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Research article

Visual comparative analytics of multimodal transportation

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A B S T R A C T

Contemporary urban transportation systems frequently depend on a variety of modes to provide residents with travel services. Understanding a multimodal transportation system is pivotal for devising well-informed planning; however, it is also inherently challenging for traffic analysts and planners. This challenge stems from the necessity of evaluating and contrasting the quality of transportation services across multiple modes. Existing methods are constrained in offering comprehensive insights into the system, primarily due to the inadequacy of multimodal traffic data necessary for fair comparisons and their inability to equip analysts and planners with the means for exploration and reasoned analysis within the urban spatial context. To this end, we first acquire sufficient multimodal trips leveraging well-established navigation platforms that can estimate the routes with the least travel time given an origin and a destination (an OD pair). We also propose TraDyssey, a visual analytics system that enables analysts and planners to evaluate and compare multiple modes by exploring acquired massive multimodal trips. TraDyssey follows a streamlined query-and-explore workflow supported by user-friendly and effective interactive visualizations. Specifically, a revisited difference-aware parallel coordinate plot (PCP) is designed for overall mode comparisons based on multimodal trips. Trip groups can be flexibly queried on the PCP based on differential features across modes. The queried trips are then organized and presented on a geographic map by OD pairs, forming a group-OD-trip hierarchy of visual exploration. Domain experts gained valuable insights into transportation planning through real-world case studies using TraDyssey.

1. Introduction

Residents in modern metropolises can adopt various transportation modes to fulfill their travel needs, such as walking, cycling, public transit, and driving. Each mode offers distinct advantages and disadvantages. For instance, cycling is environmentally friendly and low-carbon but unsuitable for long-distance travel, whereas driving is appropriate for long-distance trips but generates exhaust emissions and is susceptible to delays due to traffic congestion. Transportation authorities leverage these differences to optimize urban transportation through targeted policies aimed at specific objectives. For example, to promote low-carbon and environmentally sustainable practices, authorities might implement a public-traffic-priority policy to encourage greater use of public transportation (Chow et al., 2021; Malandraki et al., 2015). Conversely, to enhance overall urban operational efficiency, a balanced development of multiple transportation modes may be pursued.

Understanding existing multimodal transportation is a prerequisite for informed policy-making. Urban experts need to determine which mode is preferred by residents, assess how much better Mode A is compared to Mode B, and understand the reasons behind residents' preferences for Mode A. Initially, Dekoster et al. (2000) created line charts with travel distance on the x-axis and travel time on the y-axis, according to the speed of each mode, providing a theoretical comparison of different modes. For a more realistic assessment, traditional methods primarily relied on surveys (St-Louis et al., 2014; Cain et al., 2009; Cao et al., 2016;

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Tao et al., 2019) to collect resident feedback. This approach is labor-intensive and time-consuming.

The rapid development of sensing technology has resulted in a large amount of trip data, enabling the evaluation of multimodal urban transportation in a data-driven manner. Specifically, a **trip** describes how (i.e., the travel time and route) a resident travels between an **OD pair** (i.e., from an **O**rigin to a **D**estination) using a specific mode (e.g., walking). Researchers have compared travel time (Jensen et al., 2010; Faghih-Imani et al., 2017; Su et al., 2023), travel time variability (Durán-Hormazábal and Tirachini, 2016), travel choice (Zhou et al., 2019b), pollution emission (Do et al., 2014; De Nazelle et al., 2012), and convenience (Li et al., 2018) of different modes by leveraging the statistics of trips.

However, existing studies are limited to computational comparisons at a very coarse spatial granularity, which hinders in-depth exploration and interpretation. First, spatial context-aware exploration is necessary since the performance of different transportation modes varies across the urban space. For instance, while the city is generally convenient for residents to use public transit, experts need to identify and address areas where transit is less accessible (Fig. 1ⓒ). Furthermore, beyond statistical analyses with numeric figures, intuitive presentations of the multi-dimensional attributes (e.g., travel time, distance, and route) of transportation modes are essential for experts to interpret and compare mode performance comprehensively. For example, the routes where public transit is the fastest often align geographically with the public transit network (Fig. 1ⓐ and ⓑ). Similarly, cycling can be faster than driving between locations near expressways due to traffic congestion (Fig. 1ⓐ and ⓒ).

The gaps between existing methods and complex analysis tasks motivate us to develop a visual analytics approach for in-depth and exploratory evaluation of multimodal urban transportation at finer spatial granularity. Developing such an approach poses three challenges:

Data Acquisition for Fine-Grained Comparison. The comparative analysis of multiple modes across urban spaces requires substantial trip data from different modes, with consistent spatial and temporal ranges, to ensure an in-depth and fair comparison. Yet, even in New York, one of the pioneering cities in urban data transparency, only cycling and driving trips with the same time of day, origins, and destinations are available (Faghih-Imani et al., 2017). A new data acquisition method is required to obtain sufficient and detailed trip data applicable to all cities.

Multifaceted Analysis of Multimodal Trips. The comparison of multiple transportation modes and the evaluation of multimodal transportation systems involve several aspects, such as spatial selection and filtering, numerical comparison of travel times, spatial context understanding, and performance reasoning. These aspects are heterogeneous and cannot be fully addressed through purely computational methods or single visualization. It is necessary to design a visual analytics system with interactive and coordinated visualization to support the multifaceted presentation and exploratory comparison.

Many-to-Many Comparison of Multiple Modes. The basic pair-wise comparison analyzes whether mode A is generally better (worse) than mode B and how much better (worse) it is. When dealing with multiple modes, such a pair-wise assessment should be extended to a many-to-many comparison framework. For example, if mode A outperforms mode B much, it prompts exploration into the comparative performance between mode A and another mode C and quantifies the extent of this superiority. A many-to-many comparison should be established and incorporated into the visual analytics system.

In this study, we propose TraDyssey. For the first problem, TraDyssey leverages advancements in route planning and travel time estimation provided by established navigation systems (Dai et al., 2020; Fang et al., 2020). We acquire extensive trip data predicted by these systems across a wide range of origins and destinations within the study area. For the second and third problems, TraDyssey implements a hierarchical structure encompassing trip groups, OD pairs, and individual trips. This structure provides users with a flexible framework for the interactive exploration of massive trip data and facilitates the visual comparison of multiple modes. Specifically, TraDyssey coordinates a revised parallel coordinate plot (PCP) and a geographic map. The revised PCP elucidates mode differences derived from multimodal trips, serving as an entry point for many-to-many comparisons and supporting numeric analysis, while the map primarily enables geographic-aware exploration and reasoning of trips queried in the PCP. TraDyssey is evaluated with real-world case studies performed by domain experts and received positive expert feedback.

In sum, the contributions are as follows:

- ◇ A data acquisition strategy to collect massive trips for fair city-wide comparison of multiple transportation modes;
- ◇ TraDyssey, a visual analytics system based on multimodal trips for evaluating multiple transportation modes and understanding the multimodal transportation system;
- ◇ Real-world case studies based on TraDyssey, providing insights into multimodal transportation systems.

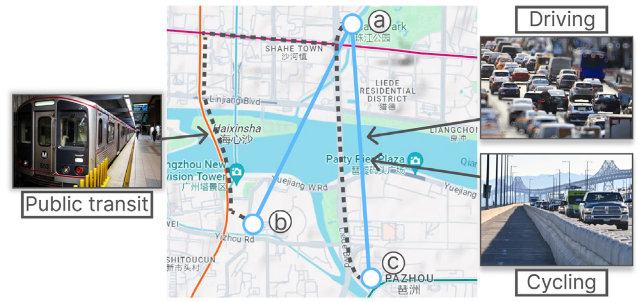

Fig. 1. Motivation Illustration. Both the locations ⓐ and ⓑ are close to the subway lines, and thus, taking public transit between them is convenient. The location ⓒ is not close to any subway line but close to the expressway, and thus, driving may be convenient for citizens here to travel to the location ⓐ; However, cycling is actually faster than driving due to traffic jams.

