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Visual Analytics for Sustainable Mobility: Usability Evaluation and Knowledge Acquisition for Mobility-as-a-Service (MaaS) Data Exploration

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Abstract: Urban mobility systems generate a massive volume of real-time data, providing an exceptional opportunity to understand and optimize transportation networks. To harness this potential, we developed UrbanFlow Milano, an interactive map-based dashboard designed to explore the intricate patterns of shared mobility use within the city of Milan. By placing users at the center of the analysis, UrbanFlow empowers them to visualize, filter, and interact with data to uncover valuable insights. Through a comprehensive user study, we observed how individuals interact with the dashboard, gaining critical feedback to refine its design and enhance its effectiveness. Our research contributes to the advancement of user-centric visual analytics tools that facilitate data-driven decision-making in urban planning and transportation management.

Keywords: shared mobility; visual analytics; mobility data analysis; spatiotemporal analysis

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1. Introduction

In contemporary urban environments, optimizing traffic flow and enhancing public transportation are critical challenges that require effective government strategies and advanced technological solutions. As cities strive to improve the quality of public transport and reduce reliance on individual vehicles, they face the dual challenge of managing increasingly complex transportation systems and leveraging vast amounts of data generated by these systems. These data, arising from the real-time monitoring of traffic and transportation infrastructures—such as surface public transport fleets and subways—as well as from innovative Mobility-as-a-Service (MaaS) schemes, exemplify a genuine big data situation [1].

The vast volume of data not only supports daily operations but also opens up numerous opportunities for in-depth analysis, enabling the detection of patterns, trends, and insights crucial for planning, operation, and management [2]. However, effectively visualizing these data to support human decision-making remains a challenge. The complexity of integrating diverse data sources, including demographic data and points of interest (POIs), and addressing issues of spatial and temporal scales complicates the creation of comprehensive yet accessible visualizations [3]. As such, developing data visualizations that allow users to interact with and explore this information is of paramount importance. Understanding which visualization methods best help users grasp significant patterns is crucial for advancing both the technical and practical aspects of mobility system management.

It is, however, still not completely clear which forms of visualization can actually enable users in grasping relevant patterns that might be found in the data, due to different issues: first of all, the sheer volume of data makes it difficult to provide comprehensive but also accessible visualizations, both from a technical point of view and with reference to the actual possibility to make sense out of it, calling for forms of summarization and abstraction that, however, do not lead to distorted impression to the viewer. To make things even harder, it is sometimes necessary to integrate additional sources not strictly speaking related to mobility, such as demographic data and points of interest (POIs), that enrich our understanding but that also amplify the challenge of effectively analyzing and visualizing big data in this context [3]. Then, there are issues of spatial and temporal scale, which could make it hard to spot phenomena that are apparent only at a given scale in space and time.

These complex, large datasets include both spatial and aspatial data, all of which must be synthesized in meaningful ways, and represented within a visualization environment [4]. While GIS methods and technology have provided analytical tools supporting logistics studies (see [5] for a last-mile delivery case study), urban planning, and mobility studies (see [6] for an analysis of potential positive impact of infrastructure investments on mobility and pollution), how to design interactive visualization interfaces supporting data filtering, exploration, analysis, and visual inspection aimed at the extraction of meaningful insights still represents a research topic, even though data visualization tools are used on an everyday basis for supporting decisions of various types on the planning, operation, and management of mobility systems. The demand for effective methods to analyze these data and extract meaningful information [1] has brought an extensive set of research in the big data area [7] and a more general consideration of the implications of interactivity and possibility to explore the effects of analytical tools on the achieved data visualization [2], leading to the definition of the term visual analytics.

User interfaces for the analysis of data, supporting them in the extraction of meaningful information, various fields, including natural resources and urban infrastructures, commonly employ map-based dashboards that incorporate elements like maps and geovisualizations [8,9]. These tools offer users a comprehensive view of geospatial information, helping them in making informed decisions [10]. They also increasingly provide effective methods to involve humans in the data exploration process, leveraging their perceptual skills and domain expertise to navigate and analyze datasets effectively, helping them to identify both anticipated and unforeseen patterns, and effectively communicate the results [11].

Map-based visual analytics tools support the presentation of a variety of data while also supporting visual learning and analytical reasoning related to geospatial information. These map-based analytical tools are developed with the aim to provide to citizens heterogeneous georeferenced information to comprehend the environment they live or work in [11]. Different map-based analytical tools serve different purposes: *real-time tracking and monitoring* [12,13] focus on live updates and immediate insights into ongoing events or movements, such as tracking vehicles, weather patterns, or real-time population movements; *historical data analysis* [14,15]; *predictive modeling and scenario planning* [16–18] use historical data to forecast future trends and scenarios, supporting decision-making processes related to urban planning, disaster preparedness, or resource allocation; *spatial analysis and queries* [19] enable users to perform complex spatial queries and analyses, such as proximity analysis, spatial clustering, or network analysis, to derive spatial insights and patterns; and *geovisualization and storytelling* [20–22] includes tools that emphasize visual storytelling and the effective communication of spatial data through interactive maps and visualizations, enhancing understanding and engagement of the final users.

However, developing map-based visual analytical tools presents unique challenges and limitations specific to each of the tool's intended purposes. Map-based dashboards typically prioritize real-time data display and updates, often lacking narrative elements. Additionally, achieving effective multi-perspective geovisualization, which involves visualizing data from various factors, demands the careful planning of dashboard layout, map elements, user interface, functionality, and interactivity. This complex process presents significant challenges.

Map-based visual analytic tools should enable users to leverage their full perceptual and cognitive abilities for analytical processes. To achieve this, these tools must be user friendly and comprehensible. Thus, it is essential that these tools undergo evaluation by their intended users [23]. Common methods used to evaluate map-based dashboards include surveys [24,25], expert interviews [26–28], think-aloud protocols [29–31], and eye-tracking techniques [11,32,33].

This paper focuses on the design and implementation of UrbanFlow Milano, a map dashboard incorporating user-centered design principles to comprehensively analyze shared-mobility data in the city of Milan. The dataset of shared mobility was acquired from Fluctuo (https://fluctuo.com/, accessed on 15 July 2024), a company specialized in collecting and providing access to shared mobility data from a large number of mobility service providers. Such data were acquired thanks to the MOST PNRR project funding (https://www.centronazionalemost.it/, accessed on 15 July 2024), within the context of the Next Generation EU program. The dataset does not include any personal data, and it is GDPR compliant.

The dashboard facilitates both simple tasks (e.g., identifying and locating) and complex analytical tasks (e.g., cluster identification and filtering) through intuitive spatiotemporal visualization and interactive experience. A user study employing think-aloud testing was conducted to identify usability issues and ensure the dashboard's effectiveness in diverse user scenarios. Additionally, it evaluates the feasibility of using a map-based dashboard for knowledge acquisition, with a focus on spatiotemporal patterns and correlations. To achieve the scope of this paper, we conducted a qualitative study to collect and analyze data on the dashboard's performance. Specifically, we assessed its effectiveness and efficiency by examining participants' behaviors while completing tasks.

Geospatial mapping techniques, such as those used by refs. [13,14], focus on visualizing spatial distributions through cluster markers and interactive exploration tools, providing insights into historical and event-based data by allowing users to zoom, draw regions, and search for locations. These methods are effective for understanding the geographical context and temporal distribution of data but primarily support static and aggregated views. *Dynamic and emotional mapping techniques*, exemplified by [15], utilize layered visualizations to represent the spatiotemporal emotional trends associated with locations. This approach integrates emotional and historical data, offering a nuanced view of how sentiments are linked to different locations over time, which is valuable for analyzing the intersection of cultural and geographical elements. *Interactive geospatial analytics* methods, such as those presented by ref. [16], employ dynamic geospatial maps to model and visualize COVID-19 spread. This technique includes interactive features like time sliders and linked views to facilitate detailed analysis of outbreak dynamics, enabling users to assess the impact of various interventions over time. *Scenario planning and economic impact analysis*, such as that employed in ref. [17], uses interactive maps to simulate and visualize the economic effects of potential infrastructure changes. This method integrates dynamic calculations and hedonic pricing models to provide real-time insights into property value changes, aiding in scenario-based decision-making. *Advanced visualization frameworks* as discussed by refs. [18,19] utilize libraries and frameworks like D3.js and WebGL to create interactive and 3D visualizations for complex datasets. These tools support the visualization of intricate spatial data, enabling interactive exploration and decision-making.

In contrast, UrbanFlow Milano employs OD Flow Maps, trajectory flow, and mobility chord diagrams to provide a comprehensive analysis of shared-mobility data. The OD Flow Map visualizes the movement patterns between origins and destinations, facilitating an understanding of mobility trends. Trajectory flow visualizes the paths taken by mobility users, allowing for the detailed analysis of travel behaviors. The mobility chord diagram illustrates the connections between different locations, highlighting the flow of users across various areas. Compared to existing techniques, UrbanFlow Milano integrates these methods to offer a dynamic, interactive, and user-centered approach to visualizing and analyzing mobility data, addressing gaps in existing tools by providing more granular and actionable insights into urban mobility patterns.

Finally, differently from the existing tools that may prioritize data presentation over user interaction, UrbanFlow Milano emphasizes user-centered design principles. By placing users at the forefront of the analysis process, the dashboard empowers them to actively engage with the data and discover meaningful insights. To evaluate the effectiveness of this approach, we conduct a comprehensive user study to assess the dashboard's usability, efficiency, and impact on decision-making.

