by the ocean, limiting roads coming into the area from the east.

The study begins with daily MSA level means and standard deviations of four primary mobility parameters – the Number of Visited Locations (N_LOC), the Number of Unique Visited Locations (N_ULOC), Radius of Gyration (R_GYR), and the Distance Traveled (D_TRAV). Additional mobility parameters are derived and considered in the study.

The second study analyzes the daily value patterns of mobility parameters in the 15 MSAs with the largest population sizes in the United States, according to population estimates for the year 2020 [11]. It builds on the results of the first study and includes only the mobility parameters identified in the first study as representing groups of associated mobility parameters. Both studies utilize the methodology presented in previous work ([12],[13]).

The overall goal of both studies is to contribute to a comprehensive understanding of daily movement patterns in these urban areas, supporting urban planners and ultimately helping to enhance the quality of life for residents.

The remainder of this paper is organized as follows: Section II outlines works focused on human mobility patterns using cellular data. Section III presents the datasets used in the two studies. Section IV details the methodology of the first study. Section V presents and discusses the results of the first study. Section VI describes the methodology of the second study. Section VII presents and discusses the results of the second study. Section VIII contains a general discussion of both studies and the implications of the findings. Section IX outlines limitations of the studies and directions for future research. Finally, Section X presents the conclusions.

II. Related work

Data on the movement of mobile devices of residents in large metropolitan areas constitutes what is referred to as "Big Data," i.e., extremely large datasets that are too complex to be processed and analyzed by traditional data-processing software. The analysis of Big Data has profoundly influenced our society, providing tools to monitor, understand, and predict human behavior [14]. This is particularly valuable in the field of mobility studies, where analyzing extensive datasets, including GPS and phone records, has significantly enhanced our understanding of movement patterns [15]–[17].

Various studies have highlighted the diverse nature of human movement. For instance, Eagle and Pentland (2009) identified unique "behavioral spaces" of individuals from their mobility data and discovered that overlapping behavioral spaces can identify communities [18]. Frias-Martinez et al. (2012) used tweeting patterns and locations to infer land use [19], while Jiang et al. (2012) explored using mobility patterns of mobile devices for city transportation system planning [20]. These studies form the basis for models and methods that categorize human movement. Researchers have also sorted individuals by travel behavior using mobile device location data [21], proposed models for movement and migration [22], and described cities through geolocated tweets [23].

Furthermore, mobile phone data has been instrumental in studying the link between human behavior and socio-economic development. Research by Eagle et al. (2010), Blumenstock (2018), and Pappalardo et al. (2015) established a strong relationship between human mobility dynamics and localized socio-economic factors, such as per capita income and poverty rates, offering invaluable insights for economic development mapping and understanding consumer behavior [24]–[26]. Additionally, Frias-Martinez et al. (2011) utilized mobile phone data to model the spread of the H1N1 virus in Mexico during the 2009 outbreak, shedding light on the impact of government lockdown measures [27].

Different methods of analyzing location data have furthered our understanding of consumer behavior. For example, Guidotti et al. (2015) identified customer groups based on supermarket purchase data, including patterns of visited stores, visit times, and purchased items [28]. Pappalardo et al. (2016) demonstrated that combining specific mobile phone usage patterns with socio-demographic parameters can improve socioeconomic predictions [29]. These studies emphasize the importance of diverse movement data sources in understanding consumer behavior and its socio-economic ties.

Movement data has also been crucial in disease prevention, including COVID-19. Xia et al. (2023) emphasized the role of movement data in managing disease spread and developing early warning systems [30]. Chen et al. (2021) studied how human movement impacted COVID-19 spread in China [31], and Mungmunpuntipantip and Wiwnitkit (2020) examined changing movement patterns in Thailand using GPS data [32].

In understanding the geographic spread of diseases other than COVID-19, movement data has been significant. For instance, Bengtsson et al. (2015) studied the spread of Cholera in Haiti using mobile phone records [33], and Belik et al. (2011) explored the role of natural human movement patterns in disease transmission [34].

In the field of spatial analysis, researchers have used mobile phone data to study human movement. Kang et al. (2010) analyzed cell phone usage in China to derive movement patterns [1]. Sevtsuk et al. (2010) identified regular movement patterns in Rome, Italy [35], while Becker et al. (2011) demonstrated the potential of using call detail records (CDRs) to examine movement in Morristown, New Jersey [36]. Song et al. (2010) found that, despite variations, human movement can be highly predictable [4]. Liu et al. (2014) analyzed GPS-equipped taxis in Shanghai, revealing daily rhythms and stable weekly mobility patterns [37]. Isaacman et al. (2011) developed algorithms to identify important personal places using cell phone location data [38]. Shi et al. (2017) analyzed collective movement patterns in Beijing, identifying different patterns based on various factors [39]. Hoteit et al. (2013) highlighted the importance of selecting the right parameters to understand movement within city networks [40].

Recent studies have focused on understanding human movement using crowd-sourced mobile phone data. Knezevic et al. (2023) and Matloub et al. (2023) studied movement in the Atlanta and Houston Metropolitan areas, showing that human movement is highly predictable [12], [13].

In summary, analyzing large datasets, particularly from mobile phones, has been crucial in understanding the links between human motion, socio-economic development, and well-being [1]. This knowledge has led to the development of models, prediction techniques, and profiling methods. It has also been instrumental in controlling the spread of diseases, including COVID-19, and has advanced our understanding of city planning, transportation, and spatial analysis. While past studies have identified consistent movement patterns, showing that individuals tend to stay mostly in a few places, a comprehensive set of mobility parameters for thoroughly describing city movement and understanding people's routines is still lacking. Moreover, the absence of comparative studies across different regions and populations underscores the need for additional research and collaborative efforts in this field.

III. Data Description

The two research studies presented in this paper utilized commercially accessible datasets comprising high-precision GPS coordinates obtained from cellular devices.

The first study utilized location information from individual mobile phones in the Atlanta-Sandy Springs-Roswell, GA, and Boston-Cambridge-Newton, MA-NH Metropolitan Statistical Areas (MSAs). The second study used location information from individual mobile phones within the fifteen most populous MSAs in the United States, according to population estimates from the United States Census Bureau for the year 2020 [11]. The data for both studies are from October 2020.

Table I presents the population size, the count of unique mobile devices from which data were included in the datasets, and the number of binned locations incorporated in these studies. It also indicates which data were used in each of the two presented studies. The data are geographically binned using Uber's H3 Hexagonal Hierarchical Spatial Index [41]. The number of locations listed in Table I is based on the h8 resolution level, corresponding to an approximate hexagonal bin radius of 531 meters. The data preparation procedure used in these studies follows the data preprocessing steps outlined in [13], selecting unique mobile devices. This approach ensures the inclusion of only those devices that appear in the dataset every day of the month and record a minimum of 24 location entries per day, or at least one every hour.

For enhanced readability, MSAs in this paper are referred to by the primary part of their name. For example, Atlanta-Sandy Springs-Roswell, GA is simply referred to as the Atlanta MSA.

IV. Study 1 Methodology

The objective of the first study is to explore associations between various mobility parameters and to identify groups of parameters that exhibit identical or highly overlapping information. If certain mobility parameters are highly or completely correlated, it may not be necessary to include all of them in further analyses. Instead, one or a few representative parameters from each group can be selected. This approach can significantly streamline the analysis of mobility patterns while ensuring that the essential mobility information encapsulated within these parameters is preserved.

A. Study 1 Mobility Parameters

The methodology presented in [13] is utilized to preprocess the raw data and evaluate the mobility parameters considered in this study. Following the data preprocessing stage, four primary mobility parameters are evaluated for each of the two studied Metropolitan Statistical Areas (MSAs):

- *Number of visited locations (N_LOC)*: This parameter represents the count of visited hexagonal bins over a given time scale.
- *Number of unique visited locations (N_ULOC)*: N_ULOC denotes the count of unique hexagonal bins visited over a given time scale.
- *Radius of gyration (R_GYR)*: R_GYR quantifies the size of an individual's mobility area. It is defined as the largest distance of an individual from their mobility center of mass.
- *Distance traveled (D_TRAV)*: D_TRAV refers to the total linear distance traveled by an individual at a given time scale.

The individuals are considered to have visited a location if they spend more than 15 minutes within the area associated with that location.

