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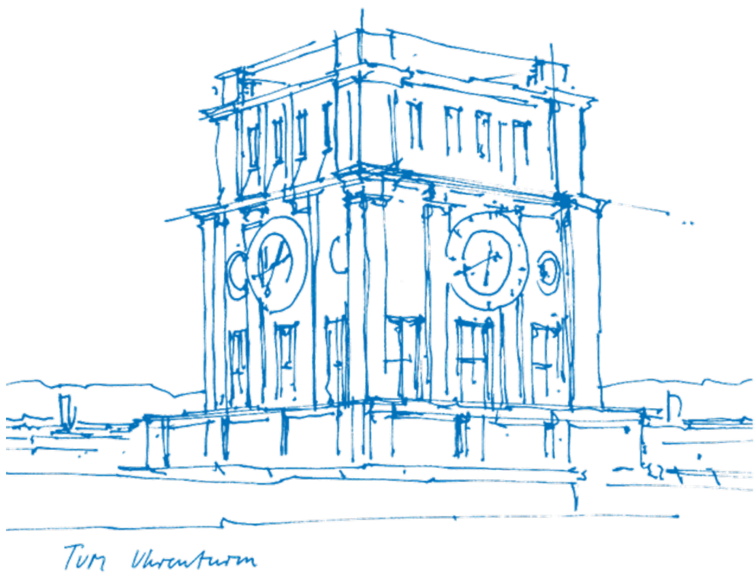

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Abstract

Estimating behavioral parameters for mode choice typically relies on revealed or stated preference data. However, applying GPS-based revealed preference (GPS-RP) panel data in modeling mode choice, particularly in response to shocks or policy interventions, is relatively rare and methodologically under-explored. This paper discusses the preparation, processing, filtering, and modeling of (semi-)automated travel diaries collected over four months. This period includes the 9-Euro-Ticket price intervention in Germany in 2022. We investigate how the ticket impacted the value of travel time savings (VTTS) across different modes by estimating three different Multinomial Logit models. Our findings reveal that the 9-Euro-Ticket led to a substantial decrease in VTTS for public transportation compared to the months following the intervention. The study provides a detailed methodology for handling complex GPS data and highlights the effects of drastic fare reductions on travel behavior, offering insights for future research and policy-making in transportation.

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1 Introduction

The analysis and modeling of transportation mode choice is one of the most extensively studied and frequently addressed topics within the transportation field (Train, 2009; Ben-Akiva and Lerman, 1985). The application of the resulting models include not only purely engineering uses (Hörl *et al.*, 2019, 2018) but also project appraisal and policy analysis (Washbrook *et al.*, 2006; König and Grippenkoven, 2020). They provide key quantitative indicators, such as marginal rate of substitutions, willingness to pay (WTP), and elasticities, which guide investments and pricing policies (Ortúzar, 2011). A popular family of discrete choice models is the so-called random utility models (RUMs), which are based on the assumption of the utility-maximizing behavior by the decision maker and capture the probabilistic nature of individual choices (Train, 2009).

In transportation modeling practice, data can generally be classified into Revealed Preference (RP) data, which describes the actual observed or reported travel behavior of individuals, and Stated Preference (SP) data, which illustrates individuals' preferences in hypothetical choice scenarios set by the researcher (Train, 2009). Besides, studies often utilize pooled RP/SP data, leveraging the strengths of both types (Ben-Akiva *et al.*, 1994; Train and Wilson, 2008; David A. Hensher *et al.*, 2008). Until the 1980s, the predominant practice involved using RP data derived from traditional pen-and-paper travel diaries. This type of data was deemed reliable for describing participants' preferences and the context of their choices, and it was easily available as travel diaries had been in use since the 1950s (Wardman, 1988; Axhausen, 1995). Nevertheless, RP data from travel diaries presented several significant drawbacks, such as captured information of a single day or week, resulting in a limited number of recorded choices per participant and necessitating large sample sizes. Additionally, the attributes of the alternatives exhibited high collinearity and low variability (Helveston *et al.*, 2018) and travel diaries were often unreliable due to misreporting and under-reporting of trips (Clarke *et al.*, 1981; Ben-Akiva and Lerman, 1985; Tsoleridis *et al.*, 2022). To address these limitations, researchers turned to Stated-Choice (SC) experiments, which involve presenting participants with different realistic choice situations in a controlled setting. Thus, since the 1970s, numerous studies have compared models based on RP and SP data, validating the economic outputs derived from SP data.

