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The mobility laws of location-based games

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Abstract

Mobility is a fundamental characteristic of human society that shapes various aspects of our everyday interactions. This pervasiveness of mobility makes it paramount to understand factors that govern human movement and how it varies across individuals. Currently, factors governing variations in personal mobility are understudied with existing research focusing on explaining the aggregate behaviour of individuals. Indeed, empirical studies have shown that the aggregate behaviour of individuals follows a truncated Lévy-flight model, but little understanding exists of the laws that govern intra-individual variations in mobility resulting from transportation choices, social interactions, and exogenous factors such as location-based mobile applications. Understanding these variations is essential for improving our collective understanding of human mobility, and the factors governing it. In this article, we study the mobility laws of location-based gaming—an emerging and increasingly popular exogenous factor influencing personal mobility. We analyse the mobility changes considering the popular PokémonGO application as a representative example of location-based games and study two datasets with different reporting granularity, one captured through location-based social media, and the other through smartphone application logging. Our analysis shows that location-based games, such as PokémonGO, increase mobility—in line with previous findings—but the characteristics governing mobility remain consistent with a truncated Lévy-flight model and that the increase can be explained by a larger number of short-hops, i.e., individuals explore their local neighborhoods more thoroughly instead of actively visiting new areas. Our results thus suggest that intra-individual variations resulting from location-based gaming can be captured by re-parameterization of existing mobility models.

Keywords: Human mobility; Mobile applications; Location-based games

1 Introduction

Location-based gaming has steadily emerged as a popular pastime on smartphones, and become a potentially effective way at promoting physical activity [1–3]. From a scientific standpoint, the most unique and interesting aspect of these games is how they encourage and promote movement, which can improve physical and mental health [4, 5], and be comparable to a health or a fitness app [1–3, 6, 7]. More generally, location-based games are examples of a broader class of smartphone applications that attempt to promote physical activity—either directly through recommendations or indirectly through objectives that are linked with physical locations [1–3, 8]. Other examples of applications in this cat-

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egory include varied location-based services [9], online location-based social networks [10] and smartphone and wearable applications for physical activity [11]. In this article, we focus on location-based games due to their immense popularity and their use of gamification, which has been shown to be among the most effective mechanisms for achieving sustained change in mobility [12, 13]. We study mobility changes in response to location-based gaming through Pokémon GO, the best known, and one of the most popular examples of location-based games. Pokémon GO remains among the most popular mobile apps in many countries, it has over 100 million active users, and has been downloaded over billion times in total. Pokémon GO is not an isolated success story either with other location-based games, such as `Zombies, Run!`, `Ingress`, `Geocaching`, `Minecraft Earth` and `Harry Potter: Wizards Unite` similarly being highly popular.

Current research understanding suggests that location-based games, and related applications, can have a sustained effect on mobility. Indeed, several studies have demonstrated smartphone applications to have an effect on the daily activity levels of their users [1, 8, 14]. As an example, empirical studies based on pedometers have demonstrated that Pokémon GO has an effect on mobility, resulting in an increase of around 1400 steps for each day that the user plays the game, and the total effect lasting for at least 30 days [1]. Similar findings have also been obtained from quantitative analyses, e.g., Colley et al. [15] characterized players through questionnaires and geostatistical analysis of game elements and highlighted that Pokémon GO may have introduced significant changes to their mobility. These studies, however, have also shown that the retention of the application and the effect on physical mobility tends to be short-lived with persuasion mechanisms, such as gamification, and social interactivity, being central to prolonging the positive effect on mobility.

While the overall effect on physical activity and movements has been established, important gaps still exist in our understanding. In particular, little information currently exists on *how* this increase affects the characteristics of the user's mobility patterns or *which factors* mediate these effects, and more importantly, how these changes affect the underlying laws governing human mobility. Indeed, as many of the game mechanisms in Pokémon GO are centered around physical movement, the changes could result from increases in everyday physical activity instead of changes in personal mobility patterns. In this article, we explore how the changes in mobility induced by Pokémon GO relate to the laws governing human mobility, in an attempt to fill up this gap in current scientific understanding. We analyse displacement data captured from two sources to obtain a detailed view of mobility patterns and how they are influenced by Pokémon GO. The first data set (Dataset-A) consists of mobile phone app logging (Carat, an energy-awareness app) from over 3900 users, and the second (Dataset-B) of location-tagged social media (Twitter) from over 21,500 users. The granularity of location information differs in these data sets, with social media providing GPS coordinates and app logging providing coarse grained estimates of total displacements with approximately 2 km resolution. Our longitudinal dataset captures time before, during and after Pokémon GO's initial peak in popularity from January 2016 to June 2017 (18 months), allowing us to better study the duration of the game's effects, as well as to account for potential novelty effects (see the Section Datasets for details about the data, data collection process, and data validity).

The results of analysis show that Pokémon GO does indeed increase mobility—in line with previous findings—but the characteristics governing mobility remain consistent with

a truncated Lévy-flight model and that the increase in mobility can be explained by a larger number of short-hops, i.e., individuals explore their local neighborhoods more thoroughly instead of actively visiting new areas. Our results thus suggest that intra-individual variations resulting from location-based gaming can be captured by re-parameterization of existing mobility models. Besides offering novel insights into variations in personal mobility and contributing to our collective scientific understanding of human mobility, our results have practical implications to transport policy planners (e.g., improve design of on-demand transport networks), epidemiology (e.g., explaining characteristics of mobility patterns and offering insights into potential disease transmission routes), urban sciences. and other fields.

2 Datasets

We analyze mobility through two datasets, one collected by instrumenting mobile phones with the Carat energy-awareness applications, and the other obtained from Twitter. We include data from January 2016 to March 2018 from Carat and January 2016 to June 2017 from Twitter. The target game Pokémon GO was released in July 2016. To assess the impact of Pokémon GO on gamers' daily mobility and to validate the generality of our findings, we make compare Pokémon GO use in each of the two datasets against contrasting but complementary baselines. For Carat we compare Pokémon GO users with players of Clash Royale, a non-location-based game that was one of the most popular games released in 2016, whereas for Twitter we compare *gamers* and *non-gamers* (i.e., *infected* vs. *control-group*).

2.1 Dataset A: Carat

The first major dataset used in this study was collected by application logging integrated as part of the Carat[1] [16] smartphone application. This Android and iOS app collects information from the mobile device it is running on and recommends personalized actions aimed at increasing battery life [17].