2. Related work

This section reviews the prior studies from three aspects, namely, multimodal traffic analysis, traffic visual analytics, and mobility visualization.

2.1. Multimodal traffic analysis

Many existing studies have leveraged the multimodal transportation system for travel route recommendation (Liu et al., 2021), traffic prediction (Yang et al., 2024; Liang et al., 2022), accessibility analysis (Tao et al., 2020), and equity (Chan et al., 2023). Our study aims to support an in-depth and exploratory evaluation of multimodal urban transportation by comparing different transportation modes. Existing studies closely related to our study can be divided into two groups based on how and where the differences in the transportation modes are:

How. This group of studies aimed to establish how the modes differ in terms of various indicators. *Travel Time/Speed* stands as the most intuitive indicator for evaluating transportation modes. Given its objective nature, previous studies commonly employ a data-driven approach for comparative analysis (Su et al., 2021; Gruber and Narayanan, 2019; Akcicek et al., 2024; Jensen et al., 2010). For instance, Faghih-Imani et al. (2017) conducted a comparison of travel times between driving and cycling in New York City. Similarly, Akcicek et al. (2024) examined the travel times of public transit versus driving in Denver. Furthermore, Durán-Hormazábal and Tirachini (2016) conducted a comparative analysis of travel time variability between driving and public transit.

In addition, *satisfaction* and *emission* of transportation modes also attracted researchers' interests. *Satisfaction* is a subjective indicator for assessing transportation modes. Surveys with questionnaires are a widely adopted approach to gauge citizens' satisfaction (Gao et al., 2024; Cao et al., 2016; St-Louis et al., 2014; Tao et al., 2019). *Emission* exhausted by vehicles of different modes is usually investigated via real-world experiments (De Nazelle et al., 2012; Do et al., 2014). These experiments arrange the vehicles to travel along specific routes, with subsequent measurements of pollution emissions.

Where. The second group of studies focuses on analyzing the spatial distribution of disparities among transportation modes. Given the inherently spatial characteristics of transportation systems, a subset of existing research has concentrated on examining the spatial distribution of different modes across various indices. To investigate spatial variations, researchers often calculate ratios or gaps between travel times for different modes across urban areas, which are then visualized using techniques such as heatmaps (Liao et al., 2020; Cats et al., 2022) or bubble charts (Lunke et al., 2023) on maps. These studies underscore the importance of considering spatial context when comparing different transportation modes. However, current methods do not support a nuanced exploration and comparison of multiple modes in the spatial dimension. For example, which mode offers the most convenient travel option for citizens in a region to reach other regions remains unanswered.

Some researchers worked on figuring out why travelers choose different modes (Zhou et al., 2019b; Liu et al., 2015). However, they only analyzed which factors (e.g., travel distance and the number of parks) affect travelers' choices rather than analyzing multimodal transportation systems. Our study proposes an interactive visualization system that enables the users to understand **how**, **where**, and **why** the transportation modes differ based on large-scale multimodal trips.

2.2. Traffic visual analytics

Visual analytics is a powerful means for addressing many important transportation problems (Deng et al., 2023a; Chen et al., 2015). We followed Deng et al.'s taxonomy on urban visual analytics (Deng et al., 2022c) to classify the traffic visual analytics approaches into visual traffic planning and diagnosis.

Visual Traffic Planning enables experts to interact with traffic data and make informed decisions for optimizing transportation systems. Traffic information can be utilized to facilitate the planning of urban facilities (e.g., billboards Liu et al., 2017, stores Weng et al., 2019, fire stations Chen et al., 2023, and houses Weng et al., 2018) rather than traffic facilities. As for traffic facilities, current approaches for traffic planning mainly focus on the bus route (Weng et al., 2021; Di Lorenzo et al., 2016; Liu et al., 2020). The core idea of these studies is to interactively re-layout the routes on the map based on the visualized traffic demands. In addition to the bus routes, Deng et al. (2023b) studied the tour route planning. Their approach can help tourists plan their tour routes based on previous tourists' routes.

Visual Traffic Diagnosis allows experts to make sense of transportation systems via the visualization of traffic data (Feng et al., 2021; Zeng et al., 2014). Existing visual analytics approaches to traffic diagnosis have been extensively studied, covering multiple steps of the diagnostic process. Take the road traffic as an example. With the assistance of visual analytics, experts can monitor road transportation systems (Lee et al., 2020), then detect abnormal events (Wang et al., 2013; Cao et al., 2018; Dong et al., 2024), and finally trace their influencing processes over the traffic networks (Deng et al., 2022b; Pi et al., 2021). Multimodal urban transportation analysis belongs to the visual traffic diagnosis. To the best of our knowledge, existing studies only focus on single-mode traffic data and we are the first to explore the visual diagnosis approach for multimodal urban transportation.

2.3. Mobility visualization

Our study attempts to visualize massive trips and thereby evaluate multimodal urban transportation. Andrienko et al. (2008) classified the visualization techniques for mobility data into three types, namely, direct depiction, summarization, and pattern extraction.

Direct Depiction means that trips are directly depicted as curves or lines on the map according to the geographic positions (Zhou et al., 2019a). The methods of this type are the most intuitive way. However, drawing trips directly with straight lines will produce serious clutter. In contrast, drawing trips along the road network (Liu et al., 2017) or bundling them (Wallinger et al., 2022; Lyu et al., 2020; Zeng et al., 2019) makes individual trips hard to distinguish. GeoNetverse (Deng et al., 2022a) addressed this issue by stacking trips on the map and included a level-of-detail rendering for improved scalability.

Summarization, instead of depicting raw trips, aims at transforming raw trips into visual summaries (Shi et al., 2021; Zeng et al., 2016; Lu et al., 2016). For example, Scheepens et al. (2011) presented trajectories using a density heatmap. Wang et al. (2017) transformed trips into flow maps. Yang et al. (2017) utilized the matrix representation to organize many-to-many trips. GeoNetverse (Deng et al., 2022a) can also be considered as a combination of the summarization and direct depiction types since it adopted hierarchical clustering to generate hierarchical summarization and depicted them on the map in an edge-stacking manner. However, GeoNetverse's scalability is currently limited to handling hundreds of trips (Deng et al., 2022a), a capacity that does not meet our requirements.

Pattern Extraction focuses on the patterns behind trips. Mobility patterns are first extracted from trips with advanced computational models beyond statistic transformation and then are exposed to users via well-designed interactive visualizations for exploration and analysis. For example, Chen et al. (2016) extracted traveling patterns from tourists' geo-referred social media. Huang et al. (2016) built upon the road network and extracted network-based mobility patterns for analyzing the road network centralities. Wu et al. (2016) studied the co-movement patterns of crowds. However, these pattern-oriented visualizations cannot support exploring trips in a large dataset for localized analysis.

We explore these kinds of mobility visualizations and design a three-level hierarchy of trip exploration.

3. Research problem and solution

This section first introduces the research problem of this study, then provides an overview of the proposed solution, and finally summarizes the requirements of domain experts.

3.1. Research problem

In the past six months, we have worked closely with three domain experts (EA, EB, and EC). EA (PhD) is a professor who has long been engaged in interdisciplinary research between computer science and transportation engineering. EB (PhD) is a researcher working in transportation engineering at a university with a research interest in transportation planning through advanced data analysis. EC is a fifth-year Ph.D. candidate in transportation engineering with an interest in transportation system evaluation.

A **transportation mode** refers to the means by which residents travel within an urban environment. Common modes include walking, cycling, driving, and public transit. In residents' daily travel behavior, the choice of transportation mode is often influenced by its perceived convenience. The convenience of a mode varies across different OD pairs, depending on static transportation infrastructure (e.g., road network) and dynamically changing traffic conditions (e.g., congestion levels).

Based on a literature review (Section 2.1) and experts' experience, existing multimodal traffic analyses are coarse-grained and challenging to implement on a city-wide scale. We follow Sedlmair et al.'s design study methodology (Sedlmair et al., 2012) and cooperate with the domain experts to characterize the domain problem through multiple rounds of expert interviews. This process includes abstracting the types of data required for analysis and designing visualizations and interactions to address the analysis challenges, informed by multiple rounds of expert feedback.