The emergence of new technologies in the past two decades, particularly the popularization of GPS and connected personal devices, has opened up new possibilities in travel data collection (Wolf, 2008; Jędrzej Gadziński, 2018; Silviya Korpilo *et al.*, 2017; Siripanich *et al.*, 2024). With dedicated smartphone apps, it is possible to capture large amounts of high-accuracy data with little to no effort from the users and produce (semi-)automated travel diaries (Gillis *et al.*, 2023;

Tabasi *et al.*, 2024; Tsoleridis *et al.*, 2022). This type of GPS-based revealed-preference data is increasingly attractive due to its relatively low data-collection cost per trip, and its use is already popular in other transport-related problems such as trip generation (Bwambale *et al.*, 2019b, 2021), destination choice (Huang and Levinson, 2017), and route choice modeling (Bwambale *et al.*, 2019a; Meister *et al.*, 2023). However, the research in this field remains limited. Investigations into mode choice utilizing smartphone-based GPS tracking have either been descriptive in nature (Arifin and Axhausen, 2012; Loder *et al.*, 2022) or have employed machine learning techniques (Tim Hillel *et al.*, 2021; Yilin Sun *et al.*, 2023; Victoria Dahmen *et al.*, 2024). Even though there is growing research using smartphone tracking for public policy appraisal (Gillis *et al.*, 2020; Link *et al.*, 2023; Molloy *et al.*, 2022) and disruptions like the COVID-19 crisis (Thayanne Gabryelle Medeiros Ciriaco *et al.*, 2023; Winkler *et al.*, 2021; Joseph Molloy *et al.*, 2021), the potential for utilizing geo-temporal data for inferential analysis is far from exhausted. There remains a significant gap in research utilizing long-term panel GPS data in combination with household surveys. This gap not only pertains to using such data to address transportation research questions but also extends to discussing methodologies and best practices for data processing required for accurate analysis.

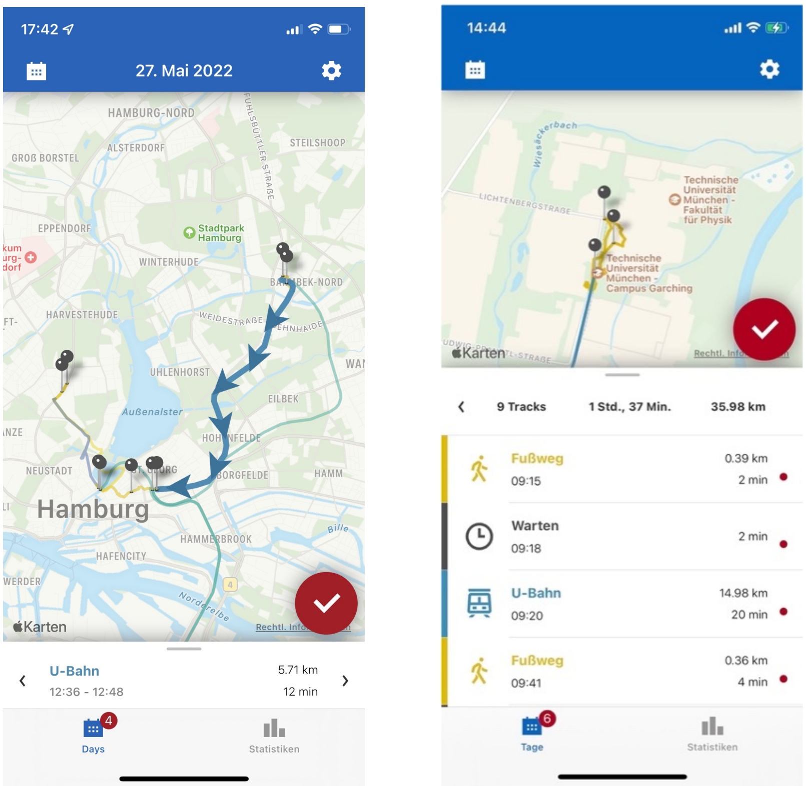
We are aware of two studies that have employed long-term panel GPS data in conjunction with household survey information to estimate theory-driven mode choice models. Tsoleridis *et al.* (2022) evaluated the VTTs using a two-week trip diary captured through smartphone GPS tracking and Link *et al.* (2023) investigated inertia effects in transportation modes before and during a German price intervention. This intervention, introduced in spring 2022 by the German parliament to alleviate rising living costs resulting from the Ukraine war, comprised a three-month fuel excise tax cut and the introduction of a Public Transportation (PT) season ticket for 9 Euros per month. This ticket, known as the *9-Euro-Ticket*, was valid on all local and regional services but excluded long-distance public transportion. The policy intervention was implemented during the months of June, July, and August, providing a quasi-natural experiment that allowed researchers to measure changes in travelers' behavior due to the ticket's availability.