UrbanFlow Milano introduces a visual analytics approach for shared-mobility data by integrating multiple map-based visualization techniques into a cohesive framework. This tool not only combines interactive maps, trajectory visualizations, and chord diagrams to address various analytical tasks but also emphasizes user-centered design through comprehensive usability testing. Unlike traditional methods that often focus on single aspects of data visualization, UrbanFlow Milano advances the field by offering a user-centric interface that supports both simple and complex analytical tasks. Its innovative application of spatiotemporal visualizations and iterative design improvements based on user feedback provide new insights into how mobility data can be effectively analyzed and understood, setting a new ground for visual analytics in urban transportation contexts.

In this paper we want to answer questions such as the following:

- RQ1. Is UrbanFlow Milano easy to be used (i.e., is easy to filter, and understand the graphical elements)?
- RQ2: Is UrbanFlow Milano as intuitive for every user, regardless of their experience in visual analytics?
- RQ3: Is an introductory guide necessary for users to fully utilize the UrbanFlow interface?

To effectively analyze and visualize complex spatiotemporal data within mobility systems, it is crucial to evaluate the usability and effectiveness of map-based visual analytics tools. In this paper, to ensure a thorough assessment of the UrbanFlow Milano dashboard's performance, we have established clear criteria for evaluating user experience, which include usability, intuitiveness, and the need for an introductory guide. These criteria are used to evaluate how easily users can filter and understand graphical elements, whether the dashboard is intuitive for users with varying levels of experience, and if an introductory guide enhances user interaction. By prominently addressing these evaluation criteria, we aim to provide a comprehensive analysis of the dashboard's effectiveness and to highlight areas for potential improvement.

2. Visualizing Mobility Data: Related Work and Visual Diagrams

In this section, we first discuss the related work on the user evaluation of map-based dashboards, and in the second subsection, we explore some leading techniques that support mobility data visualization.

2.1. Related Work: User Evaluation of Map-Based Dashboard

In this section, we review related work that evaluates map-based dashboards from a user perspective. The related work is organized into three categories: surveys, expert overviews, and think-aloud protocols along with tracking techniques.

Surveys offer a structured approach to gather user feedback on map-based dashboards. Ref. [24] focuses on the development and assessment of a geovisual analytics system called STempo. The system aims to assist users in analyzing event data related to social and political topics by providing tools for understanding known patterns and generating new hypotheses. The evaluation of STempo involved 25 users. The first task required users to understand a known pattern in a dataset, while the second task prompted users to develop new hypotheses based on a new dataset. Participants provided written responses to task prompts and survey questions to assess the system's effectiveness. The System Usability Scale (SUS) [34] was used to evaluate overall usability The survey results indicated that participants struggled with detailed analysis due to usability issues with the STempo interface. GeoFarmer system is presented in [35]. It is a monitoring and feedback tool in the agricultural domain. For the evaluation, it compares the performance of five questions in IVR (interactive voice response) surveys and five questions in face-to-face surveys using the GeoFarmer smartphone application by running them in parallel after the second training session with youth facilitators. Ref. [25] introduces SensePlace3, a geovisual analytics system for understanding spatiotemporal dimensions in real-time social media data. The evaluation of SensePlace3 involved assessing its usability and utility through a user study with participants recruited from a massive open online course. The usability metrics used were based on the System Usability Scale (SUS), feedback on the system components' effectiveness, and suggestions for improvements. Users highlighted the need for interactive help features, reduced complexity, and the better integration of tools like CoMatrix (which allows users to explore co-occurrence relationships between different types of entities, such as hashtags, Twitter users, dates, and location references).

Interviews offer a qualitative approach to understand user experience with map-based dashboards. Drosophigator is a tool discussed in [27] which focuses on supporting users in visual analytics for the spread dynamics of Drosophila suzukii, an invasive insect spreading Europe and North America. The system is presented to biologists and researchers in agriculture and horticulture, who provide valuable feedback. The system was evaluated through questionnaires filled out by participants. The questionnaire captured feedback on the visualization, interaction design, and analysis capabilities of the system. Additionally, participants were able to provide open feedback, expressing their thoughts and suggestions regarding the system. Ref. [36] introduces a unified visual interactive system and framework named Voila which is used for interactively detecting anomalies in spatiotemporal data collected from a streaming data source. The evaluation of Voila includes a quantitative comparison with baseline methods using human-labeled ground truths. Annotators manually labeled anomaly incidents in the Manhattan area over a six-month period, and the system's algorithm effectiveness was evaluated based on these labels. The study also involved feedback from a domain expert using NYC taxi-trip data, indicating the system's strengths and suggesting future improvements such as providing tutorials for non-expert users and enhancing anomaly ranking visualization. Ref. [28] instead discusses the development of a visual analytics framework called TPFlow used to explore multi-dimensional spatiotemporal data. It aims to help users in pattern discovery, comparison and verification through progressive partitioning and level-of-detail analysis incorporated into visualization. The evaluation of the system involved collecting feedback from domain experts who completed two case studies. The experts found the system efficient and effective for identifying meaningful patterns within data and verifying their reliability. They appreciated the partition interactions cababilities and highlighted unexpected patterns discovered using the system. Finally, UrbanMotion, a system designed for visual analysis of metropolitan-scale sparse trajectories, is presented in [37]. It focuses on understanding population movements in cities through visualization techniques tailored for urban planners, public safety officers, and business analysts. The system utilizes movement clustering and map matching to analyze global and local movement patterns, providing insights into commuting behaviors, etc. The evaluation of UrbanMotion involves case studies with domain experts from urban planning, public safety, and business analysis. Experts provided feedback on the system's positive and negative aspects, suggesting possible extensions to better meet their requirements. The system was compared with alternative visualization techniques through a qualitative lab experiment, highlighting its effectiveness in handling trajectory data with long-tailed temporal sparsity.

Think-aloud protocols involve observing users as they interact with a map-based dashboard and verbalize their thoughts. COPE is an interactive framework [26] which allows users to define and extract relevant events and explore co-occurrence patterns interactively, using three visualization components. Its evaluation consists of two parts: case studies and expert feedback with think-aloud tests. The expert feedback is gathered through a think-aloud protocol with 12 participants. The results show that experts valued features like trend lines, location sorting, and location search, which helped them in performing their analysis. Each participant engaged in a one-hour think-aloud session, where they interacted with the prototype while providing feedback. The study combined a qualitative coding methodology and a System Usability Scale survey to assess the readiness of the prototype for deployment. The results highlight the usability of the BubbleNet dashboard, leading to adjustments for operational deployment. Keshif, instead, is a tool for rapid and expressive tabular data exploration, displaying records in a list format and on a map with explicit interconnections and relations between numeric attributes [38]. The effectiveness of the tool was evaluated by assessing its ability to enable rapid insight discovery using a think-aloud protocol. Participants were tasked with exploring a dataset and identifying interesting patterns, trends, or insights while verbalizing their thoughts throughout the process. Despite having limited experience in visual data exploration, participants in the study averaged nearly 30 insights within 15 min. This performance is comparable to that achieved in other studies using more complex tools operated by skilled users.

Eye-tracking studies monitor participants' eye movements as they interact with a map-based dashboard. In [39], the authors explore different geospatial displays, specifically, weather maps, to assess the impact of design on performance and metacognition in geospatial tasks. Participants engaged in tasks comparing weather variables on different maps, with results showing higher accuracy on simpler maps. Participants viewed images presented on a computer screen while their eye movements were monitored using a head-mounted eye gaze tracking device. The results showed that the number of weather variables did not significantly impact accuracy, but the type of variable being compared did. Ref. [40] investigates how individuals view multi-component animated maps, specifically focusing on dynamic spatiotemporal displays. For the experiment, authors utilized an eye-tracker device to collect eye movement data. The research aimed to understand how users direct their attention to different modules and perceive presented information by comparing participants' viewing behaviors during a free examination task and a goal-directed viewing task.

A ***combination*** of different evaluation techniques is leveraged by some studies to gain a more comprehensive understanding of user experience with map-based dashboards. GeoVISTA CrimeViz [41] is a web-based mapping application for visualizing criminal activity. The evaluations include expert-based methods, such as think-aloud protocols with design experts, and user-based methods, like online surveys and feedback from target users. These evaluations leads to the identification of usability issues, programming bugs, and areas where interface functionality could be improved. Similarly, ref. [30] evaluates three map-based visual analytics tools using different user-centered methods. The evaluation of interactive maps for the visual analysis of criminal activities included both expert evaluation using the think-aloud protocol and user evaluation through an online survey. The main aim of this work was to identify various issues such as problems with the placement and visibility of important features like titles and legends, difficulties in interpreting data values, and challenges with interactive elements like selecting individual bars in the interface. Ref. [11] explores the feasibility and effectiveness of a map-based dashboard designed for spatiotemporal knowledge acquisition and analysis. The dashboard combines various types of geospatial data into an interactive interface that can be used for searching for specific locations, switching between different layers of data, and synchronizing views to provide a comprehensive understanding of the data. The evaluation used eye-tracking, benchmark tasks, and interviews. Participants completed six predefined tasks designed to assess their ability to identify specific values and summarize high-level knowledge. After completing the tasks, participants were interviewed to gather qualitative feedback on their experience with the dashboard. They rated the usability and confidence in their answers and listed design elements that were helpful or challenging.

Similarly to the above discussed works, our paper uses user-centered methods to evaluate the effectiveness and usability of our map-based dashboard. However, compared to the previous discussed work, our work differs in the (i) interface, (ii) data, (iii) functions and map types in the UrbanFlow dashboard, and (iv) tasks that users performed.