After following steps presented in [13], the resultant datasets contained means and standard deviations of the four primary studied mobility parameters for each day in the month of October 2020, resulting in a total of 8 different mobility parameters available for analysis (daily means and daily standard deviations for each of the 4 primary parameters). These 8 parameters were then combined to derive additional mobility parameters:

TABLE I
POPULATION, UNIQUE PHONES, AND BINNED LOCATIONS IN TOP 15 US MSAS

Included in Study 1?	Included in Study 2?	Metropolitan Statistical Area (MSA)	Population (2020)	Unique Phones	Population %	Locations
	Yes	New York-Newark-Jersey City, NY-NJ	20,140,470	278,742	1.90%	31,511
	Yes	Los Angeles-Long Beach-Anaheim, CA	13,200,998	74,074	1.04%	10,964
	Yes	Chicago-Naperville-Elgin, IL-IN	9,618,502	147,635	1.53%	25,113
	Yes	Dallas-Fort Worth-Arlington, TX	7,637,387	173,883	2.28%	29,723
	Yes	Houston-Pasadena-The Woodlands, TX	7,122,240	142,132	1.62%	26,276
	Yes	Washington-Arlington-Alexandria, DC-VA-MD-WV	6,385,162	71,652	2.00%	22,176
	Yes	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	6,245,051	87,404	0.56%	16,767
Yes	Yes	Atlanta-Sandy Springs-Roswell, GA	6,089,815	115,796	1.41%	32,029
	Yes	Miami-Fort Lauderdale-West Palm Beach, FL	6,138,333	86,494	1.38%	12,341
	Yes	Phoenix-Mesa-Chandler, AZ	4,845,832	70,848	1.40%	20,294
Yes	Yes	Boston-Cambridge-Newton, MA-NH	4,941,632	51,309	1.46%	12,780
	Yes	Riverside-San Bernardino-Ontario, CA	4,599,839	31,313	0.68%	20,176
	Yes	San Francisco-Oakland-Fremont, CA	4,749,008	23,100	0.49%	6,285
	Yes	Detroit–Warren–Dearborn, MI	4,392,041	71,119	1.26%	13,988
	Yes	Seattle-Tacoma-Bellevue, WA	4,018,762	50,544	1.12%	13,432

- *Coefficients of Variation (CV):* The coefficients of variation are calculated by dividing the standard deviation for a particular day with the mean for that specific day. This calculation presents the daily variation in D_TRAV, N_LOC, N_ULOC, and R_GYR as proportions of the mean, rather than in raw units of measurement or counts. Coefficients of variance are calculated for each of the four studied parameters.
- *Travel Path Shape:* This parameter is calculated by dividing the mean distance traveled for a particular day with the radius of gyration for that specific day. This calculation helps determine if travel paths tend to more closely resemble a straight line than a circular shape. Higher values of the shape of travel parameter indicate that the path is more circular around the mobility center of mass.
- *Average Distance Between Locations:* This parameter is calculated by dividing the mean distance traveled by the number of locations visited. This calculation shows the average distance covered between each visited location.

In total, this has resulted in 14 different mobility parameters used in this study.

B. Statistical Analyses

The primary objective of this study is to investigate the associations between analyzed mobility parameters in the two Metropolitan Statistical Areas (MSAs). Initial insights into their relationships were obtained by calculating correlations between the daily values of the 14 mobility parameters (details not presented in this paper).

Subsequently, an exploratory factor analysis was conducted on these parameters within each MSA. This technique is utilized to identify clusters of highly correlated mobility parameters. The process involves identifying parameters with high loadings on common factors, suggesting their potential to provide similar information and yield analogous results in analyses. The factor analysis was performed using the principal axis factoring method, coupled with a varimax orthogonal rotation for the final factor solution. Horn's parallel analysis was applied to determine the number of factors to be extracted [43].

This analysis was conducted separately on datasets from each of the two MSAs. One dataset was used to identify the factor structure of the mobility parameters, while the other served for cross-validation. This approach ensured verification of whether the observed factor structure (or a similar one) was present in both MSAs, thereby confirming that the patterns were not unique to a single MSA.

V. Study 1 Results and Discussion

An inspection of the correlation matrices between the daily values of the 14 mobility parameters within each of the two MSAs showed a strong correlation among most parameters. However, the complexity and size of these matrices render them impractical for interpretation or presentation within a research paper. To address this, an exploratory factor analysis was conducted on the mobility parameters within each MSA.

The results are detailed in Tables II and III, which display the association structures of the daily values of the 14 mobility parameters in the Atlanta and Boston MSAs, respectively. Factor loadings below 0.40 were deemed low and are not displayed for clarity.

Fig. 1 presents a scree plot comparing the eigenvalues of factors extracted from the Atlanta MSA dataset's mobility parameters against those from a simulated dataset in Horn's parallel analysis. Given the similarity, the scree plot from the Boston dataset is not included.

TABLE II
ATLANTA MSA MOBILITY PARAMETERS' FACTOR ANALYSIS RESULTS

Parameter	Factor 1	Factor 2	Uniqueness
Mean D_TRAV	0.83	0.56	0.00
SD of D_TRAV	0.85	0.47	0.05
Mean N_LOC	0.96		0.03
SD N_LOC	0.52		0.72
Mean N_ULOC	0.86	0.48	0.04
SD N_ULOC	0.91		0.10
Mean R_GYR		0.98	0.01
SD of R_GYR		0.88	0.11
D_TRAV CV	-0.81	-0.59	0.00
N_LOC CV	-0.91		0.06
N_ULOC CV		-0.80	0.30
R_GYR CV	-0.95		0.09
Travel Path Shape	0.88	-0.44	0.04
Average Distance Between Locations	0.42	0.82	0.16

TABLE III
BOSTON MSA MOBILITY PARAMETERS' FACTOR ANALYSIS RESULTS

Parameter	Factor 1	Factor 2	Uniqueness
Mean D_TRAV	0.71	0.70	0.00
SD of D_TRAV	0.55	0.81	0.05
Mean N_LOC	0.95		0.01
SD N_LOC	0.88		0.22
Mean N_ULOC	0.87	0.48	0.01
SD N_ULOC	0.90		0.16
Mean R_GYR		0.96	0.00
SD of R_GYR		1.00	0.00
D_TRAV CV	-0.86	-0.50	0.01
N_LOC CV	-0.91		0.06
N_ULOC CV	-0.44	-0.73	0.27
R_GYR CV	-0.89		0.14
Travel Path Shape	0.49	-0.87	0.00
Average Distance Between Locations		0.92	0.08

The analyses indicate that in both MSAs, the 14 mobility parameters group into two distinct factors. The first factor shows very high loadings on seven parameters in both MSAs, encompassing means and standard deviations of the number of locations and unique locations, as well as coefficients of variation of the radius of gyration and distance traveled. The second factor primarily comprises mean and standard deviation of radius of gyration, the coefficient of variance of the number of unique locations, and the average distance between locations. Travel path shape exhibits a positive correlation with the first factor and a negative one with the second, though the relative magnitudes of these correlations differ between the two MSAs.

Interestingly, both the mean and standard deviation of distance traveled show high or substantial loadings on both factors in both MSAs. Notably, the standard deviation of the number of locations visited and the coefficient of variation of the number of unique locations visited demonstrate the highest level of uniqueness in both MSAs. This suggests that these parameters share the least variance with the others. Yet, even these uniqueness values are relatively low, indicating a shared variance among most mobility parameters. In fact, the two extracted factors account for 87.9% of the variance in the Atlanta MSA dataset and 92.8% in the Boston MSA dataset.

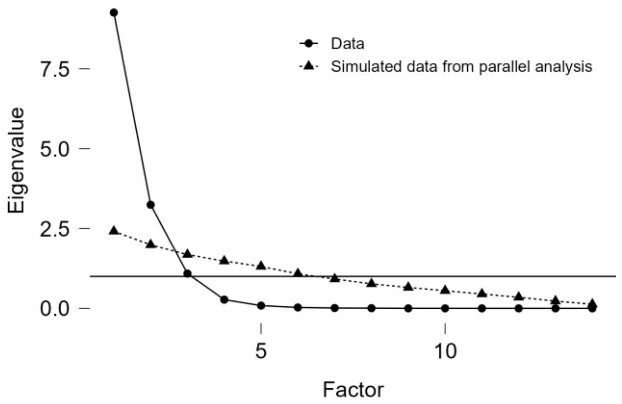

Fig. 1. Atlanta MSA Scree Plot (Horn's Parallel Analysis).

Overall, the findings from the first study reveal that the examined individual mobility parameters are not unique when compared to others; they are strongly interrelated. Linear modeling could accurately predict each parameter from the others, suggesting that all mobility parameters may not be necessary for further analyses of mobility patterns. Instead, one parameter representing each of the two factors could be sufficient. The best candidates would be those with zero uniqueness. Additionally, mean distance, which also has zero uniqueness and exhibits relatively high (in Boston) or substantial (in Atlanta) loadings on both factors, could be considered for analysis.

VI. Study 2 Methodology

The aim of the second study was to analyze the daily value patterns of mobility parameters in the 15 largest MSAs in the United States, selected based on population estimates for the year 2020.

A. Study 2 Mobility Parameters

The results of Study 1 strongly indicated that analyzing all mobility parameters, especially when examining pattern data, is not necessary. Building on the findings of Study 1, this study focuses only on data related to:

- *Mean daily distance traveled*, as this mobility parameter showed substantial loadings on both factors identified in Study 1.
- *Mean daily number of locations*, representing mobility parameters with high loadings on factor 1.
- *Mean daily radius of gyration*, representing mobility parameters with high loadings on factor 2.

An exception to this approach was made for the initial calculation of descriptive statistics, where all mobility parameters from Study 1 were utilized. This was done to provide readers with a comprehensive view of the values of these parameters across different MSAs, presented in their specific units of measurement.

