What about thematic information? An analysis of the multidimensional visualization of individual mobility

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Abstract

This paper reviews the literature on the visualization of individual mobility data, with a focus on thematic integration. It emphasizes the importance of visualization in understanding mobility patterns within a population and how it helps mobility experts to address domain-specific questions. We analyze 38 papers published between 2010 and 2024 in GIS and VIS venues that describe visualizations of multidimensional data related to individual movements in urban environments, concentrating on individual mobility rather than traffic data. Our primary aim is to report advances in interactive visualization for individual mobility analysis, particularly regarding the representation of thematic information about people's motivations for mobility. Our findings indicate that the thematic dimension is only partially represented in the literature, despite its critical significance in transportation. This gap often stems from the challenge of identifying data sources that inherently provide this information, necessitating visualization designers and developers to navigate multiple, heterogeneous data sources. We identify the strengths and limitations of existing visualizations and suggest potential research directions for the field.

Keywords: individual mobility, information visualization, spatio-temporal visualization, human mobility, thematic properties

1. Introduction

The study of human mobility has always been of great importance, whether to help understand the dispersion of humankind (e.g., migrations of *Homo sapiens* out of Africa, colonization of the New World) or to support decision-making processes that impact the lives of the individuals in a population (e.g., estimating migratory flows, traffic forecasting, urban planning, and epidemic modeling) [1]. The term "human mobility" refers to the movement of individuals and groups, but only individual movement allows for a detailed analysis of population displacement over time and space. By monitoring these movements, we can uncover personal motivations for mobility, enhancing our understanding of its impact on quality of life and spatial usage. Unlike earlier urbanization models that separated production and residential areas, leading to daily commutes to job-rich locations [2], modern mobility is shaped by a broader range of factors. Today, it is influenced not only by employment opportunities but also by leisure, tourism, and changing lifestyles, which vary significantly depending on individuals' age and geographic origins [3].

Historically, trip-based surveys have been used to assess the relative performance of transformation alternatives [4]. Activity-based surveys have also been a great source of information to unveil the links between trips and activities that explain the individuals' need for travel [5]. Thanks to recent technological advances, the wide adoption of the Global Positioning System (GPS), and the ubiquitous use of tracking technologies in personal devices, large-scale data collection for individual mobility has become easier. In the last decades, we have witnessed an exponential increase in the number, diversity, and size of datasets describing human mobility through multiple and diverse sources, such as household travel surveys (HTS), GPS-assisted surveys, or geo-referenced activity data. This multitude of data sources makes the design of effective visualizations challenging, due to the huge volume and multi-dimensional nature of the data.

Individual mobility data is inherently spatio-temporal (i.e., objects are defined over space and time) but often includes *thematic* properties such as demographics, transportation modes, and trip purposes that describe the individuals and their trips, respectively [6, 7, 8]. In this paper, we investigate how *thematic information* is represented in the (geo-)visualization literature, and how it has been used in decision-making processes within urban policies (such as transportation options, accessibility, air quality control, public health, or well-being).

This work focuses on individual mobility, and it serves as a complement to previous surveys that have mainly focused on the traffic data [9], the use of vehicles and transportation systems [10, 11], or urban mobility more broadly [12, 13]. However, while the literature extensively discusses the visual exploration of mobility data across space and time, it lacks investigation of the thematic dimension that supports in-depth activity-based analyses of individual mobility data. This paper provides a comprehensive analysis of the thematic dimension of individual mobility data by addressing the following research questions:

RQ1 How are the existing data sources leveraged to facilitate individual mobility analysis? We seek to identify the different data sources used to support the visual analysis of individual mobility, as well as the advantages and limitations of each one to support the answering of domain-specific questions.

RQ2 How do visualization systems incorporate the thematic dimension? We seek to identify to what extent and through which interaction and visualization strategies, current solutions integrate space, time, and the thematic dimensions.

RQ3 Are domain-specific tasks sufficiently supported by current information visualization systems? We seek to identify the different domain-specific tasks supported by existing visualization solutions. In particular, we focus on the relationship between thematic properties and the analysis of presence dynamics, travel flows, and individual trajectories (see Section 5).

RQ4 How are visualizations evaluated for usability? We investigate how the surveyed papers evaluate the visualization solutions in terms of methods, experimental design, and the participant's sample and profile.

RQ5 How do GIS and VIS communities approach the visualization of individual mobility data? With research becoming increasingly interdisciplinary, we aim to identify the various contributions of the

VIS (Information Visualization) and GIS (Geographic Information Science) communities towards our topic and explore whether and how their approaches differ or overlap.

The remainder of this document is organized as follows. Section 2 describes how we approach the literature to answer our research questions. Section 3 presents an overview of data sources and their classification according to geographic, thematic, and temporal information. Section 4 presents an analysis of the visualization and interaction with individual mobility data. Domain-specific questions are addressed in section 5. Section 6 presents studies describing the uses and the usability of visualization techniques. Section 7 analyses the distribution of articles between VIS and GIS venues. Section 8 summarizes the survey's outcomes, while identifying directions for future research. Lastly, Section 9 presents limitations and conclusions.

2. Methodology

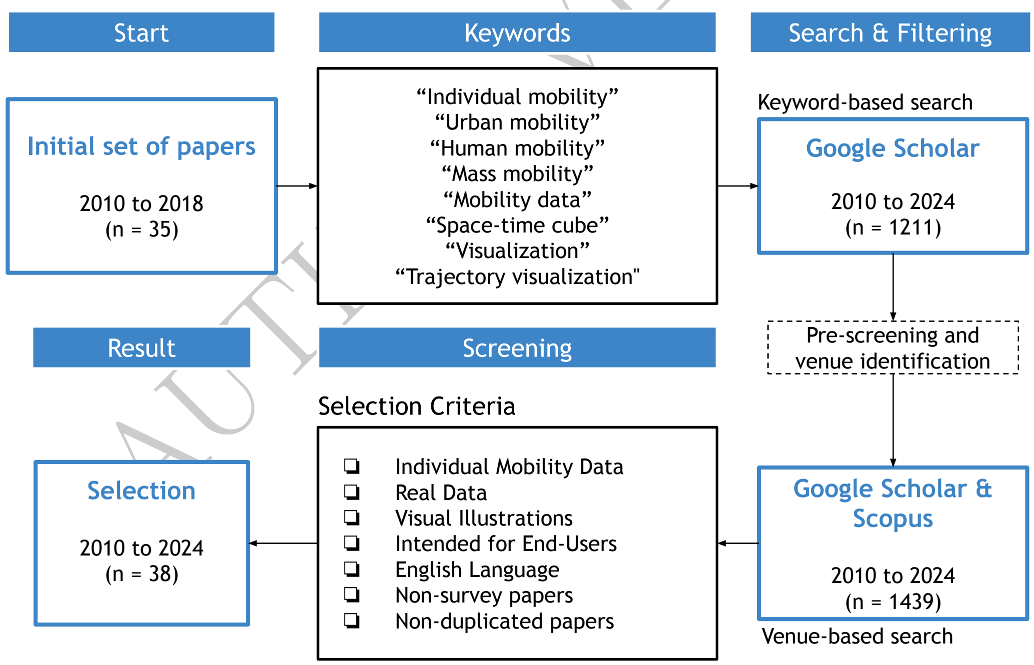

Figure 1: Overview of the survey's methodology.

To assemble a comprehensive review of existing studies, we followed a reference-driven and search-driven approach [14], as shown in Figure 1. We started from a core set of 35 state-of-the-art papers on the topic, encompassing publications from 2010 to 2018 [15], initially compiled by the authors through their previous works on the domain. From this core, we extracted a set of relevant search keywords: visualization, urban mobility, human mobility, individual mobility, space-time cube, trajectory visualization, mass mobility, and mobility data. We used those keywords as input to a two-round coarse search following a search-driven approach. In the first round, we used *Google Scholar*'s search engine to look for papers published between 2010 and 2024 that included any combination of the defined keywords. The last search dates from October 1^{st}, 2024, which yielded 1,211 papers. For each keyword combination, we recovered the 80 first papers, sorted by relevance. After reviewing the abstracts and full texts, we selected 27 papers. The second round consisted on a venue-focused search using both Google Scholar's advanced search engine and *Scopus*. For that, we tailored our search to target papers published in the identified journals and conferences of the previous phase (see the list of venues in Table 7). This search resulted in 1,439 papers. The review of abstracts and full texts of the new papers resulted in the selection of 11 additional papers, comprising a total of 38 papers. The following exclusion criteria were applied to the selected papers:

- **Papers not written in English**.
- **Duplicate papers**.
- **Visualizations not intended for end users**. We exclude papers that do not mention the use of visualization by users, which often feature research questions unrelated to information visualization.
- **Secondary studies**. We focused on the review of primary studies and thus did not include surveys.
- **Absence of figures**. We only consider papers that demonstrate visualizations through illustrations.
- **Papers that use simulated data**. We only include papers that use real-world data. Artificially generated datasets were excluded as they often hide the inherent heterogeneity, sparsity, and subjectivity of real-world data.