2.2. Related Work: Visual Diagrams

In this section, we explore the leading visual techniques for sustainable mobility data, resulting in a division into three categories: density, flow and relations. While dashboards often combine various visualizations, understanding the strengths of each type is crucial for optimal integration. For every graph, along with their use, potential interactive features are provided, as well as the key advantages and limitations to consider.

2.2.1. Density

This subsection presents various data displays to visualize the density of objects and events within a geographic area. These visualizations, common in city monitoring dashboards, are valuable for detecting anomalies in road traffic or public transportation. There are three types of density visualizations: cartograms, choropleth maps, and isosurfaces.

Cartograms (see Figure 1a for a schematic example) are a visualization technique that alters the size of areas on a map in proportion to the value of a selected variable. For instance, traffic congested neighborhoods can be represented in a stretched form to highlight dilated crossing times; conversely, neighborhoods with little movement can be shrunk. The technique has high visual impact and is therefore recommended not only for analysis but also for showcasing results. It clearly conveys differences based on the selected variable, but it is also important to note that this comes at the expense of accuracy. There are several types of cartograms, including Dorling, non-contiguous, and contiguous.

Dorling cartograms replace the original areas with simple geometric shapes such as rectangles and circles. The advantage of this approach is evident especially in the implementation phase, as these shapes are easily scalable with an algorithm. The same advantage also applies to non-contiguous cartograms, which simply scale the size of the areas, without considering the relationship with adjacent ones. On the other hand, contiguous cartograms maintain the connectivity of each cell with its neighbors, ensuring spatial relationships between areas. However, this comes with increased computational time due to the algorithm's complexity. Additionally, it is crucial to consider the perceptive factor. As ref. [42] highlights, while people can better evaluate differences between original and altered dimensions using irregular polygons like contiguous and non-contiguous cartograms, cartograms are generally challenging to interpret. When proportions are altered, it becomes challenging to pinpoint the exact location of a city or neighborhood on the map. Consequently, it can be useful to incorporate interactive features for exploring the map. The most common forms are pan, zoom, and hover. The former two allow the navigation of the map, while hover enables the visualization of labels showing the exact value of the variable, providing details that area alteration could only suggest.

Choropleth maps (see Figure 1b for a sample visualization of this type) are a visualization technique that uses pseudocolors to graphically display values of a variable within different geographic areas. These maps are effective in highlighting similarities and differences between selected areas; however, careful selection is crucial to avoid losing local information. Choropleth maps are convenient because private and public agencies frequently distribute data according to already existing parceling. These can include regions, provinces, municipalities, or neighborhoods. An essential element of a choropleth map is the legend, which should guide the user in reading the data to reduce the risk of misinterpretation. In this regard, there are some recommended design principles to follow when creating these visualizations [43]. Generally, it is best for choropleth maps displayed online to use color scales ranging from dark to light, and light to dark for printed versions. Density values are preferable to absolute values. For instance, it is better to use the number of inhabitants per km^2 rather than the total number. In cases where this is not feasible, it is important for the areas to be at least similar in size. Vast regions might show high values simply due to their size, without indicating any uniqueness in terms of variable concentration. It is also advisable to use discrete rather than continuous color scales, as the latter may be more difficult to interpret. As with most map visualizations, choropleth maps often employ interactive features for exploration. A popular form is hover, which can be used to display labels containing the value taken by the variable in the selected geographic area. Panning allows users to navigate the map, while mouse wheel movement enables zooming in and out on specific areas.

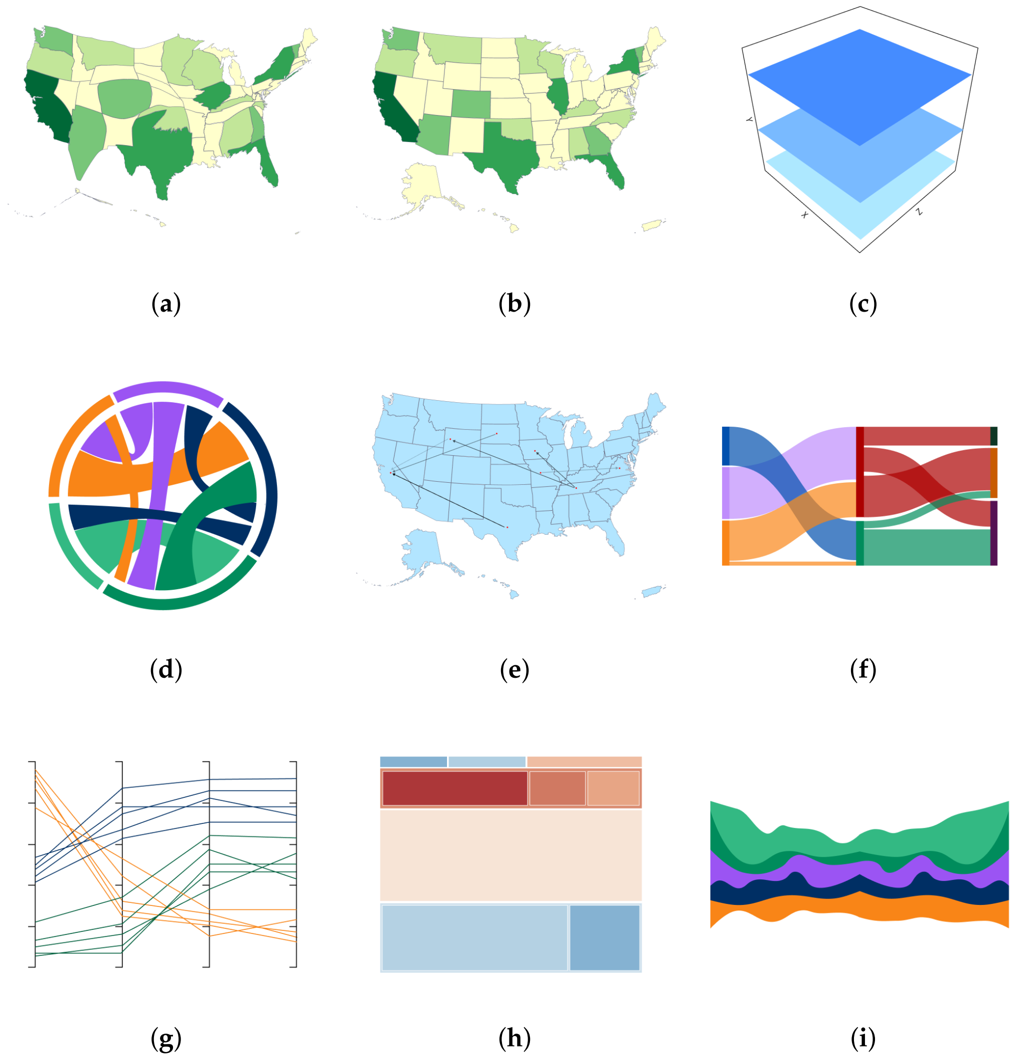


Figure 1. Examples of discussed forms of data visualization approaches. (**a**) Cartogram; (**b**) choropleth map; (**c**) isosurface; (**d**) chord diagram; (**e**) flow map; (**f**) Sankey diagram; (**g**) parallel coordinate plot; (**h**) spatial treemap; (**i**) ThemeRiver.

Isosurface (see Figure 1c for an example of this type of data visualization) is a three-dimensional visualization technique used to analyze phenomena that develop over space and time. It selects points whose value equals a specific threshold (isovalue) and represents them as a three-dimensional surface. The effectiveness of such a technique is particularly evident when accompanied by interactive interfaces that allow the figure to be rotated, thereby facilitating in-depth analysis. In the context of mobility data, a top view can help visualize the geographic distribution of traffic, while a side view facilitates the analysis of peak concentration times. It is important to note the limitations of isosurfaces when no restrictions are applied [44]. In standard visualization, surfaces are generated continuously over the entire land surface, ignoring road network constraints. As a result, traffic involving parallel but unconnected roads might be represented as a single and unified element. Constrained isosurfaces address this limitation but are also more complex to generate.

2.2.2. Flow

This subsection presents visualizations that depict the movement of people within cities, encompassing private vehicle travel, commuter journeys through public transportation systems, and shared mobility services. Such visualizations are valuable for understanding the urban context and users' behavior, thereby promoting efficient and sustainable forms of mobility. Also for the flow visualization we can distinguish chord diagrams, flow maps, and Sankey diagrams.

Chord diagrams (Figure 1d shows an example of this type of graph) are graphical tools that utilize a circular layout to visualize relationships and flows between different entities. This design can potentially reduce the length of connections and consequently decrease visual clutter [45]. Nevertheless, research indicates that people often find them more difficult to interpret than Sankey diagrams, which are linear. In a study where participants were exposed to both types of diagrams, the majority expressed a preference for Sankey diagrams [45]. They also made fewer mistakes and completed tasks more quickly. Despite the users preference, chord diagrams still offer valuable applications in several areas. For instance, in mobility-related fields, they have been used to analyze people's movements between different districts in Chengdu, China [46]. This flexibility extends to the design of the diagrams themselves. There are numerous versions of chord diagrams that incorporate bar charts or other tools to add domain-specific information. Some variants use visual cues to distinguish between incoming and outgoing flows, for instance, by leaving a blank space at the end of the link, while others rely solely on color coding. Individual links are often grouped together to form bundles with sizes proportional to the flow intensity between two nodes. The coloring of the links groups, for instance, provinces into macroregions, shifting the visualization's focus towards a higher hierarchical level. To address the interpretability limitations of these graphs, it can be useful to introduce some forms of interaction. For instance, clicking can be used to filter links.

