How far will you go? From empirical findings to formalization of walking route distances

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How far will you go?
From empirical findings to formalization of walking route distances

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Abstract

Empirically based theorization of walking range patterns is rather limited, leading researchers and planners to rely on simplistic assumptions as to the typical distance and duration that pedestrians may walk. Using high-resolution GPS data collected from over 11,000 participants in the Tel-Aviv metropolitan area, we provide an empirical estimate for the distribution of walking route distance and duration, while examining potential factors that may affect it. In addition, we develop a general analytical framework that describes walking route patterns. Our results show that the average route distance and duration in Tel-Aviv metropolitan is 630 m and 7.9 min. Factors associated with walking range include socio-demographic characteristics of walkers (age-group, socioeconomic status and number of cars in a household) and city characteristics (longer routes in cities with a larger population and in areas with high density of street intersections). Our main finding is that walking route distance distribution can be best described using the theoretical log-normal distribution and can be characterized using its mean-log and SD-log parameters. The log-normal parameters make an analytical framework that enables the evaluation of differences in walking patterns between places and identification of where interventions are required to promote active travel. We explain why the log-normal distribution is likely to be suitable to other cases worldwide.

1. Introduction

Walking is the most basic mode of travel for human mobility. Unlike other modes of travel, pedestrian movement fulfils a central role in the vitality of urban areas and is considered as eminent factor for creating a successful urbanity (Jacobs, 1961; Montgomery, 1998; Talen and Koschinsky, 2014). Pedestrian travel in cities has numerous advantages including reduced traffic congestion and negative environmental impacts (Cubukcu, 2013; Neves, 2013), increased safety (Jacobsen, 2015; Omer et al., 2017) enhanced social equity (Lee et al., 2017), positive impacts on physical and mental health (Hall et al., 2020; Hallam et al., 2018; Johansson et al., 2011; Murtagh et al., 2015) and supporting liveability of cities (Shamsuddin et al., 2012). Thus, it is unsurprising that over the last few years various studies are trying to explore and promote pedestrian movement in urban environments (Koohsari et al., 2017; Sung and Lee, 2015; Wang et al., 2016; Zakaria and Ujang, 2015).

Many factors were found to effect walkability in urban spaces, these include physical aspects related to the built environment, such as the structure of the street network, land-use distribution, topography and density; as well as socio-demographic characteristics of the individual (El-Geneidy et al., 2014; Gao et al., 2020; Kang, 2015; Koohsari et al., 2017; Sung and Lee, 2015; Sung et al., 2013). In addition, subjective factors related to human's perception exert influence on walking, such as esthetic appearance of the street surroundings (Ferrer et al., 2015), felling of safety (Foster et al., 2014) and discomfort of weather conditions (Vanky et al., 2017).

Among the aspects that were explored in the literature, accessibility in terms of distance to destination is the prominent factor considered when choosing walking as a mode of travel, as well as for choosing the preferred route to the destination (Irvin, 2008; Seneviratne and Morrall, 1985; Yang and Diez-Roux, 2012). This finding supports the basic assumption in the study of pedestrian behavior that people aspire to reduce the time and length of the travel route, and therefore, select the shortest route (Hillier, 1999; Gehl, 2011; Sharmin and Kamruzzaman, 2018; Verlander and Heydecker, 1997).

Overall, the common view asserts that to create a walkable urban environment necessitates accessibility to amenities through provision of access routes within a "walking range" for various destinations (Irvin, 2008; Kang, 2015). In this sense, land use distribution together with accessibility are key facilitators of walking. This concept is in the heart of the emerging idea of the "15 min city" model. The model suggests that urban spaces should be reorganized in a way where all the services and amenities are located within 15 min of walking for all city residents (Allam et al., 2021). This requires an effective dissemination of services, public spaces, shops, workplaces, and other facilities across neighborhoods, such that, most of the residents' needs are served within the neighborhood. Several cities have recently adopted the model among them Paris, Barcelona, Milan, Melbourne, Shanghai and Detroit (Logan et al., 2022; Papas et al., 2023).

The idea of the 15 min city is based on the "walking range" principle. Planners and researchers use a threshold that defines a distance and duration that people will be willing to walk. With that, the walking range is ambiguous and varies among studies.

For example, Gehl (2011) suggests a walking range of 500 meters, and similarly, many studies use a range of about 400, while other studies use 800 meters (Azmi and Karim, 2012; García-Palomares et al., 2013). When referring to the time component, several studies suggest that 5-10 minutes is an acceptable range that is considered accessible, when a range of five minutes refers to a local activity (bus stops) and 10 minutes refers to an activity of a higher functional order (e.g. metro station) (Azmi and Karim, 2012; Poelman and Dijkstra, 2015).

While planners, in large, maintain a common convention for walking ranges, research shows that these are not well supported by empirical findings and that they differ both in terms of distance and time, depending on multiple conditions and characteristics. Based on a large survey among U.S residents, Yang and Diez-Roux (2012) have found that the distances and durations of walking for recreation were substantially longer than those for other purposes and that people with lower income walked longer distances for work and shorter distances for recreation compared to people of higher income. Larsen et al. (2010) reveals that walking distances in Montréal varies by trip purpose, where walking routes to work are the longest. García-Palomares et al. (2013) found that young people, adults, men and immigrants, are willing to walk longer distances and are less sensitive to the effect of distance to public transit than women, children, old people, car owners and nonimmigrants. The influence of socio-demographic characteristics on walking distances to transit stops was also supported by El-Geneidy et al. (2014). They also demonstrate that walking distance is affected by the number of intersections in the neighborhood and the distance to downtown.

Nuances also exist within the elderly. A study of an elderly population revealed that those under 75 years and those with functional limitations walked shorter distances than those over 75 years (Prins et al., 2014). Moreover, fear of falls or previous experience of falling decrease the walking route distance (Plaut et al., 2021).

While the walking range is based on descriptive statistics such as the mean, or a specific percentile of the population's distribution of walking distance or duration, it may not reflect well the complexity of the walking pattern. Several studies explored patterns of human mobility by seeking a general mathematical description for the distribution of distance and duration of the trips. In their novel research, Brockmann et al. (2006) analyzed the circulation of millions of bank notes in the United States as a proxy for human travel. They discovered that the distribution of travelling distances decays as a power law and are similar to a scale free random walks, known as Lévy flights. Multiple studies found that the log-normal distribution is useful in portraying intra-urban taxi trip distances, as well as subway trips displacement (Wang et al., 2015; Xia et al., 2018, 2021; Zhang et al., 2017; Lee et al., 2011). Alessandretti et al. (2017) also found that the log-normal distribution may be relevant in portraying more general mobility patterns, including waiting times between mobility occurrences when considering all transportation modes.

In the context of walking, several studies employed distance-decay function to describe the decrease in the frequency of walking routes as distance increases (García-Palomares et al., 2013; Goel, 2018; Iacono et al., 2010; Millward et al., 2013; Tirachini, 2015; Yang and Diez-Roux, 2012). In these studies, the exponential function was employed to establish a mathematical relationship between the percentage of walking routes (y) with a distance equal to or longer than a specific distance (x): $y = e^{-\beta x}$, where β is the decay parameter estimated for the distribution, and x is the value for distance . The distance-decay function provides a continuous description of the walking probabilities and can be used to compare walking distances among different groups using the function's parameters; as well as to evaluate expected demand for different services by considering the spatial distribution of the population (García-Palomares et al., 2013).

Here we provide an empirical estimate for the distribution of walking route distance and duration in the Israeli context. Our results demonstrate that the distribution of the walking route distance in multiple cities does not fit the commonly used distance decay function; rather, it fits best to the log-normal distribution. We show that the shape of the distance distribution in each city is described by two parameters: the mean-log and standard-deviation-log. We suggest that the parameter space of the log-normal can be used to compare walking distance patterns and serves as a general analytical framework that describes walking patterns. Our study relies on a travel survey with an extensive GPS database collected in Tel-Aviv (TA) metropolitan area, Israel. This data allowed a detailed representation of the distribution of walking distance and duration, and a general formalization of distance patterns. In addition, the study examines the influence of potential factors on the walking range, including type of destination, socio-demographic characteristics of walkers and the urban settings.

2. Methodology and Data

2.1. Data

This study is based on data collected in the Ayalon Highways travel survey. The survey includes reports of daily activities and travel of a representative sample of 39,085 Individuals, from 13,506 households residing in TA metropolitan area, Israel. The survey was conducted during the years 2013-2014 and 2016-2017 and documented participants activities over 24-48 hours during weekdays. The survey is mostly based on GPS tracking of participants collected using a smartphone-based application or GPS devices. The survey was complemented by surveyors who contacted participants to complete missing information on activities.