B. Statistical Analyses

This study used the following statistical procedures:

- *Deviation from the Theoretical Normal Distribution*: Measures of vertical and horizontal deviation, namely skewness and kurtosis, are analyzed to assess the extent of deviation from the ideal normal distribution. The size of these deviations is evaluated in accordance with one of the common rules of thumb: deviations of approximately ± 1 are deemed small and are, therefore, considered to not constitute substantial deviations from the theoretical normal distribution [42].
- *Comparing Means of Daily Values of Mobility Parameters*: The means of mobility parameters' daily values across diverse MSAs are compared using repeated measures analysis of variance (repeated measures ANOVA). η^2 is used as a measure of effect size. The statistical significance threshold employed in this study is 0.05.
- *Exploratory Factor Analysis among MSAs*: Exploratory factor analysis was used to create soft categories of MSAs based on covariance of daily mobility patterns across MSAs. The factor analysis is applied to the same mobility parameters, measured in different MSAs on the same days. The data for this operation consist of selected mobility parameters across all MSAs, with each MSA's data on a single mobility parameter serving as one variable, and the different recording days being represented as entities/cases. Anderson-Rubin factor scores [44] of extracted factors are generated, subsequently used for further comparison to represent the generalized tendencies of the MSA group associated with that particular factor.
- *Comparison of Mobility Parameters on Different Days of the Week*: Mean values of factor scores that represent factors derived from daily mobility parameters of MSAs for different days of the week are compared using one-way ANOVA. Eta squared (η^2)is used as a measure of effect size.
- *Pairwise Comparison of Means*: Following analysis of variance, pairwise comparisons of means are conducted using t-test with Bonferroni correction for probability inflation [45]. All statistical significances of pairwise comparisons include the Bonferroni correction. Cohen's d values are used as effect size measures in these comparisons and interpreted in accordance with the recommendations given by Cohen [46].
- *Examination of Autocorrelations*: Correlations between a parameter and its lagged values (lag 7 and lag 1) are calculated, serving to examine the observations about weekly cycle trends. Autocorrelations are derived by pairing parameter values with their own values at future time points that differ for a fixed number of units. Here, the values are matched with the values of the same parameter on the corresponding weekday of the ensuing week, thereby validating the weekly cycle. This is contrasted with lag 1 autocorrelation, i.e., correlations of parameter values on each day, paired with their values on the following day, aiming to determine whether the weekly cycle is stronger than mere day-to-day changes.

VII. Study 2 Results and Discussion

A. Differences between MSAs and Mobility Parameter Distribution Shapes

Table IV shows values of mean, standard deviation, skewness, and kurtosis for each mobility parameter evaluated during the period from October 1, 2020, to October 30, 2020, derived from the datasets. Mean values of included Metropolitan Statistical Areas (MSAs) are compared using repeated measures ANOVA, with eta squared (η^2) serving as a measure of effect size.

TABLE IV
Descriptive Statistics and ANOVA Results for Different MSAs

Mean Daily D_TRAV (km)					**Mean SD of Daily D_TRAV (km)**				
MSA	Mean	SD	Skewness	Kurtosis	MSA	Mean	SD	Skewness	Kurtosis
Atlanta	61.88	5.7	-0.44	0.36	Atlanta	66.57	3.31	-0.91	1.28
Boston	45.51	4.74	1.05	0.76	Boston	53.62	2.95	1.14	0.86
Chicago	48.53	4.69	0.23	0.02	Chicago	59.15	2.57	-0.46	0.72
Dallas	62.8	6.15	-0.02	-1.08	Dallas	68.67	3.62	-0.38	-0.89
Detroit	52.62	5.1	-0.33	-0.18	Detroit	57.64	2.87	-0.69	0.36
Houston	62.83	5.19	0.01	-0.76	Houston	68.82	2.83	-0.23	-0.76
Los Angeles	42.68	3.41	0.75	-0.85	Los Angeles	52.57	2.06	1.04	0.08
Miami	47.12	4.14	-0.69	0.39	Miami	55.58	2.66	-1.05	0.86
New York	44.91	4.68	0.81	0.69	New York	57.16	3.54	0.98	0.31
Philadelphia	45.2	4.89	0.78	0.01	Philadelphia	51.67	2.46	0.54	-0.44
Phoenix	56.46	5.2	-0.54	-0.04	Phoenix	65.34	3.15	-0.78	0.15
Riverside	49.57	3.81	-0.19	-0.66	Riverside	61.73	2.24	-0.18	-0.45
San Francisco	37.44	3.08	0.96	-0.22	San Francisco	49.44	1.7	0.34	-0.97
Seattle	43.32	3.74	-0.53	0.05	Seattle	54.69	2.57	-1.2	1.14
Washington	46.52	5.09	0.66	0.14	Washington	58.14	2.87	0.28	0.07
F	**323.48**				**F**	**448.81**			
$\boldsymbol{\eta^2}$	**0.92**				$\boldsymbol{\eta^2}$	**0.94**			
Sig.	**<0.01**				**Sig.**	**<0.01**			
Mean Daily N_LOC					**Mean Daily SD of N_LOC**				
MSA	Mean	SD	Skewness	Kurtosis	MSA	Mean	SD	Skewness	Kurtosis
Atlanta	5.61	0.35	-0.58	0.77	Atlanta	4.24	0.1	2.88	10.89
Boston	5.1	0.31	0.12	-0.84	Boston	3.91	0.06	-0.33	-0.26
Chicago	5.17	0.32	-0.44	0.41	Chicago	4	0.06	-1.07	1.34
Dallas	5.69	0.36	-0.56	-0.02	Dallas	4.19	0.07	-0.64	-0.09
Detroit	5.26	0.34	-0.78	0.66	Detroit	3.96	0.07	-0.64	-0.03
Houston	5.66	0.32	-0.76	0.79	Houston	4.17	0.06	-0.91	0.86
Los Angeles	4.87	0.23	0.38	-0.92	Los Angeles	3.81	0.04	-0.65	-0.13
Miami	5.25	0.31	-0.77	0.55	Miami	3.98	0.07	-1.26	1.17
New York	5.17	0.34	-0.49	0.19	New York	4.03	0.06	-0.68	-0.15
Philadelphia	5.12	0.34	-0.3	-0.57	Philadelphia	3.93	0.06	-0.94	0.14
Phoenix	5.2	0.31	-0.58	0.5	Phoenix	3.89	0.08	-0.96	0.8
Riverside	4.82	0.23	-0.13	-0.23	Riverside	3.85	0.06	-0.77	0.74
San Francisco	4.56	0.21	0.64	-0.88	San Francisco	3.77	0.05	-0.8	0.84
Seattle	4.75	0.25	-0.96	0.98	Seattle	3.95	0.07	-1.25	1.66
Washington	4.79	0.32	-0.42	0.13	Washington	3.94	0.07	-1.61	1.92
F	**128.96**				**F**	**331.08**			
$\boldsymbol{\eta^2}$	**0.82**				$\boldsymbol{\eta^2}$	**0.92**			
Sig.	**<0.01**				**Sig.**	**<0.01**			
Mean Daily N_ULOC					**Mean Daily SD of N_ULOC**				
MSA	Mean	SD	Skewness	Kurtosis	MSA	Mean	SD	Skewness	Kurtosis
Atlanta	3.15	0.2	0.02	0.49	Atlanta	1.91	0.11	-0.22	0.68
Boston	2.84	0.18	0.53	-0.43	Boston	1.7	0.08	0.14	-0.49
Chicago	2.9	0.19	0.14	-0.37	Chicago	1.78	0.09	-0.49	0.4
Dallas	3.16	0.21	0.06	-0.83	Dallas	1.91	0.11	-0.26	-0.48
Detroit	2.95	0.2	-0.12	-0.42	Detroit	1.77	0.1	-0.49	0.08
Houston	3.17	0.19	0.12	-0.46	Houston	1.91	0.1	-0.27	-0.22
Los Angeles	2.79	0.15	0.74	-0.96	Los Angeles	1.73	0.07	0.26	-0.69
Miami	3.03	0.18	-0.21	0.01	Miami	1.89	0.1	-1.02	1.24
New York	2.92	0.2	0.02	-0.07	New York	1.8	0.08	-0.22	-0.42
Philadelphia	2.86	0.2	0.27	-0.67	Philadelphia	1.71	0.09	-0.31	-0.57
Phoenix	2.97	0.18	0.04	-0.21	Phoenix	1.85	0.1	-0.62	0.53
Riverside	2.75	0.14	0.41	-0.63	Riverside	1.7	0.07	-0.39	0.31
San Francisco	2.62	0.14	0.89	-0.66	San Francisco	1.66	0.07	0.53	-0.69
Seattle	2.7	0.15	-0.14	-0.31	Seattle	1.74	0.09	-0.78	0.94
Washington	2.74	0.2	0.31	-0.38	Washington	1.74	0.1	-0.65	0.54
F	**119.34**				**F**	**172.9**			
$\boldsymbol{\eta^2}$	**0.8**				$\boldsymbol{\eta^2}$	**0.86**			
Sig.	**<0.01**				**Sig.**	**<0.01**			
Mean Daily R_GYR (km)					**Mean Daily SD of R_GYR (km)**				
MSA	Mean	SD	Skewness	Kurtosis	MSA	Mean	SD	Skewness	Kurtosis
Atlanta	12.56	1.08	0.94	0.16	Atlanta	14.09	1.21	0.8	-0.5
Boston	9.46	1.33	1.16	0.45	Boston	11.74	1.72	1.03	-0.35
Chicago	10.06	1.12	1.17	0.55	Chicago	12.74	1.4	0.95	-0.39
Dallas	12.72	1.34	0.9	-0.13	Dallas	14.57	1.44	0.64	-1.06
Detroit	10.58	0.98	1.11	0.15	Detroit	11.64	0.93	0.88	-0.56
Houston	12.61	1.2	1.02	-0.14	Houston	14.52	1.47	0.64	-1.31

Mean Daily R_GYR (km) (Continued)				
MSA	Mean	SD	MSA	Mean
Los Angeles	8.94	0.9	1.01	-0.09
Miami	9.52	0.76	1.12	0.39
New York	9.4	1.39	0.93	-0.46
Philadelphia	9.27	1.17	1.19	0.68
Phoenix	11.42	0.93	1.02	-0.45
Riverside	11.19	0.97	0.93	-0.33
San Francisco	7.97	0.84	1.02	0.06
Seattle	9.18	0.78	1.17	0.47
Washington	9.89	1.25	1.21	0.43
F	295.91			
η^2	0.91			
Sig.	<0.01			