In this research, we employ a four-month sample of GPS panel tracking data from the Mobilität.Leben (Mo.Le) project to explore the effects of the 9-Euro-Ticket on the VTTS. Firstly, our contribution is primarily methodological by addressing a missing link in the existing literature and detailing the processing steps necessary to transform raw GPS data into a format suitable for discrete choice modeling. This includes the generation of mode alternatives for observed trips and an extensive filtering process to ensure the final dataset adheres to the behavioral assumptions of RUM. While our primary focus is on data processing, we also estimate three preliminary Multinomial Logit models and discuss the possible approaches to account for a price intervention using panel GPS data. Secondly, this research contributes to the transport policy assessment by comparing VTTS during and after the price intervention. The analysis focuses on short, urban trips, addressing for the first time, how the 9-Euro-Ticket influenced daily mobility patterns. The remainder of this paper is organized as follows: First, we describe the data and the processing steps. Second, we detail the generation of the choice sets and the data filtering methods used. This leads to a descriptive analysis of the final dataset. We then outline our modeling approach, which sets the stage for presenting our findings. Finally, we conclude with a discussion of the results and offer insights for future research directions.

2 Techniques for Utilizing GPS Data

With the roll-out of the 9-Euro-Ticket in June 2022, the Mobilität.Leben research project was initiated to assess the unprecedented almost-free public transportation policy, and it was later extended into 2023 following the announcement of the successor ticket, the 49-Euro Deutschlandticket. Overall, the data collection spanned 13 months (Loder *et al.*, 2022) and it included a multi-wave survey with 2,569 participants, primarily from Munich, collecting socio-demographic data, mobility tool ownership, attitudinal information, and travel behavior insights. A subset of these participants installed a GPS-based tracking app developed by the software company *Motiontag*, which recorded their movements and stays, thus creating an fully passive travel diary. Participants were encouraged to actively engage with the app by editing trips, correcting erroneous entries, modifying automatically detected transport modes, merging consecutive tracks, selecting the purpose of stays, and removing incorrect records. A typical tour in the app is illustrated in Figure 1. Since the experiment had to be set up very quickly, the recruitment of the participants limited the sample's representativeness. In this paper, we utilized a subset of the *Mobilität.Leben* data, specifically from the second month of the 9-Euro-Ticket (July), and compared it to data from September and October, when the 9-Euro-Ticket was no longer in effect. August was excluded because it was a public holiday period. The dataset encompassed three months, including 155,672 trips by 785 users, before the processing procedures detailed below.

Figure 1: User Interface of the *Motiontag App*



a) Tour-Based Map Visualization b) Track Validation Interface

3 Choice Set Generation

The sensor data, as provided by *Motiontag*, was, in the first step, validated, enriched, and transformed into a long-duration semi-passive travel survey. This pre-processing stage, described in more detail in Dahmen *et al.* (2023), provided a data source that was cleaned—by removing anomalies and invalid trips—and enriched—by merging consecutive tracks into trips, map-matching tracks to the road/street network, and labeling of trips within the MVV zone, among other enhancements. The specifics of this pre-processing are not the focus of this paper, but one important step was the generation of "non-chosen mode" alternatives. This means that, for each observed trip, we estimated the length, duration, route, cost, etc. that would have been needed to conduct the same trip with other alternative modes. In the following section, we build upon and expand the work of Dahmen *et al.* (2023), advancing the pre-processing techniques for discrete choice modeling. The first part details the identification of non-chosen mode alternative characteristics and explains the calculation of costs for both non-chosen and chosen alternatives. Subsequently, the integration of weather data is discussed. Finally, the filtering of relevant trips are examined in detail.