3.2. Trip-based solution

A trip can faithfully reflect the convenience of a transportation mode between two locations. If extensive multimodal trip data are available across the urban space, modes can be compared within their spatial context with fine granularity, facilitating the evaluation of multimodal transportation systems. For example, domain experts can identify areas well-served by the public transit system by analyzing trips where public transit is the fastest option. In addition, they can pinpoint problematic roads (e.g., those that are consistently congested) by filtering trips where cycling is faster than driving (e.g., between Fig. 1ⓐ and ⓒ).

We have reframed evaluating multimodal transportation as the problem of visually analyzing massive multimodal trips. For this problem, we propose a visual analytics approach named TraDyssey. Massive trip data allow experts to evaluate a multimodal transportation system as if they were journeying through an urban space, akin to the epic journey described in the Odyssey (Homer, 2015). One of the challenges we faced was collecting a substantial number of trips for fair comparison. To address this, we leverage modern navigation platforms to collect (or synthesize) extensive trip data. Additional challenges arise in the exploratory comparison of these trips. TraDyssey effectively coordinates a set of visualizations, enabling experts to query and compare multimodal trips from both spatial context and attribute perspectives.

4. Data acquisition

This section introduces the acquisition of multimodal OD trip data to compare multiple transportation modes in a study area.

4.1. Dataset requirements

The OD trip dataset should satisfy the following requirements. First, the OD trips should involve different transportation modes but fall within the same spatial and temporal ranges. Second, the OD trips should comprehensively cover the study area. Third, the spatial granularity of origins and destinations should strike a balance; it should not be too fine to avoid noise, nor too coarse to obscure spatial variations.

These requirements are challenging to meet with existing public datasets. To the best of our knowledge, most existing academic studies, under the constraints of the same spatial and temporal range, analyze at most two transportation modes and are limited in spatial scope, making it difficult to achieve city-wide analysis. To collect such a new dataset, one strategy is to perform a real-world study by recruiting users to travel within the study area, like the project GeoLife by Microsoft (Zheng et al., 2008, 2009). However, the real-world study is time-consuming, labor-intensive, and costly. In our study, we propose to utilize a modern navigation platform.

4.2. Estimation-based acquisition strategy

Navigation platforms provide a route recommendation API, allowing us to retrieve the fastest route for any given OD pair and transportation mode in real time.

In navigation platforms, travel times for walking, cycling, and rail transit (e.g., subways) can be reliably estimated by querying the corresponding travel distances within the transportation network, as their speeds are unaffected by road conditions. Through collaborations with relevant departments, the platforms have access to subway and bus schedules, enabling accurate estimation of waiting times. As for the travel time estimation (TTE) for vehicles on roads, AutoNavi's TTE algorithm (Dai et al., 2020) demonstrated a Mean Absolute Percentage Error (MAPE) of approximately 15% and a Mean Absolute Error (MAE) of less than 40 s per kilometer on the Beijing dataset. Baidu Map, another major map service, reported a TTE algorithm (Fang et al., 2020) with MAPEs around 25% and an MAE of approximately 120 s across datasets from Taiyuan, Hefei, and Huizhou. Research on travel time estimation continues to advance, with a recent transformer-based algorithm (Liu et al., 2022) achieving MAPEs of around 11% and an MAE of about 160 s on datasets of Chengdu and Beijing. The high accuracy of these existing algorithms provides a strong foundation for the reliability of the synthesized trips.

Specifically, we choose AutoNavi, one of China's most widely used navigation platforms, integrated into the AMap service. Amap boasts over 100 million users and is as important in China as Google Maps. Our strategy would not limited to the navigation platform and can be applied to any study area with high generalizability.

4.3. Acquisition procedure and data description

The procedure to collect an OD trip dataset is as follows. Given an area (e.g., the central area of a city) with A km^2 and the expected spatial granularity of g km^2 per location, the number of origins can be estimated: $n = A/g$. Experts suggest that a granularity of 0.5 km^2 per location is appropriate. Then, we randomly sample n origins on the map within the area and sample n destinations on the map for each origin. Given each OD pair, we utilize the API to query m OD trips, each of which corresponds to a mode. In this study, $m = 4$, and we consider walking, cycling, driving, and public transit modes. The API calls are executed within a time period (e.g., the evening rush hours) to ensure consistency in the time range. Finally, we obtain mn^2 OD trips for n^2 OD pairs.

The data format of an OD pair comprises (1) the origin and (2) the destination with geographic positions. The data format of a trip contains (1) the transportation mode, (2) the OD pair it belongs to, (3) the travel distance, (4) the travel time (in seconds), and (5) the travel route that can be considered a fine-grained trajectory and can be exactly mapped on the transportation network

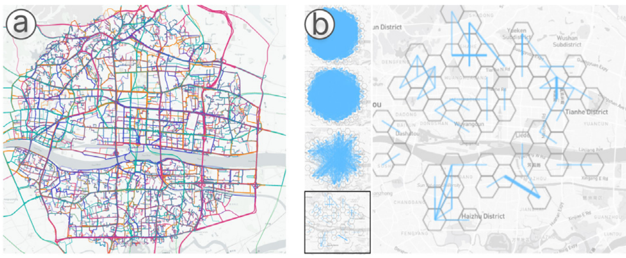

Fig. 2. Prototypes were developed during the iterative design process. (a) Multimodal trips are plotted on the map directly. (b) Multiple groups of OD pairs are first extracted to guide further exploration and analysis.

(including the road network and public transit network). In particular, a trip with the driving mode can be further divided into multiple segments ranging from tens to a hundred meters, each of which contains (6) road congestion information (e.g., congested, normal, and slow). Moreover, a trip using public transit can be a combination of walking, bus, and subway because there may be no bus or subway stations near the origin and destination.

5. Design process and system overview

This section introduces the design process, domain requirements, design goals compiled from the requirements, and finally, the system overview.

5.1. Iterative design

In Sedlmair et al.'s methodology (Sedlmair et al., 2012), the visual design process is the core stage, which iterates between the phases of Discover, Design, Implement, and Deploy, and results in multiple prototypes. Early in this stage, we tried to depict all trips as paths on the map directly by their routes (Fig. 2A). Each path of the route was colored according to its mode. As these paths seriously overlap with each other, it is challenging to start the exploration.

Afterwards, we propose another prototype shown in Fig. 2B. OD pairs are grouped based on their fastest mode and displayed on the left of Fig. 2B. The experts can select one of them to start the analysis, such as the walking-fastest or public transit-fastest group (the last two groups) that has a spatial distribution different from the others. To alleviate visual clutter, we further group OD pairs in the spatial dimension by introducing a hexagonal grid. However, further analysis is still inflexible due to the large number of trips and visual clutter. The experts commented "*it would be desirable if the grouping can be specified by users.*"

Through back-and-forth interviews with domain experts, the domain requirements become clear (Section 5.2). To design interactive visualizations that satisfy the requirements, we further condense design goals (Section 5.3) to guide the visual design. Eventually, we spent two months designing and developing the visual analytics system and invited experts to conduct case studies for validation.

5.2. Requirement analysis

The final requirements are summarized as follows:

R1. How do these modes compare to each other? Experts need to grasp the overview of the performance of each transportation mode and its difference compared to each of the other modes. They may first need to understand "*Does driving have any significant advantages over public transit?*" and "*Is it possible that walking is faster than driving?*" A basic understanding of the differences among the modes can guide experts to perform further exploration and then in-depth analyses (**R2** and **R3**).