Mean Daily D_TRAV CV				
MSA	Mean	SD	Skewness	Kurtosis
Atlanta	1.08	0.05	0.42	0.6
Boston	1.18	0.06	-0.4	-0.44
Chicago	1.22	0.07	-0.22	-0.26
Dallas	1.1	0.05	-0.12	-1.08
Detroit	1.1	0.06	0.41	-0.05
Houston	1.1	0.05	0.06	-0.68
Los Angeles	1.24	0.05	-0.5	-1.07
Miami	1.18	0.05	0.7	0.55
New York	1.28	0.06	0.38	0.76
Philadelphia	1.15	0.07	-0.4	-0.05
Phoenix	1.16	0.06	0.61	0.15
Riverside	1.25	0.05	0.39	-0.56
San Francisco	1.33	0.06	-0.92	-0.18
Seattle	1.27	0.06	0.15	-0.43
Washington	1.26	0.07	-0.42	-0.07
F	**199.17**			
η^2	**0.87**			
Sig.	**<0.01**			

Mean Daily N_ULOC CV				
MSA	Mean	SD	Skewness	Kurtosis
Atlanta	0.61	0.01	0.37	0.22
Boston	0.6	0.02	0.08	-0.54
Chicago	0.62	0.01	-0.62	-0.34
Dallas	0.61	0.01	0.13	0.07
Detroit	0.6	0.01	-0.53	-0.63
Houston	0.6	0.01	-0.1	-0.1
Los Angeles	0.62	0.01	-0.16	-0.99
Miami	0.62	0.01	0.05	-0.43
New York	0.62	0.02	0.24	0.57
Philadelphia	0.6	0.01	-0.47	0.27
Phoenix	0.62	0.01	0.3	-0.79
Riverside	0.62	0.01	-0.32	-0.98
San Francisco	0.64	0.01	-0.3	-0.59
Seattle	0.65	0.01	-0.46	0.03
Washington	0.64	0.02	-0.79	-0.27
F	**104.98**			
η^2	**0.78**			
Sig.	**<0.01**			

Mean Daily Travel Path Shape				
MSA	Mean	SD	Skewness	Kurtosis
Atlanta	4.93	0.34	-1.16	-0.23
Boston	4.84	0.32	-1.08	-0.16
Chicago	4.84	0.31	-1.31	0.47
Dallas	4.95	0.35	-1.23	0.1
Detroit	4.98	0.31	-1.43	0.77
Houston	5	0.37	-1.26	0.1
Los Angeles	4.79	0.26	-1.27	0.16
Miami	4.96	0.36	-1.16	-0.05
New York	4.82	0.35	-1.15	0.01
Philadelphia	4.89	0.32	-1.32	0.62
Phoenix	4.95	0.31	-1.24	0.22
Riverside	4.44	0.28	-1.13	0.04
San Francisco	4.71	0.24	-1.27	0.15
Seattle	4.73	0.28	-1.22	0
Washington	4.72	0.28	-1.25	0.4
F	**161.95**			
η^2	**0.85**			
Sig.	**<0.01**			

Mean Daily SD of R_GYR (km) (Continued)				
MSA	Mean	SD	MSA	Mean
Los Angeles	11.33	1.23	0.86	-1
Miami	12.1	1.29	0.94	-0.57
New York	13.2	2.14	0.82	-1
Philadelphia	10.79	1.29	0.89	-0.85
Phoenix	13.74	1.2	0.73	-0.86
Riverside	16.97	2.07	0.63	-0.7
San Francisco	10.24	0.88	0.86	-0.94
Seattle	11.68	0.92	0.99	-0.14
Washington	12.53	1.35	0.93	-0.64
F	323.42			
η^2	0.92			
Sig.	<0.01			

Mean Daily N_LOC CV				
MSA	Mean	SD	Skewness	Kurtosis
Atlanta	0.76	0.04	1.14	1.69
Boston	0.77	0.04	0.1	-0.67
Chicago	0.78	0.04	0.61	0.55
Dallas	0.74	0.04	0.81	0.12
Detroit	0.75	0.04	1.13	1.46
Houston	0.74	0.03	0.92	0.63
Los Angeles	0.78	0.03	-0.37	-0.93
Miami	0.76	0.03	0.72	0.35
New York	0.78	0.04	0.88	1.52
Philadelphia	0.77	0.04	0.36	-0.52
Phoenix	0.75	0.03	0.72	0.61
Riverside	0.8	0.03	0.01	-0.83
San Francisco	0.83	0.03	-0.54	-0.71
Seattle	0.83	0.03	0.73	0.31
Washington	0.82	0.04	0.24	0.07
F	**69.69**			
η^2	**0.71**			
Sig.	**<0.01**			

Mean Daily R_GYR CV				
MSA	Mean	SD	Skewness	Kurtosis
Atlanta	1.12	0.06	1.65	2.51
Boston	1.24	0.05	1.11	0.25
Chicago	1.27	0.06	1.68	2.87
Dallas	1.15	0.05	1.46	1.24
Detroit	1.1	0.06	1.79	2.81
Houston	1.15	0.05	1.92	2.49
Los Angeles	1.27	0.05	1.38	1.53
Miami	1.27	0.08	1.36	1.13
New York	1.4	0.07	1.57	1.87
Philadelphia	1.17	0.06	1.27	0.7
Phoenix	1.2	0.07	1.6	1.84
Riverside	1.51	0.1	1.35	0.63
San Francisco	1.29	0.05	-0.22	-0.84
Seattle	1.27	0.06	1.79	2.54
Washington	1.27	0.07	1.4	1.93
F	**292.42**			
η^2	**0.91**			
Sig.	**<0.01**			

Mean Daily Average Distance Between Locations (km)				
MSA	Mean	SD	Skewness	Kurtosis
Atlanta	11.02	0.49	-0.11	0.68
Boston	8.91	0.51	1.38	1.27
Chicago	9.37	0.39	1.09	0.61
Dallas	11.02	0.51	1.08	0.18
Detroit	9.98	0.39	0.69	0.08
Houston	11.09	0.43	1.19	0.36
Los Angeles	8.75	0.34	1.26	0.76
Miami	8.97	0.32	-0.28	0.09
New York	8.69	0.55	1.12	-0.09
Philadelphia	8.81	0.45	1.51	1.56
Phoenix	10.83	0.43	0	-0.73
Riverside	10.28	0.34	0.19	-0.25
San Francisco	8.2	0.33	1.1	0.72
Seattle	9.1	0.35	0.24	-0.22
Washington	9.69	0.48	1.52	1.43
F	**603.24**			
η^2	**0.96**			
Sig.	**<0.01**			

A review of Table IV suggests that the distribution of the majority of assessed parameters closely aligns with a theoretical normal distribution, as most skewness and kurtosis values lie within the ± 1 range [42]. Noteworthy deviations are observed in the shapes of daily travel paths, which demonstrate considerable negative asymmetry, and daily average distances between locations, which are normally distributed for 6 MSAs and positively skewed for 9 MSAs.

Despite some parameters exhibiting distributions deviating beyond the ± 1 range, after some tryouts, the choice was made to retain parametric statistics without implementing normalization transformations to the data. This was done because those initial tryouts showed that conclusions drawn from the results would be the same both with and without transformation of the data and also regardless of whether parametric and nonparametric procedures were applied. This was especially the case because most effect sizes were quite large (η^2), as can be seen in Table IV.

The data in Table IV show notable contrasts in the mean daily distance traveled across MSAs. For example, in Dallas, Houston, and Atlanta the average daily distance travelled range between 61 km and 63 km, and in MSAs like San Francisco, Los Angeles, and Seattle, these distances are much shorter being 37 km, 43 km, and 43 km, respectively. Standard deviations of daily travel distance are consistently higher than mean values, indicating a considerable range in individual travel patterns. This suggests the presence of many individuals with minimal or no travel (thus reducing the mean) as well as a smaller subset of individuals who travel extensively (thus significantly increasing the standard deviation).

Evaluation of the number of locations visited reveals that the MSAs with the most extensive and least extensive daily travel distances also recorded the highest and lowest average numbers of locations visited, respectively. A similar trend is noted when assessing the number of unique locations visited. However, the three MSAs with the smallest average daily number of unique locations visited are San Francisco, Seattle, and Washington, with Riverside and Los Angeles recording slightly higher values.

Assessment of the average radius of gyration shows that Dallas, Houston, and Atlanta MSAs have the highest values, while San Francisco, Los Angeles, and Seattle MSAs have the lowest. In terms of the average distance between locations visited, data indicates that visited locations are the furthest apart in Houston, Dallas, and Atlanta MSAs, and the closest together in San Francisco, New York, and Los Angeles MSAs.

The mean values of daily travel paths suggest that these paths are generally more linear than circular, with relatively low standard deviations. Among different areas, Riverside MSA exhibits paths most closely aligned with a linear shape, while Houston, Detroit, and Dallas MSAs show the most deviation from this shape, suggesting a more circular traffic infrastructure in these MSAs.

Comparison of mean values of the studied parameters between the fifteen (15) MSAs using repeated measures ANOVA reveals that differences between MSAs are statistically significant in all cases and of extreme size (high η^2 values). Within each MSA, differences between parameter values on different days of October 2020 tend to be smaller than those between different MSAs. The smallest difference among MSAs, though still notably large, is seen when examining mean coefficients of variation of the daily N_LOC ($\eta^2 = 17$), while the largest difference is found when comparing mean values of daily average distance between locations ($\eta^2 = 0.96$).

