Describing Explored Places through OpenStreetMap Data

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Abstract

Mobile navigation applications are good at providing efficient navigation instructions. However, they currently lack the capability to facilitate free exploration. Therefore, users are limited to encountering only places close to the shortest paths, neglecting places that could diversify navigation and foster spatial learning. To better understand what characteristics places have that users like to explore we collected a dataset with a mobile application that encourages free exploration using gamification (n = 39, t = 455 days, 106.50 km^2). Using OpenStreetMap data, we found highly frequented freely explored places comprising office, educational, retail, touristic and commercial places. When comparing the characteristics of the freely explored places to those along the shortest path, those categories were different. Based on our findings, we propose that implementing more diverse routing algorithms can enhance navigation diversity, improve spatial learning, and optimise the utilisation of urban spaces for travel.

CCS Concepts

• **Human-centered computing** → *Human computer interaction (HCI)*; *Field studies*; *Empirical studies in HCI*; *Empirical studies in ubiquitous and mobile computing*.

Keywords

describing places, exploration, field-study, navigation, alternative routing, wayfinding

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1 Introduction

Mobile navigation applications typically guide users along the fastest and most efficient routes from a point A to a point B. As a result, for any given set of potential routes between two locations, the most efficient route is frequently prioritized. This leads to large urban spaces that are typically unexplored by pedestrians [25]. The resulting navigation experiences for pedestrians can be monotonous and often hinder spatial learning due to the limited variety of route choices [19]. While basic route knowledge may be acquired, developing comprehensive survey knowledge is frequently not actively supported by current mobile navigation applications [9, 18, 23, 42, 44, 51, 56].

To develop diverse routing approaches that positively affect users' spatial knowledge, in this paper, we aim to understand the characteristics of places users like to explore. With the help of the MapUncover application, we built a unique dataset consisting of 39 participants who collectively explored 106.50 km^2, spanning 455 days. This application developed by Schade et al. encourages spatial exploration through gamification [50]. It necessitates active exploration to reveal the map in the user interface, thereby emphasising the acquisition of spatial knowledge. We utilise a map-tile-based approach, which allows us to identify and characterise these freely explored places. We use OpenStreetMap (OSM) labels from the Nominatim geocoding API to identify spatial attributes (e.g. *office*, *school*, *retail*, *commercial*) and calculate their distribution-density within the map tiles. This approach allows us to analyse the user-explored environments and their immediate surroundings to describe the places that influenced their exploration choices. We find that the places people freely explore are different from those that are along the most efficient routes provided by mobile navigation applications.

Our results show that participants highly frequented explored places include office, educational, retail, touristic and commercial places. Interestingly, those place categories are currently not considered by applications that aim to provide alternative routing approaches. Those typically opt to provide routes along parks and green spaces [45]. Even so, parks and green spaces were also in our dataset; they were not as frequently visited as retail and commercial places. The analysis allowed us to discern categories of places that have seen increases or decreases in visit frequency among participants, offering valuable insights to researchers, businesses and urban planners regarding the intrinsic factors affecting route preference and encouraging exploration. Finally, we compare the characteristics of explored places with those overlapping with efficient routes provided by shortest-path navigation. While large parts of a city overlap with the already utilized shortest-path routes, some parts have been heavily explored but are less commonly favoured

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by shortest-path routing approaches. This indicates the potential for developing more diverse routing approaches.

To summarize, our paper makes the following contributions:

(1) We describe explored places by analysing data of 39 participants over 455 days and contrast them to the places currently visited by following efficient navigation instructions.
(2) We present a methodology to collect and analyse map tile data with OSM attributes.

While current mobile map applications prioritise efficiency through the fastest path routing, they often ignore parts of the environment and, thus, the potential for spatial knowledge acquisition through diverse and alternative routing. Our research introduces a new approach to analysing and understanding spatial exploration data by generating explored place descriptions through OSM.

2 Background

This section introduces the concept of spatial exploration and how it differs from navigation through turn-by-turn instructions. Furthermore, we discuss the impact of alternative routing approaches on the spatial learning of pedestrians and how we can use exploration data to discuss and characterise urban spaces in the area of GeoHCI [17].

2.1 The Role of Exploration in Pedestrian Navigation

Pedestrian navigation is a fundamental skill for humans to orient themselves and find their way in both familiar and unfamiliar environments [12]. To navigate, humans integrate information about their surroundings, spontaneously learn the spatial configuration during wayfinding, and build cognitive maps to orient themselves in their environments [51]. This behaviour is relevant for exploration in urban spaces. However, pedestrian-focused mobile navigation technologies largely follow the same principles that govern car-centric mobile navigation, primarily emphasizing efficiency [35]. These modern technologies can discourage exploration by prioritizing efficiency using turn-by-turn instructions, which are innately incompatible with the naturally employed ways of engaging with and communicating spatial information [51]. Additionally, turn-by-turn navigation solely communicates directions at turning points, thereby supporting users in acquiring route knowledge, but limiting users' ability to gain orientation in unfamiliar environments themselves [51]. The increased mental processing of the environment and route planning would foster the development of survey knowledge [9, 23]. While earlier work from Laurier et al. from 2016 suggests that pedestrians use navigation applications as loose guides [30], a more recent study from 2021 conducted in the cities of Bologna, Italy, and Porto, Portugal, highlights that application reliance depends on user preference and environmental familiarity [14]. Long-term reliance on in-car navigation systems impairs expert navigators' spatial learning ability by limiting their ability to encode geographic information into memory, leading to increased cognitive load and poorer spatial knowledge [58]. A similar study by Kapaj et al. examined how landmark visualisation styles (abstract 2D vs. realistic 3D) affect wayfinding experts' spatial learning during mobile map-assisted navigation in an emergency scenario, finding that experts' spatial learning improved with increased visual attention to the environment but was not influenced by landmark visualisation style, suggesting that general population findings may not apply to expert navigators [26].

With the ubiquitous presence of mobile navigation applications that foster this behaviour, exploration has become an unessential activity in the places where people live and thus has a detrimental effect on people's spatial abilities. Given these existing limitations in promoting exploration and spatial learning, our study aims to provide insights into how diverse routing algorithms can enhance opportunities for more varied urban exploration.

2.2 Spatial Learning through Alternative Routes

Mobile map applications such as Google Maps[1], Waze[2], and Apple Maps[3] primarily utilise turn-by-turn (TBT) navigation. TBT navigation provides the user with navigation instructions at each decision point. The underlying algorithms optimise the route according to parameters like the shortest distance or travel time. While in most cases, this sufficiently matches the user's needs, such routing criteria are not universally ideal for all users and their contexts, particularly for pedestrians who may prioritize choosing a route with minimal risk of getting lost, want to engage with landmarks, or prefer qualitative attributes like scenic or safe routes [6, 43, 54]. The lack of variation in those routes designed for efficiency can also hinder the acquisition of spatial knowledge [36, 56]. Spatial knowledge is acquired on three levels: landmark knowledge, route knowledge, and survey knowledge. Landmark knowledge involves distinguishing one place from another. In contrast, route knowledge is obtained by repetitive routines of set paths around locations, which can then be extended to identifying shortcuts based on acquired knowledge, referred to as survey knowledge [36, 56]. Alternative routing algorithms that use other criteria to generate routes aim to offer alternative solutions. While still offering TBT directions, they also facilitate the acquisition of spatial knowledge by offering alternative routes based on a wide set of criteria ranging from scenic to e.g. safest [54]. More diverse routes thereby broaden the scope of environments users traverse and contribute to the acquisition of survey knowledge and a more comprehensive mental map [22].