- **Non-individual mobility data**. We only include papers that use data sources describing human mobility data either at the individual level (e.g., household travel surveys) or allowing it to be derived (e.g., smart card data or telecommunication).

After screening the abstracts and full texts, we selected 38 papers published between 2010 and 2024, with a notable peak in publications occurring between 2015 and 2018 (Figure 2). This relatively small number of publications underscores the limited attention given to the visualization of individual mobility data in the academic literature, irrespective of the publication venue. Hereafter, we present the selected papers, organized according to five aspects: input data, domain-specific questions, interactive visualization, evaluation aspects, and publication venue.

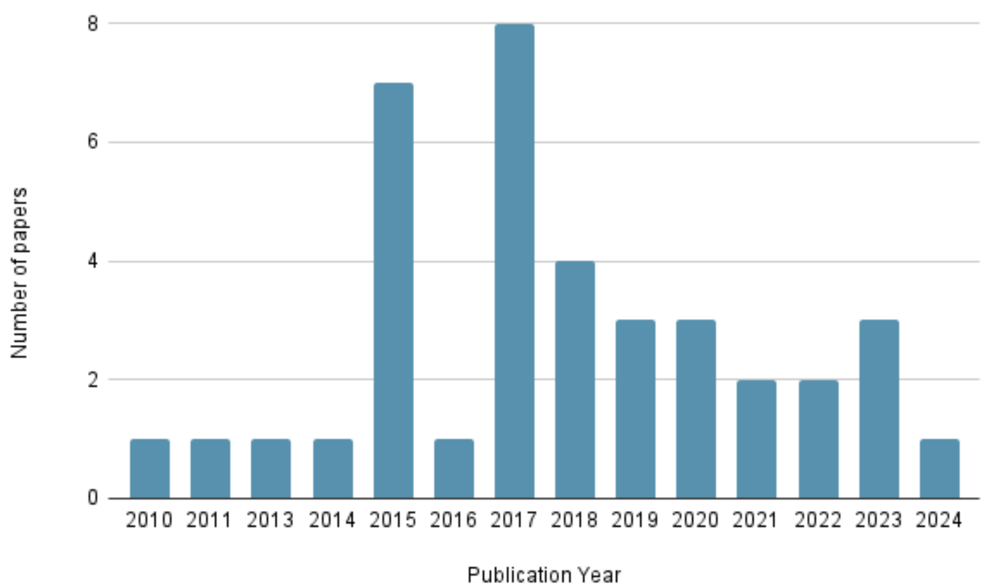

Figure 2: Distribution of the surveyed papers by publication year.

3. Input Data

To answer **RQ1**, we identified the different data sources used in the papers, and classified them according to the collection method, structured by the dimensions of individual mobility data [8]:

- **Space**: the geographic information, for which we identify the (i) spatial positions (i.e., area, origin-destination (O/D), or trajectory), (ii) granularity (i.e., division-, linear-, or coordinate-based referencing [16]), and (iii) dimension (i.e., 1D, 2D, 3D).

- **Time**: It can be described as (i) an event (e.g., a planned public or social occasion, catastrophes, etc.), (ii) a duration (i.e., a period without precise beginning or end), (iii) an interval (i.e., a period with known beginning and end), or (iv) a timestamp.

- **Theme**: It describes the thematic properties that characterize individuals and trips. The theme includes (i) demographic information, (ii) transportation modes, and (iii) trip purposes, for which we distinguish granularity (i.e., 0, 1, or N) and associated values.

Table 1 presents the different types of data sources identified within the surveyed papers, along with the data dimensions they describe. They are defined as follows:

- **Surveys** provide datasets describing single trips through space (i.e., origin and destination locations, and possibly travel route), time (i.e., start/end), and thematic information (e.g., trip purpose, transportation mode, and traveler information) [4]. *Household Travel Surveys* are the most common type of survey, capturing household members' travel practices through trip purposes and transportation modes. Alternatively, Qian et al. [17] used the *Longitudinal Employer-Household Dynamics Origin Destination* dataset, which describes (O/D) commuting trips within an urban environment.

- **Mobile phone data (MPD)** are collected via internet connections, cell towers, or applications running on mobile phones [18]. *Call Detail Records (CDRs)* are frequently used. Records generated by telephone exchanges provide details of phone calls, such as start/end time, duration, caller identifier, and O/D towers [19]. *Telco* data (exchange records between mobile phones and cell towers) can be used to analyze when users make calls, send messages, or access the internet. Senaratne et al. [20] extracted mobility patterns from *Global System for Mobile Communications* records, which provide data on network traffic, antenna operator, location, cell identifier, signal strength, and phone activity status.

- **Public Transportation System (PTS) Data** describes mobility via PTS usage. A popular data source in this category is *Smart card data (SCD)* from validation cards used in subways and buses, which provide information on where and when a passenger tapped in/out, i.e., the O/D locations describing each individual trip. Similarly, *Bike-sharing data* offer details on when and where bikes were rented and returned, along with information about the renter, such as age.

- **Social media data** is provided by applications such as Twitter or Sina Weibo, which allow one to announce their arrival at a hotel, airport, hospital, and so on. The data is often semantically enriched with users' impressions on the place or an event linked to that location [21].

- **Traffic sensors data (TSD)** is collected through traffic sensors strategically placed over an urban area to record pedestrians, bicycles, cars, and other vehicles passing a particular street. These sensors can detect a vehicle moving and estimate the speed, time, and direction of the vehicle.

- **GPS** data (collected via a GPS receiver) provides latitude and longitude information allowing one to geo-locate a person on the earth's surface. In this category, we identified Taxi and personal vehicle data.

- **Point of Interest (POI)** data provide thematic information describing spatial locations that may be of interest to individuals, businesses, or applications. It is typically used to derive the function of visited places and, thus, estimate trip purposes.

Data Source	**Space**	**Theme**	**Time**
Survey	O/D	Travel Mode, Trip Purpose, Demographics	Start/End (HH:MM)
Mobile Phone Records	Area	None	Timestamp
Public Transportation System	Point	Travel Mode	Timestamp
Social Media	Point	None	Timestamp
Traffic Sensor Data	Point	None	Timestamp
GPS	Trajectory	None	Timestamp
Point of Interest	Point	Locations' description	None

Table 1: Overview of data sources classified according to geographic, thematic and temporal information they provide.

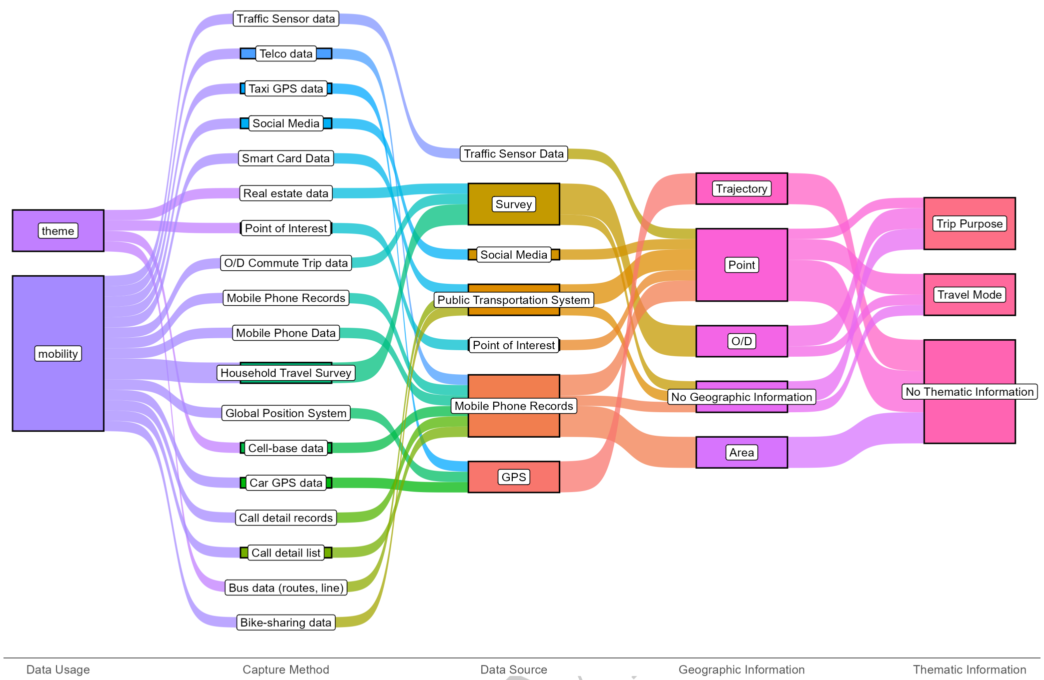

Figure 3: Distribution of data capture methods according to the type of information described (i.e., mobility or theme), the type of data source, and the spatial and thematic information provided.