This suggests that the number of locations people visit within MSAs does not vary as significantly as the average distances individuals travel. The MSAs are more similar when considering the frequency of location visits, but they diverge more substantially in terms of the average distances covered by individuals.

Results also indicate that the differences in mean values of examined mobility parameters are not universally statistically significant across all MSAs. The mean value of a given parameter in one MSA often does not differ significantly from that in several other MSAs, although it may stand out in the remaining ones. This suggests that grouping MSAs with similar mean values on the same days is feasible.

B. Comparison of Mobility Parameters across MSAs

Next, exploratory factor analysis was conducted to identify clusters of MSAs with similar patterns of daily variations in parameter values. Based on the results of study 1, the decision was made to conduct this procedure on three mobility parameters only – the average daily distance traveled, the average number of daily locations visited, and the radius of gyration. Explanation for this decision is presented in the methodology part of this study and in the results of study 1.

The results of the exploratory factor analysis conducted on the mean distance traveled across different MSAs are presented in Table V. Additionally, Fig. 2 presents the scree plot that shows the results of Horn's parallel analysis i.e., the eigenvalues of extracted factors alongside the eigenvalues of factors from a simulated matrix. It should be noted that factor loadings below 0.58 are not included in Table V.

TABLE V
FACTOR LOADINGS AND UNIQUENESS OF DAILY MEAN DISTANCE TRAVELED

Mean Daily Distance Travelled			
MSA	Factor 1	Factor 2	Uniqueness
Atlanta	0.87		0.20
Boston		0.92	0.12
Chicago	0.62	0.67	0.18
Dallas	0.82		0.08
Detroit	0.82		0.10
Houston	0.87		0.05
Los Angeles	0.67	0.71	0.06
Miami	0.89		0.19
New York		0.98	0.02
Philadelphia		0.84	0.07
Phoenix	0.95		0.01
Riverside	0.90		0.01
San Francisco		0.72	0.16
Seattle	0.89		0.10
Washington		0.79	0.11

As Table V shows, two factors were extracted in this procedure. These factors collectively account for 90% of the variance in daily mean distance traveled. Of that, 52.3% are accounted for by the first factor and 38.1% by the second.

MSAs with the highest loadings on the first factor (Factor 1) are Atlanta, Dallas, Detroit, Houston, Miami, Phoenix, Riverside, and Seattle. Similarly, Boston, Los Angeles, New York, Philadelphia, San Francisco, and Washington are MSAs with the highest loadings on the second factor (Factor 2). Interestingly, Chicago and Los Angeles stand out by displaying moderately high loadings on both factors.

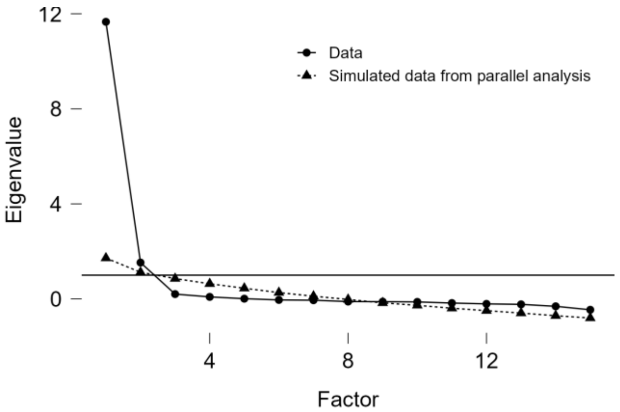

Fig. 2. Scree plot of D_TRAV extracted factors with eigenvalues in different MSAs.

MSAs with high loadings on Factor 1 are predominantly found to be inland, with the exceptions of Miami and Seattle. In contrast, all MSAs with high loadings on Factor 2, barring Chicago, are identified as coastal cities. These findings might illustrate the distinctive patterns of daily distance traveled between inland and coastal cities, allowing for a few outliers.

When these results are compared with the average daily mean distance traveled, MSAs with the highest mean values of distance traveled, such as Dallas, Houston, and Atlanta, are all found to display high loadings on Factor 1. Seattle, on the other hand, which has one of the lowest distances traveled values, also displays a high loading on Factor 1. Conversely, San Francisco and Los Angeles, the other two low mean daily distance traveled MSAs, display high loadings on Factor 2, although Los Angeles also exhibits a significant loading on Factor 1. These observations might suggest that the patterns of daily distance traveled changes responsible for this grouping are not highly associated with the average size of daily distance traveled, considering that the factor analytic procedure is conducted on the correlation matrix and correlations are not sensitive to differences in means and variances.

For the purpose of corroborating these findings, the same procedure is repeated on the mean daily number of locations visited and the mean daily radius of gyration across different MSAs, in light of the preceding results.

Table VI shows the Factor loadings and uniqueness of the daily mean number of locations visited for various MSAs. Factor loadings below 0.58 are not displayed. In Fig. 3, the scree plot illustrates the extracted factors from the mean daily number of locations visited, along with the corresponding eigenvalues derived from a simulated matrix created under the framework of Horn's parallel analysis.

Upon examining the results of factor analysis for the daily mean number of locations visited, it is found that the outcomes again consist of 2 factors. These 2 factors together explain 85.2% of the variance of the daily mean number of locations visited, specifically 51.7% and 33.4%. However, it is notable that the second factor demonstrates high loadings for the daily number of locations visited data from New York, Philadelphia, Boston, and Washington, while the remaining MSAs exhibit the highest loading on the first factor. Chicago exhibits equally high loadings on both factors, similar to the results observed for mean distances traveled.

TABLE VI
FACTOR LOADINGS AND UNIQUENESS OF DAILY MEAN N_LOC

Mean Daily N_LOC			
MSA	Factor 1	Factor 2	Uniqueness
Atlanta	0.88		0.20
Boston		0.87	0.21
Chicago	0.60	0.63	0.25
Dallas	0.82		0.14
Detroit	0.78		0.15
Houston	0.90		0.07
Los Angeles	0.77		0.14
Miami	0.83		0.26
New York		0.92	0.07
Philadelphia		0.90	0.04
Phoenix	0.94		0.06
Riverside	0.89		0.03
San Francisco	0.65		0.34
Seattle	0.83		0.13
Washington		0.79	0.14

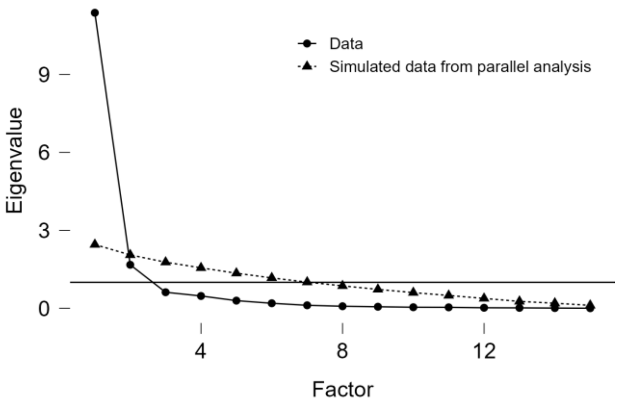

Fig. 3. Scree plot of N_LOC extracted factors with eigenvalues in different MSAs.

The total variance explained by these factors is somewhat lower compared to the analysis based on mean distances traveled. Consequently, the average uniqueness of source variables in this analysis is somewhat higher than in the one conducted on mean distance travel, approximately 0.15 here compared to 0.10 in the analysis on mean distance traveled. The uniqueness of mean daily numbers of locations visited for San Francisco, Miami, and Chicago stands out with 34%, 26%, and 25% of unique variance, respectively. This indicates that patterns of daily mean numbers of unique locations visited in each of these three MSAs is somewhat more distinct than is the case with other MSAs. In contrast to this, daily variations in mean number of locations visited of Riverside, Philadelphia, New York, or Houston MSAs can almost perfectly be predicted from daily variations of this same mobility parameter of other MSAs.

A closer examination of the MSAs highly loading on the second factor reveals that they are all situated on the U.S. east coast and adjacent to one another along the north-south axis. On the other hand, Factor 1 MSAs are located either inland or on the west or southern part of the U.S., with Chicago being an exception, as it is located inland and exhibits moderate loadings on both factors.

The results of factor analysis for the mean daily radius of gyration of the MSAs under study are presented in Table VII and Fig. 4. Factor loadings below 0.58 are not displayed. In contrast to the previous analysis, Horn's parallel analysis indicates that all mean daily radius of gyration variables for the studied MSAs form a single factor, which accounts for 86% of the variance in daily values across all MSAs. All MSAs have very high loadings on this factor.

Boston, Atlanta, and Miami stand out due to their relatively high levels of uniqueness in their daily mean radius of gyration values. However, since only one factor was extracted in this analysis, the daily radius of gyration of different cities cannot be utilized to classify them into distinct groups. Instead, they all belong to the same group, as they are characterized by the same underlying factor. This means that daily variations in the mean radius of gyration across the studied MSAs tend to follow very similar patterns.