Flow maps (a sample flow map is shown in Figure 1e) are cartographic tools that depict the movement of people or goods between locations using lines. They primarily use arrows to indicate the destination but can also express it through a variation in the curvature of the line itself [47]. The simplicity of flow maps makes them intuitive even for users without specialist knowledge. Understanding the overall flow is achieved by simply observing the features of the arcs connecting the origin and destination points. The only complications arise when the interchanges between nodes are particularly numerous, leading to visual clutter. To address this, nodes can be grouped into bundles or directed lines, where arrows indicate the destination of the link. Flow maps can encode additional information, such as flow volume, through the width or color of arcs. These visualizations can be constructed even with low-granular data. To create a basic flow map, only the starting and ending points are required. The visualization does not necessitate information about the entire route crossed during the displacement. For instance, this means trips of two drivers who traveled different routes but started and arrived at the same locations will be represented identically. It is important to note that link clustering, a common method for creating these maps, also results in some loss of information. These aspects are not necessarily disadvantageous; they can rather be useful if the goal of the visualization is to obtain general information. Flow maps can embed various interactive features. Hovering on a link may reveal details like origin, destination, and volume. Clicking on a specific node can isolate it from all others, providing an additional way to explore the data compared to classic filtering options like radio buttons, checkboxes, and sliders.

Sankey diagrams (an example is shown in Figure 1f) are widely used visualization tools, especially in physics and engineering, for representing state changes and flows over time [45]. These diagrams consist of nodes (states) and connecting links (flows), with the link color typically matching the source node for easy identification Beyond the contexts above, these diagrams also prove useful in visualizing urban mobility, such as passenger movements between subway stations. There are some considerations to be made in order to create effective Sankey diagrams [45]. The number of nodes and links should be limited to avoid visual clutter. Sankey diagrams are also most effective when links proceed hierarchically in a single direction, without forming loops. If points appear multiple times in the graph, such as being both starting and ending nodes, the interpretation would become more complex. It is also crucial to keep the opacity of connections low to enhance graph readability. When connections between nodes overlap, high opacity would prevent background links from being seen. Moreover, Sankey diagrams benefit greatly from interactive features. Alongside displaying the descriptive label of the connection upon hovering, it can also be useful to employ features to aggregate the nodes. For instance, utilizing tools such as the box select feature provided by the Plotly (https://plotly.com/python/sankey-diagram/, accessed on 15 July 2024), users can draw boxes to select entities for aggregation. This reduces complexity and allows them to focus on specific details. The interactivity of the library also extends to the ability to move visualization objects and arranges them in the most suitable order for future figure publication.

2.2.3. Relations

This subsection presents a series of visualizations useful for identifying relationship within mobility datasets. These relationships might reveal insight into different traveler profiles, such as subscribers versus occasional users, and the related statistics regarding their trips on shared vehicles. Furthermore, by examining the relationships between time coordinates, like day of the week and time of day, mobility data usage can also be informative. Such analysis can benefit not only companies operating sharing services but also public agencies responsible for planning and integrating various forms of sustainable mobility.

Parallel coordinates plots (Figure 1g shows an example of this kind of plot) are designed to represent multidimensional data on a Cartesian plane. Each data attribute has its own vertical axis, while the entities are delineated by the lines connecting these axes. This approach is particularly useful for identifying clusters and relationships within datasets. However, they present at least two challenges [48]. Firstly, those unfamiliar with this technique may find it difficult to interpret. Secondly, there is a risk of visual clutter, as displaying numerous entities and attributes simultaneously can lead to overlapping lines. In this regard, the use of interactive interfaces can provide valuable assistance. The specific interactions available depend on the visualization algorithm used. For instance, in the version implemented by the Plotly library (https://plotly.com/python/parallel-coordinates-plot/, accessed on 15 July 2024), users can select a subset of detections by drawing a vertical line on the axis from which the desired detections are to be filtered.

Spatial treemaps (Figure 1h shows a sample map of this kind) are visualizations consisting of rectangles nested according to their hierarchical level. They are similar to traditional treemaps but have the distinction of having a spatial entity as the first hierarchical level [49]. In the example from [49], the hierarchy has four levels: city area, transportation used, day, and hour. The data, sourced from the GPS on board of eCourier vehicles, are represented using colors to indicate the average speed. Treemaps become confusing as the complexity of the data increases, so it is advisable to limit the hierarchical depth to be displayed or to implement appropriate interaction modes. Clicking can be used to select a subset to view in full-screen mode for more detailed analysis. Hovering, on the other hand, can be used to display the information associated with each subset or element of the dataset.

ThemeRiver (Figure 1i presents an example of this kind of visualization) graphs are used to visualize the thematic variations within a corpus of texts. They use the visual metaphor of a river to show the evolution of each theme's popularity over time. The colors make it possible to distinguish and follow the flow of each "river", intuitively identifying the macro-trends. On the other hand, it is more difficult to identify the smaller themes and to understand the actual dimensions of the observed phenomena, as there is no vertical axis to help in reading. ThemeRivers, a variant of stacked graphs, are characterized by their smooth, continuous curves. One of the main advantages of these graphs is their continuity [50]. If we wanted to represent the same time series with stacked bar graphs, we would be forced to use numerous disconnected bars, each corresponding to a unit of time. Consequently, the user would have to manually perform the information integration operation to follow the evolution of each unit, slowing down the process. In addition to analyzing the thematic variation in the text, ThemeRiver graphs can also be applied to human mobility data. One of the most common interactions for this type of graph is to use hover to display the values associated with the amplitude of each "river".

3. Design of the Dashboard

In this section, we present an interactive and web-based mapping application that supports spatiotemporal visual analytics of mobility data in the Milan metropolitan area. The prototype is called ***UrbanFlow Milano*** (https://urbanflowmilano.streamlit.app/, accessed on 15 July 2024) to reflect the goal of its visualizations, which is to offer a tool for analyzing mobility flows in Milan. The application consists of four pages: Introduction, OD Flow Map, Trajectory Flow Map, and Chord Diagram. Each page is composed of two sections, with the sidebar on the left and the visualization panel on the right. The sidebar allows users to select the page and, depending on the type of representation, set the corresponding parameters to filter the data. The right section displays the selected data. The interface is designed for desktop use and includes navigation through a dropdown menu. The first page displayed upon launching the application is the introduction page, which serves to present the application to the user, clarify key concepts such as NIL (i.e., the *Nuclei di Identità Locale—an administrative subdivision of the municipality that can be associated to the notion of neighborhood and district; Milan is subdivided in 88 NILs, of quite different sizes*), and provide a guide for using various features. In the following, we present the four pages of UrbanFlow Milano.

3.1. OD Flow Map

The OD flow map (Figure 2) is an interactive visualization for analyzing flows between different NILs in the municipality of Milan.

Various graphical elements were used for this purpose: points, lines, arrows and pop-ups. The map was created using the Folium library (https://python-visualization.github.io/folium/latest/, accessed on 15 July 2024), with Mapbox's dark style applied to make links stand out. The points identify NILs and are placed at the coordinates of their centroids. Each point is characterized by a unique color to facilitate its recognition and to identify the links it generates. The lines are drawn with Folium's PolyLine function and connect the origin centroids with the destination ones. Their color matches that of the origin NIL, while the opacity is calculated by the ratio of trips for a particular pair of nodes to the monthly total number of trips for all NILs. Arrows at the end of the lines indicate flow direction. The pop-up panel is activated by clicking on the NILs. For each NIL, it shows the top three origins and destinations along with their associated number of trips. The number and opacity of lines and arrows are adjusted based on the following selections in the sidebar:

- **Incoming/Outgoing link filter:** Allows users to choose whether to filter incoming or outgoing connections.
- **Maximum number of incoming/outgoing links:** Limits the number of links (connections) leaving or arriving at each node. To avoid visual clutter, the value is set to three by default.
- **Minimum opacity of links:** Allow users to customize the minimum opacity of links; its default value is 0.05. Increasing this value enables the display of links that would otherwise be hidden.

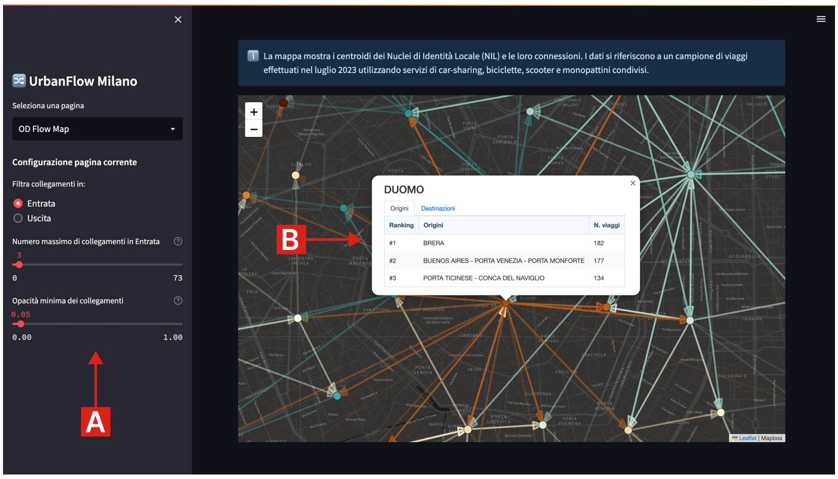


Figure 2. OD Flow Map interface: The sidebar (**A**) allows users to filter the map. The pop-up panel (**B**) shows trip ranking and can be activated by clicking on the NIL centroids.