3.1 Data Enhancement Process

3.1.1 Travel Time and Travel Distance

We decided to limit our analysis to a specific set of transport modes: walking, cycling, car, and public transportation. Following the the main mode approach (Lorenzo Varela *et al.*, 2018) no combinations of modes within a single trip were permitted, except for walking, which could complement a car or public transportation trip. Only trips within the MVV zone were included for regional comparability.

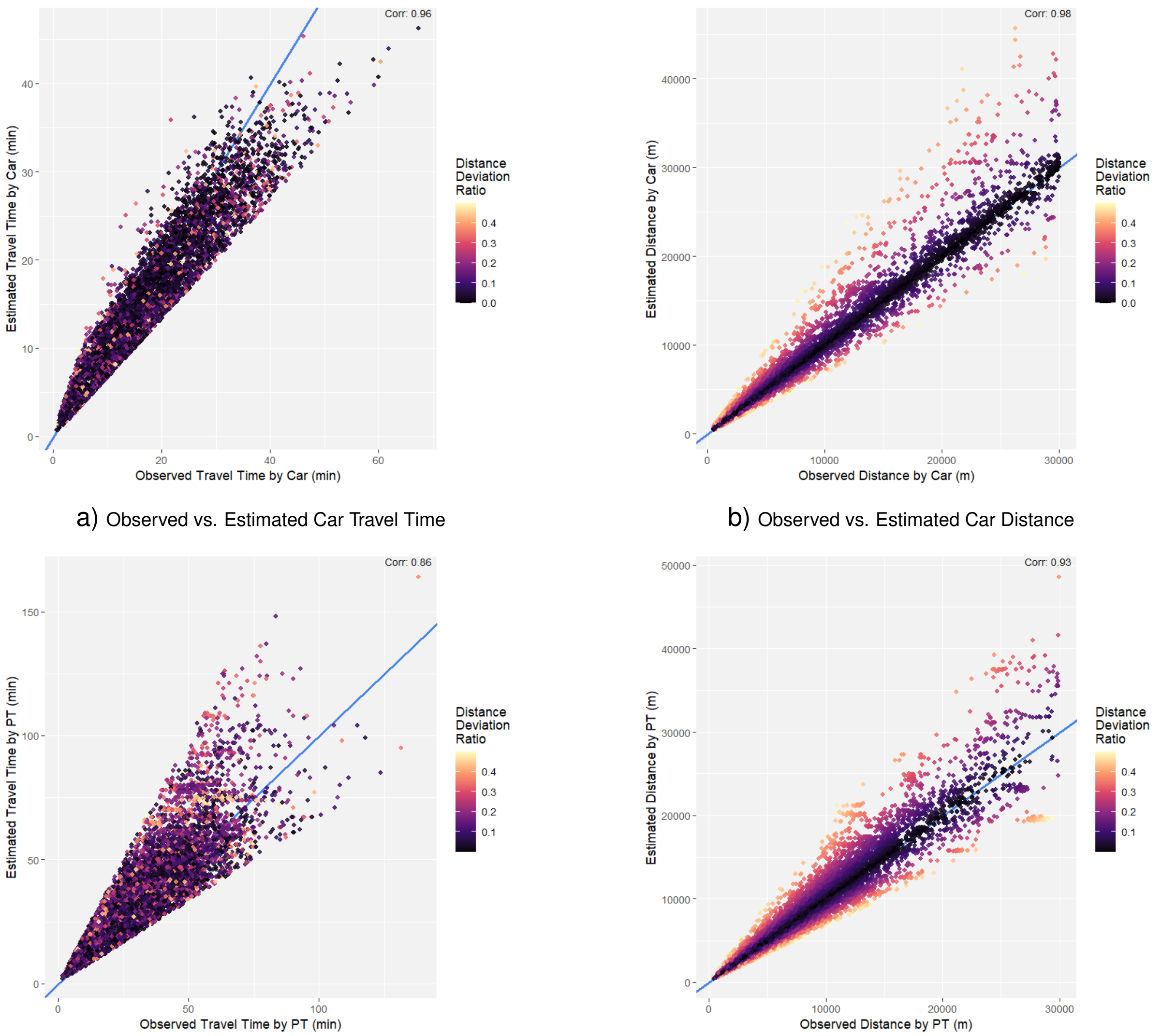
To make RP data from GPS tracking suitable for modeling, it is crucial to enrich it with information about non-chosen alternatives and their attributes (Link *et al.*, 2023; Tsoleridis *et al.*, 2022). This involves estimating travel times, costs, access/egress, and waiting times for both chosen and non-chosen modes. This allows for a comprehensive comparison between calculated and actual trips, ensuring consistency in the data generation process (Hess *et al.*, 2018). The characteristics of trips with car as the main mode were queried using TomTom Routing API (API, 2023), whereas the remaining modes were generated using the open source multi-modal trip planner *OpenTripPlanner* API (OpenStreetMap contributors, 2017) with Munich's transport network and real GTFS data (Dahmen *et al.*, 2023). For car trips, we extracted the trip characteristics based on the timestamps of the actual recorded movements. However, our experience with the TomTom API revealed a limitation: it does not account for the specific travel conditions on the day of the recorded trips but provides travel times based on typical conditions for that time of day and day of the week. For public transport trips, unlike the approach taken by Tsoleridis *et al.* (2022), we utilized historical GTFS data (GTFS.de Contributors, 2024), which allowed us to account for the scheduled services available on the day of each trip. We consider this approach to be more robust, as public transport services can vary over time due to changes in frequencies, scheduled closures, or the introduction of new lines, which would not be captured by querying future trips with similar characteristics. Lastly, for walking and cycling, OpenTripPlanner employs static travel time conditions from the *OpenStreetMap* network (OpenStreetMap contributors, 2017), which is appropriate given the minimal impact of congestion on these modes. Car and public transportation alternatives were calculated only for observed trips exceeding 500 meters.