Every data source considered in this survey contains individual movements over space and time. However, the level of granularity of information depends on the method used to capture data. The temporal information is always represented through timestamps, while spatial information exhibits variability in terms of location (area, individual point, or origin/destination points), granularity (ranging from division-based, coordinate-based, to linear representations), and dimensionality (1D or 2D). The diagram in Figure 3 shows the distribution of 18 unique capture methods identified according to the type of information they describe (i.e., movement or thematic information), the types of geographic and thematic information provided, and the type of data source.

It is worth noting that the thematic information needed to explain people's motivations for mobility is often absent from the data sources. Survey-like data sources are nearly unique in gathering thematic and mobility information. Thus, combining data from diverse sources is a growing practice, observed in 14 of the 38 surveyed papers. In particular, the goal is often to

(i) complement the data with thematic information such as trip purpose and transportation mode, a practice observed in previous work [22, 23, 17, 24] or (ii) increase data accuracy, such as by combining O/D segments from SCD with bus line and station data to derive the actual trajectory traveled by each person [25]. Thematic data from real estate data has been used to support filtering operations, such as to focus the analysis on neighborhoods characterized by high and cheap housing prices respectively [17].

Although most of the papers (n=24) do not explicitly mention the volume of data, the information we could gather indirectly still gives a glimpse into the magnitude of data processed for the visualizations. The reported values span from 119 to a staggering 272 million trips (M = 24 million trips). Additionally, 27 papers in our survey provide information about the number of individuals whose movements are documented within the dataset. These figures fluctuate between 180 and 88.9 million individuals (M =3.2 million people).

Regarding the type of data, the majority of papers rely on O/D segments (constituting 44.7% of the papers), followed by trajectories (39.4% of papers), and events (featured in 13.1% of papers). Over half of the papers explore the spatial information at the level of geographic coordinates, usually to represent individual trajectories or spatial distribution of people, while 8% aggregate the data at the level of administrative partitions, and the remaining ones adopt custom spatial division depending on their analysis (e.g., Voronoi partitions [26, 27], hierarchical grids [23]), or the data source (e.g., household travel surveys often describe the space through custom pooling areas based on the population to ensure statistical significance [28]). The time dimension is frequently treated at the level of intervals of one to three hours (60% of papers), or at the level of timestamps (36% of papers), typically when representing individual trajectories over time. Other aggregations are used according to the analysis, such as dividing the day into periods that describe the morning peak, the afternoon, and the night valley [22]. While the majority of data sources lack intrinsic information regarding the thematic attributes of trips and individuals, it is noteworthy that 26 out of the 38 examined papers do incorporate such information. Often, these thematic attributes are derived from external data sources to enrich the analysis and understanding of the mobility data.

Paper	Trip Purpose	Travel Modes	Demographics	Travel Distance	Travel/Stay Duration	Travel Speed
[29]	■	■	■			
[30]	■	■	■			
[24]	■	■				■
[31]	■	■				
[32]	■		■			
[33]	■		■			
[34]	■				■	
[35]	■				■	
[23]	■					
[25]	■					
[36]	■					
[37]	■					
[38]	■					
[39]	■					
[40]	■					
[41]	■					
[22]		■		■		
[42]		■		■		
[43]		■				
[44]		■				
[45]			■			
[21]				■		
[46]				■		
[47]				■		
[20]					■	
[18]						■

Table 2: Classification of the 26 papers that include the theme dimension based on the properties they represent.

4. Visual Mapping and Interaction

Individual mobility data is intrinsically multidimensional. Thus, diverse visualization techniques can be used alone or in combination to support analytical tasks, such as identifying the distribution, comparisons, and relationships among the different dimensions of the data. In the surveyed papers the number of visualization techniques vary from one to seven, with a median of 4 techniques per visualization system. Two papers employ a single technique for visualization (i.e., the space-time cube and isochronous map). To address **RQ2**, we classified the visualization techniques according to the supported functions and data dimensions, with particular focus on how the theme dimension is addressed.

We did not consider a timeline as a visualization technique, as it was mostly used to filter the data. We identified a total of 25 distinct visualization techniques. Table 3 presents each technique and the user tasks they support. In general, the majority of the techniques support fundamental analytical tasks, such as pattern recognition (36 papers), distribution analysis (34 papers), location identification (33 papers), comparison (33 papers), exploring relationships (28 papers), representation of data over time (26 papers), and movement or flow visualization (24 papers). Notice that different visualization techniques are used to address similar analytical tasks.

Space and time form the foundation for nearly every visualization designed to communicate individual mobility data. Representation-wise, there is little novelty: space is often represented via geographic maps, such as connection maps, flow maps, and choropleth maps, while time is represented either via time-juxtaposing or animation. Four studies explored the usage of abstract visualizations through Voronoi diagrams [27, 26] and treemaps [48]. Only one study does not provide a spatial representation of the data, as they focus on exploring individual activity patterns over time [36].

Figure 4 depicts the distribution of papers over the years according to the type of data used to represent people's movements, the data source, and the thematic representation, in terms of data and visual variables. Table 2 presents the diversity of thematic attributes considered by those papers. The most commonly represented property is trip purpose (16 papers), followed by travel mode (8 papers), individuals' demographics and travel distance (5 papers), travel or stay duration (3 papers), and travel speed (2 papers). Five papers (i.e., [29, 30, 32, 24, 31]) visually depict multiple thematic properties, whereas the others typically focus on a single thematic property, using the rest as filtering criteria. Particularly, demographics information are often used as a means of data filtering to support domain-specific tasks, such as understanding the mobility patterns of particular ethnic groups [45]. When visually integrated, thematic information is primarily depicted through visual cues like color, texture, or icons, integrated into visualization techniques that already represent space, time, or both. Hereafter, we summarize the visualization techniques employed by the surveyed papers, emphasizing how they integrate the theme dimension.

Thematic Maps. Thematic maps often convey thematic information that characterizes the usage of different regions within the studied territory. Choropleth and bubble maps have been used to represent mobility metrics such as the spatial distribution of stays per activity [30, 29], thus revealing the reason people occupy the different regions of the territory. Similarly, density maps represent people entropy (i.e., the magnitude of resources a person is con-