R2. Where are their differences present? The expert commented that the regions where a mode is inconvenient may require counter-measurement for improvement. For example, if driving is more convenient than public transit between two regions, bus lines need to be added between the two regions in line with the principle of low carbon. Thus, the experts should understand "*where are these regions?*" and even "*How these regions are distributed on the map?*"

R3. Why are the differences? Last but not least, the experts need to determine the reason for these differences. For example, the poor performance of driving mode can be due to flaws in the road network: If walking is faster than driving, is it because the roads are congested? Or is there a connectivity flaw in the road network that requires drivers to take long detours to get to the other side of the road? Another example is that the performance of public transit is affected by the infrastructure of the public transit system: Is public transit the fastest because the origin and the destination are next to the subway station?

5.3. Design goals

To fulfill the requirements in the aspects of how, where, and why, the system needs to support the flexible exploration of numerous OD pairs and the multimodal trips therein and in-depth analysis. To better design the system, we further condense the design goals listed and explained as follows:

G1. Query-First Workflow for Exploration. All requirements (**R1**, **R2**, and **R3**) emphasize that the analysis is based on OD pair groups with specific relationships between modes. For example, there will be valuable insights in the OD pair groups where "cycling is comparable to driving" or "driving is slower than public transit". The system should provide query functions for users to flexibly select interesting groups of OD pairs to start analyses.

G2. Multi-dimensional Visualization of OD Pairs. Experts must analyze the travel times of various transportation modes, as it serves as the most intuitive metric for mode comparison (**R1**). For a given OD pair, multiple trips exist utilizing different modes. Understanding travel time requires considering distance. For instance, a scenario where a short distance results in a long travel time merits attention. Consequently, the OD pair, along with travel distance and multiple travel times, forms a multi-dimensional datum, necessitating multi-dimensional visualization techniques (Zhang et al., 2024; Munz-Körner and Weiskopf, 2024).

G3. Difference-aware Visualization of Multiple Modes. The visualization should effectively capture and present the differences in travel times across various transportation modes. By visualizing these differences, users can easily query trips based on whether a particular mode is faster or slower (**R1**). Moreover, this visualization aids in deeper analysis, such as understanding the extent to which one mode outperforms another for a given OD pair, thereby supporting the *why* analysis (**R3**).

G4. Spatial Presentation of Massive Trips. The trip analysis is highly dependent on the spatial context. Not only the *where* analysis (**R2**) but also the *how* analysis (**R1**) requires viewing the spatial distribution of specific groups of trips. Furthermore, the *why* analysis (**R3**) requires inspecting travel routes. Thus, there must be a geographic map to present trips.

G5. Multi-Level Presentation of Massive Trips. It is overwhelming to draw numerous trips directly on the map. From the requirements, it can be seen that some of them only require showing the spatial distribution of trips (**R1**), while some of them require viewing details (e.g., routes) of a subset of trips (**R3**). A multi-level presentation mechanism for trips can be proposed following such different analysis levels.

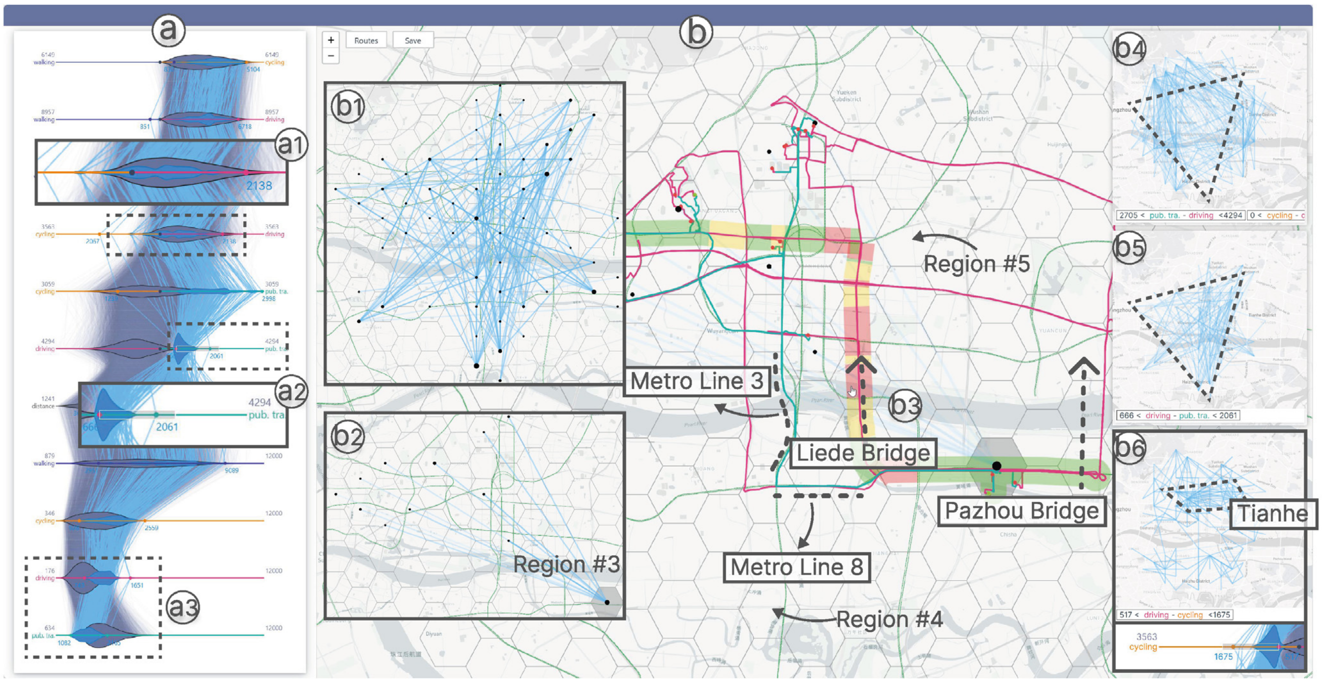

Fig. 3. The interface of TraDyssey. (a) The attribute view adopts a parallel coordinate plot to visualize the travel times and distances of multimodal trips and their differences. (a1) Cycling is faster than driving if (a2) public transit is faster than driving. (b) The map view is mainly a geographic map that supports the visual analysis of massive trips from two-level visualizations, namely, (b1 and b2) OD line visualizations and (b3) route visualizations. The map view also allows users to save snapshots as (b4, b5, and b6) small multiples where users can compare different sets of OD lines in the geographic context.

G6. Convenient Comparison of Multiple Queries. Users may query multiple times. For example, they may first query the OD pairs where driving is more convenient and then the OD pairs where public transit is faster. The following question may be: what are their spatial distribution differences? The visual design should support comparing multiple queried results and fast switching between results.

5.4. System overview

We explore the design spaces of comparative visualization (i.e., juxtaposition, superposition, and explicit encoding) (Gleicher et al., 2011; Li et al., 2023) and OD visualization (direct depiction, summarization, and pattern extraction) (Andrienko et al., 2008), navigate the trade-offs between complex analytical tasks and the visualization intuitiveness, consequently, design TraDyssey to assist domain experts in analyzing multimodal transportation systems by visually exploring multimodal trips. TraDyssey is a web-based system implemented with Vue3 plus a TypeScript framework. It comprises an **attribute view** and a **map view**.

The **attribute view** (Fig. 3a) serves as an overview and visualizes OD pairs (**G2**) by encoding the travel times of multiple modes and the travel distances in OD pairs with a parallel coordinate plot (PCP). The travel time differences of multiple modes are also derived for every OD pair (**G3**) and encoded in this PCP in a comparable manner. Users can brush on the PCP to query OD pairs (**G1**) for further analyses in the spatial context.

The **map view** (Fig. 3b) depicts the queried OD pairs and trips at two levels of visualizations, respectively, within the same geographic context (**G4** and **G5**). At the first level (Fig. 3b1), the OD pairs of the trips are aggregated as OD lines and are depicted based on the hexagonal grid. At the second level (Fig. 3b2), users can select OD lines of interest on the map, and the trip routes with different modes are depicted as finer-grained paths following the transportation network, supporting a superimposed comparison. In the map view, users can save snapshots if they are interested in the filtered trips. The snapshots are presented with small multiples (Fig. 3b3) for a juxtaposed snapshot comparison in the spatial context (**G6**).