One prominent example is scenic routing algorithms that guide users along aesthetically pleasing routes [1, 45, 53]. Either users are involved in the decision process through surveys [1], software is used to determine which paths *look better*, by using Google Street View [45], or crowdsourced images and OpenStreetMap data are combined to assess the scenic quality based on these results [53]. Others use deep learning models to quantify the aesthetics based on the greenery or even walkability [24, 45]. Keler et al., for example, present an approach where they focus on safety by using crime statistics and OSM data [28], while Bao et al. focus on the composition of attributes on the routes (e.g. lighting, width, turns) to calculate safe routes [3]. Others prioritise familiarity with specific routes to ensure more comfortable navigation and with a reduced workload on processing new environments [39]. What most of these approaches to alternative routing have in common is that the data

[1]google.com/maps
[2]waze.com
[3]apple.com/maps

they use to optimise for their criteria is often not coming directly from users' navigation experience, but is often subjectively defined by the people developing the routing algorithm [20, 38, 39, 49, 54], and also not designed to be adapted in real-time [54]. Therefore, this paper builds up on a dataset based on users freely exploring spaces and places. We present an analysis methodology to extract meaningful and objective data attributes from this dataset to describe and analyse places that affect users' route preferences and exploration behaviour.

2.3 Characterising OSM Data

Lynch analysed the mental map of place descriptions through qualitative interviews, highlighting the categories of landmarks, paths, edges, districts, and nodes as most important [33]. In today's data-abundant world, while this model by Lynch is still very relevant, research studies using data from open geographic databases often rely on OSM data [8, 15, 38]. However, the quality of this geographic data can differ depending on the geographic location that is being studied. In 2017, Barrington-Leigh et al. determined the world's street network was fully mapped with over 80 %, with an estimation of 95 % in most countries in Europe and North America [4]. When it comes to using OSM data, past studies have successfully used OSM data to describe participants' activity (e.g. shopping) based on the combination of GPS trajectories and OSM data connected to those trajectories [8, 15]. In both cases, the tags were semantically related to activities the participants were doing without directly interfering with them during the study. Crowdsourced data provided through OSM serves as a rich ground, which is well-maintained and continuously improved. Furthermore, it is used in studies to understand relationships between users' locations, and their activities [8, 15]. With this paper, we add to the use of OSM data by capturing users' intrinsic exploration preferences and using it to describe explored places.

3 Methodology

This methodology section outlines the map-tile-based place analysis used to characterise and describe the places of our dataset, freely explored by users using a mobile application using gamification features. These insights can help inform the development of navigation algorithms to provide diversified routes to support spatial learning. We detail how the map tile system was utilised to collect historic location data, and how these tiles can be used for place-characterisation using OpenStreetMap labels.

3.1 Tile-Based Place Analysis

Within MapUncover, the mobile application used to collect the data for this study, a simplified map of users' environments is presented, showing rudimentary features like terrain and water bodies in a stylised map view. As users explore their surroundings, they reveal additional details of the map, tile by tile. As studied by Schade et al., the application integrated gamification components to affect active exploration and environmental learning, e.g. quests and social challenges [50]. Central in this dataset are the traces through the tiles of every participant as they explore their environment, including the number of visits per tile. In our analysis, we combined the tile-based location history with data labels from OSM. This information was collected through the Nominatim geocoding API [37]. An upper limit of 100 recorded visits per tile prevented the introspection of private data, such as home addresses, thereby addressing privacy concerns that might limit participation in our study [27]. Additional demographic data were provided to describe the participant sample.

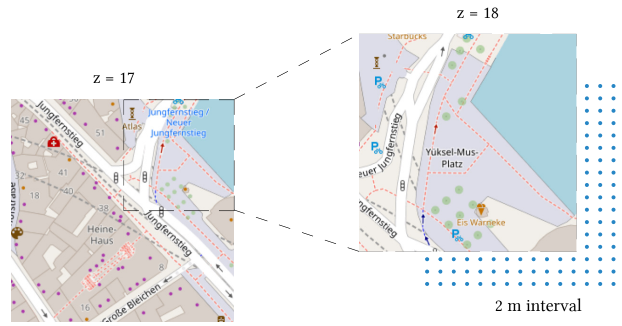


Figure 1: Category and type distribution acquisition and calculation of a tile at zoom level 18. The OSM labels are analysed for 2025 positions in the example tile (x : 138347, y : 84718, z : 18) with an accuracy interval of 2 meters. The OSM categories and types are listed in Table 1. © map data by OpenStreetMap contributors [10].

Our tile-based place analysis (illustrated by Figure 1) uses the map tiling system to segment the world map into specific sections known as tiles. Each tile references a static image and is identified by its *x, y*, and *z* coordinates, with the *z* coordinate indicating zoom levels. A greater *z* value corresponds to a smaller tile radius [10, 46]. Each of these tiles represents a quadratic area with different side lengths depending on the zoom level and latitude. For each tile, we calculate a series of geo-positions every two meters across the tile, creating a quasi-quantisation of the tile (see Figure 1). Due to shifts in latitudes of the Mercator projection, the number of points within a tile varies. These geo-positions can then be used with OpenStreetMap to retrieve attributes through nodes (individual points: e.g. lamp posts), ways (connected lines or shapes: e.g. rivers, building outlines, roads) and relations (complex interactions between elements such as forests), describing the very position on the map. To access this information, each position can be further decoded to extract address details and the related *osm_id*. With this ID, more complex details can be queried. The primary emphasis is on the open-source OSM data offered by the Nominatim geocoding server, which includes attributes such as category and *type* [37]. For instance, we can identify a *park* as the type within the *leisure* category for one specific geo-position. As each tile encompasses hundreds of geo-positions, we can compute the distribution of each category and type within each tile, as illustrated in Figure 1. In this example, the distribution is calculated among 2025 points within the example tile in Hamburg, Germany, with the coordinates x : 138347, y : 84718, z : 18 showing geo-positions being foremost labelled as tourism and amenity (see Table 1).

The two-meter interval provides granularity in identifying types of objects, but may lack precision for discerning smaller entities like

Table 1: Distribution of OSM categories and types within the tile (x : 138347, y : 84718, z : 18) of the example calculation. Colours for the different OSM categories, when included in a type table, are consistent across Table 1, Table 2, Table 3, Table 4 and Table 5.