Dim.	Technique	Analytical Task	Papers
Space	flow map	view the distribution of OD flows	[22, 49, 37, 41, 18, 50, 46]
	heatmap	view the variance of OD flow magnitude and density of population	[22, 20, 50, 38, 40]
	space-time cube	view individual trajectories or OD relationships	[32, 45, 27, 15, 51, 37, 33, 20, 24]
	connection map	view individual trajectories or OD relationships	[23, 25, 45, 21, 27, 52, 53, 26, 37, 33, 41, 31, 50, 42, 40, 47]
	density map	view people or transportation mode distribution	[25, 21, 27, 48, 54, 24, 41, 31]
	dot map	view people distribution	[45, 52, 53, 37, 41, 50, 34]
	spatial 3D bar chart	view the variance of phone calls or areas of activity	[27, 37]
	choropleth map	view people distribution, density or fluctuation	[27, 15, 17, 54, 30, 44]
	bubble map	view variance of people presence	[15, 41]
	chord diagram	view OD flows	[15, 55]
	isochrone map	view reachable areas	[43]
	contour-based treemap	view starting locations of incoming trips	[48]
	sankey diagram	view OD flows	[42]
	network diagram	view OD relationships	[42]
Time	space-time cube	view individual trajectories	[32, 45, 27, 15, 51, 37, 33, 20, 24]
	glyph	view the weekly distribution of daily stays	[23, 40, 38]
	histogram	view the distribution of trips, mobility descriptors (e.g. speed, distance) or infection risk	[25, 21, 37, 49, 33, 53, 24, 41, 18, 44, 46, 47]
	multi-ring donut chart	view the distribution of people or trips	[25, 21, 15, 33, 18, 50]
	stacked-bar chart	view the distribution of activities or transportation modes	[23, 36, 15]
	activity-time cube	view the distribution of activities	[36]
	parallel sets	view mobility transition patterns	[53]
	stacked-area chart	view the distribution of people purpose or transportation modes over a day	[15, 26, 33, 31, 38, 40]
	line chart	view the distribution of people or mobility descriptors (e.g. speed, distance)	[17, 52, 20, 33, 30, 24, 34, 46]
	contour-based treemap	view the distribution of visitors and visiting locations	[48]
	heatmap	view the distribution of purposes over a month	[56, 46]
	radial chart	view the distribution of visitors and visiting locations	[40]
	sankey diagram	view the distribution of OD flows, visitors over a day	[42]
	alluvial diagram	view the distribution of OD flows, visitors over a day	[40]
Theme	heatmap	represent transportation mode, duration or geo distance (color)	[22, 21, 39]
	scatterplot	represent distance (x-axis) and transportation mode (color)	[22]
	space-time cube	represent socioeconomic aspects or trip purpose (color)	[32, 45, 15, 33, 20, 24]
	glyph	represent trip purpose and transportation modes (color)	[23, 44, 46, 40]
	multi-ring donut chart	represent trip purpose, transportation mode or socio-demographic aspects (color)	[25, 21, 15, 33, 44]
	stacked-bar chart	represent trip purpose, transportation mode or socio-demographic aspects (color)	[36, 15, 33, 31]
	activity-time cube	represent trip purpose (color)	[36]
	parallel coordinate plot	represent socio-demographic aspects (axes) and ethnic groups (color) or POIs	[45, 31]
	dot map	represent ethnic groups or trip purpose, POI (color)	[45, 37, 38, 35]
	connection map	represent ethnic groups (color)	[45]
	histogram	represent POIs (x-axis) and transportation modes	[54, 24, 44]
	spatial 3D bar chart	represent activities (color)	[27, 37]
	bubble map	represent activities (color)	[15]
	stacked-area chart	represent trip purpose or transportation modes (color)	[15, 30, 33]
	line chart	represent activity (color)	[33, 34]
	semantic chart	represent activities and transportation modes	[31]
	sankey diagram	represent trip distribution over trip purpose	[39]
	pie chart	represent activities and transportation modes	[38]

Table 3: Overview of visualization techniques and supported user tasks and data dimensions by each paper.

nected to and the commutation frequency in daily jobs) and segment entropy (i.e., the diversity and fluidity of spatial locations based on the visits' length) metrics [54]. Gortana et al. [43] superimposed multiple isochrone curves over a map to display reachable distances for a particular spatial location accord-

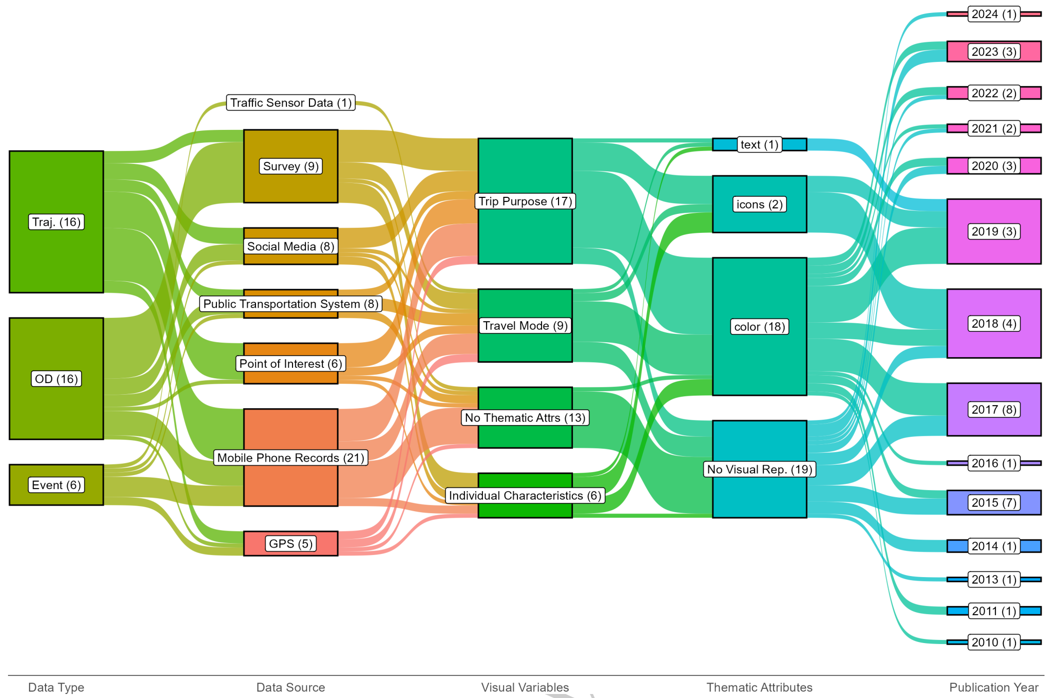

Figure 4: Distribution of papers according to the data type used to describe movements, the data source, the thematic information with the visual variables used to represent it, and the publication year.

ing to different transportation modes, travel time, and hours of the day. Yu et al. [37] represented spatial locations (i.e., home and workplaces) using a dot map, where a given spatial location (shown as a dot) can be selected to reveal the incoming and outgoing flows.

Flow-based representations. While line thickness is conventionally used to represent flow magnitude in flow maps and chord diagrams, it has also been used to represent trip distance [46] (Fig. 5A). In these techniques, the color has been used to encode thematic properties such as transportation modes [22, 29], flow direction [49, 55] (Fig. 5C), trip purpose [37, 29], or trip frequency [46]. Pérez-Messina et al. [22] used an O/D matrix to represent travel flows between spatial locations, which cells are color-coded based on the trip's transportation mode (e.g., private, public, or active). Zeng et al. [42] employ a three-component Sankey diagram to simultaneously illustrate the magnitude of flows between O/D locations, with the corresponding metro lines represented by color (Fig. 5B).