TABLE VII
FACTOR LOADINGS AND UNIQUENESS OF DAILY MEAN R_GYR

Mean Daily R_GYR

MSA	Factor 1	Uniqueness
Atlanta	0.85	0.28
Boston	0.82	0.33
Chicago	0.92	0.15
Dallas	0.98	0.04
Detroit	0.94	0.11
Houston	0.99	0.03
Los Angeles	0.99	0.02
Miami	0.88	0.22
New York	0.86	0.26
Philadelphia	0.95	0.09
Phoenix	0.92	0.15
Riverside	0.97	0.06
San Francisco	0.97	0.07
Seattle	0.91	0.17
Washington	0.96	0.09

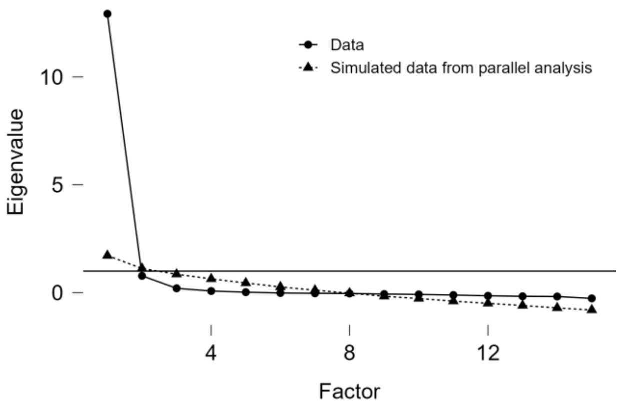

Fig. 4. Scree plot of R_GYR extracted factors with eigenvalues in different MSAs.

C. Weekly Mobility Patterns

The objective of the next set of analyses is to investigate potential weekly mobility patterns. For this purpose, Anderson-Rubin factor scores were created to represent factors obtained in the scope of exploratory factor analyses of the three mobility parameters: mean daily distance travelled, mean daily number of locations visited, and mean daily radius of gyration, presented in part B of this section.

Table VIII presents the descriptive statistics of factor score values on different days of the week. The table includes means, standard deviations, standard errors of means, and 95% confidence intervals of means for the mentioned factors. Upon examining the results, it is evident that differences between scores of factors 1 and 2 on both mean distance travelled and number of locations visited, can best be described in terms of the day of the week when they reach their peak and their bottom values. Specifically, Factor 1 scores demonstrate the highest levels on Fridays and lowest on Sundays, whereas Factor 2 scores are the highest on Saturdays and the lowest on Mondays. As the week progresses, scores for both factors generally experience an increasing trend, reaching their highest values on a specific day and then subsequently declining on the following day, to reach the lowest value two days later. After that, factor score values start increasing again, repeating the weekly cycle.

Consequently, these findings suggest a classification of the studied MSAs into two groups based on individuals' travel and location visitation patterns. The first group, Factor 1 MSAs, corresponds to MSAs where individuals tend to travel the most extensively and visit the highest numbers of locations on Fridays. In contrast, the second group, Factor 2 MSAs, consists of areas where people tend to engage in the most substantial travel and visit the highest number of locations on Saturdays. It is also notable that the weekly bottom value of factor 1 is lower than the bottom value of factor 2. However, the weekly highest value of factor 2 is higher than the weekly highest value on factor 1. This indicates that the surge in the volume of travelling on the peak day is much higher in factor 2 MSAs than in factor 1 MSAs. On the other hand, the reduction in travelling on the day of the week when the volume of travel is the lowest is stronger in factor 1 than in factor 2 MSAs.

A possible explanation for these findings in weekly mobility patterns might be differences in shopping behaviors among the two groups. Specifically, it is possible that individuals in Factor 1 MSAs conduct their shopping activities predominantly on Fridays, leading to multiple location visits on that day. Conversely, Factor 2 MSAs might be exhibiting shopping patterns primarily focused on Saturdays, resulting in a significant number of locations visited on Saturdays. Additionally, mean radius of gyration displays its highest values on Saturdays and the lowest values on Mondays. The values progressively increase from Monday to Saturday, before decreasing again on Sundays.

It is crucial to emphasize that while these findings provide valuable insights into the weekly cycle trends, comprehensive research is necessary for a thorough understanding of the observed differences. Importantly, the dataset under examination does not provide sufficient detail to ascertain the precise nature of these travel patterns. Traveling on Fridays and Saturdays could conceivably be influenced by other factors, such as social interactions or recreational pursuits. In the absence of additional research into the motivations behind these mobility patterns, attributing them solely to shopping or any other specific activity remains speculative.

TABLE VIII
DESCRIPTIVE STATISTICS OF FACTOR SCORES FOR DAILY TRAVEL AND VISITATION PATTERNS

Day	Mean	Standard Deviation	SE of mean	95% CI of mean, lower and upper bound	
Mean Daily D_TRAV – Factor 1 Scores Stats					
Monday	-0.32	0.23	0.11	-0.69	0.04
Tuesday	-0.12	0.20	0.10	-0.43	0.20
Wednesday	0.14	0.09	0.04	0.00	0.29
Thursday	0.30	0.33	0.15	-0.11	0.72
Friday	1.27	0.49	0.22	0.66	1.87
Saturday	0.41	0.31	0.16	-0.09	0.91
Sunday	-2.07	0.21	0.11	-2.41	-1.74
Mean Daily D_TRAV – Factor 2 Scores Stats					
Day	Mean	Standard Deviation	SE of mean	95% CI of mean, lower and upper bound	
Monday	-1.04	0.52	0.26	-1.87	-0.21
Tuesday	-0.63	0.26	0.13	-1.05	-0.22
Wednesday	-0.43	0.22	0.11	-0.77	-0.08
Thursday	-0.34	0.61	0.27	-1.09	0.42
Friday	0.15	0.56	0.25	-0.55	0.84
Saturday	2.04	0.31	0.16	1.55	2.54
Sunday	0.29	0.41	0.21	-0.36	0.95
Mean Daily N_LOC – Factor 1 Scores Stats					
Day	Mean	Standard Deviation	SE of mean	95% CI of mean, lower and upper bound	
Monday	-0.28	0.37	0.19	-0.88	0.31
Tuesday	-0.13	0.27	0.14	-0.56	0.31
Wednesday	0.11	0.26	0.13	-0.30	0.52
Thursday	0.29	0.70	0.31	-0.58	1.16
Friday	1.37	0.71	0.32	0.48	2.25
Saturday	0.07	0.23	0.12	-0.30	0.44
Sunday	-1.85	0.23	0.12	-2.21	-1.48
Mean Daily N_LOC – Factor 2 Scores Stats					
Day	Mean	Standard Deviation	SE of mean	95% CI of mean, lower and upper bound	
Monday	-0.86	1.02	0.51	-2.49	0.76
Tuesday	-0.21	0.42	0.21	-0.87	0.46
Wednesday	-0.10	0.40	0.20	-0.73	0.53
Thursday	-0.13	1.17	0.53	-1.59	1.33
Friday	0.34	1.00	0.45	-0.90	1.58
Saturday	1.50	0.25	0.13	1.10	1.91
Sunday	-0.60	0.54	0.27	-1.46	0.26
Mean Daily R_GYR – Factor 1 Scores Stats					
Day	Mean	Standard Deviation	SE of mean	95% CI of mean, lower and upper bound	
Monday	-0.96	0.12	0.06	-1.15	-0.77
Tuesday	-0.84	0.07	0.04	-0.96	-0.73
Wednesday	-0.65	0.08	0.04	-0.78	-0.53
Thursday	-0.47	0.05	0.03	-0.56	-0.39
Friday	0.66	0.29	0.13	0.30	1.02
Saturday	2.05	0.10	0.05	1.89	2.21
Sunday	0.16	0.15	0.07	-0.08	0.40

Table IX displays ANOVA results comparing mean values for different days of the week, based on factor scores from Table VIII. The analysis reveals significant differences in factor score means across days for all factors, with high η^2 values indicating pronounced differences. However, for Factor 2, derived from the average daily number of visited locations, the effect size is significant but less pronounced..

D. Pairwise Comparison of Means of Days of the Week

Pairwise comparisons of MSAs factor scores means for different days of the week are conducted, and the Bonferroni correction is used to account for the inflation of probabilities due to multiple comparisons. Sizes of differences between means are expressed using Cohen's d-s.

Since cases in these analyses are only the 30 days from a single month and these were distributed into 7 days of the week, differences between means needed to be quite substantial to reach the statistical significance threshold of 0.05. This data limitation is exacerbated by the use of Bonferroni correction that further increased the magnitude of difference between means needed to reach the statistical significance threshold.

In Table X, pairwise comparisons of mean factor scores across different days of the week for Factor 1 MSAs, extracted from average daily distances traveled, are presented. Bonferroni correction is applied, considering a family of 7 comparisons. Differences with significant statistical prominence are highlighted in bold.

The most significant differences, often reaching statistical significance, are observed between Friday and Sunday as compared to other days. This suggests that the mobility parameters on Fridays and Sundays are notably different from those observed on the remaining days.

Similarly, in Table XI, pairwise comparisons for Factor 2 MSAs, based on average daily distances traveled, are displayed. The most significant disparities are observed between Saturday and the other days in the week. This indicates that the average daily distance covered on Saturdays is substantially greater than on the remaining days of the week for Factor 2 MSAs.

Tables XII and XIII show pairwise comparisons for Factors 1 and 2 MSAs, respectively, derived from the average daily number of locations visited. Table XII reveals significant differences between Friday and Sunday compared to other days, with the greatest distinction observed between these two days. In Table XIII, the most substantial difference was observed between Monday and Saturday.

While many differences were noteworthy according to Cohen's d values [46], only the variations between Saturdays, Sundays, and Mondays met the commonly accepted statistical significance threshold of 0.05. This suggests that in Factor 1 MSAs, individuals, on average, frequent the greatest number of locations on Fridays and the fewest on Sundays. Conversely, in Factor 2 MSAs, the highest number of locations are visited on Saturdays, and the lowest on Mondays.