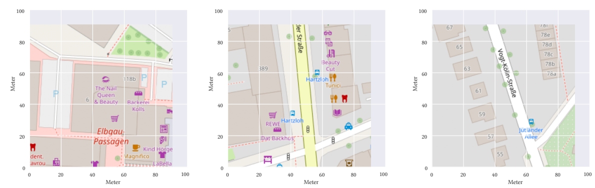
Category	%	**Type**:Category	%	**Type**:Category	%
tourism	44.79	**information**:tourism	40.49	**post_box**:amenity	3.90
amenity	33.23	**residential**:highway	10.37	**house**:place	3.85
highway	11.31	**bicycle_rental**:amenity	9.83	**commercial**:building	1.73
building	6.12	**bar**:amenity	6.91	**service**:highway	0.94
place	3.85	**ice_cream**:amenity	6.62	**clothes**:shop	0.54
shop	0.54	**restaurant**:amenity	5.78	**cafe**:amenity	0.20
historic	0.10	**office**:building	4.40	**heritage**:historic	0.10
man_made	0.05	**artwork**:tourism	4.30	**surveillance**:man_made	0.05

trees. Using geo-positions instead of area queries reveals both the distribution and size of features within tiles, enabling assessment of their relative density and comparison across tiles of different sizes. By understanding the count of how many participants visited one specific tile and the frequency, meaning how often it was visited across all participants of these areas, we can deduce their significance further. For the successful implementation of this approach, adherence to a single tiling schema, such as the x/y/z coordinate system, is crucial. The granularity can be increased by adjusting the captured tile-zoom to a higher level. When coupled with the logging of time stamps and visit frequency for each tile, we can extract a more nuanced understanding of participant behaviour without disclosing the participant's exact residential location.

3.2 Dataset

We extended the dataset provided by Schade et al. [50]. Schade et al. evaluated during a span of 83 days how gamification affects exploration, while we worked with an extended version of 455 days from the 1st of January 2022 until the 31st of March 2023.

The dataset was filtered to exclude participants who did not actively contribute to the dataset. Active contribution was defined as having more tiles unlocked than the number of times the application was opened throughout the study. This meant that participants would at least have to unlock at least 2 tiles per session, on average. Furthermore, participants had to have a minimum of at least 10 unlocked tiles in total. During the use of the app, participants were only required to complete introductory and final surveys, with no need for additional active tasks. Instead, they were encouraged to explore their environment using gamification elements. Over a period of 455 days, we gathered data from 39 participants (12 female, 25 male, and 2 did not disclose their gender). The average age was 26.46 with a range from 18 to 63 ($median$ = 24, sd = 8.11), which additionally fulfilled the previous constraint. Participants did not use the application over the entire time frame. They actively unlocked new areas at least once per week for an average of 5.13 weeks, ranging from 1 to 38 weeks ($median$ = 4.0, sd = 6.26). Participants unlocked on average of 1421 tiles, with a range between 20 and 15019 ($median$ = 406, sd = 2761.5). The users were spread over Europe, thus implicating different tile sizes. On average, the tiles had a side length of 90.33m (see Figure 2), with a minimum of 60.25m to 136.34m ($median$ = 90.72m, sd = 7.10m). Figure 2 depicts three examples illustrating the average tile size: (a) represents a shopping mall-like retail area, (b) represents a residential area with commercial buildings and a secondary street, and (c) represents a residential area near a tertiary street and detached houses. The combined uncovered surface spans 12971 individual tiles, totalling exactly 106.50 km^2.



(a) (b) (c)

Figure 2: Visualisation of the average tile size of 90.33 meters among the explored area with three examples (n = 12971 tiles). (a) A retail area. (b) A residential area adjacent to commercial buildings and a secondary street. (c) A residential area near a tertiary street and detached houses. © map data by OpenStreetMap contributors [10].

Subsequently, we refer to values derived from our total count of 12971 tiles encompassing the entire dataset. Notably, Germany emerges as the predominant location for the majority of users. Specifically, 33 users unlocked a total of 11317 tiles in Germany. Subsequently, Finland (598 tiles) had contributions from 2 users. France (520 tiles), the Netherlands (255 tiles), Slovakia (112 tiles), and Switzerland (57 tiles) each saw contributions from one user. The UK, with 78 tiles, was represented by 2 users. Within the top 10 cities to municipalities with over 250 unlocked tiles, 8 are German cities, highlighting that most exploration occurred in Germany. Among these, the German cities of Hamburg, having 2916 tiles across 11 users, and Bremen, with 2330 tiles and 18 users, stand out with the most unlocked tiles. This is followed by two distinct users: one unlocked 563 tiles in the municipality of Salla in northern Finland and the other in Paris, France with 520 tiles. It is important to highlight that participants in the original study by Schade et al. were not bound to one municipality [50]. Accordingly, participants visited on average of 7.54 municipalities, with a range between 1 and 90 ($median$ = 1.0, sd = 17.01). As evident from the observations, the entire dataset consisting of 12971 tiles is located in Central Europe, with a predominant 87.48 % originating from Germany. Furthermore, 40.44 % of the data is attributed to Bremen (22.48 %, n = 18) and Hamburg (17.96 %, n = 11). This concentration indicates that our dataset is particularly robust when analysing properties in these regions. The dataset's validity is further supported by the fact that Germany is among the best-maintained countries for OpenStreetMap [4, 57, 60].

4 Results

In this section, we evaluate the methodology we introduced and utilise it to analyse the places participants have explored within the dataset.

4.1 Classification into OSM Categories and Types

Using the methodology outlined in Section 3.1, we analysed the set of tiles. We successfully generated distributions of OSM categories and types, which we can subsequently use to describe the explored places. This analysis led to the determination of the overall distribution across all tiles and participants. We identified 22 categories and 649 types participants explored. For the categories and types, we refer to the descriptions provided by the OpenStreetMap wiki [10]. Contributors commonly use these descriptions when labelling spatial information. We use these descriptions in this paper, either word for word or by adapting the wording slightly to improve their comprehension. Table 2 displays 99.71 % of all categories in the distribution, using a cut-off of >0.1 %. Using the same cut-off, the distribution of types encompasses 93.34 %, as seen in Table 3. In terms of categories identified within those tiles, the most prevalent categories were *highways*, which made up 48.4 %, followed by buildings at 24.97 %, *amenities* and *places* at 6.86 % and 6.83 % respectively. Further, categories such as *tourism* (2.54 %), *leisure* (2.4 %), *shops* (1.96 %), *boundaries* (1.66 %), and *man_made* structures (1.51 %) fell within the one to five percent range.

Table 2: Distribution of categories within collected tiles, which occurred at least 0.1 % of the time, making up 99.71 %. The descriptions are based on or quoted content provided by OpenStreetMap [10]. We refer to the supplementary materials for the complete table. Colours for the different OSM categories, when included in a type table, are consistent across Table 1, Table 2, Table 3, Table 4 and Table 5.