Carat uses energy-efficient and non-invasive instrumentation to record the state of the device, including a list of running apps, mobile network technology being used (e.g., WiFi or LTE), and distance traveled since the last record. Each of these values is recorded at every 1% battery level change (either charging or discharging) and it also contains a uniquely identifiable id per user and timestamp. The Carat application does not run on the background, but instead registers to the smart device OS's battery change events. Because of this, Carat's data can miss events that happen when the device is in deep sleep, when the application is evicted from memory by the OS, or when the Carat application has been terminated manually by the user. This results in a temporally sparse dataset that requires preprocessing with suitable statistical methods.

Since its first release in 2012, Carat has been deployed in over one million mobile devices in dozens of countries. For our study, we analyze a subset of these data spanning from January/2016 until March/2018. We consider only Android users as the IOS version of the time no longer supported logging the list of running applications.[2] This subset includes

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[1]http://carat.cs.helsinki.fi/

[2]iOS 9.3.4 was released on August 4, 2016: https://www.macrumors.com/2016/08/04/apple-releases-ios-9-3-4-with-security-fix/.

Table 1 Left: Number of gamers on Twitter. Right: Number of gamers on Pokémon GO (PG) and Clash Royale (CR)

Twitter		Carat		
City (code), Country	N.	Country (code)	PG	CR
São Paulo (SPO), Brazil	924	USA (us)	780	134
Jakarta (JKT), Indonesia	911	Finland (fi)	746	175
London (LON), UK	853	Germany (de)	495	79
Singapore (SIN), Singapore	709	UK (gb)	153	20
Santiago (SCL), Chile	661	Canada (ca)	149	20
Tokyo (TKY), Japan	631	India (in)	122	137
Bangkok (BKK), Thailand	599	Japan (jp)	113	6
San Francisco (SFO), USA	597	Spain (es)	102	58
New York (NYC), USA	564	Italy (it)	78	43
Toronto (TOR), Canada	447	Netherlands (nl)	50	9
Paris (PAR), France	373			
Seattle (SEA), USA	348			
Boston (BOS), USA	279			
Sydney (SYD), Australia	268			
Hong Kong (HKG), China	263			
Barcelona (BCN), Spain	247			
Moscow (MOW), Russia	143			
Helsinki (HEL), Finland	92			

173.6 million records from 74,000 users out of which 3996 played the game at least once on Android. We classify a Carat user as a *gamer* from his/her first record containing Pokémon GO as a running application.

To identify the effect of Pokémon GO on mobility, in our analysis of the Carat dataset we compare the effects of Pokémon GO and Clash Royale—a non-location-based game— on their players. We ensure these gamers had records before the day of the installation of the respective app as well as records after the last day it was observed in our records. Released in March/2016, Clash Royale[3] is a multi-player game in which users battle in support of their clans. Fundamentally, while Pokémon GO requires its users to physically move to reach other players and in-game objects, Clash Royale is agnostic to any sensor in the phone and allows any two or more players to interact regardless of their location. We study a total of 1323 users who played this game at least once on Android. Table 1 lists the number of users of these two games in the Carat dataset (for the top 10 countries).

For every new Carat record, the app stores the geographical coordinates of the device locally. For that, it queries the coarse-grained last known location from the Location Manager API for Android. The individual measurements are not stored by Carat, and only distance between consecutive records is transferred to the back-end for further analysis and location information from older records is destroyed. The benefits of this approach are twofold: lower battery consumption since it does not use the power-hungry GPS chip of the device, and the privacy of the user is preserved by never disclosing the exact location of the user. One limitation of this method is the variable accuracy of these location services. The distribution of displacements from Carat shows an abrupt inflection (knee) at around 2 km. This may be due to Android's coarse-grained location granularity, which mostly seems to report location with a cell-tower precision (around 2 km accuracy).

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[3]https://clashroyale.com

2.2 Dataset B: Twitter

As our second dataset, we analyse 8.7 million geotagged tweets from over 21,500 users in 15 different countries. Studying this diversity of countries allowed us to mitigate the impact of possible regional bias in our analyses. To obtain these records, we first queried Twitter's web page following a certain criterion, resulting in a list of users. From each user account in this list, we downloaded its entire *timeline* (set of tweets) through Twitter's REST API,[4] keeping only those records with a geotag (17.4% of the total). For both *gamers* and *non-gamers* the query criteria were (i) a given location (e.g., Bangkok, Thailand), and (ii) a period within the time of our study. This approach ensures the availability of these data for reproducibility, as the access to Twitter's REST API[5] is the only requirement. Furthermore, Twitter's developer policy precludes long-term storage of location-based data.

For *gamers*, we require the string *#PokemonGo* to appear in the tweet (or some capitalization alternatives, e.g., *#pokemongo*). We collected tweets from over 8900 *gamers*. Manual inspection of 1% randomly sampled tweets from this set revealed the content of the tweet to be associated with the game in 90% of the cases (e.g., screenshots or text about in-game actions), in line with the measurements of Althoff et al. which were based on queries from a web search engine [1]. To eliminate unwanted noise from bots in our Twitter set, we used the *Botometer* [18] API and identified 3.1% of such profiles, which were then discarded. The list of cities included in this study, along with the corresponding total number of *gamers* is shown in Table 1.

The average number of tweets for *gamers* and *non-gamers* was statistically similar (mean (μ): 390 vs. 351, median: 200 vs. 159, probability of the two distributions being identical $p < 0.001$) as well as the inter-arrival-time of tweets per user (in hours, μ: 57.8 vs. 58.1, median: 7.68 vs. 8.13, $p < 0.001$). In all cities analyzed, these geo-tagged tweets were similarly distributed in space among both groups, with urban areas resulting in higher densities of tweets.

2.3 Supporting dataset—Google trends

To define the periods of highest activity of a game, we compared some of the aforementioned metrics with the Google Trends index[6] of *Pokémon GO* as a search term (*G*). This metric measures the popularity of a search term, with values ranging from 0 (lowest) to 100 (highest). It allows us to validate the *trendiness* of the game per country over a period of time.

2.4 Dataset validity

The combination of datasets used in our work gives us insights on various aspects of how mobile location-based games influence human mobility. Our two main datasets cover large amounts of users during periods before the release of the studied application, and the months during which it had its highest popularity in various countries. Carat's longitudinal dataset contains fine grained measurements about users' displacements and app usage, enabling the study of the impact of the game on mobility as well as investigating

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[4] https://developer.twitter.com/

[5] https://developer.twitter.com/en/developer-terms/agreement-and-policy

[6] https://trends.google.com/

various aspects of game retention, such as the availability of cellular networks and battery consumption. Twitter, in turn, allows us to quantify the impact of the game on users' visited areas by labeling those discussing the game as *gamers*.

