Exploring Map App Usage Behaviour Through Touchscreen Interactions

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Abstract

Mobile map apps are rapidly changing the way we live by providing a broad range of services such as mapping, travel support, public transport, and trip-booking. Despite their widespread use, understanding how people use these apps in their everyday lives is still a challenge. In order to design context-aware mobile map apps, it is important to understand mobile map app usage behaviour. In this study, we employed a novel approach of recording touchscreen interactions (taps) on mobile map apps and combined them with users' distances from their homes to capture everyday map app usage. We analysed data from 30 participants recorded between February 2021 and March 2022 and applied two different data-driven analysis techniques to evaluate map apps usage. Our results reveal two distinct tapping signatures: a "home behaviour", characterised by high interactions with map-related apps close to home, and a "travel behaviour", defined by lower interactions scattered over a range of distances. Our findings have important implications for future work in this field and demonstrate the potential of our new approach for understanding mobile map app usage behaviour.

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1 Introduction

GIScience is facing complex challenges in the digital era, including the design of mobile map apps on smartphones. These apps provide various mainstream services such as navigation, travel assistance, public transport, and trip booking. However, it remains unclear how exactly people engage with these apps on a daily basis and how to effectively design such apps based on people's needs. Research on (mobile) map design primarily uses controlled experiments for the design evaluation, such as think-aloud methods in field or lab studies, limiting the ecological validity of the findings [6, 8]. Studies conducted in real-world settings are needed to understand mobile map app usage "in the wild." To our best knowledge, to date, only one study matched this approach [7], by continuously collecting map-related usage data from users' mobile devices to identify map-usage scenarios and patterns (i.e. interaction patterns such as map-view manipulation, searching and finding a place on the map, navigating to a place). As the study was limited to a single map app (Google Maps), we argue that to understand the plurality of mobile map apps, we must explore more than just one app. Thus, new methodologies are needed to evaluate map usage behaviour in a real-world setting to understand a broader range of mobile map apps. This paper addresses this need by introducing a novel approach, tappigraphy, which records usage behaviour with mobile apps by leveraging smartphone touchscreen interaction data (i.e. taps on a device display). Tappigraphy originated and is widely used in neuroscience to uncover behavioural patterns [1]. Recently, it has been shown to be applicable to GIScience as an ecological momentary assessment (EMA) tool to study mobile map usage behaviour [5]. Unlike other EMA methods, tappigraphy solely involves recording the taps on the screen of a smartphone and deliberately does not require the knowledge of any other private information about the individual (e.g. gender, nationality). Moreover, unlike lab-based investigations, recording touchscreen tapping data offers a new, unobtrusive way to observe human behaviour in everyday activities. Furthermore, it is not limited to selected apps and can be flexibly used to evaluate multiple apps in the aggregate. With this paper, we aim to employ tappigraphy in analysing map app usage behaviour in relation to the study participants' distance from their home location. By analysing the frequency of map-related taps at various locations to the participant's home, we intend to infer similar or different user behaviour pertaining to map apps.

2 Methodology

Through the MapOnTap app, we collected data for a minimum of two-weeks from thirty-eight participants. Data recording took place between February 2021 and March 2022. Participants were asked to install the free Android MapOnTap app on their smartphones. It is based on a tap counting app, which operates in the background on a smartphone. The recording of participants' phone sessions starts the moment they began unlocking the screen and continued until it was locked again. Within each phone session, tapping data on the active foreground apps were recorded as a series of timestamps, including the total number of taps, the start and end time, the apps used during each phone session, the participant's randomised ID code, the device ID (i.e. a generated code for each participant's device) and the Google Play Store app category associated with the used app. In addition to the tapping data, the app optionally records GPS coordinates. For the purpose of our study, we asked our participants to use their smartphones as usual and activate the MapOnTap app for at least two consecutive weeks. Participants were free to stop recording, turn GPS tracking off, or delete the app any time they wished. We did not collect any other information about the participants. The data collection was approved by the ethical board of University of Zurich.

From our initial dataset, we excluded three participants whose data collection period was less than two weeks. The duration of data collection for each individual, varied from a minimum of 14 days to a maximum of 313 days (M: 121 days, SD: 94 days). We applied different pre-processing steps to analyse our data. First, we calculated the Euclidean distances to the participants' home locations for each phone session. For the participants' home locations, we assumed that the most frequent coordinate pairs corresponded to the home of our participants. Given that part of the data collection occurred during the Covid-19 pandemic-related restrictions, it is reasonable to assume that the mobility patterns of our participants may have been influenced by pandemic-induced factors. In order to analyse the data, we first calculated the distances from participants' homes for each tap record, and then we aggregated the total number of taps for each app category. We used the category list from the Google Play Store as a reference for this process. We specifically selected the categories of "Maps and Navigation" (MN) and "Travel and Local" (TL), as they are the only two categories that are explicitly related to map apps. Subsequently, we excluded five participants from the study whose tapping data did not include any recordings for the MN and TL app categories. Our dataset revealed 74,304 distance values ranging from 0 to 9,000 km from home. To identify and exclude any outliers, we applied the interquartile range method. As a result, we eliminated 2,121 extreme values from the dataset. The resulting distances ranged from 0 to 1,393 km from participants' home locations. Next, we calculated distance intervals by applying the Fisher-Jenks algorithm. With this, we were able to assign the recorded distances to 100 distance interval bins and label them with the median distance value of each bin. Our two final datasets consisted of 30 rows representing the final number of participants included in our analysis and 100 columns representing the number of taps corresponding to each distance bin that we computed for the two aforementioned app-related categories. Finally, the tap values were standardised by calculating the z-score.