Category	%	Place Description
highway	48.40	any kind of road, street or path
building	24.97	artificial (location-bound) structures with a roof
amenity	6.86	useful and important facilities
place	6.83	centre or outline of a named human settlements
tourism	2.54	tourism focus
leisure	2.40	recreational focus
shop	1.96	shops
boundary	1.66	boundaries for areas (e.g. forest, city, country)
man_made	1.51	(artificial) structures (e.g. bridges or lighthouses)
railway	0.97	transport infrastructure using rails
historic	0.79	historic interest
office	0.49	(mostly) service provider (frequently selling)
emergency	0.21	emergency related infrastructure

Each category consists of multiple related types, offering deeper insight into its characteristics, as illustrated in Table 3. The table shows 83 distinct types with at least 0.1 % occurrence in the overall distribution, making up 93.34 % of the total dataset. We merged the *house* type in the *place* and *building* categories, as both are related to residential housing [10, 37]. Types that frequently occurred, appearing at least 1 % of the time, include: *Motorway* (23.36 %), *house* (10.6 %), undefined building (7.32 %, see Table 3), *apartments* (6.76 %), *primary* (4.59 %), *unclassified* (3.55 %), *residential* (2.66 %) and *secondary* (3.22 %) streets; *administrative* boundaries (1.36 %), *detached* housing (1.32 %), *bus_stop* (1.3 %), *track* agricultural or forest paths (1.29 %), *office* buildings (1.29 %), *trunk* (1.25 %), highway *milestone* (1.2 %), *tertiary* street (1.13 %) and *school* (1.06 %). Please refer to Table 3 for all individual types. Analysing the category distribution, it is evident that 49.03 % of the total dataset inherits types that are related to pathways (*motorway, primary, unclassified, track, trunk, tertiary* etc.), while 19.85 % of the overall dataset are associated with living spaces (*house, apartments, detached, residential*). This observation confirms that the most frequented places are typically within urban settings, as the demographic and geographic analysis of the dataset already suggested.

Table 3: Distribution of types within collected tiles, which occurred at least 0.1 % of the time, making up 93.34 %. We have combined type *house* of category *building* and *place* as they relate to the same type over different naming conventions. We refer to the supplementary materials for the complete table. Colours for the different OSM categories, when included in a type table, are consistent across Table 1, Table 2, Table 3, Table 4 and Table 5.

Type:Category	%	**Type**:Category	%	**Type**:Category	%
motorway:highway	23.36	**university**:amenity	0.53	**tower**:man_made	0.17
house:building :place	10.6	**rest_area**:highway	0.52	**fast_food**:amenity	0.16
yes:building	7.32	**motorway_junction**:highway	0.49	**platform**:highway	0.16
apartments:building	6.76	**footway**:highway	0.47	**car**:shop	0.15
primary:highway	4.59	**platform**:railway	0.40	**phone**:emergency	0.15
unclassified:highway	3.55	**services**:highway	0.39	**tram_stop**:railway	0.15
secondary:highway	3.22	**memorial**:historic	0.39	**post_box**:amenity	0.15
residential:highway	2.66	**pedestrian**:highway	0.38	**university**:building	0.14
administrative:boundary	1.36	**artwork**:tourism	0.34	**terrace**:building	0.14
detached:building	1.32	**hotel**:tourism	0.33	**stop**:railway	0.14
bus_stop:highway	1.30	**kindergarten**:amenity	0.32	**nature_reserve**:leisure	0.14
track:highway	1.29	**restaurant**:amenity	0.31	**vending_machine**:amenity	0.13
office:building	1.29	**cafe**:amenity	0.30	**zoo**:tourism	0.13
trunk:highway	1.25	**social_facility**:amenity	0.29	**government**:office	0.13
milestone:highway	1.20	**supermarket**:shop	0.28	**company**:office	0.13
tertiary:highway	1.13	**place_of_worship**:amenity	0.28	**doityourself**:shop	0.13
school:amenity	1.06	**playground**:leisure	0.27	**warehouse**:building	0.12
service:highway	0.97	**cycleway**:highway	0.26	**pitch**:leisure	0.12
information:tourism	0.82	**mall**:shop	0.25	**trunk_link**:highway	0.12
bridge:man_made	0.81	**park**:leisure	0.24	**museum**:tourism	0.11
parking:amenity	0.79	**protected_area**:boundary	0.23	**community_centre**:amenity	0.11
path:highway	0.78	**works**:man_made	0.22	**stadium**:leisure	0.11
retail:building	0.77	**hut**:building	0.20	**garden**:leisure	0.11
sports_centre:leisure	0.74	**semidetached_house**:building	0.19	**dormitory**:building	0.10
industrial:building	0.60	**heritage**:historic	0.19	**exhibition_centre**:amenity	0.10
commercial:building	0.59	**fuel**:amenity	0.19	**car_repair**:shop	0.10
residential:building	0.57	**marina**:leisure	0.18	**fire_station**:amenity	0.10
camp_site:tourism	0.53	**service**:building	0.17		

4.2 Place Frequency Analysis

After examining the overall distribution of places explored by our participants, the most prevalent types are associated with *pathways*. Specifically, *highways*, *railways* and *junction* constitute 49.03 % of types. Living spaces, such as houses and apartments, as in the *accommodations* subsection of the *buildings'* category [10] represent 19.85 %. Undefined buildings are mentioned 7.32 % of the time under the *yes:building*, as shown in Table 3. In addition, geolocations labelled as *None*, which represent 0.025 % of the overall distribution, did not provide any discernible information for further analysis as well. Considering our emphasis lies on the impact of environmental properties on participants' exploration behaviour, especially in urban settings, we chose to omit pathways such as *highway, railway*, and *junction* for subsequent in-depth analysis. Additionally, considering most participants likely reside in residential zones, we omit the accommodations' subcategory of *buildings*. Furthermore, we excluded the unidentified types represented as *yes:building*, which can implicitly mean any building [10] and *None*, where further tag information was missing altogether. Our interest isn't in participants' origins but in their chosen walking environments. By filtering out the aforementioned types, we are left with a subset constituting 23.36 % of the original data. For clarity and better readability, we normalised the resulting subset, so that the total distribution of the subset sums up to 100 % again. The new distribution of categories in Table 4 reveals that amenities are most prevalent with 29.36 %. This is followed by *building* at 19.48 %, *tourism* (10.87 %), *leisure* (10.26 %), *shop* (8.41 %), *boundary* (7.11 %), *man_made* (6.48 %), *historic* (3.38 %), *office* (2.11 %), *emergency* (0.92 %), *craft* (0.52 %), *place* (0.29 %), *club* (0.24 %), *natural* (0.20 %), *military* (0.15 %), *healthcare* (0.13 %).

Table 4: Distribution of categories within collected tiles, which occurred at least 0.1 % of the time. The categories exclude pathways, living spaces, undefined buildings and geolocations. The descriptions are based on or quoted content provided by OpenStreetMap [10]. We refer to the supplementary materials for the complete table. Colours for the different OSM categories, when included in a type table, are consistent across Table 1, Table 2, Table 3, Table 4 and Table 5.

Category	%	Place Description
amenity	29.36	useful and important facilities
building	19.48	artificial (location-bound) structures with a roof
tourism	10.87	tourism focus
leisure	10.26	recreational focus
shop	8.41	shops
boundary	7.11	boundaries for areas (e.g. forest, city, country)
man_made	6.48	(artificial) structures (e.g. bridges or lighthouses)
historic	3.38	historic interest
office	2.11	(mostly) service provider (frequently selling)
emergency	0.92	emergency related infrastructure
craft	0.52	production-focused places
place	0.29	centre or outline of a named human settlements
club	0.24	social or recreational group-focus
natural	0.20	naturally occurring (e.g. lakes, mountains, or forests)
military	0.15	areas or structures designated with military purpose
healthcare	0.13	medical services and facilities

In Table 5, we present the updated distribution of types, focusing on those with at least a 0.1 % distribution after normalisation. To give the reader an idea about the dimension of the dataset after filtering out less relevant types and normalising the remaining data, the least prevalent type displayed in the table is *books* (category = *shop*). This type constitutes 0.1 % of the normalised distribution, corresponding to 119 tiles and represents 0.02 % in the original distribution. Types that frequently occurred, appearing at least 2 % of the time, include: *administrative* (5.83 %), *office* (5.54 %), *school* (4.55 %), tourist *information* (3.52 %), *bridge* (3.47 %), *parking* (3.39 %), *retail* (3.29 %), *sports_centre* (3.18 %), *industrial* (2.56 %), *commercial* (2.51 %), *camp_site* (2.26 %) and *university* (2.25 %).