6. TraDyssey

This section elaborates on TraDyssey's visual designs.

6.1. Colors

We use a consistent color scheme throughout the system. First, the OD pair is colored with navy or blue based on whether it is filtered or not. Second, we also distinguish each transportation mode by assigning it a unique color because color is the most effective channel for categorical data. We assign deep blue, orange, purple, and green to walking, cycling, driving, and public transit modes, respectively.

6.2. Attribute view

The attribute view visualizes OD pairs, reveals the differences between modes in travel times, and enables flexible querying of OD pairs.

Visualizing OD Pairs. For an OD pair, there are m trips for m transportation modes, respectively. Each trip records the time a citizen spends traveling between an OD pair using the corresponding mode. Fig. 4a illustrates an OD pair with four travel times of different modes and the average travel distance. Such a five-dimensional datum is visualized with the PCP (the top part of Fig. 4c). The axis for the travel time of a mode is colored according to the mode, and the axis for the distance is colored gray. Each OD pair is represented as a navy polyline passing through the axes.

Revealing Differences in Travel Times. In addition to looking at travel times in a given mode, users also want to obtain the travel time difference between different modes. Although the difference is explicitly encoded with the slope channel in the PCP,

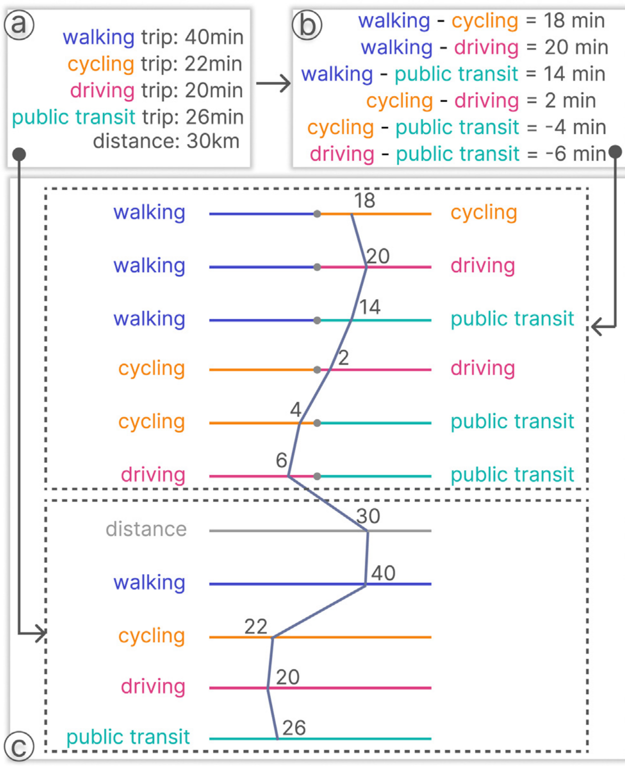

Fig. 4. Parallel coordinate plot (PCP) for OD pairs. (a) The five dimensions (travel times and the travel distance) of an illustrative OD pair. (b) The differences between modes in travel times are derived from the illustrative OD pair and are considered the extra dimension of the OD pair. (c) The tailored PCP for visualizing all dimensions of the OD pair.

the channel is not intuitive. Thus, we propose a tailored data transformation and revisit the PCP.

We compute the difference in travel times for any two modes. Given m modes, we obtain $\binom{m}{2}$ differences for each OD pair (Fig. 4b). These differences are considered extra dimensions of the OD pair and visualized in the same PCP but with revised axes, as illustrated in the top part of Fig. 4c. Specifically, each revised axis represents the difference between the travel times of the two modes, with the mode names placed at the respective ends of the axis. The polyline of the OD pair intersects the axis according to the computed difference for the two modes. In Fig. 4, cycling is faster than walking, so the polyline intersects the walking-cycling axis closer to the right end of cycling.

Massive OD pairs may lead to an overplotting issue and users cannot clearly obtain the value distribution. To this end, we overlay a violin-like area chart (Fig. 3a3) to show the distribution on each axis, inspired by previous methods (Palmas et al., 2014; Janetzko et al., 2016). Area charts will be filled navy since they are computed based on the navy polylines for all OD pairs.

Querying OD Pairs. The PCP allows users to filter OD pairs by brushing on the axes. Filtered OD pairs are then highlighted in blue. A blue area chart is generated based on these filtered OD pairs and is superimposed on each axis (Fig. 3a3). To accommodate cases with few filtered OD pairs, each axis's area chart has its own scale. The filtered OD pairs will be visualized on the map view, enabling users to interpret them within the spatial context. The modes featured on the brushed axes are designated as target modes, which are subsequently utilized in the map view.

For instance, to identify OD pairs where driving significantly outperforms public transit, users can brush near the end of the "driving-public transit" axis closest to the driving mode, as shown in Fig. 6b. Subsequently, these filtered OD pairs (and the trips) will be displayed on the map view, allowing users to discern the differences between public transit and driving modes.

6.3. Map view

The map view provides the spatial context for OD pairs and multimodal trips. The queried OD pairs are first depicted as straight lines, and the trip routes are displayed as needed.

Visualizing OD Pairs. We depict each OD pair with a straight line connecting the origin and destination on the map. We call the straight line an OD line. To ease the clutter, we adopt spatial simplification inspired by previous studies (Andrienko and Andrienko, 2011; Weng et al., 2021). The OD pairs are regularly collected within the study area and will be evenly distributed on the map. Hence, we do not apply data-driven approaches for spatial simplification. Instead, we partition the study area into a hexagonal grid with uniformly sized grid cells, as shown in Fig. 6d. Specifically, based on expert recommendations, we set the diameter of each grid cell (twice the side length) to be 1 km. Subsequently, we offset the endpoints of each OD line to the center of the nearest hexagonal grid cell. A black circle is then placed within each cell, with the size indicating the number of filtered OD lines associated with that cell. Furthermore, to improve perception, we encode the distance between OD pairs using transparency. OD lines become more transparent as the distance between pairs increases, and vice versa.

Users can filter OD pairs on the map by clicking the cell (e.g., the cell of Fig. 6d1). Only the OD pairs involving the clicked cell are left (e.g., Fig. 6e).

Visualizing Trips. Users can click individual OD lines to inspect the trips that belong to the clicked OD pair (e.g., Fig. 6f). In addition, users can turn on the "route" switch, and then all trips (e.g., Fig. 7a) that belong to the OD lines on the map are visualized (e.g., Fig. 7b).

Recall that a trip describes how people should travel from an origin to a destination via a specific mode. We visualize each trip with a path on the map according to the geographic position of its travel route. The route strictly follows the transportation network, which maintains the spatial context. The path is colored according to the mode of the trip to distinguish the mode. Furthermore, given the query-first workflow, we assume that the modes the user has not brushed in the PCP are not concerned with his current analysis. Thus, only the trips related to the target modes will be displayed, preventing users from being overwhelmed. For the trip of the driving mode, the traffic condition can be depicted by hovering over the path for inspection. The road conditions are visualized as a wider path beneath the trip path, with less opacity, segmented according to traffic status. We adhere to the conventional color-coding scheme for traffic conditions: red indicates extreme congestion, orange signifies slow traffic, and green denotes smooth traffic.

When trips are visualized, a trip table will pop up, showing the travel times and distance for every OD pair (See supplemental video).

Comparing Spatial Distribution. The map view allows users to save map snapshots so that they can compare different query results with the spatial context. Snapshots are displayed as small multiples for side-by-side comparison (Fig. 3b4, b5, and b6). To clearly show the spatial distribution, each snapshot only shows OD lines instead of routes. The query constraints in the PCP are also displayed for each snapshot.

7. Evaluation

This section introduces the dataset used for evaluation, the statistics analysis of the dataset, the case studies conducted by domain experts, and collected feedback.