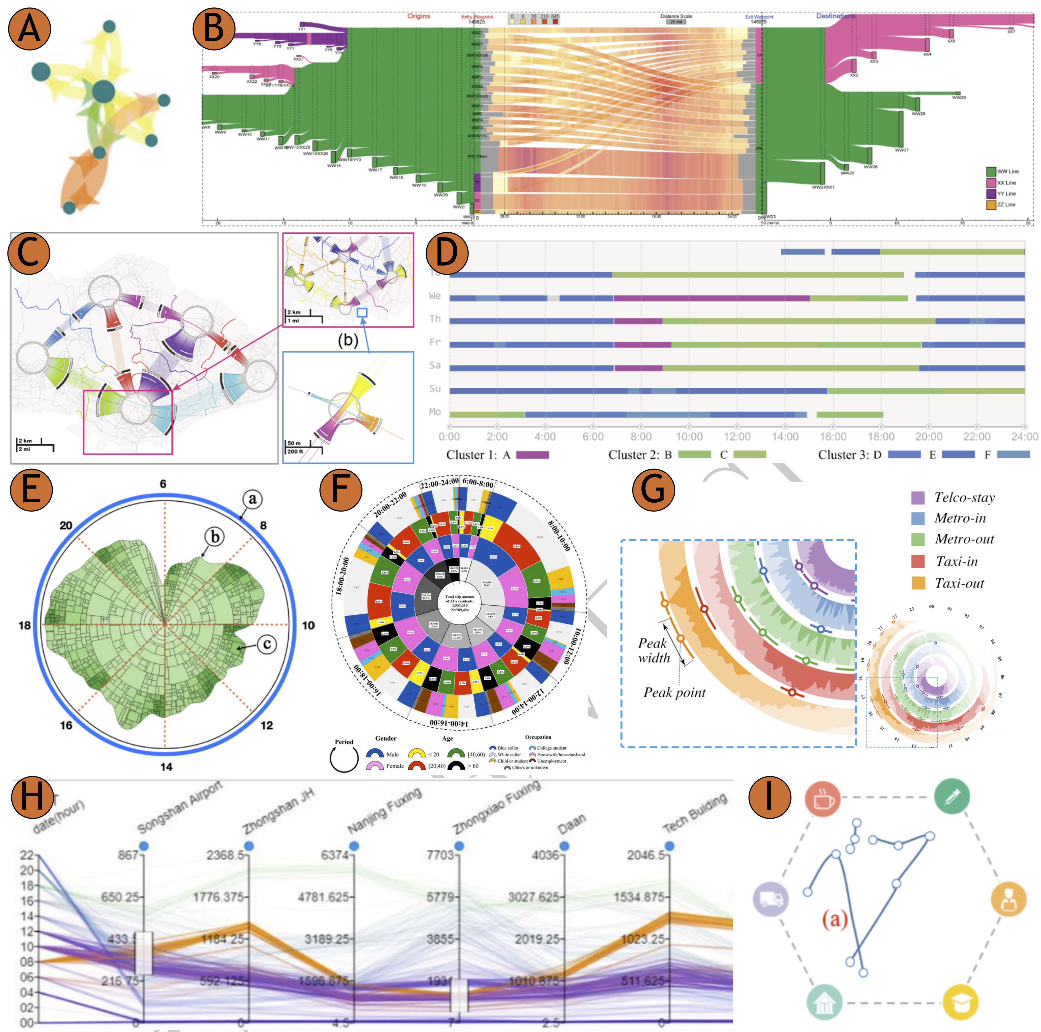

Figure 5: Thematic integration in flow- and time-based representations. (A) Sankey diagram [42]. (B) Flow map [46]. (C) Chronogram [23]. (D) Chord diagram [55]. (E) Multi-ring donut chart [33]. (F) Contour-based Treemap View [48]. (G) Multi-ring stacked-area chart [44]. (H) Semantic graph [31]. (I) Parallel coordinates plot [56].

Linear time-based representations. Line charts and histograms are used to represent the distribution of stays [17], trip count [52, 33], segregation index [30], and mobile network usage amounts [20]. In this context, color has been used to encode thematic information, such as the purpose of trips [33, 49] and trip direction [37, 33]. Stacked-area charts are often used to represent the distribution of trips over time per trip purpose [29, 30, 33], transporta-

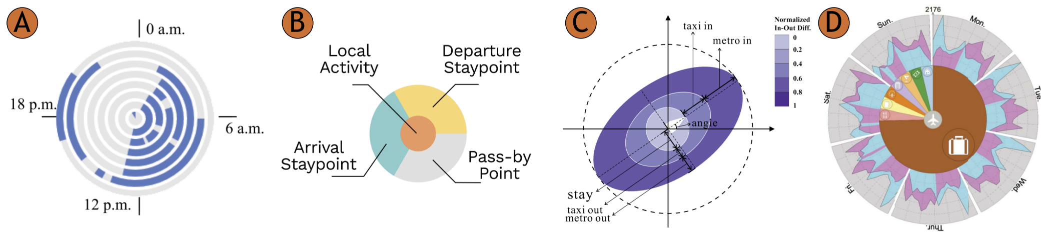

Figure 6: Glyph-based representations commonly placed on top of geographical maps: (A) distribution of an individual's activities over the day and week [23], (B) the proportion of arrivals, departures, and stays [49], (C) the distribution of arrivals, departures, and stays via taxi and metro [44], and (D) the distribution of arrivals, departures, and activities [38].

tion mode [40, 29, 30] and travel speed [26]. Similarly, chronogram techniques are used to represent the sequence of activities or transportation modes that comprise the trajectory of a person during the day [29, 36, 23] (Fig. 5D).

Treemaps. Traditionally used for representing hierarchical data, treemaps have been employed in innovative ways to illustrate individual mobility data. Wu et al. [48] present a *Contour-based Treemap View* that combines treemaps and a radial chart to visualize human co-occurrence (Fig. 5E), displaying the spatial origins of visitors at a selected location. The radial chart is divided into seven sectors representing 2-hour intervals from 6 am to 8 pm, and a sector for the nighttime period from 8 pm to 6 am. Each sector corresponds to the arrival time of visitors in a region indicated as a rectangle inside the sector. The size of the region encodes the number of visitors, while the color indicates the distance between the origin and the destination of visitors.

Cyclic time-based representations. Inspired by clock designs, multi-ring donut charts have been used to visualize the distribution of stays or trips over time-based on factors such as trip purpose or transportation mode [29, 23], as well as socio-demographic characteristics like gender, age, and occupation [33], either for specific spatial locations or across an entire area (Fig. 5F). This method involves multiple concentric donut charts, each divided into sectors representing time intervals. These sectors are either color-coded to indicate a particular thematic variable or further subdivided to display the distribution of stays or trips for each variable within that period. In a variation of this approach, Wu et al. [44] use stacked-area charts in place of color-coded sectors to depict the distribution of trips in- and outbound, via metro or taxi, alongside the fluctuation of stays throughout the day (Fig. 5G).

Theme-specific representations. Parallel coordinates plots are effective for representing multiple attributes simultaneously and have been utilized to illustrate the variation of trips across POIs [56] (Fig. 5H), trip aspects such as distance, number of people, and time periods [48], and demographic characteristics [45]. In the latter, factors like age, language, education level, and income are plotted as vertical axes, with color-coded lines connecting them to represent different ethnic groups [45] (fig ref). Scatterplots have also been employed to depict the influence of geographic distance and transportation mode on travel flows [22], where the y-axis indicates the number of individual trips and the x-axis represents varying travel distances. The intersecting values are illustrated by circles, with color and size encoding transportation mode and trip count, respectively. Sankey diagrams have been used to represent the variation of trips over trip purpose [39]. Additionally, Huang et al.[31] introduced a novel technique called the *semantic graph*, which represents individual trajectories as polylines within a topic hexagon (Fig. 5I), where the vertices correspond to points of interest (POIs). This design enables users to identify (i) trajectories associated with specific purposes and (ii) the purposes that drive varying activity levels.

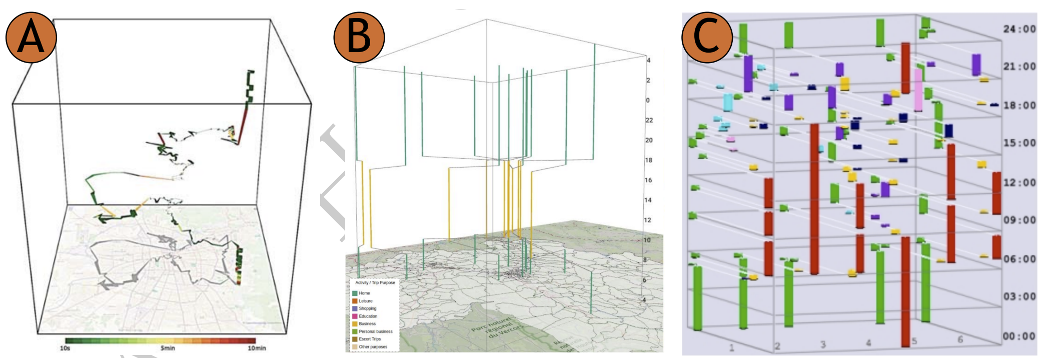

Figure 7: 3D-based representations. (A) Space-time cube (STC) for GPS-type trajectories with color encoding inter-sample time interval [20]. (B) STC for O/D trajectories with color encoding activities [15]. (C) Activity-time cube representing activity sequences over time [36].

Glyph-based representations. As noted by Borgo et al. [57], due to their ability to convey multiple attributes within a compact visual space, promoting enhanced cognitive engagement during the visualization process, glyphs are popular for representing individual mobility data. A common practice observed in the surveyed papers is to position glyphs on a map based on geographic coordinates, thereby characterizing a location by the temporal distribution or aggregation of attributes such as trip purpose, transportation mode, or trip direction. For instance, Chen et al. [23] proposed a glyph in the form of a multi-ring donut chart to represent the temporal distribution of activities of an individual at a particular location (Fig. 6A). Often, glyphs are used to represent the repartition of trips in and out of a particular spatial location [46, 49, 44, 40, 38]. For instance, Silva et al. [49] proposed a donut-shaped glyph with a filled center to characterize spatial locations as a local activity, departure, arrival, or pass-by point according to the trip direction and destination (Fig. 6B). A stacked elliptical glyph design [44] was proposed to summarize and compare activities in different spatial locations according to number of stays and trips per transportation mode (Fig. 6C). Cyclic stacked-area charts are employed to visualize the temporal distribution of activities [40] as well as the arrivals and departures of people [38]. Zeng et al. [38]'s glyph positions the stacked-area chart along the circumference of a pie chart, representing both the arrivals and departures of people and the distribution of activities at a given location (Fig. 6D).