Carat records are captured without user intervention but contain only displacements between samples. Twitter records contain a precise geographical location but their availability is subject to the user's desire to share the information. These different characteristics allow us to study complementary aspects of the effect Pokémon GO has on its gamers which would not be possible through a single source.

3 Methods

In this section, we describe the methods and metrics used to study the datasets described in Sect. 2. Table 2 lists the probability functions $P(x)$ of the distributions used to model our data.

3.1 Spatial clustering

Given the strong urban aspect of the game and small range of distances traveled while playing it (<10 km, <6.2 mi) [15, 19], we applied a series of clustering algorithms to identify which records are from the user's normal geographic area. Specifically, we classify Twitter records as *local* or *away* depending on their distance from the user's city. These labels were computed with respect to the city from which a user was initially discovered. Since users may visit other cities and countries which may be many kilometers *away*, we focus our study in the *local* area of each city and discard all samples labeled as away.

We classify a given city C using a two-stage clustering process. Let (C_S) denote all of the geographical coordinates of C regardless of user-id. We first cluster C_S using DBSCAN [20] with $\epsilon = 2$ km (maximum distance for two points to be in the same cluster). We then calculate the center of mass C_{cm} of the cluster with the most records and compute the distances between every point in C_S and C_{cm}, namely $d_{s,cm}$. Finally, we cluster the log transformation of these distances ($\rho = \log(d_{s,cm})$) using KMeans with $k = 2$ clusters (number of clusters the algorithm should look for). These algorithms were chosen for their simplicity and their characteristics making them well-suited for the two phases. DBSCAN is a density-based clustering algorithm that allows grouping points based on a maximum distance, whereas KMeans offers control for the number of clusters to extract in the second phase.

The resulting probability distribution of ρ showed a consistent separation between the *local* and *away* clusters at around $\rho = 5$ (100 km or 62 mi) in all 18 cities studied. We conjecture that this is the typical maximum commuting distance a person would regularly travel, regardless of geographical location. From the classified records, for a given city C, we studied the trajectories of *local* tweets of users who have at least 25% of their records at C.

Table 2 Probability functions for different distributions

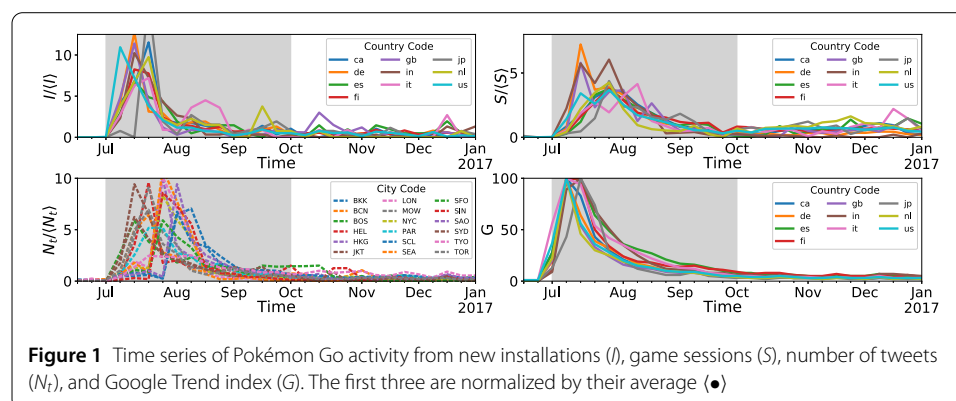| Distribution	Probability function $P(x)$
Power law	$x^{-\alpha}$
Truncated power law	$x^{-\alpha}e^{-\lambda x}$
Exponential	$e^{-\lambda x}$
Stretched exponential	$x^{\beta-1}e^{-\lambda x^{\beta}}$
Log-normal	$\frac{1}{x}\exp[-\frac{(\ln x - \mu)^2}{2\sigma^2}]$

3.2 Place extraction

For analysing mobility using displacement data, we need to identify hops that correspond to successive trajectories of users. We accomplish this using an approach that is motivated by algorithms designed for extracting significant locations from sequence data [21]. First, we define a *stop* as a sequence of records following three rules: (1) no displacements are observed, (2) intervals between samples are shorter than a threshold ($\Delta T < \tau$), and finally (3) the sequence spans a minimum amount of time (also τ for simplicity). Furthermore, we define a *movement* following rule (2) as well as being interrupted by any *stop*. To further benefit from Carat's faster sampling rate, for our analysis we require a *movement* to be immediately preceded (also within a max interval τ) by a *stop*. This approach significantly decreases the uncertainty about when a movement actually started and allows us a more accurate view of the users' mobility. For this analysis, we set τ to 15 minutes, allowing us to capture *stops* of that duration while accounting for sampling bias as well as very shorts stop along the way (e.g. traffic lights) and ensuring *movements* are more likely to start from important locations the user might visit.
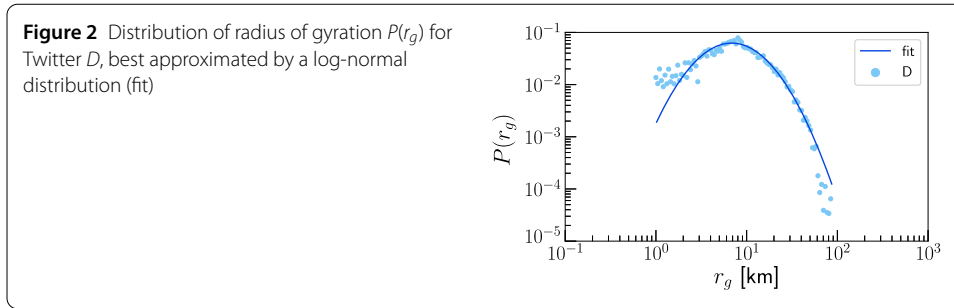
3.3 Temporal analysis

Figure 1 shows the level of *Pokémon GO* activity in the second half of 2016, through 4 different metrics: number of installations (*I*, Carat), number of gaming sessions (*S*, Carat), number of tweets with *#pokemongo* (N_t), and the Google search index for *Pokémon GO*. The shaded area in all plots highlights the highest levels of activity, between July/2016 (release of the game) and end of September/2016. For the analysis of the Twitter dataset, we therefore define 3 equally long periods for our study: *before* the game (April–June/2016), *during* (July–September/2016) and *after* (October–December/2016).