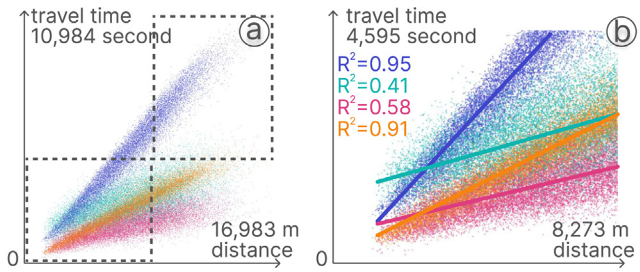

Fig. 5. Statistics analysis of the acquired dataset. (a) A scatterplot for travel time versus travel distance of each trip, where each dot is colored according to the mode. (b) The enlarged version of the left-bottom part of the scatterplot of (a). The lines are linear regression results for different modes, respectively.

7.1. Dataset

Guangzhou, one of the largest cities in China, has a mature transportation system with a well-developed road network, a well-planned bicycle network, and public transportation services. The study area was a circular area with a radius of 5 kilometers, with Zhujiang New Town as the center, covering the most prosperous regions of Guangzhou. The area size was about 78 km^2, and we sampled 150 origins (150 destinations for each origin) to approximate the spatial granularity of 0.5 km^2 per location. During the sampling, we also ensured that the distance between the origin and destination was greater than 1 kilometer. Initially, we obtained 150 $\times$ 150 OD pairs. An OD pair was invalid if the origin or destination fell into the river. After filtering out them, 18,573 OD pairs were left. The time span was the weekday evening rush hour from 18:00 PM to 19:00 PM. The operation of the transportation system at this time is the most representative and can well reflect the system's flaws. For each pair, we called AutoNavi's API and queried four trips with walking, cycling, driving, and public transit, respectively, and eventually obtained 74,292 trips.

7.2. Statistics analysis

Dekoster et al. (2000) drew a line chart with distance on the x-axis and travel time on the y-axis according to the theoretical speeds of different modes. The result is theoretical. To revise their result, we performed statistics analysis on our acquired dataset. In the scatterplot of Fig. 5a, each trip is plotted as a dot according to the travel time and distance. The dot is colored according to the mode of the trip. The left-bottom part of Fig. 5a is enlarged in Fig. 5b. For each mode, we perform linear regression for the dots of the mode. The regression equation is visualized as a line with the mode's color in Fig. 5b. The coefficients of determination R^2 are also displayed. We can obtain the following insights:

Reliability. The R^2 of walking and cycling are larger than 0.9, which means that the travel distance largely determines the travel time of walking or cycling. The road network connectivity mainly causes the residuals. In contrast, the R^2 of driving and public transit are smaller than 0.6, mainly due to the uncertain traffic conditions on roads.

Advantages and disadvantages. Walking is generally the slowest mode, except for the following situation: if the travel distance is very small, walking can be faster than public transit because the time of waiting for the subway or bus is long enough to walk between the origin and destination. Besides, driving and cycling are generally faster. The benefit of cycling is that it is not affected by uncertain traffic conditions. As for driving, its benefit is that vehicles can go very fast. When the travel distance is long enough (to the right of the intersection of the two lines), the advantages of driving become obvious.

These analyses stay at the macro level. The case studies below, supported by TraDyssey, answer specific questions of How, Where, and Why in comparing transportation modes.

7.3. Case study

We invited four domain experts (EA, EB, EC, ED) and hosted a mixed online and offline meeting to conduct a case study based on this dataset. ED is an expert from a company particularly invited by EA. His company focuses on smart transportation applications and provides solutions to government departments. EA used the visual analytics system in person, and the screen was shared with the other experts, EB, EC, and ED. The system was also deployed during the meeting so that other experts could use it on their sides. Before the case study, we introduced in detail the visual encoding of each visualization in the system and the interactions supported by the system. Through the case study, the experts obtained valuable insights and highly appreciated the system.

Background. Driving and public transit are the two most important transportation modes in an urban transportation system. Driving is a comfortable and convenient way. Travelers can sit quietly in a private space to complete the point-to-point trip. Besides, driving is theoretically the fastest transportation mode because its speed can reach hundreds of kilometers per hour. However, driving is prone to delays due to the traffic conditions on the road network and is not environmentally friendly in terms of transportation efficiency (number of people per vehicle). Public transit is the opposite of driving. It is a low-carbon mode of transportation. However, it is less comfortable because each traveler has to share the space with other travelers, and it requires travelers to wait for, board, and get off the bus/subway at designated stops/stations.

How Does Driving Outperform Public Transit?

The area chart in the "driving-public transit" axis showed that driving is faster than public transit for most OD pairs (Fig. 6a). The leftmost OD pairs first attracted the experts (Fig. 6b2), where driving is much faster than public transit, and the superiority can be more than one hour (4294 s). The experts brushed these OD pairs. He noticed cycling was also faster than public transit in these OD pairs (Fig. 6b1). EC commented that "*the public transit fails to serve these travel demands.*"

Where and Why Driving is the Best?

Experts want to obtain those OD pairs where driving was the best choice. They further brushed the right on the "cycling-driving" axis (Fig. 6c1) and obtained the PCP shown in Fig. 6c. The polylines of these remaining OD pairs mainly intersected the middle and right parts of the "distance" axis (Fig. 6c2), which meant that the travel distances were long. The map view (Fig. 6d) plotted these OD pairs with OD lines. The OD lines were transparent, which also suggested the long travel distances observed in the attribute view.

Two regions (denoted as Region #1 and Region #2) attracted the experts' interest with their larger black circles.

Region #1 (Fig. 6d1). This region included Luhu Park, the foot of Baiyun Mountain, Guangzhou Chest Hospital, and Cancer Hospital. After the expert clicked the region, only those lines that involved this region were left on the map (Fig. 6e). The spatial context of the region and lines becomes clearer. There were no subway lines (the green lines on the map) and subway stations near the region #1. Moreover, the directions of these OD lines are concentrated within a 90-degree range from east to south, almost perpendicular to the subway lines. Therefore, it was inconvenient for citizens here to take the subway. The experts picked up two OD lines for inspection.