3 Results and Discussion

3.1 Descriptive Statistics on Tappigraphy Data

A total of 1087 unique apps were found in our dataset, catalogued in 33 categories according to Google Play Store (e.g. Social, Communication, etc.). Of these categories, only MN and TL refer to map-related apps were selected. We found 25 unique apps related to the MN category. For instance, navigation tools, mapping, and public transportation apps (e.g. Petal map, a mapping service from Huawei and apps of public railways companies, such as SBB). For the TL category, we identified 63 unique apps. For example, travel-booking tools, ride-sharing apps, trip management tools, and tour-booking apps (e.g. Booking, TripAdvisor, Publibike). Upon examining the total number of taps in our dataset, the TL category has, on average, more than twice as many taps recorded (M:3,798, SD:5,775) as the MN category (M:1,707, SD:4,218). Further, the TL category also had a greater maximum number of taps (132,923) than the MN category (59,734). The relatively high standard deviation can be attributed to the varying degrees of participation and data collection duration among participants, as the data collection period spanned almost a year. This unbalanced nature of the dataset is a trade-off of the study design, and may have impacted our results.

In terms of tap records in association with distances from home, the tapping data is not uniformly distributed but concentrated within a range of 200 km, with 84% of taps recorded for the MN category and 62% of taps for the TL category falling within this distance range.

3.2 Hierarchical Cluster Analysis (HCA) and Archetypal Analysis

Our main goal was to uncover potential map app usage patterns at varying distances from participants' home locations. To this end, we focused on two methods: HCA and Archetypal Analysis. HCA is an unsupervised algorithm that forms ordered subgroups, which can help individualise data clusters that are more closely or distantly related [4]. We employed Ward's criterion to optimise homogeneity within clusters by minimising the within-cluster sum of squares. HCA is typically represented by a dendrogram, where the height of branches represents the distance or dissimilarity between clusters. To determine the optimal number of clusters, we partitioned the dendrogram to maximise nodes' distances between the tree [4]. The HCA analysis resulted in two clusters, with cluster 1 comprising 17 participants, and cluster 2 comprising 13 participants. Figure 1 illustrates the mean standardised tapping counts of participants for both the MN and TL categories over distances from participants' home location of both clusters. It can be observed that participants in cluster 1 exhibit a strong interaction pattern within approximately 1 km of distance to their home location for both app categories. In contrast, cluster 2 is characterised by a more dispersed interaction

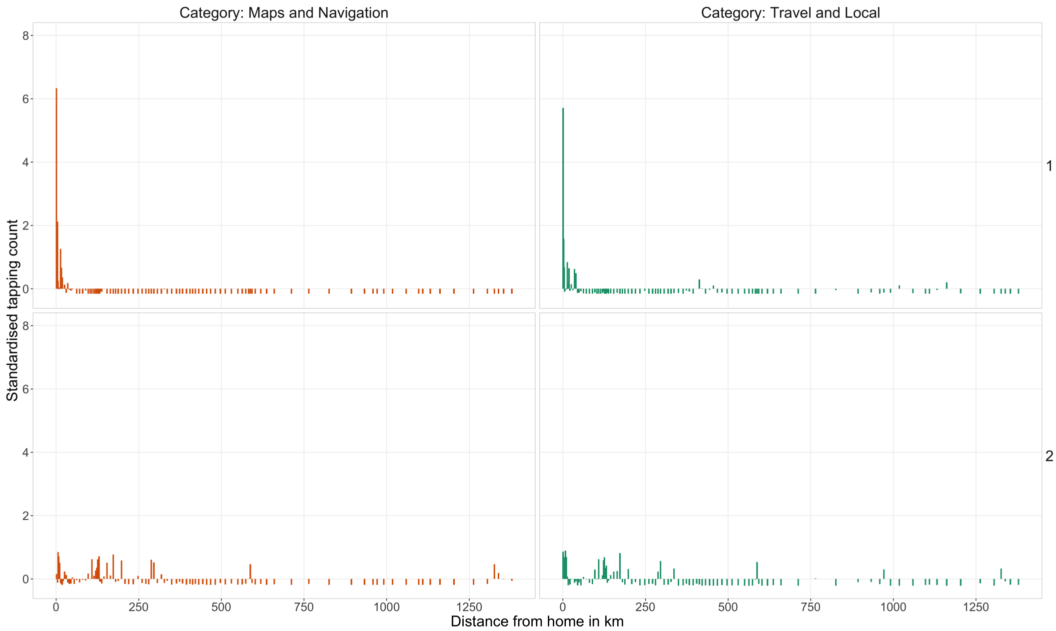

Figure 1 Bar chart displaying the HCA clustered mean tapping counts of participants, for two categories: Maps and Navigation (left) and Travel and Local (right).

behaviour, with peaks at distances ranging from 5 km to 10 km, 100 km to 150 km, around 300 km and an additional smaller interaction peak at a distance of 1300 km from home. This trend is similar for both categories.