Since we are analyzing the overall impact of the game on *gamers*' mobility, and comparing it with *non-gamers*, we only consider users who had records in all three of the periods as well as *gamers* whose first game activity (e.g., tweet containing *#pokemongo*) was between beginning of July and end of September/2016.

To ensure the validity of our results, we compare observations across the two datasets. From Twitter, the average time between the first and last tweet containing *#pokemongo* is 59.2 days (median: 34.6 days, σ: 69.2 days), significantly smaller than the number of days gamers were observed playing Pokémon GO on Carat (99 days). Despite this difference, both present very similar power law exponents for the distribution of these reletable time intervals (Carat: α = 1.285, Twitter: α = 1.305).

Figure 1 Time series of Pokémon Go activity from new installations (*I*), game sessions (*S*), number of tweets (N_t), and Google Trend index (*G*). The first three are normalized by their average $\langle \bullet \rangle$

Figure 2 Distribution of radius of gyration $P(r_g)$ for Twitter D, best approximated by a log-normal distribution (fit)

3.4 Radius of gyration (r_g)

This commonly used mobility metric [22] conveys the size of the dispersion of a user's studied trajectories. It can be interpreted as the radius of a circle covering the trajectories of a user, centered at the center of mass of all observed points. A gamer that moves to new areas would thus have an increased r_g, but it would remain the same for a gamer playing in the same area. The radius of gyration r_g is calculated with Equation (1):

$$r_g(t) = \sqrt{\frac{1}{n_c(t)} \sum_{i=1}^{n_c} (\overrightarrow{r_i} - \overrightarrow{r_{cm}})^2}, \tag{1}$$

where $\overrightarrow{r_{cm}} = \frac{1}{n_c} \sum_i^{n_c} \overrightarrow{r_i}$ represents the center of mass of all visited locations by a given user, and $\overrightarrow{r_i}$ represents location $i = 1, \ldots, n_c(t)$ up to time t.
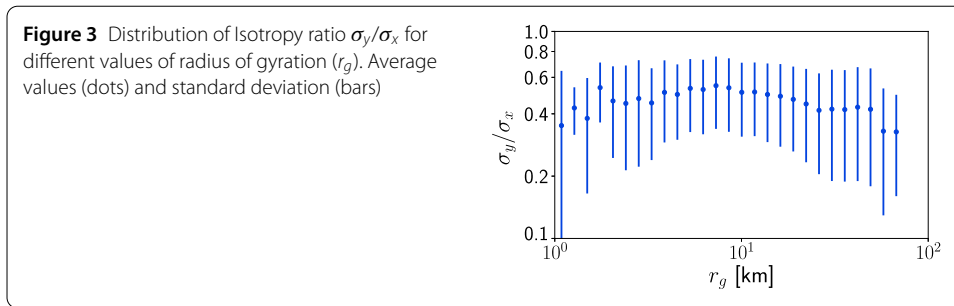
For the Twitter data set, Fig. 2 depicts the probability distribution $P(r_g)$ and the corresponding best fit model of a lognormal distribution (i.e., $\ln(r_g)$ is normally distributed). Given that our analysis is constrained to *local* points, we therefore also limit trip lengths (i.e., we study regular flights of less than 100 km in the studied cities). Under similar constrained circumstances, a lognormal distribution has been observed by Zhao et al. [23]. Both user groups had very similar distribution parameters, $\mu = 2.44$ and $\sigma = 0.705$ for *gamers* and $\mu = 2.43$ and $\sigma = 0.7244$ for *non-gamers*.

The distribution of $P(r_g)$ being well described by a lognormal function implies that this mobility metric is a result of a multiplicative random process [24]. Therefore, we conjecture that the area covered by a user's *local* trajectories is a result of mechanisms such as transport prices, locations of origin and destination and availability of certain means of transportation.

3.5 Isotropy ratio (σ_y/σ_x)

While the radius of gyration r_g describes the size of the area covered by a user's trajectory, isotropy [22] describes how a user's trajectories are dispersed inside this area given a common reference frame (e_x, e_y). For example, a highly anisotropic set of trajectories would have most of its points dispersed along one of these axes and fewer close to its orthogonal axis. This metric allows us to capture changes in the visits of gamers who play in the vicinity of previously visited locations (and whose r_g may not change).

As proposed by Gonzalez et al. [22], using moment of inertia, we calculate the intrinsic reference frame of a user's trajectories (e_1, e_2), then rotate it around its center of mass into a common reference frame (e_x, e_y). Finally, the dispersion of the observed points of a user

Figure 3 Distribution of Isotropy ratio σ_y/σ_x for different values of radius of gyration (r_g). Average values (dots) and standard deviation (bars)

can be calculated along each axis of this common reference frame. We use the ratio (σ_y/σ_x) of these two since it captures the proportionality of these dispersions along both axes.