3.2. Trajectory Flow Map

The Trajectory Flow Map (Figure 3) visualizes individual trip trajectories for shared transportation within Milan.

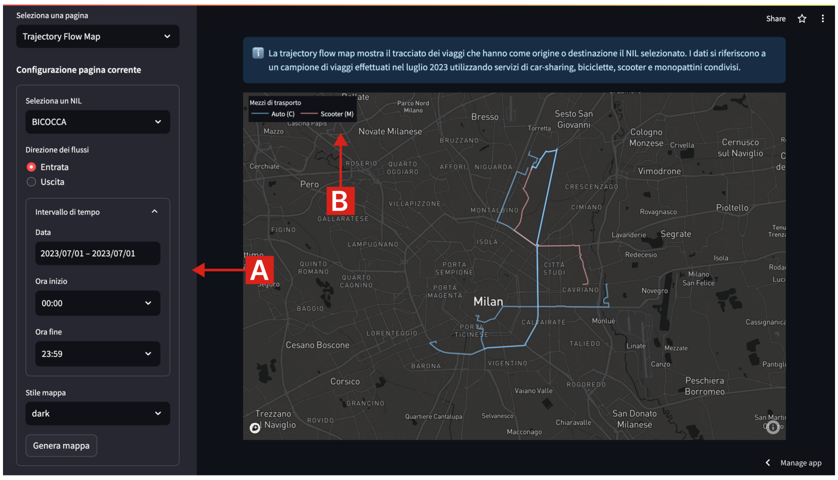


Figure 3. Trajectory Flow Map: The sidebar (**A**) allows users to filter data and choose the style map to display. The legend (**B**) enables filtering trips by vehicle type.

Like the OD Flow Map, it uses Mapbox Dark Map as the default. However, Plotly (https://plotly.com/python/, accessed on 15 July 2024) is chosen as the reference library due to its capabilities in handling data in linestring format. To avoid visual clutter and focus the mobility analysis on individual NILs, the data representation is limited to one NIL at a time. Selecting the origin or destination of interest and pressing the "Generate map" button triggers the visualization panel to display lines corresponding to the trip trajectories. These lines are colored based on the used vehicle type. Although the application initially shows all vehicle types, users can filter them through the legend. Other filters and customizations are listed below:

- **Select a NIL:** This feature allows users to choose a specific NIL to view its associated trips.
- **Flow Direction:** This option enables users to select to view trips entering or exiting the selected NIL.
- **Time Range:** Users can customize the time range of the displayed data by specifying the start and end dates and times.

- **Map Style:** Users can personalize the map's appearance according to their preferences. Available options include dark, light, satellite, and OpenStreetMap styles.

3.3. Mobility Chord Diagram

Unlike previous representations based on maps, in this case, the mobility between the different NILs in Milan is showed by a graph (Figure 4). Chord Diagram allows the connections between nodes to be represented by arcs of different sizes. The width of these arcs denotes the number of trips, while the colored circles at the edge indicate the associated NIL. The Holoviews library (https://holoviews.org/, accessed on 15 July 2024) is used to implement the visualization, while Bokeh (https://bokeh.org/, accessed on 15 July 2024) is chosen as an extension due to its interactivity capabilities, which Matplotlib lacks in the context of chord diagrams. One of the limitations of this type of chart is that it fails to provide an accurate impression of the extent of the displayed flows. For this reason, the page includes a tab that allows user to switch the type of visualization. In this way, it is possible to identify the most important flows by the graph's arcs and then read the actual magnitude of the flows through the table. The user can decide which data to display by setting the following two filters:

- **Vehicles to display:** This option allows user to select the type of vehicles to be displayed in the graph, choosing from car sharing, bicycles, scooters and motorcycles.
- **Minimum number of trips between two NIL:** This option allows the user to display only those links that have a number of trips equal to or greater than the selected number.

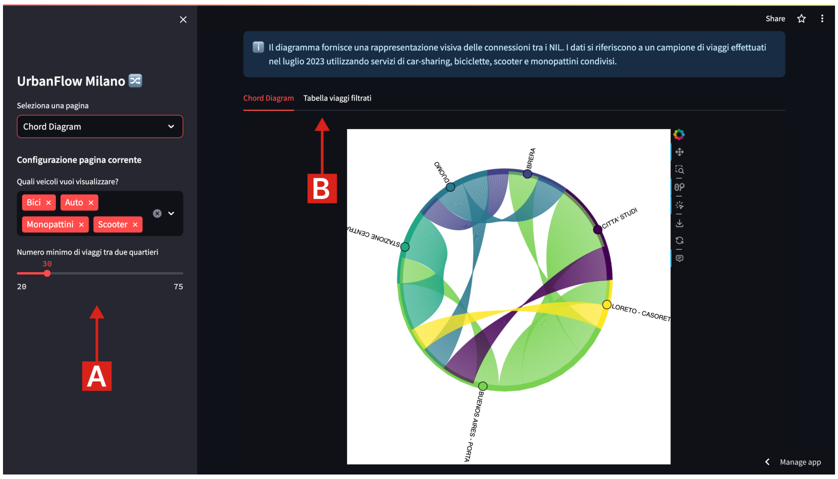


Figure 4. Chord Diagram: Sidebar for filtering data (**A**); tab that allows switching between graph and table views (**B**).

4. Design of the Evaluation Experiment

In this section, we introduce the design of the experimental settings to evaluate the user accessibility of the three newly designed maps of the UrbanFlow Milano dashboard. The aim of this experiment is to identify potential usability issues and gather user feedback.

4.1. Context Definition

Firstly, we need to define the context, i.e., information gathered about the *dataset*, the *prototype*, and the *type of the experiment* for which we are evaluating the UrbanFlow Milano dashboard.

Dataset: The dataset utilized for this study is provided by Fluctuo, a French company specialized in collecting shared mobility data, and includes trip records for Milan throughout 2023, organized in different files by month. The dataset records a total of 360,247 trips for July, categorized by vehicle type as follows: 174,712 Moped (M), 131,597 Car (C), 44,390 Scooter (S), and 9548 Bike (B). The mean trip duration is 9.53 min, and the mean trip length is 4372.57 m. On average, there are 4144 departures and arrivals per NIL. It aggregates information from the main shared mobility operators active in the city and includes several attributes describing the trips: travel ID, start and end dates and times of the trip, type of vehicle used, estimated duration of the trip in minutes, estimated distance traveled in meters, latitude and longitude of the starting and ending points, and an estimate of the route traveled during the trip. These trips are estimations of the real trips, reconstructed using the Valhalla (https://github.com/valhalla/valhalla, accessed on 15 July 2024) library's route generator.

While the dataset contains a rich set of information, this prototype focuses primarily on geospatial data, such as the geographic coordinates of the trip's start and end points, as well as the route. Therefore, information related to the duration and distance traveled during the trip is omitted. For the scope of the experiment, a sample of July 2023 data is selected. These data are then processed to enable aggregation for visualization purposes. For each trip, based on the departure and arrival coordinates, the corresponding NIL and the coordinates of the centroid of the NIL is calculated. *Prototype:* The UrbanFlow dashboard prototype aims to provide a tool for analyzing mobility flows within Milan. The application is structured into four pages: *Introduction, OD Flow Map, Trajectory Flow Map, and mobility chord diagram*. Each page consists of two blocks, the sidebar on the left and the visualization panel on the right (see Section 3). It has different options to filter, aggregate, or cluster mobility data.

Type of the experiment: For the scope of this paper, we conduct an evaluation of our prototype by the think-aloud method. In the think-aloud test, participants use the prototype to accomplish a task while verbalizing their thoughts, providing real-time insight into their user experience. This method reveals their perceptions and misconceptions about the design, offering actionable recommendations for improvement. By understanding why users misinterpret certain elements and find others intuitive, designers can make adjustments to enhance usability and overall user satisfaction during free exploration and a post-survey.

4.2. Task Definition

Different dimensions of the prototype's usability can be assessed through various tasks using the think-aloud test. In this experiment, the tasks are designed to evaluate the comprehensibility of the graphic elements and the usability of the interactive features. For each map, we propose specific tasks. The tasks are presented as action statements to be executed by the participants. Table 1 summarizes the map along with its corresponding task statements. The execution of these tasks involves different cognitive operations, dashboard interactions, and data availabilities.

4.3. User Profiling and Recruitment

To determine the recommended sample size for identifying issues in the user interface, similarly to [30], we use the sample size calculator available at MeasuringU (https://measuringu.com/calculators/problem_discovery/, accessed on 15 July 2024). This tool estimates the number of participants required to uncover a specified percentage of total issues. The calculator employs the Good–Turing and normalization procedures, and its calculations are based on the binomial probability formula [51]. Based on this formula, to discover 95% of the interface issues, we would need to test an average of 14 users. This calculation assumes that the probability of encountering any given problem is 20%. It must be noted that, although the number of users that performed the experiment is too low for performing a study having proper statistical relevance and power, our main goal for this experiment is to identify most issues in our user interface from both expert and non-expert users of mobility visualization tools, especially the most frequent and substantial issues hindering the effectiveness of the visualizations and overall visual analytics system. It must be stressed that the largely adopted heuristics in the Research-Based User Experience industry suggest performing frequent small user tests throughout the design and development process (see Jakob Nielsen's article on this point suggesting running tests with just five users—https://www.nngroup.com/articles/why-you-only-need-to-test-with-5-users/, accessed on 15 July 2024), so this practice is not uncommon in the field.