The final survey includes an activity log for each participant that specifies for each activity the start and end time, type of activity, travel mode (TM) to the activity, travel duration and distance. The travel distance specified in the survey refers to the aerial distance between the origin and destination of travel.

Several inaccuracies can arise regarding the travel distance. Aerial distance may fail to capture the real distance covered, mostly since the movement in urban areas is based on roads and is restricted by the built environment that may prevent progress in a straight line. In addition, aerial distance fails to reflect the distance covered in (semi) circular routes. Moreover, the reports of participants that were not using GPS may be biased given the limited ability of human cognition to estimate distance (Ralph et al., 2020).

To overcome these inaccuracies, we analyzed the survey data only for participants that had GPS tracking data and survey log records (25,683 participants, 65% of all survey participants). Using the GPS data, we identified the travel routes for each participant and calculated the distance and duration based on the GPS coordinates and their recorded time. In the following sections we describe in detail the analysis.

2.2. Data processing

Relating the GPS points to the log records: The GPS points were preprocessed for removing missing data, inaccurate GPS, duplicated times, and points located outside the borders of Israel. Then, each GPS point was related to the survey's log record based on the time record. Following this process each GPS point was labelled with the type of activity or with TM (in case of travel) and the additional information as reported in the activity log.

Identifying travel routes based on GPS points: The GPS data records the location of individuals every few seconds (frequency varies between 1-20 seconds). Using the GPS data, we extracted the travel routes of individuals independently of the information reported in the activity logs. The extraction of routes provided the actual travel trajectory including the duration and distance which are not subjected to self-report bias.

To identify the travel routes of individuals from the GPS points we implemented a two-stage process. The first stage identified clusters of points where an individual stayed without much movement. These areas were assumed to be areas where activity takes place and where the individual is not travelling. The second stage identified the GPS points between the "stay" locations, which were assumed to be the travel routes. We defined a "stay" location as an area (defined by a radius of 10 meters) where an individual stayed for at least 160 seconds. Where several "stay" locations overlapped they were united into one "stay" location.

This procedure was implemented using the DBSCAN (Density-Based Spatial Clustering of Application with Noise) algorithm which identified the GPS points forming the "stay" clusters. After identifying the "stay" locations, the travel routes were identified. We defined a route as a movement from one "stay" location to another. GPS points in a consecutive time order between two "stay" locations formed the polyline of the travel route. Based on the GPS coordinate forming each polyline and their recorded time, we calculated the distance and duration of the route.

Assigning the travel mode: To identify the mode of travel for each route we used the survey's log information that was linked to the GPS points. The mode of travel for each route was assigned based on the labels of the GPS points that formed the polyline. Separated polylines that were reported in the survey as one continuous journey (labelled with the same log ID) were united into one route. In total, 172,244 travel routes were identified, 50% were labelled as "Driving/Riding a car", 12% as "Walk", 2% bicycle, 1.5% bike and 16.5% public transportation. 18% of the routes were not labelled with TM because they were either not reported in the survey's log or the reported time of travel was inaccurate (didn't match the recorded time of the GPS routes).

Inferring travel mode: To infer the mode of travel for routes that were not labelled, we used a classification algorithm. We used routes that were labeled with TM (multi-modal routes were excluded) and recategorized them into three types of TM: Walk, Bicycle and Vehicle. Several statistical measures of movement were calculated based on speed, acceleration, and angle changes along the route. These measures were used to establish a classification function that predicts the TM. Then, this function was implemented to infer the TM of the routes that were missing TM label (Tables A.1&A.2 in Appendix A).

2.3. The walking routes

The final walking routes database includes 31,798 walking routes from 11,446 individuals who walked at least once during the survey period. The socio-demographic characteristics of the participants are presented in Table 1. Walks that were reported as part of multimodal trips were excluded to avoid a mixture of several modes in one continuous trajectory. The walking routes spread throughout the TA metropolitan area, covering 280 settlement of various sizes (Fig.1).

Table 1: Socio-demographic characteristics of participants[1].

Attribute	Subgroup	Count (%)
Gender	Male	5201 (45.4%)
	Female	6205 (54.2%)
Age group	0-11	639 (5.6%)
	12–17	979 (8.6%)
	18-29	2039 (17.8%)
	30-55	4688 (41%)
	55+	3061 (26.7%)
Socio-economic status	Low	2244 (19.6%)
	Middle	4475 (39.1%)
	High	4692 (41%)
No. cars in household	0	3040 (26.6%)
	1	4832 (42.2%)
	>1	3539 (30.9%)
Settlement's population	<10,000	528 (4.6%)
	10,000-100,000	2816 (24.6%)
	>100,000	8067 (70.5%)

[1]Note that 40 participants were missing data on gender and age, and 35 participants were missing SES.

Each route was linked to the characteristics of the walker, including gender, age and number of cars in the household. In addition, the socio-economic status (SES) of the walker was assigned based on the Socio-Economic Index (SEI) of the home residence (CBS, 2015). Low SES includes individuals below the 30^{th} percentile of the SEI; Middle SES those between 30^{th}-70^{th}, and High SES those above the 70^{th}.

The destination activity is specified according to the following categories: home, studies, work, work related (matters outside the main workplace), errands or prayer, health services, entertainment or restaurant, shopping, escort, social visit, and sport activity. Some of the walking routes took place within facilities such as: mall, university campus, industrial area and walks from parking lots to buildings. Therefore, for these routes we added a category of "within a facility". For walking routes that were identified but not reported in the log, the destination of travel was determined using information from OpenStreetMaps.

2.4. Analysis

To examine the distribution of the walking routes distance and duration, the routes were aggregated into distance and duration intervals. The distance intervals increase by 100 meters (50-100, 100-200, 200-300...), and the duration intervals increase by 1.5 minutes (0.5-1.5, 1.5-3, 3-4.5...). The percentage of routes within each interval was calculated for multiple stratifications: socio-demographic characteristics of walkers, destination activities, and for cities.

To study the combined effect of socio-demographic characteristics, destination activity and urban settings on the walking distance, we used a multilevel regression modelling. The independent variables included pedestrian's socio-demographic characteristics (gender, age group, number of cars, SES), activity at the destination, city population size and street intersection density at the statistical zone of routes' origin. Street intersection density was calculated for each statistical zone by dividing the number of intersections within a zone by the area of that zone. Intersection density was categorized into four levels (low, medium, high, very high) based on quartiles division of the density in statistical zones in the research area. We treated the walking routes (level-1) as nested in individuals (level-2). Since the walking distance was not normally distributed, we used log(distance) as the dependent variable, which is normally distributed.

After examining the walking routes distance distribution, we hypothesized that its shape fits one of the theoretical distributions of the exponential family: Exponential, Gamma, Weibull, Log-normal. To test this, we fitted the four theoretical distributions, using maximum likelihood estimation, to the empirical distribution in the TA metropolitan, as well as, for each city that included at least 200 walking routes. The fitting was implemented using *fitdistplus* function in R software (Marie Laure and Dutang, 2015). We then, measured the fit between the frequencies of each distance interval in the empirical and the fitted theoretical distribution using the route mean square error (RMSE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i}^{N}(f^{theo}(d_i) - f^{emp}(d_i))^2} \quad (1)$$

Where N is the number of distance intervals and $i \in \{1, ..N\}$ refers to an element in the set of N intervals. $f(d_i)$ denotes the frequency of distance interval d_i in the theoretical (f^{theo}) and in the empirical distribution (f^{emp}).
Where $f^{theo} \in \{Exponential, Gamma, Weibull, Lognormal\}$. The frequency is measured as percentage of all routes.

We calculated additional measures of the fit: the maximal difference (MD) between the frequency of an interval in the theoretical distribution and the corresponding interval in the empirical distribution; and the square of the Pearson correlation (R^2) between the intervals' frequencies in the two distributions.

3. Results

The mean walking route distance and duration in TA metropolitan are 620 m and 7.9 min, respectively, while the median is 390 m and 5.5 min (Table 2). Only 10% of the routes exceed the distance of 1250 m and the duration of 15.9 min. As the route distance increases from 50 meters to 300 m, the percentage of routes increases, reaching a peak at 300 m, and then decreases as the route distance increases (Fig.2). The distribution of route duration is similar, where the percentage of routes reach a peak at 3 min and then declines.