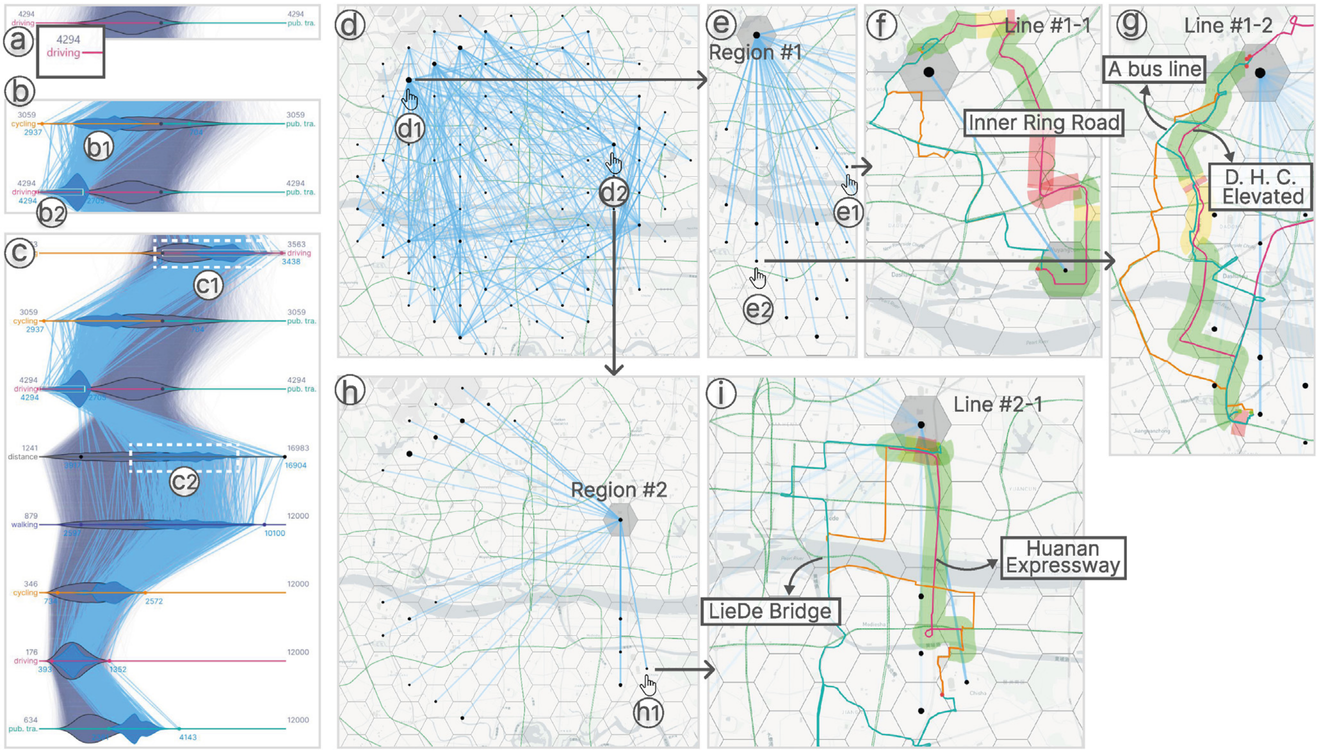

Fig. 6. Analyzing how, where, and why driving much outperforms public transit. (a) In most cases, driving was faster than public transit. (b) When (b2) driving was much faster than public transit, (b1) cycling was also faster than public transit. (c) When driving was faster than (b2) public transit and (c1) cycling, (c2) the travel distances tended to be large. (d) The OD lines of the queried OD pairs in (c). (e) Region #1 involved many OD lines, and (f and g) two OD lines were inspected in detail. (h) Region #2 also involved many OD lines, and (i) one OD line was inspected in detail.

- *Line #1-1.* The first one was from the region #1 to the region #e1 (Fig. 6e1) in the south. Since the OD line crossed multiple subway lines, the experts speculated that public transit is inconvenient for traveling. The experts clicked the line #1-1 to view the routes of the trips (Fig. 6f). Although the driving and public transit routes are of similar length, public transit users may suffer from problems of transferring, waiting for buses, and frequent stops for passenger boarding and alighting, making the journey time-consuming and uncomfortable. In contrast, driving offers greater flexibility and comfort for point-to-point trips, despite some congestion on segments of the Inner Ring Road.
- *OD Line #1-2.* This line was from the region #1 to the region #e2 (Fig. 6e2) in the south. Sun Yat-sen University is located here. Fig. 6g shows the routes of the trips. After inspecting these routes, the expert further explained the superiority of driving: although the bus route and the driving route are geographically close, the driving route utilizes the D.H.C. Elevated, while the bus route cannot, as the bus must shuttle between blocks to pick up and drop off passengers.

Region #2 (Fig. 6d2). Jinan University is located in this region. Fig. 6h showed the routes that involved the region #2. No subway lines (the green lines on the map) and subway stations near the region #2, which is similar to the situation of the region #1. The OD lines also exhibited spatial patterns similar to Fig. 6e: the lines' directions were almost perpendicular to the subway lines. One representative line was inspected as follows:

- *Line #2-1.* This line was from the region #2 to the region #h1 (Fig. 6h1), where is Guangdong University of Finance & Economics. The routes that belong to this line were shown in Fig. 6i. The public transit trip (in light green) predominantly follows the road network, resulting in a big detour. This highlights the disadvantage of fixed bus routes, leading to longer distances and longer travel times. If citizens want to take public transit, they need to walk to the bus stop nearby, take the bus to the subway station, take on and take off the subway, and finally walk to the destination, which is time-consuming and tiring. In contrast, citizens can easily drive between these two regions through the Huanan Expressway. The experts also noticed that the cycling route detoured to LieDe Bridge because "*the Huanan Expressway only allows motor vehicles to pass*".

How Does Public Transit Outperform Driving?

The small subset of OD pairs where public transit outperforms driving also drew the experts' attention (Fig. 6a). The experts brushed the rightmost section on the "driving-public transit" axis in the PCP (Fig. 3a2). Considering all OD pairs, in these OD pairs, public transit is faster, while driving takes longer (Fig. 3a3). Moreover, the advantage of driving over cycling diminishes in these cases (Fig. 3a1). The experts speculated that congestion on the roads between these OD pairs could be the underlying cause.

Where and Why Does Public Transit Outperform Driving?

Fig. 3b1 showed the spatial distribution of the OD lines of these OD pairs. The OD lines were semi-transparent and nearly covered the study area, indicating long travel distances. There were three regions (denoted as Region #3, Region #4, and Region #5, respectively) with larger black circles and shooting many OD lines towards diverse directions. The experts analyzed the three regions one by one.

Region #3 (Fig. 3b2). Canton Fair, the oldest, largest, and most representative trade fair in China, will be held in this region. When participants want to return home or to hotels in the north after participating in the Canton Fair, they can conveniently walk to the subway station nearby to take the subway. In addition, the origin or destination of these OD pairs falls on the regions

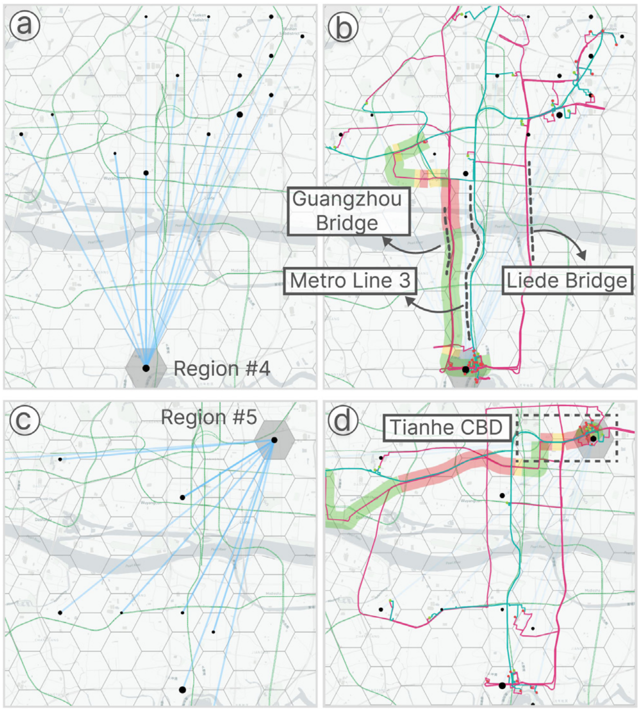

Fig. 7. Analyzing where and why public transit outperforms driving. (a) The OD lines involving the region #4 and (b) their trips. The Guangzhou and LieDe Bridges are congested during the evening rush hour, and thus, taking public transit with Metro Line 3 is better than driving. (c) The OD lines involving the region #5 and (d) their trips. The Tianhe CBD is very busy, making passing through there with public transit faster than driving.

near subway lines, making it more convenient for citizens to take public transit between these regions. In contrast, people who use driving mode must pass through the LieDe Bridge or Pazhou Bridge (Fig. 3b3). Unfortunately, the northbound roads of these two bridges are bound to be congested during evening rush hours, evidenced by the traffic conditions of LieDe Bridge in Fig. 3b3.

Region #4 (Fig. 7a). Haizhu Lake and Haizhu National Wetland Park are great places to play and camp near this region. The other end regions of these OD lines were located on the up half of the study area. After analyzing the routes of the trips (Fig. 7b), ED commented that if citizens return home from camping, the LieDe Bridge and Guangzhou Bridge are almost the must-pass roads. "*As long as it is the evening rush hour, there will be serious traffic jams on both bridges*", commented EA. The traffic conditions of Guangzhou Bridge and LieDe Bridge are evidenced in the 'red' traffic condition in Figs. 7b and 3b3, respectively. In contrast, citizens can avoid traffic congestion with Metro Line 3.

Region #5 has the biggest computer plaza in Guangzhou and the hospital of Sun Yat-sen University (Fig. 7c). When citizens want to return to their homes in the north, they must pass through the Tianhe CBD (Fig. 7d), one of the most crowded and congested areas in Guangzhou. Alternatively, the Metro Line 3 nearby is a better choice.