Table 1. Tasks users performed for each type of map.

	Task
OD Flow Map	Identify a connection with many trips and one with few trips
	Get more detailed information about the Brera hub.
	Which NIL ranks second in the origins list?
	Which NIL ranks third in the destinations list?
	Set the maximum number of incoming connections to 10.
	Is there an imbalance in the concentration of trips across different city zones?
	Set the number of outgoing connections to 1 and adjust the opacity according to your preferences.
Trajectory Map	Display the outgoing trips from Bovisa from July 1 to 15.
	Display only the Scooter trips.
	Expand the view to full screen.
	Download the view as a PNG.
	Identify the roads with high and low traffic levels.
	Display the incoming trips to Central Station on July 4 from 10 a.m. to 12 p.m., using the satellite map.
Chord Diagram	What do the arcs represent?
	What do the points on the edge of the circle represent?
	Set the minimum number of trips to 20 and filter to display only Bike and Scooter trips.
	Identify the NIL with the highest and lowest number of trips.
	How many trips were recorded between Loreto and Buenos Aires?
	Return to the graph and display only the connections related to Sarpi.
	Set the minimum number of trips to 30 and identify the NILs with the most and fewest trips.

Since acquiring the impressions and points of view of both expert and non-expert users of mobility visualization tools is a primary requirement of the study, we recruited a balanced sample of participants with varying levels of expertise.

The participants were students and researchers of the University of Milan-Bicocca, Italy. The experiment took place between February and June 2024. Table 2 presents the distribution of participants, including information about their gender, level of education and experience in the field of cartography and web maps. Participants interacted with the prototype remotely using their computer's web browser. The user were asked to share the screen and comment on the execution of each task.

4.4. User Study Composition

The user survey would take on average around 25 min to be completed. For half of the users taking the experiment, we recommended to read a guide (called the guided group) which explained how the dashboard worked and some information on the features of the map-based visualization we implemented into UrbanFlow Milano. The other half consisted of users who did not read the guide (called the not-guided group). The experiment was designed in two parts. In the first part, we asked users three background questions in the form of choosing the best answer which described them. The second part was about task execution.

Table 2. Background information about users participating in the study.

Gender Distribution	Male	9
	Female	5
Level of Education	High school	3
	Bachelor degree	6
	Master degree	2
	PhD or higher	3
Expertise	Experts	7
	Non-experts	7

4.5. Evaluation Metrics

User performance was evaluated based on their ability to complete tasks independently. Tasks were categorized as successful if participants completed them without assistance, or as failures if they required help. Qualitative analysis included using a predefined set of questions to investigate user behaviors and system characteristics.

5. Evaluation Results

In this section, we present and discuss the results of the user study. This section is divided into three subsections, one for each map.

5.1. OD Flow Map

The think-aloud test revealed no issues in any of the seven tasks evaluating the usability of the OD Flow Map. Participants from both groups, whether they read the guide or not, were able to complete the tasks successfully. The ease of using this interface was evident across all participants in the user study, regardless of their knowledge and experience in data analytics and GIS.

However, five participants did provide suggestions for improving the OD Flow Map. One participant recommended enhancing the color differentiation to make it easier to distinguish between different data points. Two participants preferred entering numbers using the keyboard instead of using a slider. They suggested incorporating keyboard input as an option. Another user wanted to see the area of the NIL instead of centroids. Lastly, due to limited color options, one participant suggested using line patterns (such as dashed lines) to differentiate data. This change can help avoid confusion between the color and the opacity.

5.2. Trajectory Map

For the Trajectory Map interface, we provided participants of the think-aloud test with six different tasks. However, users experienced difficulties in completing only three of these tasks, as shown in Table 3.

More specifically, for the task of displaying only scooter trips, two participants could not complete the task because they could not find the legend to filter the trips and select only the scooter ones. This issue was evident only among participants in the group without a guide, whereas those in the guided group had no problems completing the task, achieving a success rate of 100%.

Table 3. Problems identified in the Trajectory Flow Map.

Task	Problems	S. Rate with Guide	S. Rate without Guide
Display only the Scooter trips	Participant did not find the legend (2).	100%	71%
Download the visualization as PNG.	Participant did not find the icon to click on (2).	86%	86%
View incoming trips to Central Station on July 4 from 10 a.m. to noon by choosing the "satellite map".	Participant did not find the map selector (1).	100%	86%

A second problematic task was downloading the visualization as a PNG file. Two participants were unable to complete this task because they could not find the icon to click on. Interestingly, one of these participants was from the guided group, while the other was from the group without a guide. As a result, the success rate for this task was 86% in both groups.

The final task that posed a challenge was the visualization of incoming trips to Central Station on July 4 from 10 a.m. to noon using the "satellite map" option. One user was unable to complete this task because he could not find the map selector. This difficulty was encountered by a participant from the group without a guide, resulting in a success rate of 86% for this group.

Despite struggling to complete a few of the tasks, participants had some suggestions to improve the interface of the Trajectory Map. In particular, one participant mentioned that he expected to find the satellite view option in a different location and that the dark map style reminded him of a font rather than a map. Another suggestion was to use a vertical checkbox for filtering options, as it would be more visible compared to the current legend. Additionally, they recommended using different line styles, such as dashed, dotted, and solid lines, to indicate the type of vehicle used, instead of relying on color. However, for this change, another participant suggested the opposite, as he noted that replacing color with dashed lines might be counterproductive, as continuous lines could obscure the dashed ones. This user also suggested enlarging the legend to make it more readable. Several users found the opacity settings confusing and suggested making the opacity more evident to highlight travel concentrations better. They also noted that it was only after enlarging the map that they understood the varying concentrations of trips. Participants suggested removing the option to input text in the sidebar menu and making error messages more meaningful. Finally, they recommended placing the table next to the chart for better clarity and usability.

5.3. Chord Diagram

The think-aloud test included six different tasks for the participants to complete with the Chord Diagram visualization. Similar to the Trajectory Map interface, participants encountered difficulties with only three of these tasks (refer to Table 4).

Table 4. Problems identified in the mobility chord diagram.

Task	Problem	S. Rate with Guide	S. Rate without Guide
What do the arcs identify?	Participant gave an incorrect answer (6).	57%	57%
What do the dots on the edge of the circle identify?	Participant gave an incorrect answer (1).	86%	100%
How many trips were recorded between Loreto and Buenos Aires?	Participant did not see the tab to open the Table view (8).	43%	43%

The first task that participants struggled with involved identifying what the arcs represent. A total of six participants, three from each group (with and without a guide), were unable to complete this task successfully. The difficulty was mainly related to the colors, which were too similar and resulted in confusion among participants. Moreover, some of them erroneously believed that the flow volume between the NILs was represented by the overlap of the arcs in the center of the figure.

Additionally, one participant provided an incorrect answer when asked to identify what the dots on the edges of the circle represent. He described them as the geographic positions of NILs. This participant was from the group with the guide.

Finally, the task with the highest number of participants unable to complete it involved determining the number of trips recorded between Loreto and Buenos Aires. In fact, from 14 participants taking this user study, 8 had problems completing it, 4 from each group. All participants that could not complete the task could not see the tab to open the table.

Participants provided several suggestions for improving the Chord Diagram visualization. Some users with ultrawide 27 monitors found it easier to complete the tasks, as they could view all functionalities on the screen. They noted that on smaller monitors, the tab to open the table would disappear, making navigation more challenging. A suggestion was made to place the table next to the chart to create a more connected and cohesive display, enhancing the user's ability to analyze data.

Additionally, it was suggested to change the label for opening the table, as the current one caused confusion. Users felt that the Chord Diagram provided limited information compared to a simple table, and integrating these two elements more effectively could enhance clarity. Several participants did not understand the meaning of the arcs in the Chord Diagram, with some thinking they should focus on where the arcs overlapped in the center of the diagram. This confusion highlighted the need for better explanatory labels or guides.

6. Qualitative Analysis

While the research questions we faced in the paper were essentially about the usability of the proposed forms of data visualizations, we want to show some forms of qualitative analyses that the present prototype already supports. Thus, in this section, we present various forms of data exploration from a visual analytics perspective, which highlight some initial insights into shared mobility in the city of Milan during the studied period.

6.1. OD Flow Map

We start by showing a set of screenshots of the OD Flow Map visualization, presented in Figure 5: the depicted data are about the whole month of July, 2023. Figure 5a presents an initial visualization centered on the city center, extending to areas where connections between NIL centers are sparse, indicated by minimal represented travels.