3.1. The impact of individual characteristics and urban settings

In general, the distribution of route distance and duration holds a similar shape for multiple stratifications of pedestrians' socio-demographics as presented in Fig 3. All distributions are skewed to the right, with an initial increase in the percentage of routes as distance increases up to around 300 m, followed by a steep decline. The distribution of route distance for male and female is similar, though minor differences are noticed in the duration distribution, as female have slightly higher percentage of routes of longer duration (Fig.3). This difference is likely the result of a slower average walking speed that was measured for female (4.4 km/h) compared to male (4.7 km/h) pedestrians. The mean walking routes distance and duration for male and female are 640 m (7.8 min) and, 610 m (8.0 min) respectively (Table 2). The multilevel regression implies that the difference in distance based on gender is non-significant (Table 3).

Age-group has the most profound impact on the distribution of walking routes distance and duration, as reflected by the statistically significant coefficient in the multilevel regression model (Table 3). The mean route distance ranges between 460-650 m among age groups, and the mean duration ranges between 6.8-8.7 min (Table 2). Routes walked by the youngest age group are the shortest on average (450 m, 6.7 min) while

[2]Note that 164 routes were missing the gender and age of the walker and 135 routes were missing SES and number of cars.

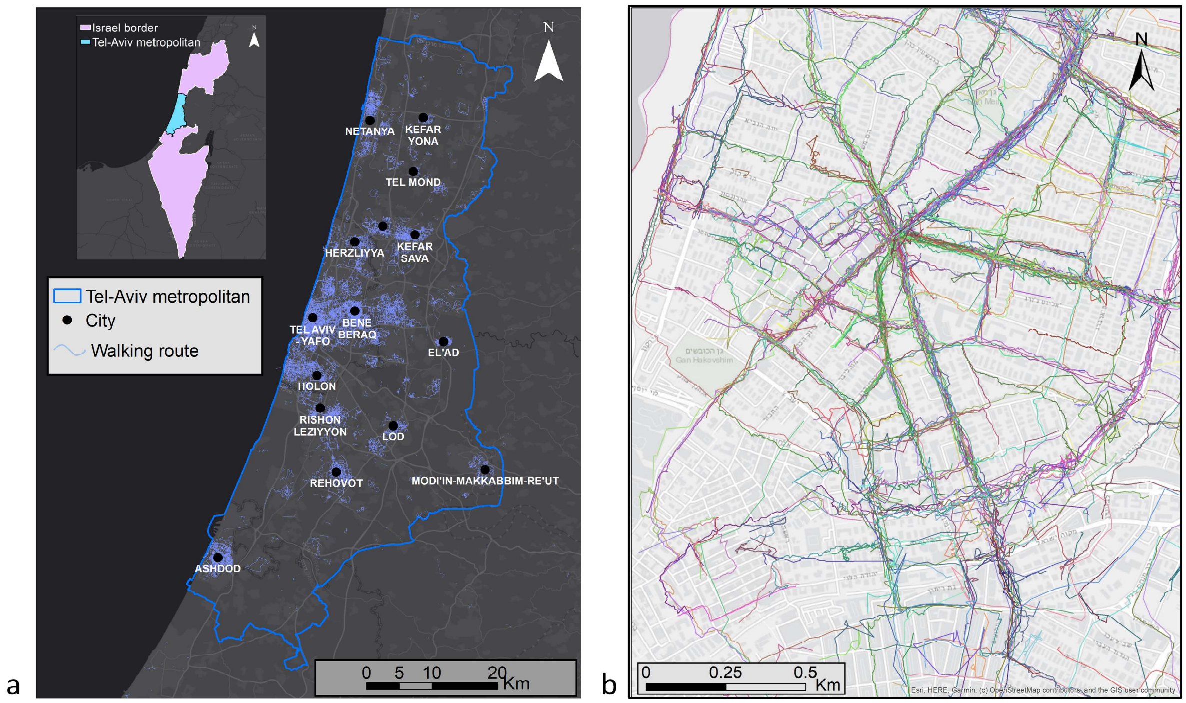

Figure 1: Spatial distribution of the walking routes in TA metropolitan.(a) Routes within the TA metropolitan area. (b) Selected routes within TA city; routes are distinguished by line color.

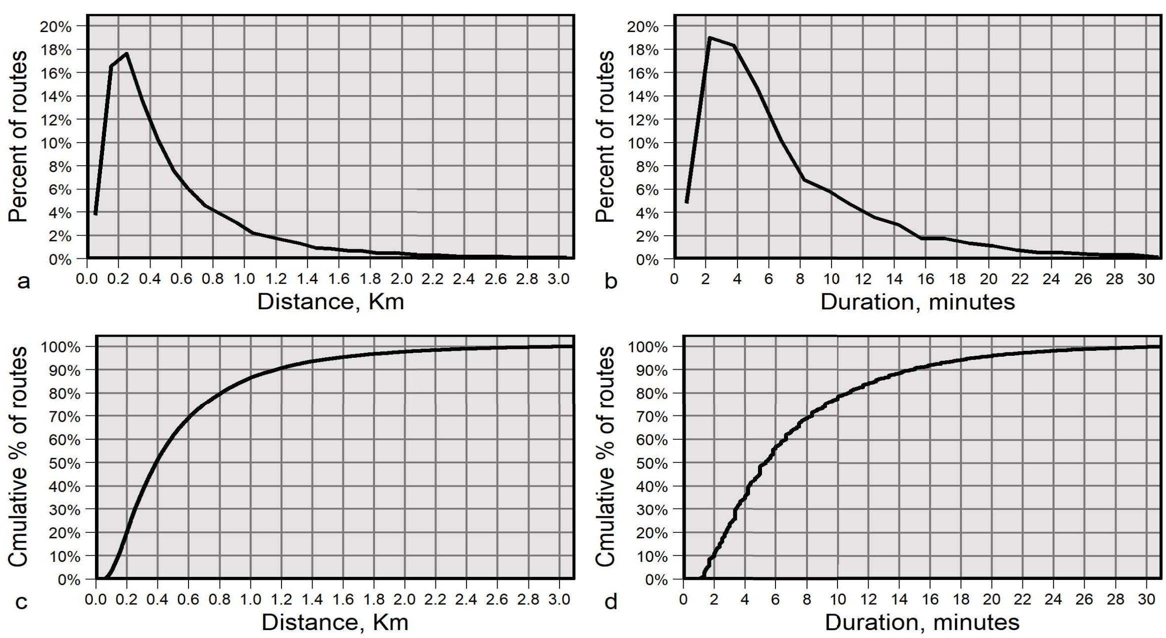

Figure 2: Walking route distance and duration. Percent of walking routes by (a) distance and (b) duration. Cumulative distribution by (c) distance and (d) duration.

routes walked by 12-17 years old are the longest ($p<0.001$) on average (650 m, 6.3 min) of all age groups (Tables 2 & 3). The distributions of walking route distances and duration show that the age group 12-17 years old have a higher percentage of routes of longer distance and duration compared to the other age groups (Fig.3c-d). As for the older age groups, as the age

Table 2: Statistics of walking route distance and duration by socio-demographic attributes of walkers [2].

Group	Sub group	No. (%)	Distance, Km					Duration, minutes				
				Percentile					Percentile			
			Mean	P25	P50	P75	P90	Mean	P25	P50	P75	P90
Overall	Overall	31798 (100)	0.62	0.23	0.39	0.72	1.25	7.9	3.3	5.5	9.7	15.9
Gender	Male	14778 (46.5)	0.64	0.23	0.39	0.72	1.28	7.8	3.0	5.1	9.2	15.8
	Female	16856 (53)	0.61	0.23	0.4	0.73	1.23	8.0	3.3	5.7	10.0	16.0
Age group	0-11	1701 (5.4)	0.46	0.21	0.34	0.57	0.88	6.8	3.0	5.0	8.7	13.3
	12-17	2859 (9)	0.65	0.27	0.48	0.87	1.35	8.3	3.3	6.3	11.1	17.0
	18-29	6091 (19.2)	0.64	0.25	0.43	0.77	1.28	7.9	3.3	5.7	9.8	15.8
	30-55	12547 (39.5)	0.61	0.22	0.39	0.69	1.22	7.6	3.2	5.0	9.2	15.0
	55+	8436 (26.5)	0.65	0.21	0.37	0.72	1.32	8.7	3.3	5.7	10.2	18.0
SES	Low	8205 (25.8)	0.61	0.24	0.42	0.74	1.23	7.8	3.3	5.8	10.0	15.7
	Middle	11826 (37.2)	0.6	0.22	0.38	0.7	1.22	8.0	3.1	5.3	9.7	16.6
	High	11632 (36.2)	0.66	0.23	0.4	0.73	1.3	8.0	3.1	5.4	9.5	15.9
Cars	0	11255 (35.4)	0.61	0.25	0.43	0.77	1.21	8.1	3.3	5.8	10.3	16.0
	1	12698 (39.9)	0.64	0.22	0.39	0.72	1.3	8.0	3.2	5.3	9.7	16.3
	>1	7710 (24.3)	0.62	0.21	0.35	0.65	1.24	7.6	2.9	5.0	8.7	15.3

group goes up, the average route distance decreases ($p<0.001$) (Table 2 & 3). With that, the coefficient in the multilevel regression of age groups 30-55 and 55+ is similar, suggesting no difference in walking distance between these groups (Table 3).