To evaluate the quality and accuracy of the calculated alternatives, the ratio of the difference between the calculated and observed distances/travel times for the chosen mode was computed. The closer this ratio is to zero, the more closely the calculated metrics align with the observed ones. A threshold ratio of 0.5 was employed, meaning that if the alternative measures were more than double or less than half the observed trip measures, they were excluded from the analysis. Consequently, approximately 42% of trips with car as the main mode, around 21% of observed public transportation and bike trips, and 39% of trips made by walking were excluded. These exclusion rates suggests that real routes vary to the calculated trip via the API. Figure 2 shows the estimated vs. the observed trip attributes for each mode after filtering trips with excessively high ratios. For car trips, the observed travel times are generally higher than the estimated ones, likely due to the inability of estimated travel times to account for short-term disturbances, congestion, and traffic lights. Conversely, for public transportation, observed travel times tend to be shorter than estimated travel times, even after filtering outliers. The exclusion of over a third of walking trips indicates that people often choose walking routes based on factors beyond the shortest path, such as built environment, safety, and walkability (Gregory Lue and Eric J. Miller, 2019; Broach and Dill, 2015; Zhan Guo, 2009). This underscores the complexity of observed walking behavior, making it challenging to predict accurately. Overall, the correlation analysis in Table 1 reveals that discrepancies in travel times are more pronounced than those in distances, even after excluding outliers.