4.3 Place Description Classification

The updated distribution of types previously discussed offers insights into the prevalent characteristics of places that participants commonly travelled through. With the visit frequencies for each type, meaning how often users visited a tile featuring the respective type, we can use these values to weight the distribution accordingly. This weighted distribution allows us to identify types that saw an increase in relevance within the distribution and types that saw a decrease. Types that saw an increase, thus, were found on tiles which were more frequently visited by users compared to types

Table 5: Distribution of types within collected tiles making up 23.36 %, excluding pathways, living spaces, undefined buildings and geolocations. In this case, the table shows 91.67 % of the newly filtered dataset. For example, the type books (category = *shop*) appeared in 0.1 % of cases after normalising the new distribution. In contrast, it appears in 119 tiles and has a distribution of 0.02 % in the original distribution. We refer to the supplementary materials for the complete table. Colours for the different OSM categories, when included in a type table, are consistent across Table 1, Table 2, Table 3, Table 4 and Table 5.

Type:Category	%	**Type**:Category	%	**Type**:Category	%
administrative:boundary	5.83	**stadium**:leisure	0.49	**furniture**:shop	0.21
office:building	5.54	**garden**:leisure	0.47	**peak**:natural	0.19
school:amenity	4.55	**community_centre**:amenity	0.46	**civic**:building	0.19
information:tourism	3.52	**museum**:tourism	0.45	**hamlet**:place	0.18
bridge:man_made	3.47	**car_repair**:shop	0.45	**police**:amenity	0.18
parking:amenity	3.39	**exhibition_centre**:amenity	0.42	**building**:historic	0.18
retail:building	3.29	**fire_station**:amenity	0.41	**wastewater_plant**:man_made	0.17
sports_centre:leisure	3.18	**bicycle_rental**:amenity	0.40	**caravan_site**:tourism	0.17
industrial:building	2.56	**golf_course**:leisure	0.39	**kindergarten**:building	0.17
commercial:building	2.51	**attraction**:tourism	0.38	**castle**:historic	0.17
camp_site:tourism	2.26	**college**:amenity	0.38	**pharmacy**:amenity	0.16
university:amenity	2.25	**clothes**:shop	0.36	**water_park**:leisure	0.16
memorial:historic	1.65	**train_station**:building	0.36	**kiosk**:shop	0.15
artwork:tourism	1.44	**school**:building	0.35	**courthouse**:amenity	0.15
hotel:tourism	1.43	**shelter**:amenity	0.34	**stables**:amenity	0.15
kindergarten:amenity	1.37	**allotment_house**:building	0.34	**bar**:amenity	0.15
restaurant:amenity	1.34	**swimming_area**:leisure	0.32	**taxi**:amenity	0.14
cafe:amenity	1.31	**recycling**:amenity	0.32	**construction**:building	0.14
social_facility:amenity	1.25	**charging_station**:amenity	0.32	**diplomatic**:office	0.14
place_of_worship:amenity	1.21	**postal_code**:boundary	0.30	**convenience**:shop	0.14
supermarket:shop	1.20	**bank**:amenity	0.30	**bus_station**:amenity	0.13
playground:leisure	1.17	**bakery**:shop	0.30	**sports_centre**:building	0.13
mall:shop	1.08	**public**:building	0.29	**library**:amenity	0.13
park:leisure	1.04	**insurance**:office	0.28	**bicycle**:shop	0.12
protected_area:boundary	0.98	**theatre**:amenity	0.28	**florist**:shop	0.12
works:man_made	0.92	**warehouse**:shop	0.27	**fitness_centre**:leisure	0.12
hut:building	0.85	**pub**:amenity	0.26	**research**:office	0.12
heritage:historic	0.82	**apartment**:tourism	0.26	**waste_basket**:amenity	0.12
fuel:amenity	0.80	**dog_park**:leisure	0.26	**electronics**:shop	0.12
marina:leisure	0.76	**arts_centre**:amenity	0.26	**hostel**:tourism	0.12
service:building	0.75	**street_cabinet**:man_made	0.25	**bbq**:amenity	0.11
tower:man_made	0.72	**hospital**:amenity	0.25	**square**:place	0.11
fast_food:amenity	0.70	**fountain**:amenity	0.25	**water_works**:man_made	0.11
car:shop	0.64	**parcel_locker**:amenity	0.24	**telephone**:amenity	0.11
phone:emergency	0.63	**car_sharing**:amenity	0.24	**events_venue**:amenity	0.11
post_box:amenity	0.62	**biergarten**:amenity	0.24	**farm_auxiliary**:building	0.11
university:building	0.59	**lifeguard**:emergency	0.24	**fishing**:leisure	0.11
nature_reserve:leisure	0.58	**tunnel**:man_made	0.23	**cinema**:amenity	0.10
government:office	0.57	**pier**:man_made	0.23	**nightclub**:amenity	0.10
zoo:tourism	0.57	**marketplace**:amenity	0.22	**garage**:building	0.10
doityourself:shop	0.54	**car_wash**:amenity	0.22	**atm**:amenity	0.10
vending_machine:amenity	0.54	**miniature_golf**:leisure	0.22	**animal_training**:amenity	0.10
company:office	0.54	**doctors**:amenity	0.21	**resort**:leisure	0.10
warehouse:building	0.52	**hairdresser**:shop	0.21	**dentist**:amenity	0.10
pitch:leisure	0.51	**bench**:amenity	0.21	**books**:shop	0.10

that were found on tiles that participants less frequently visited. Figure 3 shows the top 20 types that saw an increase, while Figure 4 shows the 20 types that experienced a decrease due to the frequency weighting. In the subsequent section, the respective sign (+/-) indicates these increases and decreases. It is crucial to recognise that this distribution stems from an initial type of filtering, followed by normalisation and then frequency-based weighting. While this distribution does not represent the entire dataset, it highlights trends among the types we deemed essential to elaborate on properties of walking-friendly environments.

4.3.1 Increase. This section examined the top 20 most substantial types, that also saw an increase in distribution, as shown in Figure 3. Notably, the places surrounding universities had a high number of participant visits, with an increase of 2.27 %, likely because many study participants were university students. This was followed by increments in sectors such as retail containing *shops* (+ 0.87 %), *commercial* buildings not consisting primarily of shops (+0.83 %), *golf_courses* (+0.59 %), *parks* (+0.36 %), *nature_reserves* (+0.28 %), *social_facilities* (+0.27 %) and *places_of_worship* such as churches (+0.20 %). Improvements in type distribution help identify key type groups that shape the most interesting places to walk through.