Differences in the distribution of route distances and duration among SES are small (Fig.3e-f). The middle SES group walks shorter routes on average (600 m) compared to the low SES (610 m) and high SES (660 m). When accounting for the combined effect in the multilevel regression model, the high SES is statistically significant variable that increases the average walking route distance ($p<0.05$).

Availability of cars in the household decreases the distance of the walking route ($p<0.001$) as individuals in households with more cars walk shorter distance on average (Table 3). Having multiple cars in the household has more impact (coefficient=-0.1) on reducing the travel distance than the increase in distance due to being of high SES (coefficient=0.04). Therefore, it is likely that households of high SES that are also associated with multiple car ownership, will walk shorter routes overall. Pedestrians without a car tend to have a higher percentage of routes of longer distances and duration compared to pedestrians with a car (green line in Fig.3g-h).

The route mean distance differs among different activities at the destination (Fig.4, Table 4). According to the multilevel regression model, the mean distance of walking to work (the reference activity) are statistically longer ($p<0.001$) than to other activities (Table 3). The mean walking route distance to work is 720 m and duration of 8.16 min (Table 4), where only 10% of the routes to work are longer than 1470 m and 27 min. The shortest walking route mean distance is to destinations within facilities, with a mean of 310 m and a duration of 4.65 min.

While the mean distance difference among activities is statistically significant, it is relatively small, ranging between 600-700 m (7-8.5 min) for most activities,with a median range of between 400-470 m (5-6.5 min). Walking routes to sport activities have a relatively low median (330 m) compared to other activities while their mean distance is the highest (900 m). This is a result of a combination of high percentages of routes of short distance (under 300 m) and high percentage of routes of long distances compared to other activities, as reflected in the highest 90^{th} percentile of 2350 m. As presented in Fig 4, the shape of the distribution of routes to a sport activity differs from other activities. The walking routes to a destination of sport activity may include various purposes, such as short walks to a gym or a recreation center, where the sport activity takes place, and longer walks or runs for sport in which the walk itself is the purpose.

The urban settings influences route distance, where walking routes in cities with population of 100,000-200,000 are longer than in cities with smaller population ($p<0.05$) (Table 3). In cities with population larger than 200,000 the regression coefficient suggests increased walking distances, but it is only marginally significant ($p=0.1$) (Table 3). As for the junction density at the routes' origin, high density increases the routes' distance ($p<0.001$) (Table 3).

It is important to note that the multilevel regression model explains 26.8% of the variance in route distance (R^2 cond.=0.268). While the variables in the fixed effect are statistically significant, they explain only 4.4% (R^2 marg.= 0.044) of the variance in route distance.

3.2. The distribution of walking route distance

To test our hypothesis that the distribution of walking route distance follows one of the theoretical distributions of the exponential family, we fitted the theoretical to the empirical distribution for the whole TA metropolitan and for multiple cities. The results for the TA metropolitan are presented in Table 5 and in Fig 5. The best fit is achieved for the log-normal distribution, which has both the lowest RMSE (0.35%) and MD (1.8%) (see section 2.4). The correlation between the intervals' frequencies

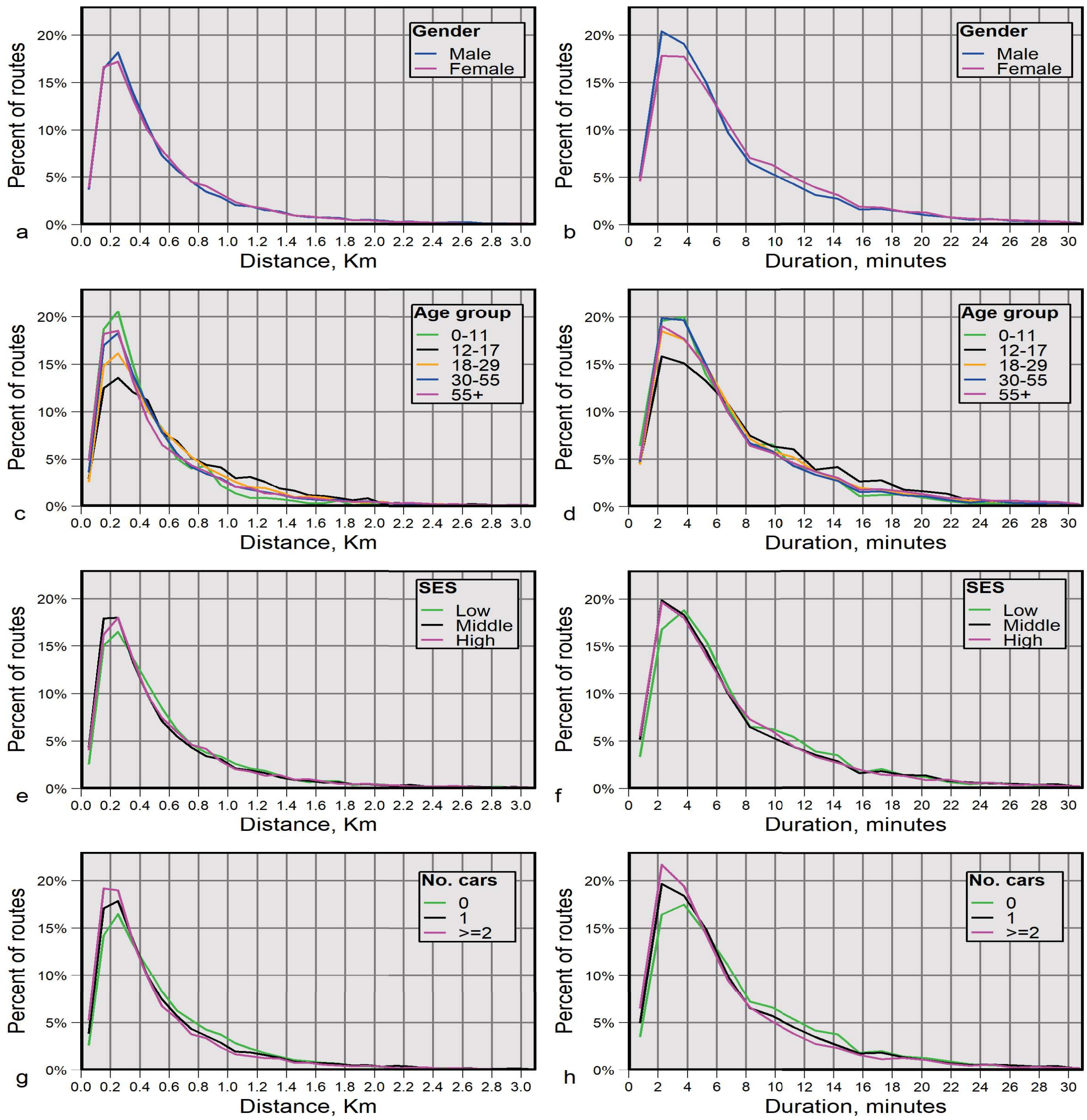

Figure 3: Distribution of walking routes distance and duration by walkers' socio-demographics. Routes distance (left panels) and duration (right panels) by: (a-b) Gender, (c-d) Age group, (e-f) SES, (g-h) No. cars per household.

of the empirical and the log-normal distributions is 0.993, and the loglikelihood is the highest compared to the other theoretical distributions (Table 5).

In addition to fitting the theoretical distributions for the entire TA metropolitan area, we tested the fit at the city scale. We tested the fit for 21 cities with at least 200 walking routes. Altogether these cities include 88% of all walking routes in our data.

In all cities, the log-normal distribution has the best fit, see Tables B.1&B.2 in Appendix B. At the city scale, the minimum RMSE is 0.23% for the city of Bene Beraq, while the maximal RMSE is 0.83% in the city of Ramat Hasharon. The median and mean RMSE are 0.41% and 0.46%, respectively. The largest MD among the cities is 6% (Ramat Hasharon), the mean and median MD are 2.7% and 2.4%, respectively. Both measures suggest a good fit. Fig B.1 presents the empirical and best fitted log-normal distributions for each city.

3.3. Comparing walking route patterns

The shape of the fitted log-normal distribution of each city is defined by the log-normal mean (μ) and log-normal standard deviation (σ). Therefore, the differences in the distributions of

[3]The best-fitted parameters are specified.