This map shows that the usage of shared mobility services in Milan drops when moving from the city center towards the periphery. While this might already represent a pattern worth considering, this picture per se is not sufficiently informative. By interacting with the map, however, the user might access the top origins from which travels reach a given NIL and the top destinations of travels originated from that NIL. Figure 5b shows, for instance, that travels from the Duomo NIL mostly reach the Brera NIL (city center district, with relevant cultural/artistic points of interest, and some popular nightlife venues—over 2000 trips), Buenos Aires NIL (city center, with relevant commercial areas—about 1750 trips), and Porta Ticinese NIL (city center, with several tourist attractions as well as a popular nightlife area—about 1340 trips). A nearby NIL, Porta Vigentina depicted in Figure 5c, slightly south of the Duomo NIL, interestingly originates fewer than 750 trips towards the Duomo NIL, slightly more than 500 towards the Porta Ticinese NIL, and fewer than 450 towards the neighboring Porta Romana NIL. Despite being central, it is an object of much lower demand (both in terms of trips having origin or destination in the NIL). Comparatively, the Central Station NIL—shown in Figure 5d (in which Milan's Central Station is situated but that is slightly farther from the city center and that is much less interesting from the cultural/artistic point of view)—is the origin of over 2400 trips towards the Buenos Aires NIL, over 1200 towards the Brera NIL, and about 1200 to the Duomo NIL. The "light" and complementary nature of Mobility as a Service is reflected in these data, showing that many travelers (probably from outside the city) have an additional choice to use public transport, and that their destinations are mostly related to touristic attractions, commercial areas, nightlife, or work-related venues located mostly in the city center. The demand for shared mobility services does not appear strictly tied to the distance from the city center.

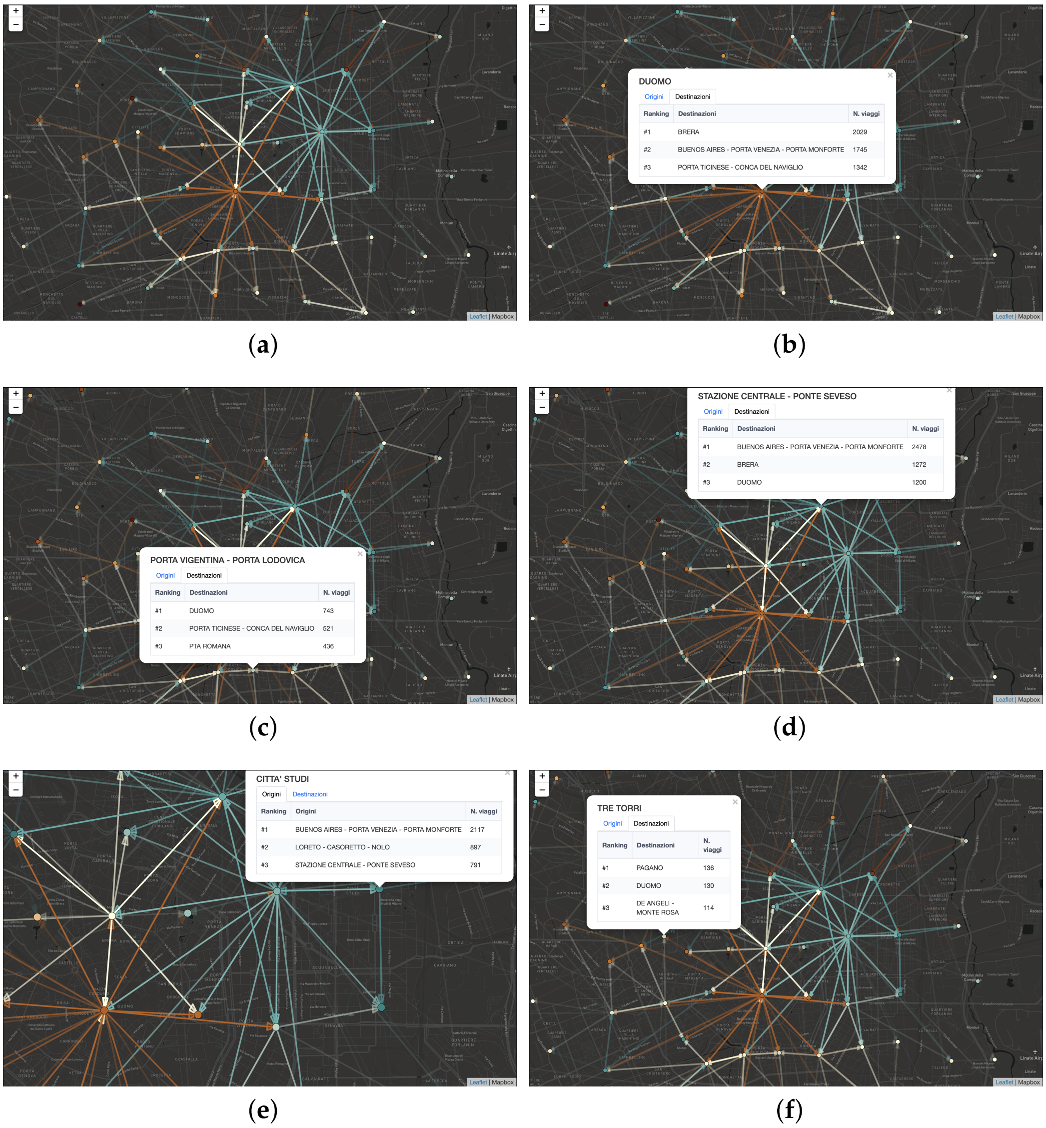


Figure 5. OD Flow Maps from different NILs. (**a**) Overall O/D map; (**b**) Duomo top destinations; (**c**) Porta Vigentina; (**d**) Stazione Centrale; (**e**) Città Studi; (**f**) Tre Torri.

The above statement is further supported by Figure 5e, which shows travels originating from the Città Studi NIL, which houses various university buildings including the Leonardo campus of Politecnico di Milano. The number of trips originating here is significantly higher than those from the more central Porta Vigentina NIL mentioned earlier. The most frequent destinations from Città Studi are Buenos Aires NIL (over 2100 trips), Loreto NIL (which hosts a major subway station where two lines intersect—about 900 trips), and Stazione Centrale NIL (about 800 trips). The comparatively more central Tre Torri

NIL (hosting a recent modern residential development including some iconic skyscrapers) sees a much lower travel demand as shown in Figure 5f. The top three most frequent destinations have fewer than 500 trips combined, and the associated district has clearly not become a pole of attraction in a poly-centric urbanization perspective. This second form of qualitative analysis also shows the potential for the integration of POI (and potentially also associated popularity) data for supporting the interpretation of interactive visualizations about mobility.

The OD Flow Map therefore represents a useful tool to investigate combinations of structural spatial elements of the considered urban context and travel demand, already providing insights that could be combined with background information about the considered districts, also acquired by means of integration with Knowledge Graphs and datasets of Points of Interest.

6.2. Trajectory Flow Map

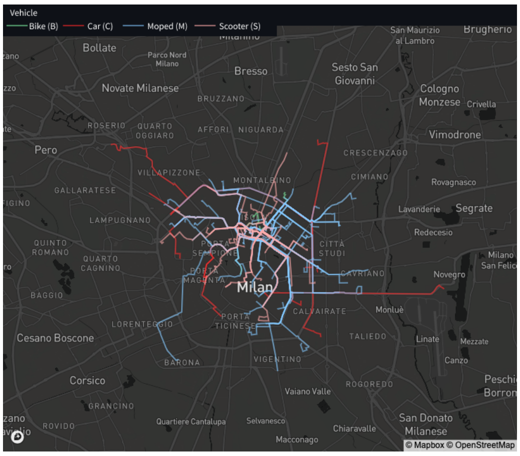
The Trajectory Flow Map supports more fine-grained forms of analysis, involving specific trajectories as well as distances covered by displayed trips, potentially filtered for time intervals.

Figure 6 shows some sample Trajectory Flow Maps, and the associated data in terms of number of trips subdivided into the different modes are provided in Table 5. In particular, let us consider that on 7 July 2023 (a workday, in particular, a Friday), there was a strike of employees of the local public transport company in Milano. During the time frame between 8:45 and 15, there was no guarantee that surface lines and subways were working, while the trains (both long distance and regional ones) were not affected. Figure 6d shows trips originated by the Garibaldi—Porta Nuova NIL between 8:15 and 15:30 on that date: it shows that all travel modes were actually employed, although shared cars and scooters were used for longer trips than mopeds and bikes (that represent the least-adopted shared vehicle). It can be seen that the destinations are mostly within a ring around the city center, reflecting the concentric layout of the city and employing the radial street plan for travels moving towards the periphery; however, few travels end up in the peripheries (in agreement with the considerations proposed in Section 6.1).

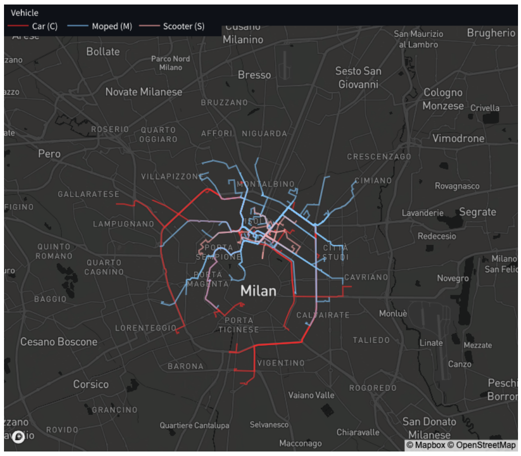
Table 5. Trips subdivided by travel mode originated by the Garibaldi—Porta Nuova NIL in different dates in 2023 (8:15–15:30).