Table XIV presents pairwise comparisons for Factor 1 MSAs based on the average daily radius of gyration. Upon applying the Bonferroni correction, it becomes evident that the differences between the means of nearly all days of the week are very large in terms of effect size, but they do not reach the statistically significant threshold between the first four days of a week. Statistically significant differences are observed between days in the first part of the week, on one side, and the last 3 days of the week (Friday, Saturday, Sunday), on the other, as well as among those last 3 days.

TABLE IX
ANOVA RESULTS FOR MEAN VALUES ACROSS DAYS OF THE WEEK ON EXTRACTED FACTORS.

Factor score	F	Statistical Sig.	η^2
Factor 1 mean daily D_TRAV	48.26	<0.01	0.93
Factor 2 mean daily D_TRAV	19.92	<0.01	0.84
Factor 1 mean daily N_LOC	17.78	<0.01	0.82
Factor 2 mean daily N_LOC	3.74	0.01	0.49
Factor 1 mean daily R_GYR	200.16	<0.01	0.98

TABLE X
MEAN D_TRAV FACTOR 1 SCORES FOR DAYS OF THE WEEK WITH BONFERRONI CORRECTION

Factor 1 - Mean Daily D_TRAV						
Days	Weekdays	Mean Difference	SE of difference between means	t	Cohen's d	Statistical Sig. (Bonferroni correction)
Monday	Tuesday	-0.21	0.22	-0.95	-0.67	1.00
	Wednesday	-0.46	0.22	-2.15	-1.52	0.88
	Thursday	-0.62	0.20	-3.04	-2.04	0.12
	Friday	**-1.59**	**0.20**	**-7.77**	**-5.21**	**<0.01**
	Saturday	**-0.73**	**0.22**	**-3.41**	**-2.41**	**0.05**
	Sunday	**1.75**	**0.22**	**8.13**	**5.75**	**<0.01**
Tuesday	Wednesday	-0.26	0.22	-1.20	-0.85	1.00
	Thursday	-0.42	0.20	-2.04	-1.37	1.00
	Friday	**-1.38**	**0.20**	**-6.77**	**-4.54**	**<0.01**
	Saturday	-0.53	0.22	-2.45	-1.74	0.47
	Sunday	**1.96**	**0.22**	**9.08**	**6.42**	**<0.01**
Wednesday	Thursday	-0.16	0.20	-0.77	-0.52	1.00
	Friday	**-1.12**	**0.20**	**-5.50**	**-3.69**	**<0.01**
	Saturday	-0.27	0.22	-1.25	-0.89	1.00
	Sunday	**2.21**	**0.22**	**10.28**	**7.27**	**<0.01**
Thursday	**Friday**	**-0.97**	**0.19**	**-5.01**	**-3.17**	**<0.01**
	Saturday	-0.11	0.20	-0.55	-0.37	1.00
	Sunday	**2.37**	**0.20**	**11.61**	**7.79**	**<0.01**
Friday	Saturday	0.85	0.20	4.18	2.80	0.01
	Sunday	**3.34**	**0.20**	**16.34**	**10.96**	**<0.01**
Saturday	**Sunday**	**2.48**	**0.22**	**11.53**	**8.16**	**<0.01**

TABLE XI
MEAN D_TRAV FACTOR 2 SCORES FOR DAYS OF THE WEEK WITH BONFERRONI CORRECTION

Factor 2 - Mean Daily D_TRAV						
Days	Weekdays	Mean Difference	SE of difference between means	t	Cohen's d	Statistical Sig. (Bonferroni correction)
Monday	Tuesday	-0.40	0.32	-1.27	-0.89	1.00
	Wednesday	-0.61	0.32	-1.92	-1.36	1.00
	Thursday	-0.70	0.30	-2.32	-1.56	0.62
	Friday	**-1.18**	**0.30**	**-3.91**	**-2.62**	**0.02**
	Saturday	**-3.08**	**0.32**	**-9.65**	**-6.83**	**<0.01**
	Sunday	**-1.33**	**0.32**	**-4.18**	**-2.95**	**0.01**
Tuesday	Wednesday	-0.21	0.32	-0.66	-0.46	1.00
	Thursday	-0.30	0.30	-0.99	-0.66	1.00
	Friday	-0.78	0.30	-2.58	-1.73	0.35
	Saturday	**-2.68**	**0.32**	**-8.39**	**-5.93**	**<0.01**
	Sunday	-0.93	0.32	-2.91	-2.06	0.16
Wednesday	Thursday	-0.09	0.30	-0.30	-0.20	1.00
	Friday	-0.57	0.30	-1.89	-1.27	1.00
	Saturday	**-2.47**	**0.32**	**-7.73**	**-5.47**	**<0.01**
	Sunday	-0.72	0.32	-2.26	-1.60	0.71
Thursday	Friday	-0.48	0.29	-1.69	-1.07	1.00
	Saturday	-2.38	0.30	-7.86	-5.27	<0.01
	Sunday	-0.63	0.30	-2.08	-1.40	1.00
Friday	**Saturday**	**-1.90**	**0.30**	**-6.27**	**-4.20**	**<0.01**
	Sunday	-0.15	0.30	-0.49	-0.33	1.00
Saturday	**Sunday**	**1.75**	**0.32**	**5.48**	**3.87**	**<0.01**

TABLE XII
MEAN N_LOC FACTOR 1 SCORES FOR DAYS OF THE WEEK WITH BONFERRONI CORRECTION

Factor 1 - Mean Daily N_LOC						
Days	Weekdays	Mean Difference	SE of difference between means	t	Cohen's d	Statistical Sig. (Bonferroni correction)
Monday	Tuesday	-0.16	0.33	-0.47	-0.33	1.00
	Wednesday	-0.39	0.33	-1.18	-0.83	1.00
	Thursday	-0.58	0.32	-1.82	-1.22	1.00
	Friday	**-1.65**	**0.32**	**-5.20**	**-3.49**	**<0.01**
	Saturday	-0.35	0.33	-1.06	-0.75	1.00
	Sunday	**1.56**	**0.33**	**4.68**	**3.31**	**<0.01**
Tuesday	Wednesday	-0.24	0.33	-0.71	-0.50	1.00
	Thursday	-0.42	0.32	-1.32	-0.89	1.00
	Friday	**-1.49**	**0.32**	**-4.70**	**-3.15**	**<0.01**
	Saturday	-0.20	0.33	-0.59	-0.42	1.00
	Sunday	**1.72**	**0.33**	**5.15**	**3.64**	**<0.01**
Wednesday	Thursday	-0.18	0.32	-0.58	-0.39	1.00
	Friday	**-1.26**	**0.32**	**-3.96**	**-2.66**	**0.01**
	Saturday	0.04	0.33	0.12	0.08	1.00
	Sunday	**1.96**	**0.33**	**5.85**	**4.14**	**<0.01**
Thursday	**Friday**	**-1.07**	**0.30**	**-3.58**	**-2.27**	**0.03**
	Saturday	0.22	0.32	0.70	0.47	1.00

Factor 1 - Mean Daily N_LOC (Continued)						
Days	Weekdays	Mean Difference	SE of difference between means	t	Cohen's d	Statistical Sig. (Bonferroni correction)
	Sunday	**2.14**	**0.32**	**6.75**	**4.53**	**<0.01**
Friday	**Saturday**	**1.30**	**0.32**	**4.08**	**2.74**	**0.01**
	Sunday	**3.21**	**0.32**	**10.13**	**6.79**	**<0.01**
Saturday	**Sunday**	**1.92**	**0.33**	**5.73**	**4.05**	**<0.01**

TABLE XIII
MEAN N_LOC FACTOR 2 SCORES FOR DAYS OF THE WEEK WITH BONFERRONI CORRECTION

Factor 2 - Mean Daily N_LOC						
Days	Weekdays	Mean Difference	SE of difference between means	t	Cohen's d	Statistical Sig. (Bonferroni correction)
Monday	Tuesday	-0.66	0.57	-1.16	-0.82	1.00
	Wednesday	-0.77	0.57	-1.36	-0.96	1.00
	Thursday	-0.74	0.54	-1.37	-0.92	1.00
	Friday	-1.20	0.54	-2.24	-1.51	0.73
	Saturday	**-2.37**	**0.57**	**-4.19**	**-2.96**	**0.01**
	Sunday	-0.26	0.57	-0.46	-0.33	1.00
Tuesday	Wednesday	-0.11	0.57	-0.20	-0.14	1.00
	Thursday	-0.08	0.54	-0.15	-0.10	1.00
	Friday	-0.55	0.54	-1.02	-0.68	1.00
	Saturday	-1.71	0.57	-3.03	-2.14	0.13
	Sunday	0.40	0.57	0.70	0.50	1.00
Wednesday	Thursday	0.03	0.54	0.06	0.04	1.00
	Friday	-0.44	0.54	-0.81	-0.55	1.00
	Saturday	-1.60	0.57	-2.83	-2.00	0.20
	Sunday	0.51	0.57	0.90	0.64	1.00
Thursday	Friday	-0.47	0.51	-0.92	-0.58	1.00
	Saturday	-1.63	0.54	-3.04	-2.04	0.12
	Sunday	0.48	0.54	0.89	0.60	1.00
Friday	Saturday	-1.16	0.54	-2.17	-1.46	0.85
	Sunday	0.94	0.54	1.76	1.18	1.00
Saturday	**Sunday**	**2.11**	**0.57**	**3.73**	**2.64**	**0.02**