For Twitter, Fig. 3 shows the distribution of σ_y/σ_x for varying values of r_g. Given that our analysis is constrained to *local* points, the average ratio observed is higher than in previous works [22, 25], especially for higher values of r_g. This outcome possibly captures the tendency for more isotropic trajectories in urban environments. The behavior was similar for both *gamers* and *non-gamers*.
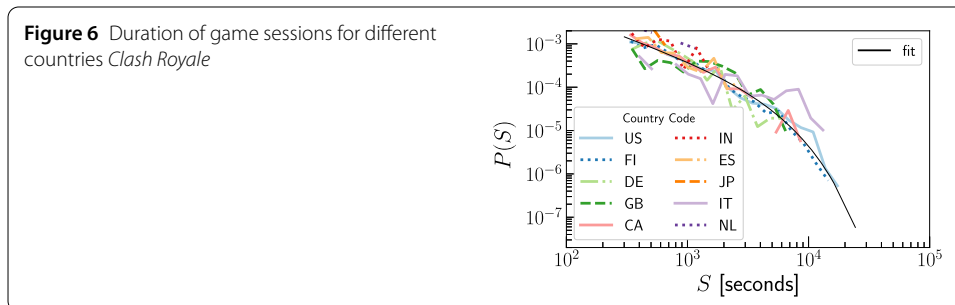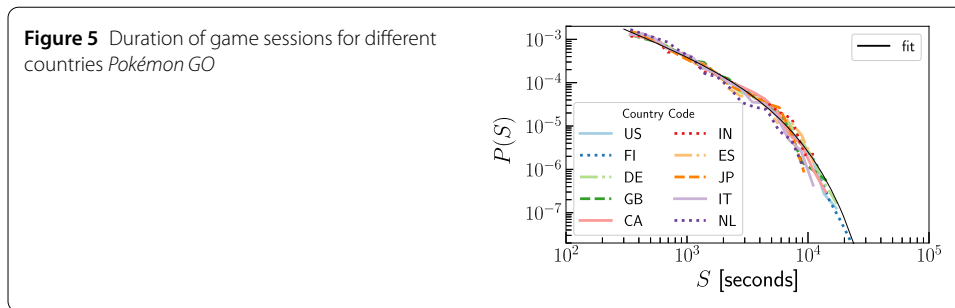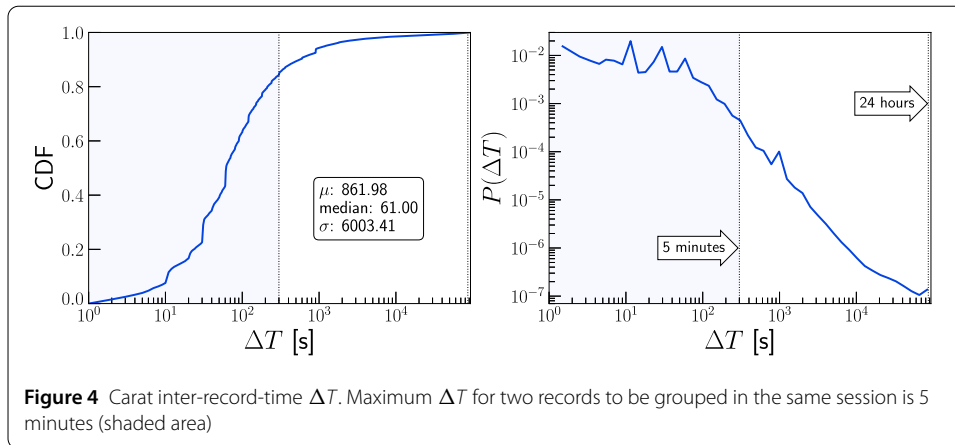
3.6 Number of visited locations (φ)

To perform a user-centric as well as a location-centric study of visits, we perform spatial binning of the observed tweets. We bin every observed point to the nearest intersection of a mesh grid of 250 meter by 250 meter square cells. Every studied city is covered with this grid. The binning allows us to correct for GPS inaccuracies, as well as group visits which may fall within the area of a large city block.

For Twitter, the distribution of the number of visited locations (φ) between January/2016 and June/2017 is well-described by a stretched exponential (Table 2). For this analysis, we only considered users who were registered before 2016. With a stretching exponent β close to 1, its behavior can be approximated to that of an exponential distribution. This allows us to estimate the number of visits a user will make after some time t by $\varphi(t) = 1/\lambda(t)$, where $\lambda(t)$ is the average number of visits per user, and the value of $\varphi(t)$ will be independent of the users already sampled. If this observation persists for *gamers* while playing, the game would have a different impact on each player's visitation distribution. The distribution fit parameters for *gamers* were $\lambda = 0.0226$ and $\beta = 0.946$, whereas for *non-gamers* we observed $\lambda = 0.0193$ and $\beta = 0.916$. Note the higher average visitation ($1/\lambda$) for *non-gamers*.
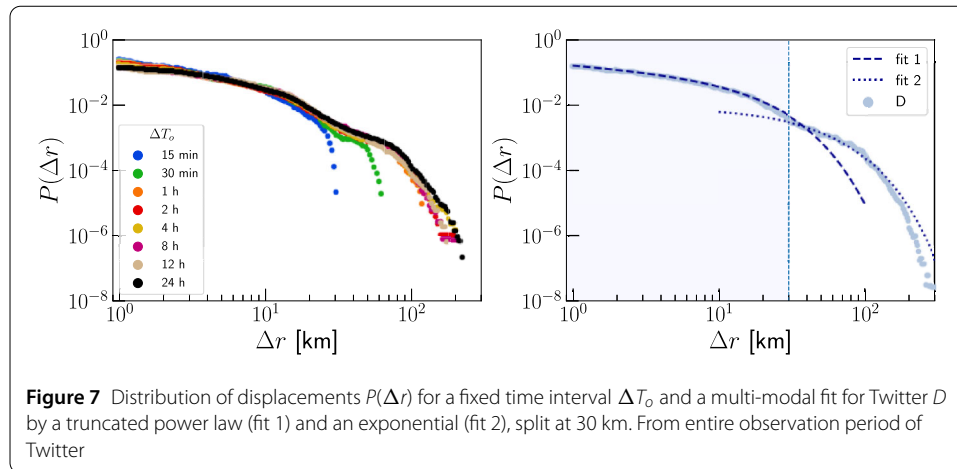
3.7 Gaming session (S)

To better understand the behavior of users while playing the game, we define a gaming session (S). Figure 4 depicts the distribution of inter-record-time (ΔT) for all Carat users. A *gaming session* is then defined as a sequence of records (containing the game) in which $\Delta T < 5$ minutes (shaded area in $P(\Delta T)$). A limitation of the Carat dataset is that the application can only record device behavior when running. The background process of Carat may be terminated by the OS at any time when the user is not actively using the Carat app. Therefore the data from Carat are inherently sparse, and records may be missing throughout the day. Given these constraints, for any analysis of S, we only consider those longer than 5 minutes.

Figure 4 Carat inter-record-time ΔT. Maximum ΔT for two records to be grouped in the same session is 5 minutes (shaded area)

Figure 5 Duration of game sessions for different countries *Pokémon GO*

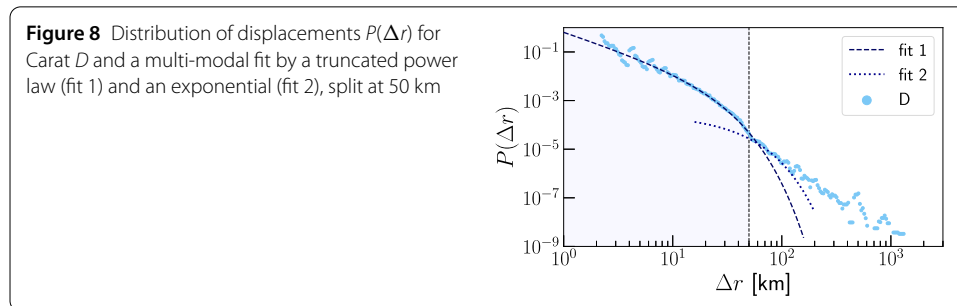**Figure 6** Duration of game sessions for different countries *Clash Royale*

Mobile application usage has been shown to reflect geographic and cultural boundaries [26], which suggests that cultural factors could mediate the results. To demonstrate that this is not the case, and that Pokémon GO usage is highly similar across countries, Fig. 5 and Fig. 6 compare the gaming session times of Pokémon GO and Clash Royale across different countries included in our analysis. From these plots we can observe that the session times for both Pokémon GO and Clash Royale are highly similar across all countries, suggesting that cultural factors have little or no effect on how the games are played. Indeed, the distributions of gaming sessions shown in Fig. 5 and Fig. 6 are consistently similar across the different countries.