Travel Mode	June 29	June 30	July 6	July 7	July 20	July 21
Car	16	19	22	21	23	18
Moped	74	36	65	64	69	49
Scooter	27	9	18	19	19	11
Bike	4	0	2	6	7	1

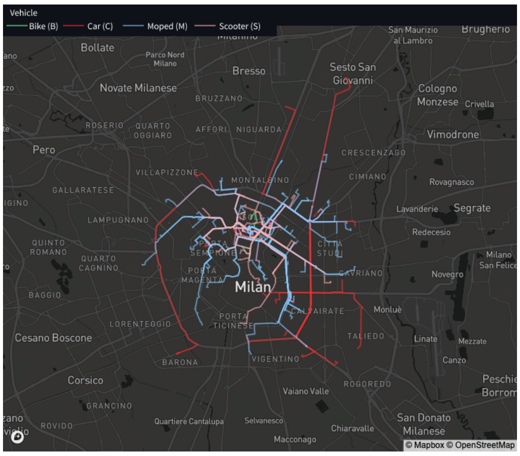
It is particularly interesting to compare first this map to the one associated to the same time frame of June 30, one week before, shown in Figure 6b: apparently there were fewer trips, and bikes were not employed. Considering July 6, the day before the strike and a Thursday, shown in Figure 6d, the number of trips seems quite similar, although with some differences in the trajectories. Available reports about urban mobility in Italian cities (see https://datamobility.it/come-sta-cambiando-la-mobilita-nel-new-normal/, accessed on 15 July 2024) show that—after the end of the COVID-19 outbreak and related restrictions—Mondays and Fridays are characterized by lower levels of traffic congestion, due to the adoption of remote work. This could represent one of the motivations of the drop in usage of shared mobility between June 29 and June 30, as well as between July 20 and July 21 (for which we do not show Figures but only report data about the number of trips in Table 5). July 7 could therefore represent an outlier in which the number of trips lost due to remote work choices is actually compensated for by additional travels due to the fact that the public transport option was not available or not convenient (due to longer waiting times and/or more crowded buses/trams). The Trajectory Flow Map can therefore represent a useful instrument to investigate micro-level impacts of events on mobility patterns.



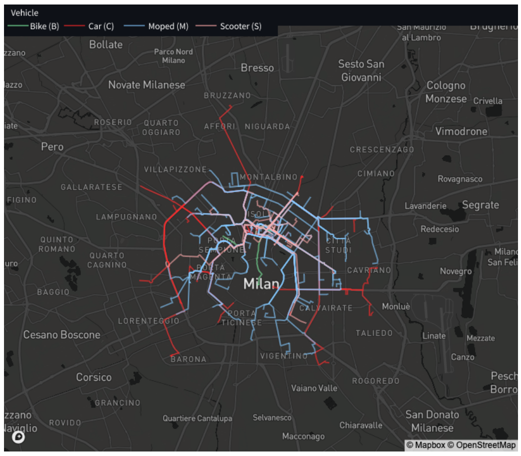
(**a**) Thursday, regular public transportation.



(**b**) Friday, regular public transportation.



(**c**) Thursday, regular public transportation.



(**d**) Friday, public transportation strike.

Figure 6. Trajectory Flow Map for trips originated in the Garibaldi—Porta Nuova NIL in different dates (8:15–15:30). (**a**) Garibaldi—Porta Nuova, June 29; (**b**) Garibaldi—Porta Nuova, June 30; (**c**) Garibaldi—Porta Nuova, July 6; (**d**) Garibaldi—Porta Nuova, July 7.

Additional forms of analysis that could be enabled by this visualization could be associated to the evaluation of the effect of the introduction of bike lanes and/or traffic calming zones on the adoption of bikes and mopeds. It could be interesting to have also the possibility to show a layer depicting these zones and lanes as a background to the displayed trajectories.

7. Evaluation of Usability and Intuitiveness of UrbanFlow Milano

In this section, we address the three research questions posed in this study regarding the usability and intuitiveness of the UrbanFlow Milano interface.

RQ1: Is UrbanFlow Milano easy to be used (i.e., is easy to filter, and understand the graphical elements? To assess the ease of use of UrbanFlow Milano, participants interacted with three different maps: OD Flow Map, Trajectory Map, and Chord Diagram. Overall, participants found UrbanFlow Milano easy to use, particularly with the OD Flow Map interface. In the think-aloud test, all participants, despite of their expertise and familiarity with data analytics, successfully completed the tasks without significant difficulties. This suggests that the OD Flow Map is intuitive and user friendly, requiring minimal guidance for effective navigation and task completion. Suggestions for improvement are primarily focused on enhancing visual elements such as color differentiation and input methods like keyboard integration for numerical entry.

RQ2: Is the UrbanFlow Milano as intuitive for every user, regardless of their experience in visual analytics? This study also investigated whether UrbanFlow Milano maintains its intuitiveness across users with varying levels of experience in map-based visual analytics. Participants with and without prior experience in GIS and data analytics were included in the study. Participants with experience in visual analytics generally navigated the interface more seamlessly. For instance, in tasks involving data filtering and interpretation on the Trajectory Map and Chord Diagram, experienced users demonstrated higher success rates compared to their less experienced counterparts. On the other hand, tasks such as interpreting the meaning of arcs in the Chord Diagram or locating specific functionalities were more challenging for participants without prior experience, resulting in lower success rates. This suggests that while UrbanFlow Milano is intuitive for users with background knowledge in visual analytics, less experienced users may require additional support or training to effectively utilize all features of the interface.

RQ3: Is an introductory guide necessary for users to fully utilize the UrbanFlow interface? The necessity of an introductory guide for users to fully utilize the UrbanFlow Milano interface was explored through participant performance and feedback. The results indicate that while the presence of an introductory guide benefited users across all maps, its impact varied depending on the complexity of the visualization. Tasks that involved specific functionalities or interpretation, such as filtering specific trip types on the Trajectory Map or understanding the flow representation in the Chord Diagram, were completed more successfully with the aid of the guide. However, even with the guide available, some participants encountered challenges, particularly in interpreting detailed visual elements like arc meanings in the Chord Diagram. This suggests that while an introductory guide is beneficial, additional interface improvements or supplementary materials may be necessary to address more complex user needs.

8. Conclusions

In this paper, we introduced UrbanFlow Milano, an advanced visual analytics tool designed to enhance the understanding of MaaS data through interactive and diverse map-based interfaces. The tool comprises three distinct analytical maps: the OD Flow Map for analyzing mobility flows between nodes, the Trajectory Flow Map for visualizing shared transportation trajectories, and the Chord Diagram for illustrating node connections with varying arc sizes. Each interface incorporates interactive features such as filtering, clustering, and selection, which support a comprehensive exploration of the data. Our study aims to investigate the role of visual analytics for sustainable mobility, particularly in the context of MaaS data. The dashboard has been evaluated from a user perspective employing think-aloud protocols. Users were asked to complete 20 different tasks using all the three interfaces. The results have highlighted the usability and effectiveness of the dashboard across various user scenarios.

Theoretical Contributions: This study advances the field of visual analytics by developing and validating a tool that integrates multiple visualization techniques tailored for sustainable mobility analysis. By focusing on user interaction and feedback, our work contributes to the theoretical understanding of how different visual analytics methods can be employed to address complex mobility patterns. The effective combination of various visualization styles in UrbanFlow Milano provides new insights into how users can better interpret and analyze large-scale mobility data, thereby advancing knowledge in the domain of visual analytics applied to urban transportation systems.

Practical Contributions: From a practical point of view, UrbanFlow Milano offers a significant enhancement for professionals working with mobility data. The tool's design and functionality address real-world needs by supporting both basic tasks like data identification and more complex analyses such as cluster identification and data filtering. User feedback has revealed the dashboard's usability and effectiveness, highlighting its potential to aid decision-making processes in urban mobility management. The iterative feedback process and subsequent refinement of the tool based on user experiences highlight its practical relevance and utility in optimizing transportation strategies and planning. The UrbanFlow Milano dashboard exemplifies a user-centric design approach, characterized by its extensive customization options and adaptability to diverse analytical needs. Users can filter data based on specific criteria such as incoming and outgoing links, vehicle types, and time ranges, which allows for a tailored analytical experience. Additionally, the dashboard's flexibility in switching between different visualization styles and creating various map types further empowers users to personalize their interface. This customization not only enhances the overall user experience but also facilitates more focused and effective analyses. By integrating these features, UrbanFlow Milano stands out as a powerful tool for GIS-based urban planning and mobility studies, aligning with the growing demand for adaptable and user-friendly map-based visual analytics tools.

Future Work: Building on the insights gained from the user study, our future research will focus on three key areas. Firstly, we will refine the interface design to address user feedback, enhancing elements such as label clarity, color schemes, and overall usability. Secondly, we plan to conduct quantitative experiments to evaluate the impact of various design elements on user attention and spatiotemporal knowledge acquisition. Thirdly, we aim to explore the integration of additional data sources, including demographic information, event data, and social media geotagging, to further enrich the understanding of human mobility patterns and improve the tool's analytical capabilities.

Finally, we plan to increase the number of participants of the user study for future evaluations of UrbanFlow Milano releases.

Supplementary Materials: The source code for the proposed visual analytics prototype is available at https://github.com/l-delfini/urbanflow_milano_app, accessed on 15 July 2024.

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Data Availability Statement: Data used to generate the visualizations and analyses described in the paper were acquired from Fluctuo (https://fluctuo.com/, accessed on 15 July 2024), a company specialized in collecting and providing access to shared mobility data from a large number of mobility service providers. Such data were acquired thanks to the MOST PNRR project funding (https://www.centronazionalemost.it/, accessed on 15 July 2024), within the context of the Next Generation EU program. We are, of course, authorized to employ the data for sake of scientific research. The above indicated repository for the source code of the proposed prototype includes a sample of the data supporting basic operations and inspection. The dataset does not include any personal data and it is GDPR compliant.

Conflicts of Interest: The authors declare no conflicts of interest.

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