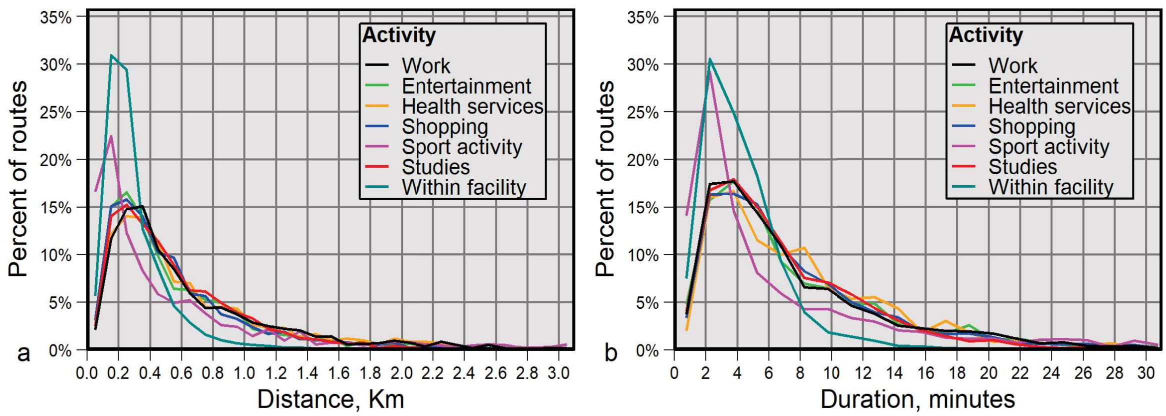

Figure 4: Distribution of walking route distance and duration by activity at the destination. (a) Distance (b) Duration.

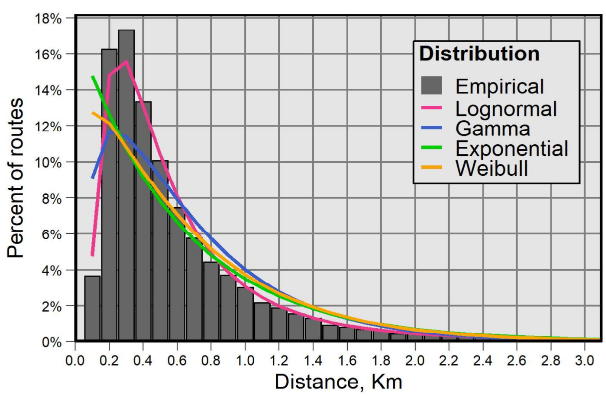

Figure 5: Distribution of walking route distance in TA metropolitan and the fitted theoretical distributions of the exponential family.

cities are reduced to two parameters that reflect the shape of the distribution. Fig 6a presents the parameter space of the cities based on μ and σ of each city.

While most cities are located around the center of the parameter space, the cities of Bene Beraq, El'ad, Ramat Hasharon and Hod Hasharon are further out. To demonstrate the variation of distance distribution given different combination of the log-normal distribution, we present in Fig 6b-c five value combinations of *mu* and *sigma*. Four of the combination represent the extreme corners of the parameter space (marked by colored circles in Fig.6a) and one is the center (black circle). Bene Beraq, which is close to the red circle have a distance distribution which is close to the one marked by the red line, while Ramat Hasharon and Hod Hasharon are closer to the green circle and therefore their distance distribution is similar to the one marked by the green line (Fig.6b-c). Similarly, El'ad is close to the blue circle and to the distribution marked by the blue line.

The fact that the shape of the distance distribution in cities is described by the log-normal distribution allows for a simpler way to compare, understand differences, and identify outliers among a large number of cities. The comparison is based on values of only two parameters (μ, σ) that define the log-normal distribution, as presented in Fig 6. One direct inference that can be made between the log-normal distribution and the "real" non-converted distribution, is that cities with an equal mean-log (μ) have equal median of route distance (for the non-converted distance distribution), even when their SD-log (σ) differs. As can be seen is Fig 6c, the red and orange distributions, that have the same "high" value of mean-log, intersect at 0.5 Km, where 50% of the routes are accumulated; while the green and the blue distributions, that have the same "low" value of the mean-log, intersects at 0.4 Km where 50% of the routes are accumulated. The distance distribution of cites with higher SD-log, converge more gradually to accumulate 100% of the routes as distance increase, compared to cites with lower SD-log.

4. Discussion

Our results show that the mean walking route distance in TA metropolitan (620 m) is similar to findings in London (601 m) and Santiago (624 m), and shorter than Berlin (691 m), Sydney (795 m) and Halifax (670 m) (Millward et al., 2013; Tirachini, 2015). Although differences may be attributed to cultural and environmental factors, it is also possible that our utilization of high-resolution data enabled the identification of shorter routes that reduced the average distance.

The study explored the impact of socio-demographic characteristics on walking route distance. We found small differences in the mean walking route distance based on gender, with slightly longer distance for men (statistically non-significant). This result is in line with similar findings in other studies (Guzman et al., 2020; Larsen et al., 2010). Lue and Miller (2019) explored pedestrian route choice, and found that females were slightly more sensitive to changes in route length than males. Studies that analyzed factors influencing walking route choice, including attractiveness, safety, accessibility, and comfort, found no differences in preferences between females and males (Broach and Dill, 2015; López-Lambas et al., 2021). On the contrary, studies have shown that female route choice is more influenced by route characteristics that support safety, such as land-use mix, low presence of vacant land, and street

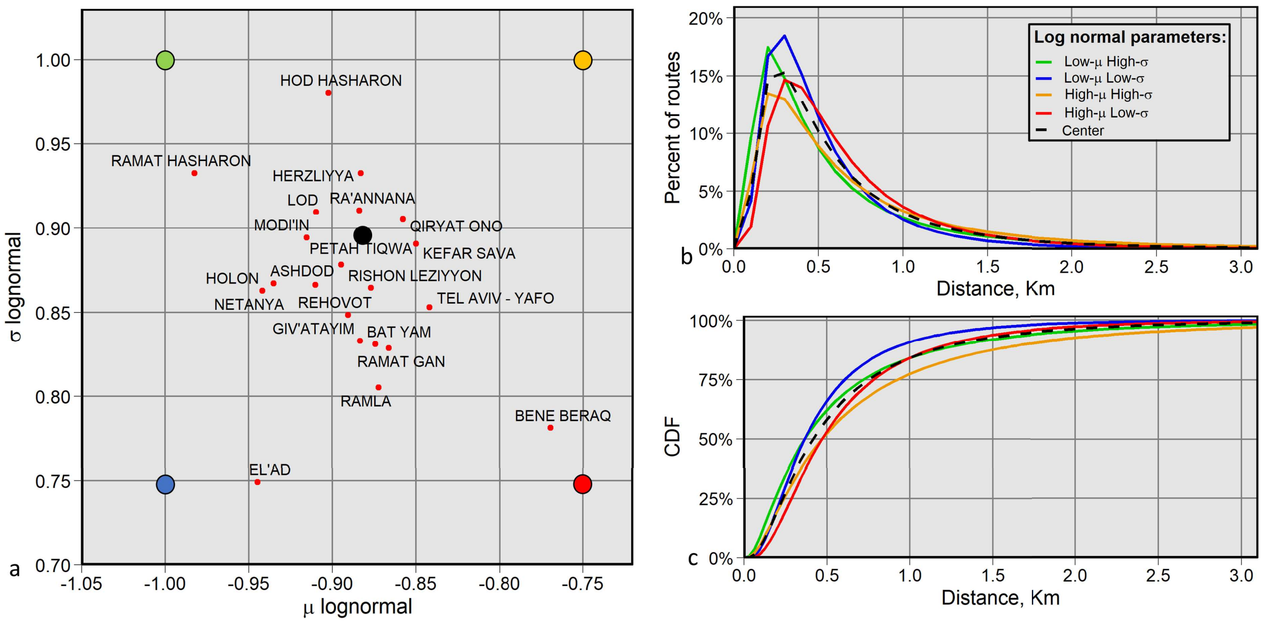

Figure 6: Parameter space of the cities' fitted log-normal distributions. (a) Scatter plot of the log-normal parameters for each city: x-axis presents the log-mean (μ) and y-axis the log-standard deviation (σ). The four edges of the parameter space are marked by colored circles and the center by black circle (b) Distance distributions using five combinations of parameters from the edges and center of the parameter space (marked by the colored circles in a).(c) Cumulative distribution function (CDF).

lighting (Basu et al., 2021, 2023). Although our findings suggest no gender-based difference in route length, further exploration is required to understand to what extent these varying route choice preferences impact the route distance.