3.8 Distance traveled between consecutive records (Δr)

Given the set of (*local*) tweets from a user, Δr is the computed distance between two consecutive records. For simplicity and scalability, this distance is calculated as a straight line between these two points, and not the length of the shortest path between them [27]. Since

Figure 7 Distribution of displacements $P(\Delta r)$ for a fixed time interval ΔT_o and a multi-modal fit for Twitter *D* by a truncated power law (fit 1) and an exponential (fit 2), split at 30 km. From entire observation period of Twitter

Table 3 Distribution parameters for fits in Fig. 7

Twitter users	Truncated power law (fit 1)	Exponential (fit 2)
Gamers	$\alpha = 0.279, \lambda = 0.089$	$\lambda = 0.036$
Non-gamers	$\alpha = 0.329, \lambda = 0.083$	$\lambda = 0.036$

Figure 8 Distribution of displacements $P(\Delta r)$ for Carat *D* and a multi-modal fit by a truncated power law (fit 1) and an exponential (fit 2), split at 50 km
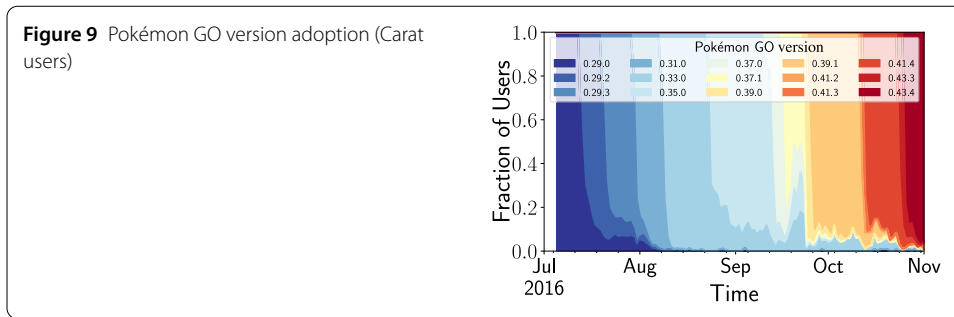

we are only considering points within an urban environment, we discard all Δr where the corresponding velocity was >120 km/h (75 mph, maximum speed limit on highways).

For Twitter, Fig. 7 depicts the probability distribution $P(\Delta r)$ for a fixed time interval (ΔT_o) as well as for the entire dataset (*D*). The former shows that $P(\Delta r)$ is not affected by different sampling rates when only *local* records are considered. The latter shows a multi-modal distribution of $P(\Delta r)$, composed by a truncated power law (fit 1) and an exponential (fit 2), divided at an inflection point around 30 km (18.6mi). Similar to results by Jurdak et al. [25], this result validates the multi-modal aspect of human mobility, where short and long distances are covered using different means of transportation. Parameters of each distribution fit had similar values between user groups, summarized in Table 3.

The first part of the model (fit 1) being a truncated power law implies a relative proportionality between a distance traveled and its probability, up to a cut-off point from which probabilities decrease much faster ($\sim 1/\lambda$). Likewise, the second part of the model (fit 2) being an exponential implies that the probability of distances traveled diminishes very fast, rendering very high values of Δr extremely rare.

Since we are not able to distinguish between *local* and *away* points for Carat as we did for Twitter, we limit our analysis of the former to displacements which are smaller than 100 km (62 mi). Similar to our Twitter analysis, Fig. 8 depicts a multi-modal fit for

Figure 9 Pokémon GO version adoption (Carat users)

$P(\Delta r)$ with a truncated power law (fit 1) and an exponential (fit 2), although for Carat data, the distribution is split at 50 km (31 mi). Note that Twitter users are more likely to share their location while at their destination, whereas Carat is capable of sampling intermediate displacements. These scaling differences can explain the different exponents of the power laws ($\alpha_{\text{Twitter}} = 0.329$, $\alpha_{\text{Carat}} = 1.469$). It is interesting to note the similarities between datasets in the decay parameters of the exponential cut-off in fit 1 ($\lambda_{\text{Twitter}} = 0.08386$, $\lambda_{\text{Carat}} = 0.08346$) and the exponential in fit 2 ($\lambda_{\text{Twitter}} = 0.03589$, $\lambda_{\text{Carat}} = 0.04505$).

3.9 Performance and usability mediate mobility change

To obtain further insights into factors mediating mobility, we next perform an analysis of how the increase in mobility correlates with different release versions of Pokémon GO. To understand changes in technical functionality, we also correlate our findings against Pokémon GO changelogs.

From Carat's user base, the percentage of adoption for each version during the first four months of its release is depicted in Fig. 9. Changelogs of these early versions point to battery issues being addressed in versions 0.31 and 0.33. Analysis of the expected time a user played the game given the initial version they first played shows a statistically significant increase of 117% (3.5 days to 7.6 days) between these two versions. This result suggests that performance and usability effects mediate mobility changes (and retention). Conversely, our results suggest that location-based games may struggle at achieving persistent change in mobility if they have performance or usability issues.

4 Results

4.1 Location based online game introduces significant changes to mobility

We first validate that Pokémon GO indeed has a significant effect on mobility. To demonstrate this, we split the records in Dataset-A (i.e., Carat) between week-days and weekends, and categorize users into three groups: low, intermediate, and high engagement users, according to the number of days they were observed playing (A: $[1, 21)$ days, B: $[21, 90)$ days, C: 90 or more days). Separating week-days and week-ends is essential for eliminating possible biases resulting from daily and weekly routines in mobility characteristics [28, 29], whereas categorizing the users is necessary to control for differing engagement levels [30, 31] (see Sect. 3). To control for the effect of location-based game design features, we compare Pokémon GO against Clash Royale, a mobile game without location-based features that was highly popular during the observation period. The average daily displacements calculated from Dataset-A are summarized in Table 4. Statistically significant increases were found for groups B and C (over 2 km and 1 km, respectively)

Table 4 Daily movements (in km), per group according to the number of days playing—A: [1, 21) days, B: [21, 90) days, C: 90 or more days, highlighting statistically significant changes, for Pokémon GO (PG) and Clash Royale (CR). The sample sizes were (995, 1051, 1160) and (257, 317, 230) for (A, B, C) on PG and CR respectively

Game	Period	A	B	C
CR	Week-day	30.3	30.2	32.5
	Week-end	28.7	26.0	28.3
PG	Week-day	27.3 → 31.2	**28.0 ⇒ 29.9**	**30.6 ⇒ 31.6**
	Week-end	29.3 → 29.4	**28.1 ⇒ 30.4**	**29.6 ⇒ 31.4**

when comparing Pokémon GO use to time before it. The increase is significant for both weekdays and weekends ($p < 0.02$). For low engagement users and users of Clash Royale, no statistically significant differences were observed ($p > 0.09$). For groups B and C, the increase in mobility persists even after Pokémon GO use ends.