3.1.2 Cost

The calculated alternatives included information on mode, travel time, and distances; however, price estimation for car and public transportation was missing for both the observed trips and the alternatives. For bicycles, the use of shared bikes was excluded, and the cost of bicycle usage was assumed to be zero. For cars, the vehicle registration as of January 1, 2023, by the German Federal Motor Transport Authority (Kraftfahrt-Bundesamt, 2023) was examined to identify the 76 most common car models, which account for approximately 60 % of the passenger vehicles in Germany. The average cost per kilometer for these models was obtained from (ADAC, 2022) and weighted according to the number of car per model to estimate a fleet-representative average price of 50.17 cents per kilometer. This price approximation did not consider the concurrent reduction in fuel taxes implemented from June to August or general fuel price fluctuations. Similar to other studies (Lorenzo Varela *et al.*, 2018; Tsoleridis *et al.*, 2022), the cost calculation based on the ADAC data (ADAC, 2022) included expenses associated with vehicle purchase, maintenance, insurance, and other long-term costs. Due to Munich's highly complex parking system, which provides for various zones, free parking options, and parking costs that vary depending on time and location, parking fees were excluded from the cost

Figure 2: Observed vs. Estimated Trip Characteristics Car and PT



a) Observed vs. Estimated Car Travel Time

b) Observed vs. Estimated Car Distance

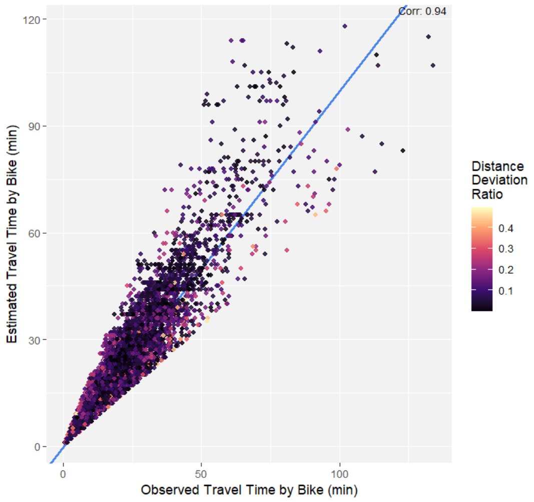
c) Observed vs. Estimated PT Travel Time

d) Observed vs. Estimated PT Distance

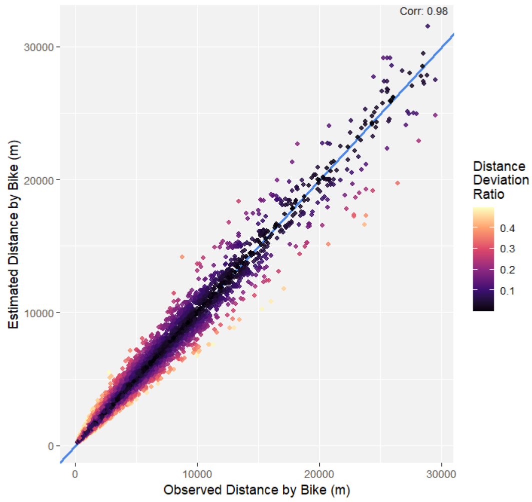
calculation per trip. Additionally, the generally low parking costs in the city further justified their exclusion and the assumed cost of 50.17 cents per kilometer is higher than other estimates for Germany (Kuhnimhof and Eisenmann, 2023; Andor *et al.*, 2020), accounting for additional cost burdens such as parking fees.

A dual approach was employed for public transportation cost calculation. For individuals without a subscription, *single trip costs* were calculated according to the Munich's transit authority—*Münchner Verkehrs- und Tarifverbund* (MVV)—fare structure (München, 2022) by identifying the MVV transit zones at the start and end of the trip and matching them with the corresponding costs. Other ticket options, such as day tickets, regional tickets, or strip tickets available in Munich, were excluded. This introduces noise and uncertainty into the cost

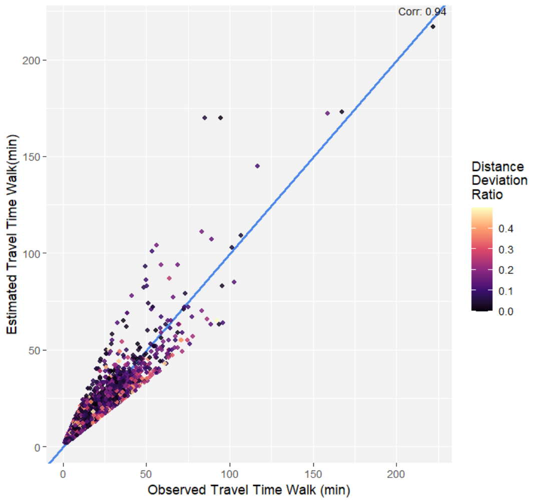
Figure 2: Observed vs. Estimated Trip Characteristics Active Modes