Our results suggest that residents of higher SES are associated with longer walking routes compared to those of lower SES, though the impact is smaller compared to other socio-demographic factors. Studies have shown that living in lower SES areas is associated with lower likelihood of walking (Fairnie et al., 2016; Sugiyama et al., 2017). A positive effect of SES on walking distance could be the outcome of adopting a more active lifestyle that combines active travel to work and walking for exercise and leisure activity and is strongly associated with higher SES groups (Ghimire and Bardaka, 2023). In addition, populations with higher income have the option to select neighborhoods with desirable urban settings, providing walkable areas that facilitate walking (Cerin et al., 2009; Handy et al., 2006).

We also found that car ownership reduces walking route distance and, in turn, has a stronger impact than SES on walking route distance. Carless individuals have more limited accessibility options and, therefore, are more likely to engage in longer walking routes to their activities. Studies have shown that car ownership is a dominant factor in travel mode choice that reduces the number of walking trips engaged by a person (Ding et al., 2017). The impact of car ownership on walking mediates the complex interrelationship of the urban environment (Ramezani et al., 2021; Sehatzadeh et al., 2011). As Ding et al. (2017) show, a household decision to own a car is intertwined with the nature of the built environment around the home, and therefore, the effect of car ownership on walking partially reflects an indirect influence of the urban setting.

Of the socio-demographic attributes we explored, age has the strongest impact on the walking route distance. Children's (under 11 years) mean walking route distance is the shortest, while adolescents' (12-17 years) the longest. For adults, the walking distance declines as the age-group gets older, however, there is no significant difference between walking distance of age-groups 30-55 and 55+. The differences in the distribution of the walking route distance among the age-groups may be explained by the distinctive patterns of daily activities and destinations associated with each age-group. Furthermore, the reliance of adolescents on active travel, as opposed to adults, may contribute to the longer walking distances of this age-group.

Our study examined the impact of urban setting on walking route distance by examining intersection density in the area of the walking route and the city's population size. We found that walking routes are longer in areas where junction density is highest, and in cities of larger population size. Studies have found that road intersection is a dominant variable of the built environment in explaining walking duration for commuting and utilitarian purposes (Gao et al., 2020; Yang et al., 2022). In addition, street network connectivity was associated with a larger proportion of walking trips of all trips taken (Lamíquiz and López-Domínguez, 2015).

It should be noted that most of the studies that we referred to, examined walks per day, whether in frequency, duration or distance. However, our study explored walking distance and dura-

Table 3: A multilevel linear regression model to explain the average log(distance) of walking routes.

Fixed effects:	**Estimate**	**Ref. variable**
(Intercept)	-0.93***	
Female	-0.02 .	Male
Age 12-17	0.33***	Age 0-11
Age 18-29	0.24***	
Age 30-55	0.16***	
age 55+	0.16***	
Car=1	-0.04**	No car
Car>1	-0.1***	
SES-mid	-0.03 .	SES-low
SES-high	0.04*	
Work related	-0.13 ***	Work
Escort	0.04	
Entertainment or restaurant	-0.12***	
Health services	-0.03	
Home	-0.1***	
Errands/prayer	-0.15***	
Shopping	-0.13***	
Sport activity	-0.24***	
Studies	-0.14***	
Social visit	-0.15***	
Within a facility	-0.68***	
Pop 10,000-50000	0.03	Pop <10,000
Pop 50,000-100,000	0.04	
Pop 100,000-200,000	0.07*	
Pop >200,000	0.06 .	
Junction density-Mid	0.02	Low density
Junction density- High	0.02	
Junction density-Very high	0.06 ***	
Random effects:	**Variance**	**Std.Dev.**
Participant (Intercept)	0.165	0.4062
Residual	0.5404	0.7351
R^2 cond. = 0.268, R^2 marg. = 0.044, ICC = 0.234		
Loglik = -37738.2, AIC = 75722.584, BIC = 75989.671,		
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1		

tion per trip. We suggest that the association of route distance with built environment may be weaker than aggregated measures of walking (e.g. daily trips) due to two opposing effects. On one hand, walkability related factors such as high density, connectivity, and mixed land-use enhance accessibility and decrease the walking distance, as the routes to daily destinations are shortened. While on the other hand, walkable environments encourage walking, even when the trip is longer, therefore increasing the portion of longer routes.

One of the main contributions of this study is the identification of the log-normal distribution as the most suitable for

Table 4: Statistics of walking route distance and duration by destination activity.

Destination	**No. (%)**	**Distance, Km**					**Duration, minutes**				
			Percentile					**Percentile**			
		Mean	**P25**	**P50**	**P75**	**P90**	**Mean**	**P25**	**P50**	**P75**	**P90**
Sport activity	1860 (5.8)	0.9	0.14	0.33	0.85	2.35	10.25	2.07	4.17	11.07	27.01
Work	1830 (5.8)	0.72	0.28	0.47	0.88	1.47	8.16	3.33	5.83	10.32	17.3
Work related	1101 (3.5)	0.71	0.22	0.37	0.69	1.33	7.61	3.1	5	8.67	15.08
Health services	609 (1.9)	0.7	0.27	0.47	0.84	1.43	8.62	3.53	6.67	11.18	16.7
Escort	879 (2.8)	0.69	0.29	0.48	0.78	1.28	8.35	3.61	6.67	10.75	16.48
Entertainment/ restaurant	1418 (4.5)	0.66	0.24	0.43	0.79	1.34	8.67	3.42	5.83	10.83	18.07
Home	9423 (29.6)	0.66	0.25	0.43	0.78	1.31	8.4	3.33	5.83	10.52	16.67
Errands/prayer	3875 (12.2)	0.61	0.24	0.4	0.72	1.23	7.77	3.33	5.67	9.81	16
Shopping	2833 (8.9)	0.61	0.24	0.42	0.74	1.22	8.26	3.42	5.98	10.07	16.47
Social visit	1558 (4.9)	0.61	0.23	0.42	0.76	1.22	8.26	3.33	5.83	10.09	16.31
Studies	2394 (7.5)	0.57	0.25	0.44	0.76	1.13	7.24	3.33	5.83	9.4	13.82
Unknown	1926 (6.0)	0.46	0.19	0.3	0.48	0.87	6.47	2.7	4.17	7.05	11.67
Within facility	2092 (6.6)	0.31	0.17	0.24	0.37	0.56	4.65	2.46	3.53	5.59	7.52

Table 5: The fit measures for the theoretical distributions and the actual distribution of walking route distances in the TA metropolitan.

Distribution	**Parameters**[3]	**RMSE**	**MD**	R^2	**Loglik.**
Lognormal	Mean = -0.88, SD = 0.85	0.3%	1.8%	0.993	-12133.5
Gamma	Shape= 1.37, Rate= 2.19	1.0%	5.9%	0.893	-15947.3
Exponential	Rate= 1.6	1.4%	11.1%	0.770	-16824.4
Weibull	Shape= 1.07, Scale= 0.64	1.3%	9.1%	0.818	-16677.3

describing the distribution of walking route distances. This important trend was overlooked in past studies, which applied the negative exponential function, most likely due to the lower resolution of distance intervals that were used in the distribution (Goel, 2018; Millward et al., 2013). We demonstrate that the negative exponential function (as well as other functions of the exponential family) does not fit well to the initial increase in route frequency up to 300 m. The log-normal distribution outperforms the other functions in describing the route distance distribution both for the metropolitan area and for multiple cities, based on all fit measures. Accounting for frequencies of short-distance routes is significant since they comprise a large portion of the routes. We argue that the log-normal function allows for representation of the entire shape of the distribution of walking route distances and that the functions' parameters are a useful tool for comparing walking patterns between places or populations. Using the parameters, we can characterize the norm and identify outliers and unique cases.

We suggest that the log-normal distribution is general enough to approximate walking trips, in various spatial contexts. While we only examined data from the TA metropolitan area, we found that the log-normal distribution demonstrated the best fit, regardless of the municipality within the metropolitan area, compared to other distributions. We believe that similar studies should be conducted in other countries with different cultural and urban contexts to confirm this argument. The variation in many aspects of municipalities in the TA metropolitan area, including socio-demographics and urban morphology, further supports the potential to generalize our findings to other cases.

For example, based on their location in the parameter space, we can easily identify a different nature of walking patterns between Bnei Brak and Hod Hasharon (Figure 6a). In Bnei Brak, 50 percent of the routes are accumulated within the range of 450 m (high mean-log) with a low variance, implying a relatively large activity space for pedestrians compared to Hod Hasharon, where 50 percent of the routes are accumulated within the range of 380 m (low value of the mean-log) and high variability. This difference that is reflected by the location of the cities in the parameter space is in line with the contrasting characteristics of the two cities. Bnei Brak is characterized by a large share of traditional ultraorthodox population from low SES with a low number of cars per household, that is more reliant on walking. The city is dense with a well-connected built area, where most of the services are concentrated within the city boundaries, which increases walking and reduces walking distance variance. In contrast, Hod Hasharon is characterized by affluent populations with more cars per household. The city has a lower density of built-up area with a discontinuous activity space for pedestrians.