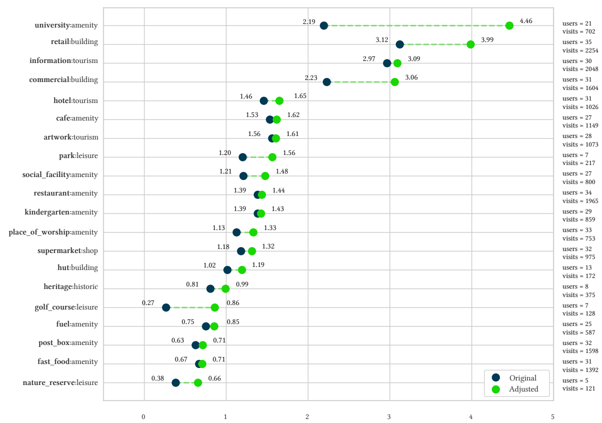


Figure 3: Top 20 filtered types that also noted an increase through frequency weighting (distribution in %). The unweighted distribution is depicted by dark dots, while the green dots illustrate the altered distribution, accounting for the visit frequency distribution increase of these types. Categories are indicated for each type following the colon.

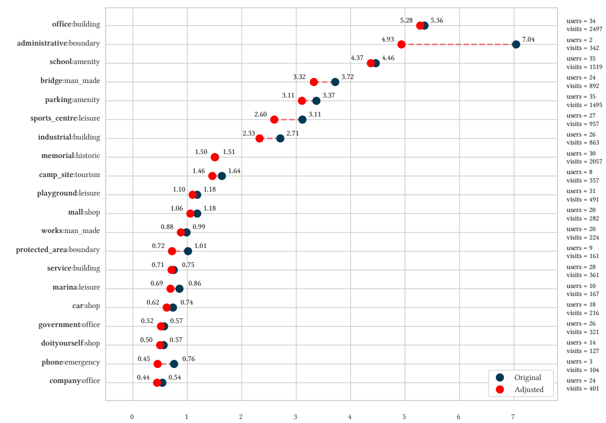


Figure 4: Top 20 filtered types that also noted a decrease through frequency weighting (distribution in %). The dark dots represent the unweighted distribution, while the red dots visualize the altered distribution, incorporating the impact of visit frequency on these types. Categories are indicated for each type following the colon.

4.3.2 Decrease. Conversely, when examining the top 20 type distribution which noticed declines, places close to recognised administrative boundaries showed the most pronounced decrease, with a change of -2.11 %. This decline was succeeded by decreases in *sports_centres* (-0.51 %), *bridges* (-0.40 %), *industrial* zones (-0.38 %) and *phones* (-0.30 %). For environmental or cultural reasons, protected areas also experienced a drop of -0.29 %. The trend continued with *parking* (-0.26 %), *camp_sites* (-0.18 %), and *marinas* (-0.17 %). It is noteworthy that marinas account for a surprisingly low distribution of 0.69 %, especially considering that most participants were exploring places in and around prominent river cities like Bremen (n = 18) and Hamburg (n = 11).

4.4 Explored Places versus Shortest Path Places

The previous sections present the OSM categories and types of explored places by analysing data from 39 participants over 455 days. We now contrast these places with the places currently explored by following efficient navigation instructions. We compare the tiles that were visited in our exploration dataset with those that were visited using a simulated shortest walking path navigation in two specific urban environments from our dataset, namely Bremen (n = 18) and Hamburg (n = 11). Since the data set does not provide timestamps indicating the user's path start or end points, we specifically investigated the density region of both cities, as most of the exploration happened around the cities' centres. The simulation was performed using the shortest path algorithm from the OSMnx Python library, which is based on a standard implementation of Dijkstra's algorithm [7].

4.4.1 Overlap and Difference. Considering the city boundaries of Hamburg, participants visited 3.25 % of tiles, and in Bremen, 6.04 %. By calculating a radius from the city centre based on the city's population (Hamburg: 1884000 vs. Bremen: 560000), we can assess the density area of each city [5, 55]. In the case of Bremen, 31.01 % of tiles cover the density region, whereas in Hamburg, participants explored 10.93 % of the density area. Furthermore, we choose a suitable number of shortest walking paths to compare our data against. We used the elbow methodology to identify the number of the shortest path that sufficiently exhausts the density area without adding too much noise [47]. Using a fixed random seed, we generated random origin-destination pairs which resulted in 170 paths for Bremen with a visited tiles coverage of 85.92 % and 230 paths for Hamburg covering 66.70 % to provide a balanced coverage throughout the majority of relevant types, excluding less widely used paths (see Figure 5 and Figure 6). The graph for both cities was extracted using OSMnx with the `network_type` parameter `walk` [7]. Both cities have significantly differently sized urban environments. Even when considering the density area of Hamburg, with its significantly higher population, the explored tiles are spread around the city area with one denser area. This area has a denser frequency while having little to no shortest path going through it. Compared to Bremen, with evenly spread visited tiles and highest frequencies around shortest path junctions.

4.4.2 Categories and Types. Similar to the characterization of explored tiles, we now analyse the category and type overlap of those with the shortest path. As before, we follow the same exclusion of pathways and accommodating types, in addition to normalizing them based on the visit frequency. With Bremen being the smaller city, the category *tourism* (18.84 % vs. 11.93 %) is more common within the explored tiles overlapping with the shortest paths, followed by *office* (1.75 % vs. 0.16 %), *junction* (1.03 %), *craft* (0.31 % vs. 0.02 %) and *healthcare* (0.11 %). Outside the shortest path are *buildings* (33.57 % vs. 32.42 %), *amenities* (29.97 % vs. 32.83 %), *man_made* (8.50 % vs. 5.69 %), *leisure* (5.03 % vs. 4.58 %), *shop* (2.99 % vs. 2.62 %) and *historic* (4.81 % vs. 2.34 %). In the case of Hamburg, there are some differences in the distribution of categories that overlap and do not overlap with the shortest paths. The category *amenity*

Figure 5: Overlap of explored tiles with their visit frequency in the population-dense region of Bremen and their overlap with the 170 shortest walking paths. The paths are highlighted in red, with thickness increasing proportionally to the frequency of traversal along them. The frequency hereby represents the absolute number of visits within 455 days across all participants. We refer to the supplementary materials for an interactive version of this figure. © map data by OpenStreetMap contributors [10].

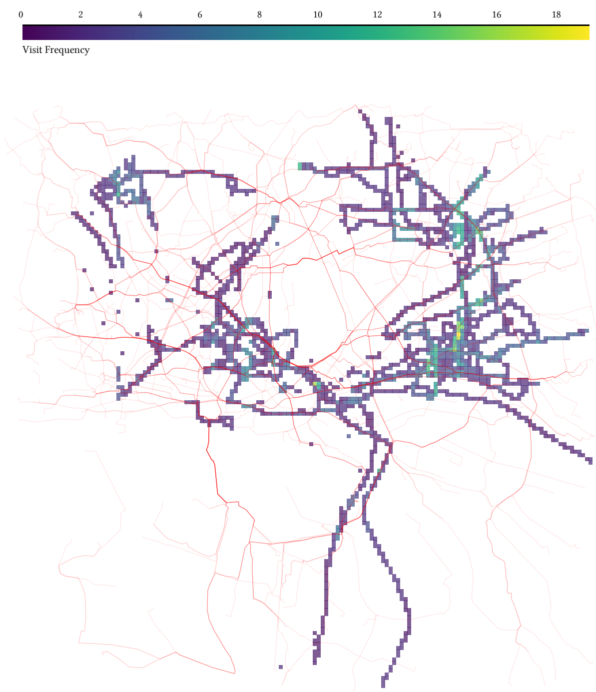


Figure 6: Overlap of explored tiles with their visit frequency in the population-dense region of Hamburg and their overlap with the 230 shortest walking paths. The paths are highlighted in red, with thickness increasing proportionally to the frequency of traversal along them. The frequency hereby represents the absolute number of visits within 455 days across all participants. We refer to the supplementary materials for an interactive version of this figure. © map data by OpenStreetMap contributors [10].