To validate that the increase in daily displacements is not biased by the use of app logging as a sampling mechanism or the user population of said app, we separately compute the total daily Δr from Dataset-B for all users with at least 3 records per day. We split the users into a `gamer` and a `control` group depending on whether they had used Pokémon GO or not. Similarly to the results for Dataset-A, we observe a statistically significant increase in total daily Δr for gamers during week-days, from 13.1 km to 14.6 km ($p = 0.03$). Conversely, there is a decrease in Δr for `control` group from 16.2 km to 15.9 km ($p = 0.03$). The small, but nevertheless statistically significant, decrease in mobility for the control group is likely explained by a combination of different factors with seasonality and decreased retention, and hence reduced Twitter activity, over time being among the contributing factors. During week-ends, there were no statistically significant differences for `gamers`, but there was a decrease in total daily Δr for `control` group users between the last two periods (16.7 km to 15.2 km, $p = 0.007$).

4.2 Increased mobility from exploring nearby vicinity

The increase in mobility could be explained by three hypotheses: (i) individuals move to and explore new regions, (ii) they explore familiar regions more carefully, or (iii) they engage in higher level of physical activity without exploring any new areas. For example, an increase in step count, could result from increased everyday routine activity instead of changes in personal mobility patterns. As Pokémon GO incorporates several game mechanics that require physical activity from the users to progress and to accumulate achievements with the game, it is essential to separately analyze the extent to which increased mobility affects underlying mobility laws (hypotheses (i) and (ii)) and to which it results from the game mechanics (hypothesis (iii)). To explore the first hypothesis, we use Dataset-B to calculate the evolution of r_g, i.e., the radius of gyration across the different periods. We cluster users by their r_g before, during, and *after* the game at intervals of 5 km, up to 50 km and an additional cluster for $r_g > 50$ km. We observe a strong monotonic relationship in the distributions of r_g between each studied period (for all comparisons: Spearman's rank correlation coefficient $r_s > 0.75$, $p = 0$). However, there were no significant changes in r_g across those months. For both the gamer and the control groups, only those with initial r_g values of 5 km and 10 km showed changes greater than 10%: `gamers`: 7.38 km and 11.18 km, `control`: 7.08 km and 11.36 km, respectively. For all clusters and

observed periods, a statistical test for distribution similarity between gamers and control had ps > 0.05. The results thus strongly indicate that the geographic area within which users move remains consistent over time regardless of the user playing Pokémon GO or not, i.e., we find no support for the first hypothesis.

To explore the second hypothesis, we assess the total number of locations visited (φ) by users. For gamers we observe a small but statistically significant increase during gameplay. Before exposure to the game (April–June/2016), gamers visited on average 15.4 locations ($p < 0.001$) whereas for control users the respective average number is 18. However, during the game, gamers visited two more locations than before (17.4, $p < 0.001$) while for control, there was no statistically significant difference in the number of locations visited before and during (18.9, $p = 0.08$). This increase in visited locations implies that mobility changes are not a result from trivial increases in everyday activity, but also a result from individuals exploring familiar regions more thoroughly (i.e., hypothesis (ii)).

We next examine potential changes in the spatial distribution of mobility by analysing isotropy ratios σ_y/σ_x (see Methods 3.5), i.e., uniformity of mobility. We cluster users by their ratio before the game, at intervals of 0.2, from 0.2 to 0.8, and analyze changes during Pokémon GO use. For users with a high anisotropy, we find that Pokémon GO significantly increases their isotropy, i.e., their geographic distribution of mobility becomes more homogeneously distributed, further supporting hypothesis (ii). For users with $\sigma_y/\sigma_x = 0.2$ before the game, we observed gamers to have more isotropic trajectories than the control group users during gameplay (0.299 and 0.270 respectively, with $p = 0.016$). For all other clusters and periods there was no statistically significant difference between user groups ($p > 0.05$). Analysis of isotropy thus shows that characteristics of mobility largely remain intact, with only individuals with a low isotropy (i.e., high anisotropy) experiencing changes. These correspond to individuals whose mobility is dominated by long hops, whom Pokémon GO can improve the balance of the mobility distribution.

Given the location-based nature of Pokémon GO, increases in mobility could be associated with higher game playing time instead of an actual effect on physical mobility. To explore this potential bias, we first calculate average session times for Pokémon GO and Clash Royale players from Dataset-A. These are $\mu_{P_S} = 26$ minutes (median: 14.2 minutes, σ: 29.3 minutes) for Pokémon GO, and $\mu_{P_S} = 28.6$ minutes (median: 16.4 minutes, σ: 35 minutes) for Clash Royale, respectively. The usage patterns thus are similar to other non-location-based games. Similar patterns can be observed with the number of days users continue to play Pokémon GO. Specifically, on average, we observe Pokémon GO gamers to play for 99 days (median: 52.8 days, σ: 119.5 days), 21.5 total gaming sessions (median: 7 sessions, σ: 45.9 sessions). For Clash Royale, gamers play on average for 95 days (median: 35 days, σ: 135 days), 16.1 sessions (median: 4 sessions, σ: 40.65 sessions). For both the session times and the playing time we can observe significant differences between mean and median values, suggesting the distributions are heavily skewed. As shown in Sect. 3.7, the session times are also similar across different countries.