While in this study we focused on walking routes, it is unclear how this aspect of walking is related to the daily number and accumulated distance of walking routes. Future studies should explore whether longer walking route distances increase or decrease the values of these variables and how these associations are moderated by urban settings. In addition, our study did not explore the interaction of walking routes with other travel modes like private car and public transportation that were used by individuals.

The general pattern of walking route distance that we revealed is the outcome of a complex process that takes place within cities. Self-organization processes and top-down planning schemes shape urban settings and in turn the potential for walking (Batty, 2012; Omer and Zafrir-Reuven, 2015). Walking patterns emerge as the city organizes itself based on multiple interactions and feedbacks between peoples' walking capabilities, social norms, the spatial distributions of urban functions with their accessibility, and the availability and affordability of various modes of transport.

Therefore, the walking route distances presented in this study reflect peoples' walking habits under the current urban structure and should not be interpreted as the pure willingness of the population to walk. We suggest that planners should be cautious when defining a "walking range" based on empirical findings, and rather focus on creating environmental conditions that support active travel. It is likely that implementation of plans, such as the "15 min city", will potentially change the affordance of walking and result in a modification in the walking pattern. The method we suggest here can be utilized to monitor changes and assist in further understanding of the relationship between urban settings and walking patterns.

5. Conclusions

Using GPS tracks of thousands of individuals, we identified walking routes in the TA metropolitan area and calculated their distance and duration. We found that both socio-demographic characteristics of walkers and urban settings affect the route distance. The distributions of walking distance to various activities were very similar in shape, with the exception being sport activities and walks within facilities, showing a different pattern. Routes to work were the longest on average, when controlling for other variables.

Our main finding is that the distribution of walking routes distance in the TA metropolitan, and in multiple cities, follows the log-normal distribution, which has the best fit compared to other distributions of the exponential family. The log-normal parameters (mean-log and SD-log) could be used to evaluate differences in walking patterns between places and identify where suitable intervention measures are required to promote active travel.

Moreover, the log-normal distribution could be utilized to calibrate or verify simulation models of pedestrians and serve as a tool to guide planning that facilitates active travel in new neighborhoods and cities. Such planning should account for the spatial distributions of different population groups together with the characteristics of the urban environment.

Future studies should examine if this general pattern that applies to Israel also applies to other regions in the world. In addition, further research is required to explore how various characteristics of the urban settings affect the pattern of walking route distances, and whether there is an optimal pattern that is desirable for walkability of places.

Appendix A. Classification algorithms for travel mode

We used 85,528 routes that were labelled with a travel mode (TM) and didn't include multi-modal trips. Movement characteristics were calculated for each route based on speed, acceleration, and changing angle. The statistical measures of the movement included: mean, 90th percentile and standard deviation for each movement feature.

The routes were categorized into three modes: Walking, Bicycle and Vehicle. Vehicle includes any form of motorized movement such as car, bus, train, taxi and bike. The routes were randomly split into a training set (70%) and a test set (30%). The training set was used to the build a classification function that determines the class of each route based on movement characteristics.

Three types of classifiers were implemented: Naive bayes, Support Vector Machines (SVM) and K – Nearest Neighbor. The calibration function was implemented on the test set to infer the TM and evaluate the quality of prediction. The confusion matrix for the classification is presented in Tables A.1 and the measures of the classifiers' prediction in A.2.

The classifiers were implemented using e1071 package in R software (`https://cran.r-project.org/web/packages/e1071/index.html`). The calibrated classification function was used to infer the TM for the routes which had no TM based on the majority prediction of the 3 classifiers. Therefore, routes were labelled as walking, only if at least two classifiers predicted walking.

Table A.1: Confusion matrix for the classifiers: SVM, Naïve-bayes, KNN.
The matrix compares the (known) travel mode label with the prediction of the classifier.

Naïve-bayes Prediction

		Bicycle	Vehicles	Walk
Label	Bicycle	347	75	83
	Vehicles	3186	16363	313
	Walk	46	9	1993

KNN-Prediction

		Bicycle	Vehicles	Walk
Label	Bicycle	126	325	54
	Vehicles	55	19608	199
	Walk	4	72	1972

SVM- Prediction

		Bicycle	Vehicles	Walk
Label	Bicycle	0	449	56
	Vehicles	0	19648	214
	Walk	0	59	1989

Table A.2: Measures for the quality of the predictions for the three classifiers.

	NaiveBayes			**SVM**			**KNN**		
Measure	Bicycle	vehicles	Walk	Bicycle	Vehicles	Walk	Bicycle	Vehicles	Walk
Sensitivity	0.10	0.99	0.82	0.77	0.98	0.91	0.72	0.98	0.90
Specificity	0.99	0.57	0.99	0.99	0.92	0.99	0.99	0.91	0.99
Pos pred value	0.69	0.83	0.94	0.30	0.98	0.96	0.40	0.98	0.94
Neg pred value	0.88	0.97	0.96	1.00	0.90	0.98	1.00	0.91	0.98
Prevalence	0.13	0.68	0.19	0.01	0.81	0.18	0.01	0.81	0.18
Detection rate	0.01	0.67	0.16	0.01	0.80	0.16	0.01	0.79	0.16
Detection prevalence	0.02	0.81	0.17	0.02	0.81	0.17	0.02	0.81	0.17
Balanced accuracy	0.55	0.78	0.90	0.88	0.95	0.95	0.86	0.94	0.95

Appendix B. Fit parameters and measures for each city

Table B.1: Parameters of best fit for the theoretical distributions in each city.

		Parameters			
City	**Routes**	**Log-normal**	**Gamma**	**Exponential**	**Wiebull**
BENE BERAQ	4791	Mean=-0.77 SD= 0.78	Shape= 1.76 Rate= 2.78	Rate= 1.58	Shape= 1.26 Scale= 0.69
TEL AVIV - YAFO	6163	Mean=-0.84 SD= 0.85	Shape= 1.35 Rate= 2.07	Rate= 1.53	Shape= 1.06 Scale= 0.67
KEFAR SAVA	1156	Mean=-0.85 SD= 0.89	Shape= 1.32 Rate= 2.03	Rate= 1.53	Shape= 1.07 Scale= 0.67
QIRYAT ONO	256	Mean=-0.86 SD= 0.91	Shape= 1.21 Rate= 1.78	Rate= 1.48	Shape= 1 Scale= 0.68
RAMAT GAN	1443	Mean=-0.87 SD= 0.83	Shape= 1.39 Rate= 2.21	Rate= 1.59	Shape= 1.06 Scale= 0.65
RAMLA	295	Mean=-0.87 SD= 0.81	Shape= 1.61 Rate= 2.74	Rate= 1.7	Shape= 1.19 Scale= 0.63
BAT YAM	898	Mean=-0.87 SD= 0.83	Shape= 1.52 Rate= 2.54	Rate= 1.67	Shape= 1.16 Scale= 0.64
RISHON LEZIYYON	1189	Mean=-0.88 SD= 0.86	Shape= 1.39 Rate= 2.25	Rate= 1.61	Shape= 1.1 Scale= 0.65
HERZLIYYA	791	Mean=-0.88 SD= 0.93	Shape= 1.1 Rate= 1.58	Rate= 1.44	Shape= 0.95 Scale= 0.67
GIV'ATAYIM	362	Mean=-0.88 SD= 0.83	Shape= 1.47 Rate= 2.44	Rate= 1.66	Shape= 1.12 Scale= 0.63
RA'ANNANA	636	Mean=-0.88 SD= 0.91	Shape= 1.23 Rate= 1.88	Rate= 1.53	Shape= 1.02 Scale= 0.66
REHOVOT	1133	Mean=-0.89 SD= 0.85	Shape= 1.45 Rate= 2.42	Rate= 1.66	Shape= 1.12 Scale= 0.63
PETAH TIQWA	1566	Mean=-0.89 SD= 0.88	Shape= 1.27 Rate= 1.99	Rate= 1.57	Shape= 1.03 Scale= 0.65
HOD HASHARON	261	Mean=-0.9 SD= 0.98	Shape= 1.01 Rate= 1.4	Rate= 1.39	Shape= 0.92 Scale= 0.68
LOD	419	Mean=-0.91 SD= 0.91	Shape= 1.17 Rate= 1.78	Rate= 1.53	Shape= 0.98 Scale= 0.65
ASHDOD	1918	Mean=-0.91 SD= 0.87	Shape= 1.39 Rate= 2.32	Rate= 1.66	Shape= 1.11 Scale= 0.63
MODI'IN	311	Mean=-0.92 SD= 0.89	Shape= 1.36 Rate= 2.24	Rate= 1.65	Shape= 1.1 Scale= 0.63
HOLON	1273	Mean=-0.94 SD= 0.87	Shape= 1.34 Rate= 2.26	Rate= 1.68	Shape= 1.06 Scale= 0.61
NETANYA	2189	Mean=-0.94 SD= 0.86	Shape= 1.39 Rate= 2.38	Rate= 1.72	Shape= 1.09 Scale= 0.61
EL'AD	834	Mean=-0.94 SD= 0.75	Shape= 1.65 Rate= 3.04	Rate= 1.84	Shape= 1.12 Scale= 0.57
RAMAT HASHARON	246	Mean=-0.98 SD= 0.93	Shape= 1.05 Rate= 1.62	Rate= 1.55	Shape= 0.92 Scale= 0.62