(33.88 % vs. 30.55 %) is slightly more frequent within the shortest path compared to outside, followed by *building* (22.49 % vs. 19.59 %), *shop* (8.79 % vs. 6.02 %) and *historic* (8.27 % vs. 4.90 %). In contrast, outside the shortest path categories such as *leisure* (16.45 % vs. 9.53 %), *tourism* (9.09 % vs. 7.65 %), *man_made* (7.35 % vs. 6.92 %), *office* (4.73 % vs. 1.78 %), *craft* (0.64 % vs. 0.29 %), *club* (0.27 % vs. 0.15 %) and *boundary* (0.36 % vs. 0.02 %) are more prevalent. Moreover, evaluating the types of both cities and comparing those that intercept the shortest path and those that do not, shows more distinctions between both cities (see Figure 7). Both have a higher occurrence of *office* within the shortest path. Additionally, *retail*, *bridge* and *commercial* show a higher saturation within the shortest path in both cities. Types such as *school* and *industrial* show an increase outside the shortest path in both cities. The highest increases outside the shortest paths in Bremen are the *school* (3.87 % to 10.71 %), *industrial* buildings (1.94 % to 8.79 %), *exhibition_centre* (2.47 % to 7.07 %), *pier* (1.27 % to 7.05 %) and *marina* (0.14 % to 2.71 %). In Hamburg, the highest increases outside the shortest path are the *school* (5.43 % to 7.63 %), *university* (1.56 % to 5.51 %) and *stadium* (0.20 % to 3.75 %). Otherwise, *information:tourism* has a low occurrence in Hamburg but shows an increase outside the shortest path (0.43 % to 0.70 %), while they show a decrease in Bremen (11.31 % to 7.14 %).

Similarly, among several other examples, *parking* increased outside the shortest path in Hamburg (1.88 % to 3.40 %) and decreased in Bremen (4.89 % to 2.29 %) or *playground* increased outside in Hamburg (0.67 % to 2.12 %) and decreased in Bremen (1.63 % to 1.23 %). There are two outliers, whereby *works:man_made* (0.39 %) in Bremen can only be found intercepting the shortest path and in Hamburg *arts_centre:amenity* (0.38 %) can only be found outside of it. Finally, both types *university* and *heritage* are only found in Hamburg. For further details, refer to Figure 7.

As a final step, we evaluate the proximity of explored tiles to universally relevant Points of Interest (POIs) for pedestrians in both cities using data retrieved from Google Maps API. POIs and similar landmarks are used as references in pedestrian navigation [13, 43]. Thus, we were interested in whether a majority of tiles would be close to these places. We utilize the search term: "city name + points of interest" and consider 50-meter proximity to visited tiles in the density region of both cities. For touristic points of interest, 60.00 %

Figure 7: Top 20 filtered types of explored tiles for Hamburg and Bremen that do or do not intercept the 170 (Bremen) and 230 (Hamburg) random shortest walking paths through their respective density regions. The results are normalized with the visit frequency and represent their distribution in percentage. OSM categories are indicated for each type following the colon.

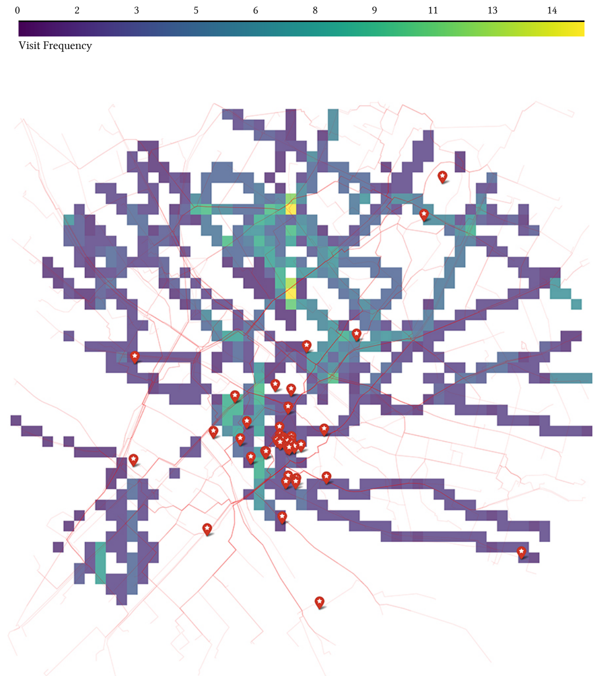


Figure 8: Overlap of explored tiles with their visit frequency in the population-dense region of Bremen, popular POIs (red markings), and their overlap with the 170 shortest walking paths. The paths are highlighted in red, with thickness increasing proportionally to the frequency of traversal along them. The frequency hereby represents the absolute number of visits within 455 days across all participants. We refer to the supplementary materials for an interactive version of this figure. © map data by OpenStreetMap contributors [10].

are near visited tiles in Bremen, compared to 37.14 % in Hamburg. For further details, refer to Figure 8 and Figure 9.

5 Discussion

Our data allows us to describe the places participants explored using OSM categories and types. In this section, we discuss how well our methodology worked to characterise explored places, how the exploration data can be interpreted, and, most importantly, how it can help us understand and improve our interactions with mobile navigation technologies.

The idea of using OSM classification for interpreting spatial information is gaining traction as many works use OSM as a foundation [2, 59]. In our case, when investigating the OSM type distributions above 0.1 % in Table 5, the most explored places included administrative boundaries, office buildings, and educational amenities such as schools. Most frequently visited places were universities, retail buildings, tourist information and commercial buildings (see Figure 3). In contrast, offices, administrative boundaries, and schools showed a decreased distribution due to lower visit frequencies, though they remain highly frequented (see Figure 4). We find explored places characterised by a wide range of OSM types, including administrative, commercial, educational, recreational, cultural, and hospitality-related places commonly found within urban areas (see Table 5). While these places paint a common picture of the typical central European city, the mainly explored area within the study, the places are also different from what is generally discussed in the literature regarding alternative routing algorithms. In the past, researchers aimed to contrast the typical shortest path routing with greener routes [1, 45, 53]. Our data suggests that we can generally improve routing not only by offering alternative paths along parks and water bodies, but also by making them more useful by routing along the relevant places within urban areas as described above. Instead of offering contrasting alternatives to the shortest path routing, we can improve it by focusing on relevant parts of a city.