TABLE XIV
MEAN R_GYR FACTOR 1 SCORES FOR DAYS OF THE WEEK WITH BONFERRONI CORRECTION

Factor 1 - Mean Daily R_GYR						
Days	Weekdays	Mean Difference	SE of difference between means	t	Cohen's d	Statistical Sig. (Bonferroni correction)
Monday	Tuesday	-0.12	0.11	-1.11	-0.78	1.00
	Wednesday	-0.31	0.11	-2.83	-2.00	0.20
	Thursday	**-0.49**	**0.11**	**-4.52**	**-3.19**	**<0.01**
	Friday	**-1.62**	**0.10**	**-15.76**	**-10.57**	**<0.01**
	Saturday	**-3.01**	**0.11**	**-27.79**	**-19.65**	**<0.01**
	Sunday	**-1.12**	**0.11**	**-10.33**	**-7.31**	**<0.01**
Tuesday	Wednesday	-0.19	0.11	-1.73	-1.22	1.00
	Thursday	**-0.37**	**0.11**	**-3.41**	**-2.41**	**0.05**
	Friday	**-1.50**	**0.10**	**-14.60**	**-9.79**	**<0.01**
	Saturday	**-2.89**	**0.11**	**-26.68**	**-18.87**	**<0.01**
	Sunday	**-1.00**	**0.11**	**-9.23**	**-6.52**	**<0.01**
Wednesday	Thursday	-0.18	0.11	-1.68	-1.19	1.00
	Friday	**-1.31**	**0.10**	**-12.77**	**-8.57**	**<0.01**
	Saturday	**-2.71**	**0.11**	**-24.96**	**-17.65**	**<0.01**
	Sunday	**-0.81**	**0.11**	**-7.50**	**-5.30**	**<0.01**
Thursday	**Friday**	**-1.13**	**0.10**	**-11.00**	**-7.38**	**<0.01**
	Saturday	**-2.52**	**0.11**	**-23.27**	**-16.46**	**<0.01**
	Sunday	**-0.63**	**0.11**	**-5.81**	**-4.11**	**<0.01**
Friday	**Saturday**	**-1.39**	**0.10**	**-13.53**	**-9.08**	**<0.01**
	Sunday	**0.50**	**0.10**	**4.87**	**3.27**	**<0.01**
Saturday	**Sunday**	**1.89**	**0.11**	**17.46**	**12.34**	**<0.01**

E. Examination of Autocorrelations

To validate observations of weekly patterns, autocorrelations between daily values of factor scores from the preceding analysis were calculated. Based on earlier findings pointing to a 7-day cyclical trend [13] and the findings from this study presented above, autocorrelations with a 7-day lag were calculated. For a clearer contrast, 1-day lag autocorrelations were also calculated. These findings are detailed in Table XV.

TABLE XV
AUTOCORRELATIONS OF FACTOR SCORES WITH LAG7 AND LAG1

Factor score	Lag7 autocorrelation	Lag1 autocorrelation
Factor 1 MSAs Mean Daily D_TRAV	0.94	0.16
Factor 2 MSAs Mean Daily D_TRAV	0.81	0.33
Factor 1 MSAs Mean Daily N_LOC	0.84	0.28
Factor 2 MSAs Mean Daily N_LOC	0.38	0.29
Factor 1 MSAs Mean Daily R_GYR	0.99	0.38

Upon examination of Table XV, it is observed that 7-day lag autocorrelations are consistently much higher compared to the 1-day lag ones. This implies that weekly cycles offer a much better description of daily changes than mere day-to-day comparisons. However, an outlier is noted in Factor 2, derived from the average daily number of locations visited (N_LOC). For this factor, the 7-day lag autocorrelation is noticeably subdued compared to other factors and is only marginally above the 1-day lag, indicating a weaker 7-day trend for this specific factor.

VIII. General discussion and implications of the Findings

The presented results indicate that mobility patterns in different geographical areas exhibit many strong similarities. Notably, we found groups of regions that, despite often being geographically distant, demonstrate intriguing similarities in their daily mobility patterns.

In terms of data reduction and efficiency, the results of study 1 revealed pronounced correlations between mobility parameters within an MSA. These correlations allow researchers and policymakers to focus on a smaller set of parameters without compromising essential information. This approach simplifies the analytical process and optimizes resource utilization.

When examining geographic mobility traits, the classifications from the factor analysis provide critical insights. The differences, particularly between inland and coastal MSAs or between the east coast and other areas, suggest significant impacts of geographical or regional socio-cultural and economic factors on mobility patterns. These insights are valuable for urban planning and infrastructural development.

Moreover, the mobility data reveals a consistent weekly pattern, which is significant for multiple sectors:

- In transportation planning, distinguishing between peak and non-peak days can inform public transport scheduling, roadwork planning, and traffic control.
- For businesses, understanding these patterns enables refinement of services, operational hours, and promotional efforts to align with peak mobility days.
- Governmental bodies can use this data to formulate policies that align with established mobility trends, ensuring efficient implementation and public adherence.

The discovery of a singular dominant factor in the daily radius of gyration raises intriguing possibilities for further research. This includes exploring the dominant influence of this factor and the mechanisms behind it.

For future research focused on health or safety, understanding these mobility patterns is crucial. They are key to enhancing efforts in disease containment, emergency planning, or health awareness initiatives.

In summary, the data reveals interesting mobility patterns across different MSAs. These insights are essential for urban planners, policymakers, businesses, and researchers, and are particularly valuable when integrated with the broader objectives and context of the study.

IX. Limitations of the study and future Work

The two studies presented in this paper provide an initial exploration of mobility patterns within the 15 most populous Metropolitan Statistical Areas (MSAs) in the U.S. However, there are several limitations to consider. Crucially, data for both studies were sourced exclusively from October 2020. This timeframe may not capture the full complexity of mobility patterns in the MSAs. Additionally, during October 2020, the COVID-19 pandemic (2019-2023) was at a critical stage. Although initial stay-at-home orders were mostly lifted, measures for physical distancing were still in effect, potentially impacting mobility patterns compared to pre- or post-pandemic periods.

Another limitation is the reliance on a sample of mobile devices from users who consented to location data collection via a specialized app, subject to data availability conditions. The sample size, ranging from 0.49% of the MSA population in San Francisco to 2.28% in Dallas, was small relative to the overall population, potentially affecting the representativeness of our findings.

Future research could address these limitations and expand our understanding of urban mobility. Key areas for further investigation include examining causes of mobility pattern variations across different MSAs, potentially using census data and structural characteristics of these areas. Broadening the scope to include smaller cities, rural areas, and international locations could offer a more comprehensive view of global mobility patterns.

Additionally, incorporating temporal changes due to seasons, holidays, and significant events would enrich our understanding of mobility over time. Integrating data from various sources like social media, transportation networks, and traffic monitoring systems could provide a more nuanced view of urban mobility.

The influence of external factors like climate changes or global health events on mobility patterns also warrants exploration. Such insights are vital for urban planning and preparedness. Furthermore, the data gathered could underpin the development of predictive mobility models, aiding urban planners and policymakers.

Exploring behavioral analytics in more depth, by aligning mobility data with sociological research, might uncover deeper motivations behind movement patterns.

In Summary, while the two studies contribute significantly to urban mobility research, they open numerous avenues for further investigation, promising richer insights and more effective urban planning strategies.

X. Conclusions

This paper presented results of two studies of daily mobility based on location data from mobile phones. Study 1 explored covariations of a series of daily mobility parameters within one coastal and one inland MSA. Exploratory factor analysis of daily values of 14 different daily mobility parameters within the same MSA, indicated high levels of covariation between many of them and yielded two factors. The results were repeated in both MSAs included in this study. They point to the conclusion that individual analyses for each mobility parameter are inefficient and not warranted.

Due to this, analyses conducted in the scope of study 2 focused on three key mobility parameters representing the whole set: mean daily D_TRAV, which showed a strong correlation with both factors extracted from the studied set of mobility parameters, and Mean Daily N_LOC and R_GYR, each of which had particularly high loadings on the first and the second factor extracted in the applied factor analytic procedure, respectively.

It is imperative to note that mobility parameters that load highly on the same factor inherently correlate with one another. This correlation implies not only that one parameter can be predicted from the others with notable accuracy, but also that executing separate analyses based on associations on individual highly correlated parameters would yield analogous results.

Comparison of mean values of daily mobility parameters across the 15 most populous U.S. MSAs conducted in study 2, yielded statistically significant differences between MSAs. Moreover, the magnitudes of these differences were substantial and often extreme across all parameters.

Exploratory factor analysis of the daily mean distance travelled across different MSAs uncovered two primary factors that meet the parallel analysis criteria. Soft categorizations of MSAs were then created based on these factors: the first factor predominantly comprised inland MSAs, and the second mainly included coastal MSAs. A similar two-factor structure emerged when analyzing the mean daily number of locations visited, with one factor aligning with east coast MSAs and the other encompassing MSAs situated inland or in the southern or western regions of the U.S. Results of factor analysis of the daily radius of gyration points to the existence of just one dominant factor, accounting for most of the variance in daily differences. This indicates that daily variations of mean radius of gyration values were very similar across the 15 studied MSAs.

Investigating further, a pronounced weekly cycle trend emerged. MSAs classified under Factor 1 displayed their longest mean travel distances on Fridays and the shortest on Sundays. In contrast, those with the highest loadings on Factor 2 travelled the furthest on Saturdays, less so on Sundays, with Monday being their least mobile day. A similar pattern was identified in the number of daily locations visited by both groups: Factor 1 MSAs reached their peak activity on Fridays and showed their lowest levels on Sundays, while Factor 2 MSAs reached their peak on Saturdays and showed the minimum of activity on Mondays.

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