3D-based representations. Due to the multidimensionality of individual mobility data, 3D representations are becoming popular. A frequent example is the *space-time cube* (STC) [58], a technique that represents geographical space on the cube's base and time along its height. In nine of the surveyed papers, the STC has been used to simultaneously represent space, time, and thematic properties through symbols and colors. For instance, Kveladze et al. [45] used the technique to represent individual trajectories across socioeconomic aspects, such as ethnicity and education level. Senaratne et al. [20] used the STC to inspect data uncertainty by coloring the individual trajectories according to the inter-sample time interval (i.e., the time interval between two data records) (Fig. 7A). The STC by Yu et al. [37] supported the exploration of mobility patterns by representing individual trajectories or clusters, where color encoded the trip direction (i.e., going home or to work). In general, the STC was used to represent individual activity patterns across space and time, where color encoded the different activities or trip purposes [29, 33, 32] (Fig. 7B). Alternatively, the *activity-time cube*, proposed by Vrotsou et al. [36], encoded the temporal distribution of activities per individual through a three-dimensional space, where the x-axis holds the individuals, the y-axis is the time axis and the z-axis can display activities, places, or companionship (Fig. 7C).

User Task	Mobility elements / indicators	Papers
Select	Data and view parameters	[45, 21, 15, 17, 52, 43, 49, 48, 54, 51, 26, 24, 41, 31, 18, 44, 40, 56, 46, 35, 39, 47]
	Time periods	[23, 32, 45, 21, 29, 17, 52, 43, 49, 48, 54, 53, 26, 30, 20, 24, 42, 40, 47]
	Spatial locations	[29, 52, 48, 54, 26, 37, 20, 24, 31, 50, 38, 40, 56, 47]
	Individuals trajectories or trips	[22, 25, 36, 27, 29, 52, 49, 53, 31, 50, 42, 47]
Filter	Individuals trajectories or trips	[23, 32, 45, 21, 29, 17, 43, 49, 51, 53, 31, 50, 42, 39, 47]
	Socio-demographic aspects	[48, 26, 30, 29, 23, 25, 32, 30, 34, 44, 40, 56, 46]
	Spatial locations	[32, 29, 45, 21, 54, 53, 26, 24, 38]
	Time periods	[54, 29, 24, 41, 31, 18, 55, 46]
	Mobility indicators	[29, 54]
	Purposes	[35]
Change over Time	Mobility flows or trajectories	[22, 23, 27, 52, 49, 26, 37, 33, 24, 31, 18, 50, 55, 56]
	Mobility indicators	[29, 48, 54]
	Travel time	[43]
	Socio-demographic aspects	[30]
Pan	Map view	[36, 32, 45, 21, 29, 52, 43, 49, 51, 24, 44, 40, 56, 46, 47]
Zoom	Spatial locations	[23, 36, 32, 45, 21, 27, 29, 17, 52, 43, 48, 51, 53, 20, 24, 31, 18, 50, 44, 40, 56, 46, 47]
	Get more or less details	[49, 41, 55]
Rotate	Camera	[36, 32, 45, 29, 51]
Reorder	Mobility patterns	[21, 53, 42, 34, 40]
	Sort activities	[38, 35]
	Spatial locations	[31]
Annotation	Identify activities	[38, 35]
	Spatial locations	[34, 31]

Table 4: Classification of papers based on user tasks and the mobility elements or indicators they address.

Interaction. Table 4 provides an overview of the user actions supported by the different visualization tools as well as the data items (e.g., spatial locations, time units, etc.) or mobility indicators (e.g., activity patterns, presence density, etc.) that can be manipulated through user actions. Overall, the visualization tools support familiar analytical tasks–including selection, filtering, zooming, change over time, panning and rotation, reordering, and annotation–which are widely recognized in visualization [59]. Most papers rely heavily on the mouse and keyboard for physical interaction, even in 3D visualizations. However, one study [29] explores spatial interaction using a tablet's tilting motion to control time-based changes. In this approach, tilting angles are mapped to time units on a timeline, which then animates a thematic map.

5. Domain-specific questions

To answer **RQ3**, we categorize the papers based on three common questions frequently raised by mobility experts, including geographers and urban planners: (i) What are the commuting and travel patterns of individuals within urban areas and how do these patterns influence the configuration of the urban landscape?, (ii) How do the socioeconomic attributes of individuals and the activities they engage in influence land usage within urban regions?, and (iii) How does the geographic context of a given area influence the scheduling of individuals' activities and journeys throughout the day? [15]. We further classify the papers according to the addressed mobility issue and the different mobility indicators derived from the data. Using the pyramid framework introduced by Mennis et al. [8] as a foundation, we classified the queries into four distinct categories that define the connections between the different aspects of the data needed to support users in addressing domain-specific questions. These queries are defined as follows:

- *when + where + theme* $\rightarrow$ *what*: describe a particular (set of) object(s) based on a particular (set of) thematic attribute(s) existing at a given (set of) location(s) at a given (set of) time(s);

- *when + what + theme* $\rightarrow$ *where*: describe a particular (set of) location(s) occupied by a given (set of) object(s) based on a particular (set of) thematic attribute(s) at a given (set of) time(s);

- *where + what + theme* $\rightarrow$ *when*: describe a (set of) time(s) that a particular (set of) object(s) occupied a given (set of) location(s) based on a particular (set of) attribute(s); and

- *when + where + what* $\rightarrow$ *theme*: give the (set of) thematic attribute(s) describing the (set of) object(s) existing at a given (set of) location(s) at a given (set of) time(s).

Table 5 presents the surveyed papers classified by domain-specific task, according to the above taxonomy. The papers mostly focused on exploring human behavior within an urban environment in terms of when people

Type	Task	Papers
when + where + theme → **what**	Identify **who** is performing an activity at a given place and time	[29, 37, 32, 23, 38]
	Identify demographic **groups** visiting a location at a specific time	[25, 45, 30]
	Compare **trajectories** over space, time and demographic groups	[29, 45]
	Identify **trips** using a given travel mode at a given place and time	[22, 29]
	Compare individual **trajectories** per trip purpose	[37, 23]
	Identify **trips** with a given purpose at a given place and time	[29]
	Identify **events** at given location and time	[56]
when + where → **what**	Identify the **individuals** visiting a specific location at a given time	[29, 17, 30, 37, 32, 27, 53, 55, 42, 34, 40, 46]
	Identify similar **trajectories** at a given location and time	[49, 21, 52, 27, 20, 45, 51, 24, 37, 39]
	Identify the number of **trips** at a specific location and time	[33, 26, 30, 50, 31, 29, 18, 20, 37]
	Identify the number of **individuals** sharing the same O/D locations	[49, 29]
	Count the **trips** to or from a specific location at a given time.	[48, 49]
when + theme → **what**	Count the **individuals** engaged in a given activity and time.	[23, 29, 36, 31, 30]
where + theme → **what**	Count the **individuals** engaged in a given activity and location.	[23, 29, 30]
when + what + theme → **where**	Identify **where** people engage in a given activity and time	[29, 30, 37, 32, 34]
	Compare **locations** over time based on land use	[33, 29, 30, 44]
	Identify reachable **locations** by a given travel mode in a given time	[43, 22, 52]
	Identify **locations** visited by various demographic groups	[30, 45]
when + what → **where**	Explore visitation patterns of spatial **locations** over time	[49, 41, 18, 21, 27, 37, 31, 32, 54]
	Explore movement patterns on **roads (locations)** over time.	[24, 18, 21, 26, 55, 46, 35, 47]
	Identify the **locations** where other locations co-occur	[48, 49, 50]
	Identify spatial **locations** where people co-occur	[48, 49, 40, 47]
what + theme → **where**	Identify working and residential **locations**	[18, 37, 56]
when + theme → **where**	Characterize **locations** by travel modes at a given time	[22, 29]
where + what + theme → **when**	Identify **when** locations are visited for various purposes	[30, 29, 37, 32, 42]
	Identify **when** given demographic groups visit given locations.	[30, 45]
where + what → **when**	Identify when given locations are visited	[29, 27, 21, 37, 32, 17, 48, 40]
	Identify **when** people co-occur in given locations	[48, 23, 34]
theme + what → **when**	Identify when individuals engage in given **activities**	[32, 29, 36, 23, 31, 33]
where + theme → **when**	Identify **when** different demographic groups stayed at given locations.	[33, 29, 30]
	Identify **when** people visit places for a given purpose or travel mode	[29]
when + where + what → **theme**	Identify and compare individual **activity patterns**	[29, 23, 37, 32]
	Compare **activity distribution** over space and time	[29, 30, 33, 38]
	Identify the main **travel mode** to reach a location at a specific time.	[43, 29, 22]
	Compare **travel mode** distribution over space and time	[29, 44]
	Identify the **trip purposes** of trajectories	[31, 29]
	Compare the **demographic** share at a location over time.	[33]
when + what → **theme**	Identify the **distribution of activities** over time	[33, 29]
	Compare **activity patterns** over time	[29, 31]
	Identify **shared activities** at a given time	[36, 29]
	Compare **modal share** of trips for a given distance and time	[22]
where + what → **theme**	Identify the **activities** individuals engage in at given locations.	[33, 29, 30, 35]
	Identify the **demographic share** of people at a given location	[33]
when + where → **theme**	Identify **activities** performed in a given location and time	[33, 29, 30, 46]
	Identify the **travel modes** to reach a given location at a given time.	[29, 30]