4.3 Pokémon GO increases the likelihood of short hops
We next analyze the mobility distribution before and after Pokémon GO to understand how the changes affect the underlying mobility model. We use Dataset.B to analyze the distribution of placements for both the gamers and the control group. For both groups, mobility is consistent with a truncated Lévy-flight model, but the ratio between short

and long displacements changes between the two groups. Specifically, the distribution of displacements follows a truncated power law combined with an exponential (see Methods). Compared to baseline values shown in Table 3, the value of long-tailed parameter α changes to significantly higher values for `gamers` ($\alpha_g = 0.35 \pm 0.02$) than for `control` ($\alpha_c = 0.33 \pm 0.02$), i.e., `gamers` exhibit an increase in the probability of short hops and a decrease in the probability of long hops compared to `control`.

4.4 Better power management by the app led to greater effects on mobility

Pokémon GO was chosen as representative example of smartphone applications that can promote physical activity, and other applications could have similar effects on mobility. Findings in literature appear mixed on this aspect, showing that many applications only have a temporary effect on mobility [11]. This contrasts with studies on Pokémon GO, which have almost consistently reported sustained change [1–3]. To better understand this discrepancy, we analyzed how the increase in mobility differs across different versions of Pokémon GO, and correlated our findings against technical change-logs (see Sect. 3.9). We find mobility increases to be significant only from Pokémon GO version 0.33 onward, which introduced significant battery saving strategies. Specifically, the impact on daily mobility when starting to play these initial versions of the game is statistically significant only with highly-engaged users (i.e., players of group C, >90 days), whereas all users (i.e., groups A, B and C) starting Pokémon GO with a later version significantly change their mobility while playing the game. Early reports of Pokémon GO linked the app with high battery drain [32], which in turn has been linked with high attrition [33]. Our results suggest that application design mediates mobility changes and that the discrepancy in findings across different applications may be a result from differences in application design and user-friendliness.

5 Discussions

Lack of physical activity has been tightly associated with several health problems [34–36], and ranks high amongst risk factors for premature death as well as disability [37]. Understanding of how location-based games can alter users' mobility can have a significant impact on future policies aimed at incentivizing physical activity [36]. Indeed, physical activity can have health effects comparable to those brought by medications [38], making our findings relevant for physicians and public health.

Mobility laws are of paramount importance for disease transmission modeling as mobility results in opportunities to meet other people and hence creates possible situations where diseases can be transmitted [39–41]. Our results showed that location-based games as an exogenous factor result in higher number of short hops and hence can cause higher local transmission rates [42]. Reversely, while our study focuses on the *increase* of mobility through location-based games, a *reduction* of mobility could be also achieved with the appropriate game elements [15]. Such idea could be implemented in order to curb the spread of infectious diseases by gamifying the adoption of curfew measures as well as social distancing. Physical activity could be retained by, e.g., rewarding users for increased step count or physical activity (e.g., measured by heart rate sensors in a smartwatch) while requiring them to stay within a small geo-fenced area.

Our findings are also interesting to urban scientists and policy makers. The analysis showed how exogenous factors can result in increased exploration of the local region,

which in turn is essential for understanding districts and their dynamics. Our results also offer opportunities for transport and city planning through more detailed mobility models and mechanisms that can be used to shape mobility. Indeed, while extensive literature exists on the utilization of current urban spaces (e.g., [43, 44]), more investigation is needed on how to change such patterns and our work offers an important first step in this direction. For example, a possible example is the use of a location-based game to shape the use of public spaces by driving pedestrians away from congested areas or better planning of public transport.

Pokémon GO had and has a large, worldwide user base, which lends itself well to studying mobility. Applications with smaller and more localized user bases could be used to study the population of a city, speakers of a particular language, a specific socioeconomic group [15], or a geographical area where the app is popular [45]. As these types of applications target specific groups, the characteristics of mobility may differ [46]. Our results shed light on the characteristics and laws that govern the changes when they do occur, showing that re-parameterization of existing models is sufficient to account for the changes in mobility.

Our results corroborate with strong evidence the link between location-based online games and changes in human mobility found in existing research [1, 8, 14], even though our study was limited to a single, albeit exceptional, location-based online game. Other location-based applications, including location-based recommender systems and other location-based games, are likely to have similar effects—provided that they can induce a positive change in the first place. Previous studies on other location-based games have not always shown an effect on mobility, which can be due to lack of suitably engaging content, small user-base, or technical issues. Indeed, our analysis also showed that early versions of Pokémon GO failed to increase mobility and only later versions that improved the end-user experience were successful in motivating people to increase their mobility. Further research is needed to better understand the factors that mediate possible increases in mobility.

6 Conclusion

In this paper, we have studied the mobility laws governing location-based gaming, an important exogenous factor affecting variations in personal mobility across individuals. We analyzed measurements collected through two different means, a location-based social network (Twitter) and mobile app-logging. Our results show that exposure to location-based gaming can significantly influence an individual's mobility but the characteristics governing mobility remain consistent with a truncated Lévy-flight model. The main difference in mobility is an increased degree of short hops, evidenced from a more homogeneous isotropy ratio, but unaffected radius of gyration. We showed that mobility changes are explainable by a higher degree of exploration of previously visited regions, instead of a consistent change in mobility patterns. Our results improve our collective understanding of human mobility, demonstrating how exogenous factors can help to explain inter-individual variations, and showing how these variations can be modeled using prevalent mobility models with adjustments to their parameters. Specifically, variations in an individual's mobility can be captured using personal-level models that account for the individual's exposure to different factors. Taken together, our results corroborate the effect of location-based online games of changes in human mobility found in existing research

[1, 8, 14], while offering novel insights into the laws governing the characteristics of these changes.

Beyond improving our collective understanding of mobility, the results provide insights into mobility characteristics of location-based smartphone applications and provide suggestions on how to improve their potential in promoting physical activity. For example, the game mechanics of Pokémon GO have been designed around so-called (Poke)stops, which are important locations around which the game activity is centered. Previous research has shown that these stops are not uniformly distributed, but cover different regions of cities [15], with a strong bias towards densely populated urban areas where most of mobility already took place before the game. Our results showed that exploration largely takes place in close proximity of previously visited places, suggesting that stops or other focal areas near familiar regions have the highest likelihood of attracting the user.

Abbreviations
GPS, Global Positioning System; DBSCAN, Density-Based Spatial Clustering of Applications with Noise; REST, Representational State Transfer; API, Application Programming Interface; OS, Operating System.

Availability of data and materials
The anonymized version of the Carat data that support the findings of this study are available at https://www.cs.helsinki.fi/group/carat/mobility-games-data/.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
EL was responsible for the Carat dataset, LT collected the remaining datasets. LT, EL and PN conceived the research idea and co-wrote the manuscript with input from all authors. LT and EL analyzed the data, and PN, JO, ST and AD supervised the project. All authors read and approved the final manuscript.

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