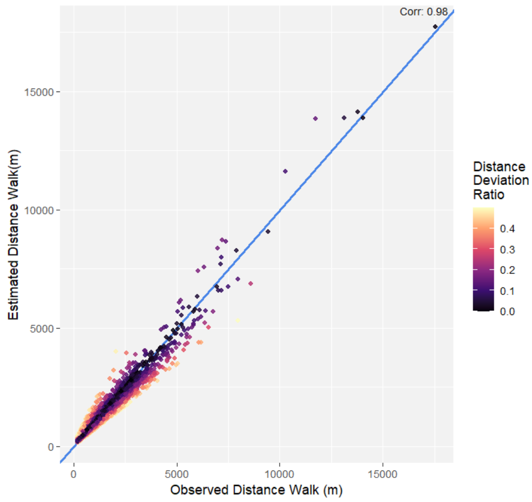
e) Observed vs. Estimated Bike Travel Time



f) Observed vs. Estimated Bike Distance



g) Observed vs. Estimated Walk Travel Time



h) Observed vs. Estimated Walk Distance

calculation. In the first approach, for those individuals with a subscription, the cost of a single trip was set to zero. In the second approach, we introduced the concept of *experienced cost* in which, for subscription holders, the monthly subscription cost is apportioned across the public transportation trips made by the individual n within the respective month. To avoid unrealistic values for users with few observed public transport trips in a month, the experienced cost per trip must be equal to or less than the cost of a single trip (see Equation 1).

$$\text{experienced cost}_n = min(\frac{\text{monthly subscription cost}_n}{\text{number of tracked PT trips of that month}_n}, \text{single trip cost}) \quad (1)$$

During July, the implementation of this methodology was straightforward due to the high prevalence of individuals in the final dataset who possessed the 9-Euro-Ticket. This approach suggests that the experienced cost per trip diminishes with an increase in the number of trips made by subscription holders, thereby potentially incentivizing greater utilization of PT services to maximize the marginal benefit per trip. For September and October, determining the cost and type of subscription involved several assumptions. The respective survey only inquired about general monthly subscription ownership without specifying the exact type of ticket and its validity range. Monthly subscription prices ranged from €63 (zone M) to €242 (zones M-Z6) (München, 2022), making the use of a mean value unfeasible. For individuals indicating subscription ownership, the PT subscription (IsarCard) was assumed, as it is valid for all days and times throughout the month and can be purchased for specific zones, making it the most attractive option for commuters. To estimate the type of monthly subscription for a particular individual in the dataset, the most frequent MVV zones for home and work/study were calculated, and the corresponding subscription valid for these zones was assumed.

3.1.3 Weather

To account for the impact of weather conditions on mode choice, day- and hour-specific weather information was assigned to each trip. We utilized data provided by the German Weather Service for Munich (Wetterdienst, 2020), which included measures of wind speed and precipitation, as well as dummy variables indicating the presence of rain. Wind speed and minimum, maximum, and mean temperatures were recorded on a daily basis. Additionally, a rolling aggregation of precipitation effects was calculated to capture the influence of precipitation over a three-hour window. Due to constraints in data availability, weather measurements were uniformly applied to the entire Munich area. Consequently, these measurements did not account for regional variations or microclimates within the analysis area.

3.2 Filtering Trips Through a RUM Lens

Another key challenge in utilizing GPS data for discrete choice modeling is filtering trips that adhere to rational and compensatory considerations. This behavior is predominantly observed in activity-based travel, where individuals travel for specific purposes, primarily to meet essential needs. Consequently, this excludes recreational and pleasure trips, which follow a different logic. Differentiating between a leisurely walk with a dog, which includes a stop at a local kiosk, and a quick shopping errand is inherently complex. Various approaches have been proposed for defining mode availability and the consideration of alternatives to form the final set of choices contemplated during the decision-making process. These methodologies vary in complexity; from including probabilistic models for forming choice sets (Chiara Calastri *et al.*, 2019; Manski, 1977; Joffre Swait and Moshe Ben-Akiva, 1987) to using soft cutoff terms in the utility function that constrains the availability of an alternative (Cascetta and Papola, 2001; Francisco Martínez *et al.*, 2009). Following a methodology similar to Tsoleridis *et al.* (2022), we defined the consideration of alternatives in a deterministic manner with fixed thresholds. This approach allows for a structured and clear-cut selection of trips that fit within our analytical framework, securing that the trips analyzed reflect genuine economic decision-making processes.