Table 5: Classification of papers according to domain-specific tasks.

visit different spatial locations or where people are at a given time. A few papers focus on understanding the commuting behavior of the population, which supports the identification of residential and working locations [37, 18]. Similarly, Le Roux and Vallée [30] supported a deeper analysis through the exploration of a segregation index revealing the temporal evolution of land use within the urban environment. According to the domain-specific questions, we classified the papers according to three distinct objects of interest: (i) presence dynamics, (ii) travel flows, and (iii) individual trajectories, respectively. Twenty-five publications represent presence dynamics through the variation of people present at different spatial locations and time intervals while eighteen support the visualization of travel flows and trips and sixteen represent individual trajectories of people or activity sequences.

Although every task in the taxonomy is supported at some level by the set of surveyed papers, a domain expert would have to perform an ad-hoc analysis by combining the visualization solutions provided by several different papers to be able to answer all three domain-specific questions. Only three visualization solutions [27, 37, 29] enabled the analysis of individual mobility data through the exploration of all three objects of interest. Both Gao et al. [27], and Yu et al. [37] employed 3D visualization techniques to simultaneously represent spatial and temporal information. However, these solutions have limitations when examining thematic data, which is restricted to describing the trip as going home or to work. Menin et al. [29] had a deeper focus on the spatiotemporal evolution of individual mobility across diverse thematic aspects. For instance, they covered trip purpose over eight categories (i.e., home, work, leisure, education, shopping, business, personal business, and escort trips, and travel modes over four categories (i.e., biking, driving, PTS, and walking), while providing a clustered exploration of individual trajectories based on daily activity sequences.

6. Usability Evaluation

To address **RQ4** and understand whether and how user-based evaluations are employed to assess the usability and effectiveness of visualizations in the domain, we classified the papers according to their experimental design, the evaluated features (e.g., effectiveness, usability, satisfaction, etc.), the sample size, and whether the participants meet the profile of the target users of the application, i.e., mobility experts, including researchers in geography or transportation and urban planners. Table 6 presents the classification of papers according to these criteria.

The 38 papers analyzed in detail in this survey consistently provided some sort of validation of the proposed visual analytics system, mostly through case studies, where the visualization approach was applied to a real dataset or the usefulness of the approach was demonstrated through use case scenarios. For instance, Chen et al. [21] applied their approach to datasets describing the movements of tourists within two different cities, showing step-by-step how their system supports the discovery of knowledge such as typical tourist routes and popular destinations.

Twenty-two papers (about 60%) conducted user-based experiments to evaluate of their systems. Seventeen evaluations were conducted through a *non-experimental* design (i.e., without comparison [60]). Among these, fifteen studies interviewed a small group of experts (from 1 to 14 individuals). These experts were then presented with the system's interactive components, visual encoding, and a series of case studies and asked to provide feedback on the visual encoding and the suitability of the visualization for exploring the dataset. Three studies used a quasi-experimental design, where the visualization solution was compared across non-randomly assigned groups.

Experimental design	Sample size	Profile	Papers
Experimental	7	expert	[45]
	7-20	non-expert	[36, 45, 29]
Quasi-experimental	3-7	expert	[29, 40]
	24	quasi-expert	[29]
	10-20	non-expert	[29, 49, 40]
Non-experimental	1-11	expert	[22, 23, 48, 53, 26, 41, 31, 18, 38, 42, 44, 56, 47]
	unknown	expert	[52, 50]
	4-14	non-expert	[24, 35]

Table 6: Classification of papers according to experimental design, sample size, and participants profile.

Three studies conducted formal experiments involving a larger sample of participants (from 7 to 20 individuals), Vrotsou et al. [36] investigated the efficiency of 2D (stacked-bar chart) and 3D (activity-time cube) representations of individual activity sequences, showing that search time and error rate increases proportionally to the number of activity sequences displayed in either technique. Kveladze et al. [45] investigated the performance of two distinct groups of users (i.e., expert and non-expert relative to the application domain) while exploring individual mobility data using a system comprising a 2D base map of the study area, a parallel coordinate plot, and four views on the 3D STC, each representing the trajectories of different ethnic groups of individuals. They observed that domain experts performed the tasks using logical and strategical reasoning while the non-experts did not follow the logical sequence of task execution. Probably due to more experience with the type of data and the different representations, the expert users also used all the available visualizations while the non-experts focused mainly on the STC, which the authors suggested was due to their enthusiasm toward the 3D visualization. Finally, Menin et al. [29] investigated the usability and effectiveness of a movement-based animation technique compared to the traditional one, and their results showed that both are equally effective for simple identification and comparison tasks.

Almost two decades ago, Ellis and Dix [61] highlighted the limited presence of user-based evaluations in the field. In their survey of over 65 papers, they found that only 12 of them included evaluations. In the context of individual mobility, we observed more promising numbers, although the number of formal experiments remains limited. The challenges associated with recruiting real users are evident in the limited group sizes of domain experts and the reliance on non-expert participants in experiments that require larger sample sizes.

7. Publication Venues

The problem of visualizing individual mobility data can be addressed from multiple perspectives, which can vary across research communities. We hypothesize that the VIS community addresses the visual representation of multiple data dimensions while dealing with human cognitive and perceptual limitations, while the GIS community mostly addresses the challenge of understanding the dynamics of people and their impact on the urban environment, where visualizations are used to support the study, instead of being the main goal. Thus, to address **RQ5**, we classified the surveyed papers based on the type of venue where they were published, i.e., VIS or GIS.

Table 7 presents the papers according to the publication venue. The majority of papers were published in VIS venues (n=22, such as IEEE TVCG, PacificVis, IEEE VIS), or other subareas of Computer Science (n=3). Ten papers were published in GIS venues, such as the Journal of Transport Geography and IEEE Transactions on Intelligent Transportation Systems, and three papers were published in interdisciplinary venues (i.e., the International Conference on Cross-Cultural Decision Making and the International Conference on Computer Supported Cooperative Work in Design).

Type	Venue	Papers
VIS	IEEE Transactions on Visualization and Computer Graphics (TVCG)	[21, 52, 48, 24, 41, 31, 18, 50]
	Computer Graphics Forum	[55, 42, 40, 47]
	IEEE Pacific Visualization Conference (PacificVis)	[34, 44, 56]
	Journal of Visualization	[53, 35]
	IEEE Conference on Visual Analytics Science and Technology (VAST)	[37]
	IEEE Visualization & Visual Analytics (VIS)	[43]
	International Conference Information Visualization (IV)	[36]
	International Conference on Graphics, Patterns and Images SIBGRAPI	[29]
	International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP)	[49]
GIS	IEEE Transactions on Intelligent Transportation Systems	[26, 20, 38]
	Journal of Transport Geography	[32, 30, 33]
	ACM International Conference on Advances in geographic Information Systems (SIGSPATIAL)	[51, 39]
	International Journal of Geographical Information Science	[45]
	Cartography and Geographic Information Science (Taylor & Francis)	[46]
CS	ACM Transactions on Intelligent Systems and Technology	[23]
	MDPI Journal Algorithms	[22]
	Human-centric Computing and Information Sciences Journal	[54]
MULTI	IEEE International Conference on Computer Supported Cooperative Work in Design (CSCWD)	[25]
	Advances in Cross-Cultural Decision Making	[17]
	Spatial Cognition & Computation (Taylor & Francis)	[27]

Table 7: Classification of papers according to publication venue (**VIS**: Visualization, **GIS**: Geographic Information Science, **CS**: Computer Science, **MULTI**: multi-disciplinary.