Which Routes Suitable for Driving, Cycling, and Public Transit, Respectively?

Figs. 6d and 3b1 were saved as the snapshots of Figs. 3b4 and 3b5, respectively. The experts were also interested in the OD pairs, where cycling was faster than driving. Thus, he brushed the left side of the "cycling-driving" axis and saved the obtained spatial distribution of the OD pairs as Fig. 3b6. These snapshots (Fig. 3b4, b5, and b6) displayed the OD lines where driving, public transit, and cycling were faster, respectively. (1) For long-distance travel passing through the downtown area (Fig. 3b5), public transit is more suitable due to road congestion and the extensive coverage of the subway network. (2) For short-distance travel within the Tianhe District (Fig. 3b6), cycling is advantageous because of its quick nature and the frequent road congestion. (3) In other scenarios, driving is the preferred option (Fig. 3b4).

Case and Insight Summaries.

In this case study, the experts (1) obtained the performance overview of multiple transportation modes and the difference overview regarding the travel times and distances, (2) queried OD pairs that were inconvenient to travel by public transit and by driving, respectively, and (3) figuring out the reasons by analyzing the trips in the geographical context combined with the transportation infrastructure. The entire workflow of TraDyssey was demonstrated, and the experts gained valuable insights into the multimodal transportation system.

First, the convenience of driving is influenced not only by the accessibility of the static road network (particularly expressways) but also by the actual traffic conditions. For instance, on heavily congested roads like LieDe Bridge, public transit, and even cycling can outperform driving. Second, the convenience of public transit is contingent on the accessibility of the public transportation network, consistent with findings from previous studies (Kamw et al., 2020; Feng et al., 2021). Third, Guangzhou's subway system largely overlaps with congested urban roads, attracting drivers to switch to public transit, thereby alleviating road congestion. This highlights the rationality of the subway line design. Finally, to further reduce the number of vehicles on the roads, the public transportation system needs to be enhanced. Given that public transit is less comfortable than driving, it must offer greater advantages in terms of travel time and economic cost to attract more citizens. As EB remarked with a laugh, "*Of course, such improvements are challenging and require long-term planning.*"

7.4. Expert interview

After the case study, we interviewed each expert individually to collect feedback. Each interview lasted for around 20 min. Their feedback is summarized as follows.

Intuitiveness. All experts said that the visualizations are very intuitive and can be easily understood with a little explanation. The parallel coordinate plot is a commonly seen chart, and the attribute view is built upon it with minor but effective revisions. OD pairs and trips are plotted on the map with straight lines and paths, respectively. Such map-based visualization is familiar to domain experts. The OD-trip hierarchy also ensures the visualization readability.

Effectiveness. All experts praised the effectiveness of TraDyssey. In particular, the attribute view supports the classic *how* analysis of comparing different modes at the city-wide scale but in a more flexible and intuitive manner. "*I can flexibly query trips for further analysis according to my preference*", EB commented. Moreover, the combination of the attribute view and map view pushes multimodal transportation analysis towards finer-grained urban spaces. EC appreciated that "*it is useful to show detailed travel routes on the map, which helps explain the mode performance on OD pairs.*"

Limitations and Suggestions. The experts raised constructive suggestions. Traffic demands are not incorporated into the existing system. While the regions with high travel demands or potential residential areas are identifiable on the map, the experts emphasized the importance of visualizing travel demands on the map or encoding the demands into OD lines. EC and ED suggested estimating traffic demands through taxi GPS data previously collected because "*taxi pick-up and -off records can be regarded as samples of OD demands*" (Liu et al., 2017; Du et al., 2021) and "*city-wide traffic demand is stable within several years*".

8. Discussion and conclusion

This section discusses the significance of this study, its limitations, and future work, and finally concludes this study.

Significance. This study is significant in the transportation analysis from the following perspectives.

Fine spatial granularity analysis. Despite extensive research on the comparative analysis of different transportation modes, our proposed visual analytics approach is the first to extend this analysis to fine-grained urban spaces, offering an intuitive interface for exploratory analysis. This advancement is primarily due to our data acquisition strategy, which facilitates the collection of extensive multimodal trip data across large urban areas. Additionally, our implementation of a query-and-explore workflow allows users to focus on relevant data subsets, preventing them from being overwhelmed by the sheer volume of trips.

Trade-off between overview and flexible query. Our query-and-explore workflow is slightly different from the common overview-first workflow. It is effective in scenarios where users need to identify specific subsets of data with low-level abstraction or summarization for targeted questions. For example, we can only summarize massive trips into the attribute view as a tailored PCP. An overview with a higher-level abstraction would prevent users from identifying trip subsets of interests based on the relative magnitudes of travel times across different modes. Nonetheless, we must clarify that the attribute view also partially serves as an overview, enabling a basic understanding of different transportation modes.

Analysis beyond one-to-many reachability. Existing reachability studies (Zeng et al., 2014; Kamw et al., 2020; Wu et al., 2017) typically examine mobility from a single origin to multiple destinations. For example, isochrone maps (Vuillemot et al., 2021) visualize regions that are reachable within specific time constraints. In contrast, our study investigates the mobilities from multiple origins to multiple destinations. Adhering to conventional methods for such many-to-many reachability would demand comparing multiple isochrone contours across maps or plotting them on one map, both of which are less inefficient. We address this by breaking down the complex task into a query-and-explore workflow and proposing a visual analytics approach to support it.

Analyses that works for any city. The challenge of collecting traffic datasets encompassing multiple modes has previously limited the scope of many studies. In our work, the scalable data acquisition strategy overcomes these limitations, making it possible to conduct analyses in new cities. Furthermore, the proposed visual analytics approach is not confined to specific city settings, thus ensuring its applicability across diverse geographical contexts.

Future Work. In addition to addressing the limitations raised by experts during interviews, we plan to pursue the following research directions:

Accommodating dynamic performance. Our study is currently confined to a specific time period, yet transportation systems exhibit varying performance across different times of day, such as during morning and evening rush hours. Analyzing and comparing mode performance across these periods presents a complex challenge that remains unexplored.

Including automated data analysis. We aim to enhance the exploratory analysis of massive multimodal trip data by integrating automated pattern mining. For example, we plan to identify regions with significant traffic congestion or areas where certain modes demonstrate inefficiency or anomalies. These insights will then be used to recommend regions as starting points for further exploratory analysis.

Evaluating travel combining multiple modes. This study mainly aims to compare different transportation modes. Future work will explore evaluating travel involving combinations of multiple modes. As multimodal travel becomes increasingly important, addressing challenges such as data acquisition and visual design will be critical. Advances in algorithm and platform support for multimodal recommendations are expected to enable richer analyses.

Conclusion. We propose a visual analytics approach, TraDyssey, that assists traffic analysts and planners in evaluating and comparing the performances of multiple transportation modes, finally understanding the modern multimodal transportation system. First, massive trips with different modes are collected via a navigation platform for a collection of OD pairs. Such a data acquisition strategy can be applied to any city. Second, we conclude a streamlined query-and-explore workflow based on domain requirements and iterative prototyping. Following this workflow, TraDyssey couples a set of user-friendly and effective interactive visualizations for massive trips, so users can compare mode performance from the How, Where, and Why perspectives. The case study performed by experts reveals important domain implications and demonstrates the effectiveness of TraDyssey.

CRediT authorship contribution statement

Zikun Deng: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Haoming Chen:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation. **Qing-Long Lu:** Writing – review & editing, Investigation, Conceptualization. **Zicheng Su:** Writing – review & editing, Investigation, Conceptualization. **Tobias Schreck:** Writing – review & editing, Investigation, Conceptualization. **Jie Bao:** Conceptualization, Investigation, Writing – review & editing. **Yi Cai:** Supervision, Resources, Project administration.

Ethical approval

This study does not contain any studies with Human or animal subjects performed by any of the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.visinf.2025.01.001.

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