To make this contrast more apparent, we discuss the difference between places explored in this study with those that people generally encounter when following the shortest paths using turn-by-turn navigation. Certain areas within a city are more relevant to mobile navigation applications because they intersect more of the shortest paths than others, given a random distribution of trips through a city. For this, we zoom in on the two largest cities in our dataset, Bremen and Hamburg. As expected, there is a high overlap of places that the shortest paths cover with the explored places in our study. In Bremen, 85.92 % of visited tiles in the density

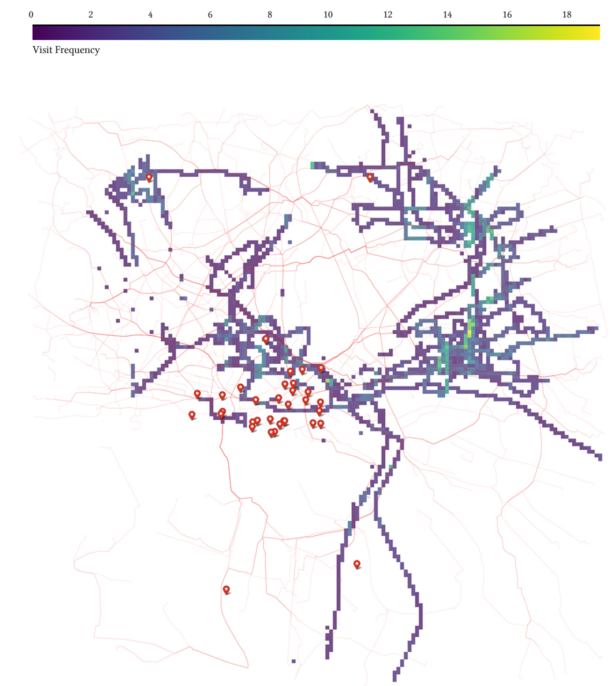


Figure 9: Overlap of explored tiles with their visit frequency in the population-dense region of Hamburg, popular POIs (red markings), and their overlap with the 230 shortest walking paths. The paths are highlighted in red, with thickness increasing proportionally to the frequency of traversal along them. The frequency hereby represents the absolute number of visits within 455 days across all participants. We refer to the supplementary materials for an interactive version of this figure. © map data by OpenStreetMap contributors [10].

region were covered by representative 170 shortest paths, while in Hamburg, 66.70 % with 230 paths. However, certain areas that were frequently explored by participants do not align with these shortest paths. In Bremen, *buildings*, *amenities*, *shops* and *historic* sites appear more frequently on the shortest paths, while in Hamburg, these categories are more common outside of them. Additionally, Hamburg has higher frequencies of *leisure*, *tourism*, *man_made* and *office* categories of the shortest paths, whereas Bremen sees more *tourism* on these paths (see Figure 7). This matches the observation that we see a denser frequency of exploration that falls outside the shortest paths in Hamburg (see Figure 6). Additionally, *schools* are more frequented types outside the shortest path in both cities. We see *exhibition_centres*, *piers*, *art_centres*, and *marinas* that are highly frequented in Bremen, as well as *parking*, touristic *artworks*, *universities*, *zoos*, *stadiums*, *industrial* and factory (*works:man_made*) buildings in Hamburg (see Figure 7). Free exploration often diverges from the most efficient paths, in these cases to visit educational, recreational and cultural areas. However, when we evaluate the overlap of explored places with areas that include touristic POIs, only 60.00 % (Bremen) and 37.14 % (Hamburg) are in a 50-meter perimeter around explored areas. In our case, exploration was not centred around touristic places, but rather around areas that have less frequent traffic, especially in Hamburg (see Figure 6).

The difference in POI intersections between Bremen and Hamburg also reflects their urban layouts and city sizes, with Hamburg's larger area leading to fewer overlaps with our participant pool. This result complements the previous analysis of explored OSM types which showed a high percentage of tourism labels and supports the general notion of developing landmark-based pedestrian navigation [6, 43, 54]. These findings emphasize the role of landmarks in shaping exploratory behaviour and their potential for navigation algorithms that encourage free exploration.

Our data suggests that also along the less often proposed shortest path lie interesting and exploration-worthy places that are, in some parts, neglected by today's mobile navigation systems. This research has several implications for various stakeholders, including the designers and developers of novel navigational technologies, city planners, and businesses. First and foremost, our findings suggest the need for adjustments to routing algorithms to prioritize the qualitative aspects of places, making the routes themselves more interesting and varied. This shift in emphasis can enhance user satisfaction and spatial knowledge acquisition. Integrating user-defined preferences, especially those related to explored places, into routing criteria selection can lead to more holistic and user-centric routing algorithms, particularly beneficial for pedestrian, cyclist, or e-scooter routing in urban environments [38, 40]. Furthermore, our work highlights the potential of leveraging additional OSM tags to offer users more personalised and dynamic navigation experiences. Allowing users to select routes based on specific places of interest can simplify trip planning and enhance user engagement.

6 Limitations

In this study, we analyse the place characteristics of explored places in urban environments based on the usage of a gamified mobile map application. Given the prevalence of mobile map applications such as Google Maps, many nowadays trust and follow the turn-by-turn instructions of these maps [31]. The algorithms are thereby optimized for efficiency through shortest-path routing, a concept that applies to both vehicular and pedestrian navigation [35]. While strict adherence may be lower for pedestrians based on factors like environmental familiarity or preference [14], relying on these instructions can limit the variety of paths taken [19]. Frequent usage can impair the users' spatial cognition, thereby reinforcing their reliance on them [11, 21]. Incentivizing exploration behaviour with a mobile application, as we have portrayed in this study, proved to be an effective way to collect data from pedestrians not necessarily following a shortest path. However, we agree that spatial exploration behaviour assisted by technologies is different from natural wayfinding behaviour not assisted by technologies. While it is possible to record user locations using apps like Organic Maps[4], privacy concerns of continuous location tracking impact prolonged active participation [16, 27, 29]. As such, our data provides a realistic dataset of how people are guided by navigation applications as well as technologies to explore their environment more freely, with a usage period of 1 up to 38 weeks primarily incentivized by the

[4]organicmaps.app/

app's gamification. It can thereby serve as a valuable proxy. Furthermore, there are limitations to our dataset due to the geographical bias of our study [48, 55]. We encourage future work to explore the deployment of similar apps in different city types as well as in rural areas, and use the place categories as an example. We also acknowledge that user behaviour in general, and navigation behaviour in particular, can differ vastly due to geographic location and cultural biases [34, 48]. Similarly, in this context, gender influences walking behaviours, particularly among females for whom personal safety is also an important factor [32, 41].

7 Conclusion

Frequently, mobile navigation technologies prioritise the shortest path, enabling users to reach their destination as quickly as possible. In this study, we examine the types of places people tend to explore, aiming to identify which locations are considered significant when the destination is not the primary focus. These insights can inform the development of pedestrian navigation systems that prioritise areas of interest, making the journey more engaging by routing through points of interest rather than following the most direct route. By shifting the focus from algorithmic efficiency to the qualitative experiences of users, this research provides a foundation for designing navigation technologies that better align with individual preferences and encourage spatial exploration. Our findings suggest that navigation technologies can be designed to enhance users' spatial knowledge acquisition while using these systems. Additionally, our results highlight a user preference for office, educational, retail, touristic and commercial places over green spaces. We also observed a high frequency of routes coinciding with the shortest path, but depending on the city layout, neglecting preferred educational, recreational and cultural areas. These insights are crucial for developing alternative routing algorithms, where the emphasis, in the context of scenic routing, shifts from traditional notions of aesthetic appeal to a focus on actual user preferences.

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