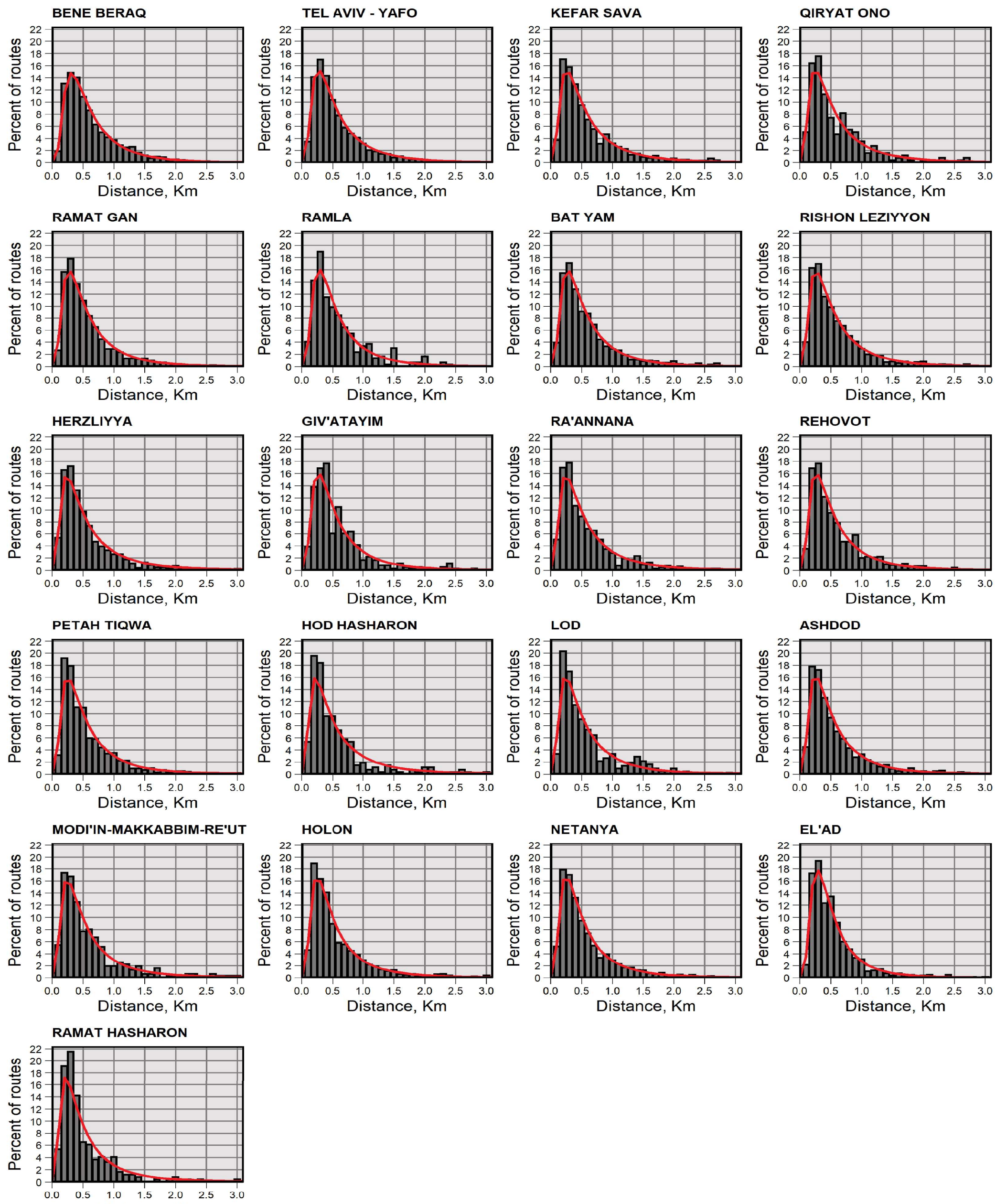

Figure B.1: Distribution of walking route distance and the fitted log-normal distribution, by city. Bars represents empirical route distance, and the red line is the fitted log-normal distribution.

Table B.2: Fit measures for each of the theoretical distributions with the empirical distribution of walking distance in each city. The distributions names appear as follows: Log-normal (L), Gamma (G), Exponential (E), Weibull (W).

	RMSE				**MD**				R^2			
City	**L**	**G**	**E**	**W**	**L**	**G**	**E**	**W**	**L**	**G**	**E**	**W**
BENE BERAQ	0.2%	0.7%	1.5%	1.0%	1.5%	3.6%	12.7%	6.6%	0.99	0.94	0.73	0.89
TEL AVIV-YAFO	0.3%	1.0%	1.4%	1.3%	1.9%	6.0%	10.7%	9.1%	0.99	0.89	0.77	0.81
KEFAR SAVA	0.4%	1.0%	1.4%	1.2%	2.5%	5.7%	10.5%	8.4%	0.98	0.88	0.78	0.82
QIRYAT ONO	0.6%	1.1%	1.3%	1.3%	3.0%	7.1%	8.6%	8.6%	0.96	0.86	0.80	0.80
RAMAT GAN	0.3%	1.1%	1.6%	1.4%	2.1%	6.5%	12.1%	10.2%	0.99	0.88	0.74	0.78
RAMLA	0.5%	0.9%	1.5%	1.1%	3.0%	6.8%	11.6%	7.6%	0.97	0.91	0.75	0.86
BAT YAM	0.3%	0.8%	1.4%	1.1%	1.5%	5.2%	11.5%	7.2%	0.99	0.92	0.78	0.87
RISHON LEZIYYON	0.3%	0.9%	1.4%	1.2%	1.6%	5.5%	10.9%	7.9%	0.99	0.91	0.79	0.85
HERZLIYYA	0.4%	1.2%	1.3%	1.4%	2.5%	7.0%	8.1%	9.7%	0.99	0.84	0.80	0.77
GIV'ATAYIM	0.7%	1.1%	1.6%	1.4%	4.5%	6.8%	11.4%	8.0%	0.94	0.87	0.72	0.80
RA'ANNANA	0.5%	1.1%	1.3%	1.3%	2.8%	6.9%	9.1%	8.6%	0.98	0.87	0.80	0.81
REHOVOT	0.4%	1.0%	1.5%	1.2%	2.0%	5.8%	11.8%	8.3%	0.98	0.90	0.76	0.84
PETAH TIQWA	0.6%	1.3%	1.6%	1.5%	3.8%	7.4%	11.4%	10.5%	0.97	0.84	0.74	0.76
HOD HASHARON	0.7%	1.5%	1.5%	1.7%	4.0%	8.5%	8.6%	10.5%	0.95	0.76	0.76	0.71
LOD	0.7%	1.4%	1.6%	1.6%	4.5%	8.5%	10.8%	11.6%	0.95	0.80	0.74	0.72
ASHDOD	0.3%	1.0%	1.4%	1.2%	2.2%	5.7%	10.9%	7.8%	0.99	0.90	0.78	0.85
MODI'IN	0.4%	1.0%	1.3%	1.1%	2.1%	5.2%	9.8%	6.9%	0.98	0.90	0.81	0.86
HOLON	0.4%	1.1%	1.4%	1.3%	2.9%	6.7%	10.8%	8.9%	0.98	0.88	0.78	0.82
NETANYA	0.3%	0.9%	1.4%	1.2%	1.6%	5.3%	10.6%	7.8%	0.99	0.91	0.80	0.85
EL'AD	0.5%	1.1%	1.8%	1.5%	2.7%	6.3%	14.7%	11.1%	0.98	0.91	0.69	0.79
RAMAT HASHARON	0.8%	1.7%	1.7%	1.9%	6.0%	10.9%	11.0%	11.8%	0.94	0.75	0.73	0.68

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