For comparison purposes, we also applied Archetypal Analysis as an unsupervised machine learning technique. Archetypal analysis finds unique combinations of features (or "pure types") in a dataset (i.e. archetypes) that best represent its properties [3, 2]. Data points of the dataset are then positioned on a spectrum between archetypes without being assigned to only one particular archetype (unlike the results of cluster analysis). With archetypal analysis, we can assess the membership of each data point to these different archetypal signatures (similar to cluster analysis) while preserving individual differences [2]. Based on the RSS value, we chose four archetypes to best represent our data (RSS value of 0.68)

Figure 2 shows the participants' distribution on the archetypal spectrum of the four calculated archetypes. Most of our participants have strong affiliations to archetype A2, as most data points are around that archetype. The directional lines of each data point indicate the direction and strength of affiliation to the different archetypes. Based on that, most data points near A2 also have strong affiliations to archetype A3. Figure 3 visualises the standardised tapping counts for each archetype over home distances and for each app category. While the signature of each archetype differs in some ways, the tapping behaviour between the two app categories for each archetype is rather similar. Archetype A2 is defined by a strong usage behaviour of both app categories and a distance that is close to home (mainly within a range of 13 km). Many of our participants also have strong affiliations to archetype A3. A3 is defined by a usage behaviour that is mainly distributed over a distance range up to 200 km from home. Comparing archetypes A2 and A3, it is possible to derive differences in interaction behaviour. A2 consists of a behaviour where participants used both app categories and are close to home; A3 indicates a behaviour where participants are also farther away from home, with a scattered and predominant usage behaviour of the TL

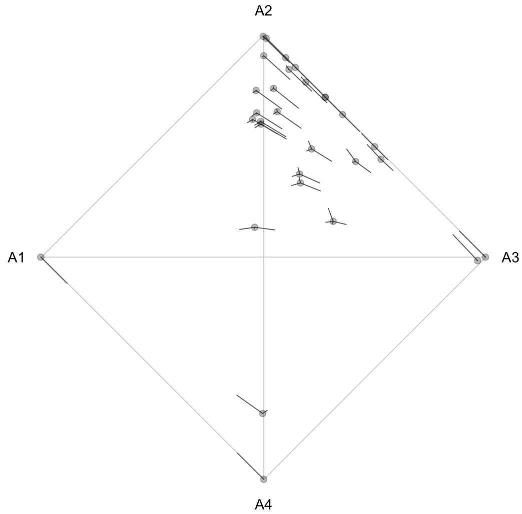

Figure 2 Distribution of participants on the archetypal spectrum.

Figure 3 Bar chart displaying the results of the archetypal analysis. Tapping data distribution is plotted for the four archetypes for the selected categories of Maps and Navigation (left) and Travel and Local (right).

app category. Hence, we see a distinction between A2 (home behaviour) and A3 (travel behaviour). Archetypes A1 and A4 show distinct behaviour and could be considered outliers, with one and two participants affiliated with these archetypes, respectively. The tapping signature of A1 and A4 is defined by using both app categories at distances mostly between 300 km and 600 km for A1 and between 100 km and 200 km for A4.

Comparing the cluster analyses results with those of the archetypal analysis, we found two main interaction behaviours: home behaviour and travel behaviour. However, archetypal analysis also allowed us to identify a spectrum of participants' interactions and their direction towards the different archetypes, which is an advantage over cluster techniques such as HCA. In terms of limitations, we aggregated map-related apps to the category level of each app that the Google Play Store provided. Although we initially aimed to analyse each app's individual tapping data, the recorded apps exhibited high usage variability and frequency among participants. This resulted in scattered contributions from each app, which we considered insufficient for an individual analysis. Future studies should include more participants and collect consistent data points for individual apps to overcome this limitation.

4 Conclusion

This study aimed to expand our understanding of everyday map app usage by extracting as much information as possible from a minimal set of data. Our results provide distinct tapping signatures that point to how participants' app usage behaviour may differ at different distances from home. This is a valuable starting point for evaluating tappigraphy as a method for collecting behavioural data on mobile map use in a non-intrusive and continuous manner. In future studies, we plan to extend our research by using tappigraphy in combination with additional sensors of smartphones (e.g. accelerometer, gyroscope, ambient light sensor, etc.) to consider interactions with map apps in relation to environmental factors.

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