In VIS and Computer Science-related venues, the motivations are typically centered on the challenges of extracting mobility patterns from heterogeneous data and the design of novel visualization approaches. The latter is also a motivation in the GIS community, which is also often interested in knowledge extraction. Regardless of the venue, the papers often cover mobility-related issues such as urban dynamics, activity patterns, population distribution, crowd behavior, and commuting patterns. VIS and other Computer Science communities often exploit huge datasets extracted from sources such as mobile phone records, social media, POI data, and CDRs. Moreover, the combination of multiple data sources is more prevalent in the VIS and Computer Science communities. In contrast, GIS studies predominantly focus on survey data. The most outstanding difference concerns the user-based evaluations, which seem to be more prevalent within the VIS community (18 out of 22 assessments involving users) compared to the GIS community (only 3 out of 10 assessments with users).

8. Discussion and Research Agenda

In this paper, we surveyed 38 papers covering the visual analysis of individual mobility data. We focused on understanding how the thematic data dimension is integrated into existing visualization solutions. Below, we also highlight potential research perspectives within the domain.

8.1. Theme integration

The six key thematic dimensions covered in the surveyed papers include trip purpose, travel mode, demographics, travel distance, travel duration, and travel speed. While these provide valuable insights into mobility patterns, several critical aspects remain underexplored. For example, spatiotemporal factors like climate change (temperature, air quality, CO2, pollution) can significantly impact movement. Mobility also varies widely, from short commutes to global travel, requiring a broader view of both routine and exceptional movements. Complex patterns, such as those of migrants, often involve interrelated reasons and collaboration among individuals, highlighting the influence of economic conditions and policies. These factors shape mobility by affecting the distribution of services like healthcare and education. Despite the availability of data, these elements are rarely considered in mobility studies. Expanding research to include such correlations could offer a fuller understanding of how policies and environmental factors affect human mobility across different contexts.

8.2. 3D Visualizations

Due to its capacity to represent multiple data dimensions, 3D visualization is inherently an asset for visualizing individual mobility data. In particular, the Space-Time Cube (STC) is a prominent 3D visualization technique in the domain and has been widely employed in the surveyed papers. Although the STC was introduced as early as 1976 [62], research questions about its effectiveness in supporting data exploration remained [63]. The more recent studies by Kveladze [45] and Gonçalvez et al. [64] have shown that combining the STC with 2D representations of data can be beneficial for the analysis and even preferred by the users, who gain multiple perspectives on the data. The main limitation of the STC, and every other 3D representation for that matter, is the perceptual and interactive restrictions imposed by conventional desktop setups [65]. For that, we suggest that *immersive visualizations* and *spatial interaction* can help overcome some of the limitations of the STC.

Immersive Visualization. One option for achieving immersion in the past was through confined spaces surrounded by retro-projected walls, known as CAVE environments. When coupled with head-tracking technology, such setups provided users with an immersive experience [66]. However, more affordable off-the-shelf Head-Mounted Display technologies such as the Meta Quest have exhibited significant traction in the field. This is primarily due to the rapid technical advancements in the industry, leading to increased affordability and ease of integration into the work environments of data analysts [67]. Interactive STCs have been applied to visualize movement trajectories in various domains, including vessel navigation [68], running sports [69], historic events [69], and urban mobility [70, 71, 72, 73]. In individual mobility visualization, the closest approach in the literature involves using an immersive STC to explore simulated trajectories [74]. This immersive method has been shown to improve usability and reduce mental workload. However, it lacks integration of the thematic dimension. Future research should focus on leveraging the benefits of immersive visualization for individual mobility data exploration, where it could significantly enhance analysis.

Spatial Interaction. Spatial interaction facilitated by mobile controllers has the potential to bridge the gap between the physical and virtual information realms [75]. This interaction paradigm involves mapping real-world movements in directions such as forward/backward, up/down, and left/right to manipulate the virtual camera, enabling users to navigate and explore virtual environments more naturally [76, 77]. Although spatial interaction is not widely applied in the surveyed papers, it could enhance user engagement with 3D visualizations. With the widespread availability of smartphones, which can serve as intuitive physical interaction devices, this approach could also become more accessible and impactful.

8.3. Geo-collaborative and Immersive Visualization

As data volumes and complexity grow (in terms of uncertainty, more ambiguous definitions, and larger scopes [78]), tackling analytical problems becomes more challenging and might require the collaboration of multiple experts. The concept of geo-collaborative visualization, where data and models utilized by participants are closely tied to geographical locations [79]) emerges as a suitable approach to enact the collaboration of multiple experts. Collaboration can happen in physical spaces, e.g., in front of wall-sized visualizations [80], or virtually, through video-conference tools. In this context, and building on previous research in this area [78], immersive VR technologies offer new possibilities for collaborative visualization. Although immersive collaborative visualization has been explored in other fields, its use in individual mobility analysis is still underdeveloped, presenting an opportunity for future research.

8.4. Understanding Users Reasoning through Analytical Provenance

Analytical provenance research is dedicated to understanding users' reasoning processes by examining their interactions with visualizations [81]. The surveyed visualization tools often support individual mobility data analysis through various indicators that describe mobility across dimensions like space, time, and theme. Users employ multiple interactive visualization techniques to explore this data, and the specific path of exploration–comprising queries, visualization choices, and interactions–can vary depending on the user's analytical task or profile [45]. Thus, gaining insight into how domain experts utilize a visualization system to answer domain-specific questions, such as through which mobility measures, spatiotemporal granularity levels, and thematic attributes they select and in what sequence, can be valuable for enhancing user experience and effectiveness, leading to the development of tailored exploratory workflows that align well with different tasks and user needs. However, the surveyed papers barely tapped into the potential of analytical provenance. Although Menin et al. [29] records some information, such as when and where a specific visualization was opened, closed, or modified, no provenance studies based on this data have been reported.

8.5. Data Management through Knowledge Graphs

The heterogeneous nature of individual mobility data poses a significant challenge for the field. Our analysis revealed that most studies combine data from multiple sources to reconstruct individual movements and enrich them with thematic information. Each paper introduces a distinct data collection and combination process based on (i) the type of data source and (ii) the analytical objectives of the proposed visualization system. In this context, Resource Description Framework (RDF) knowledge graphs (KGs) could be beneficial for data management, through the use of innovative methods for structuring, publishing, discovering, and integrating data. The strength of the RDF lies in its inherent interoperability and capacity to link resources and properties across the web, enabling access to additional information [82]. We observe a growing use of KG-based representations in the domain, such as modeling territorial changes [83], urban mobility events [84], and urban mobility data [85]. Future research should explore KG representations to enhance data transparency and improve analyses of individual mobility data

8.6. Visualization of Spatial Changes underlying Individual Mobility

All surveyed papers concentrate on individual mobility over short time frames, such as days or weeks. While this approach addresses many domain-specific questions, there is a notable absence of longitudinal studies examining mobility behavior over extended periods, like years. This gap likely stems from changes in territorial nomenclatures and geographical boundaries, which hinder the comparability of mobility data over time. Without recalculating past data according to current geographic areas—a complex process that obscures territorial changes—statistical series experience breaks, leading to potential misinterpretations or biases in the statistics if not properly documented [83]. We have yet to encounter visualization solutions that simultaneously convey changes in both mobility and spatial context. Given the importance of understanding historical mobility behavior to support more sustainable transportation modes, we believe this topic warrants further exploration in the future.

9. Conclusion

In this paper, we presented a comprehensive survey of the literature focusing on the visualization of individual mobility data, i.e., data that describes the trajectories of individuals within urban environments. We analyzed 38 papers published since 2010 in GIS and VIS venues. While the literature has extensively covered the spatiotemporal visualization of movement data, relatively little attention has been devoted to the representation of thematic information describing individuals' motivations for mobility.

Our findings indicate that while thematic attributes are frequently included in visualization solutions, they are often represented only partially. We examined the visualizations based on three domain-specific questions for presence dynamics, travel flows, and individual trajectories. Only three solutions effectively assist mobility experts in addressing all three questions. Furthermore, consistent with prior research [61, 86], we observed a deficiency in formal experiments to assess the effectiveness and value of the proposed visualizations for practical applications. Expert-based interviews were conducted in more than half of the papers; however, they typically involved a limited number of participants, highlighting a persistent challenge in the field. Notably, publications in VIS venues exhibited a higher tendency to incorporate evaluations than those in GIS venues.

Based on our analysis of the existing literature, we identified several research opportunities. These include the need for analytical provenance studies to gain insights into user reasoning during data exploration, the development of novel visualizations capable of effectively integrating spatial changes, the design of collaborative setups and virtual environments to support visual analytics, the exploration of 3D visualization using immersive technologies and spatial interaction, and the need of interoperable technologies such as RDF KGs to facilitate data integration from multiple sources.

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