Validity requirements are summarized in Table 1. We included only those observed trips in the analysis that were longer than 200 meters and shorter than 30 kilometers. This constraint was chosen because trips shorter than 200 meters were almost always walking trips and could introduce noise due to GPS inaccuracies. Conversely, trips longer than 30 kilometers were sparse in the cleaned dataset, and to avoid a great impact of a few outliers, these were excluded. This approach also reflects the focus of the analysis on urban mobility (Chiara Calastri *et al.*, 2019). To eliminate recreational trips round trips were precluded. We used only trips for which a valid alternative for the same mode could be calculated. To ensure regular usage of the tracking app, we kept only trips from users with at least 25 recorded trips. In the *Montiontag* app, the trip purpose was automatically detected, but respondents had the option to change and correct the trip purpose later on (Dahmen *et al.*, 2023). Purposes ranged from assistant and medical visits to eating out. For the analysis, we grouped trip purposes into the larger categories work/study, shopping and leisure. Other trip purposes were excluded from the analysis. This led to a crucial reduction of the dataset since approximately half of all trips recorded were assigned the label unknown (Adenaw *et al.*, 2022).

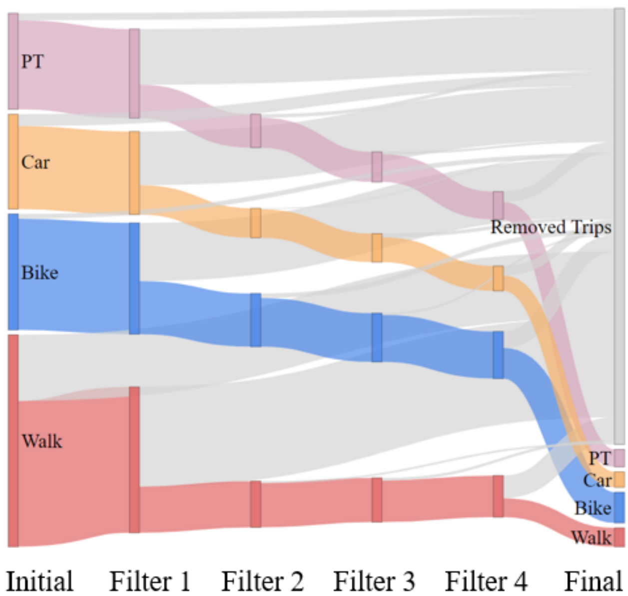
Although a trip-based approach was utilized for this analysis, trip-chain information is critical in activity-based models (Md Sami Hasnine and Khandker Nurul Habib, 2021). For instance, when

Table 1: Validity Requirements for Observed and Calculated Trips

	Main Mode			
Attributes of the observed trip	**Walk**	**Bicycle**	**Car**	**PT**
Min Distance (km)	0.2	0.2	0.2	0.2
Max Distance (km)	5	20	30	30
Max Speed (km/h)	9	-	-	-
Max Waiting Time (min)	-	-	-	60
Max Access Time (min)	-	-	-	60
Attributes of the calculated trip				
Min Distance (km)	-	-	0.5	0.5
Max Distance (km)	5	20	40	40
Correlation analysis Before filtering for deviation ratio				
Correlation Distance	0.77	0.94	0.94	0.84
Correlation Travel Time	0.51	0.51	0.70	0.18
After filtering for deviation ratio				
Correlation Distance	0.98	0.99	0.98	0.96
Correlation Travel Time	0.94	0.94	0.96	0.86

Note: The correlation metrics correspond to trips after being filtered based on a deviation ratio of 0.5 for both travel time and distance.

Figure 3: Loss of Trips Due to Filtering



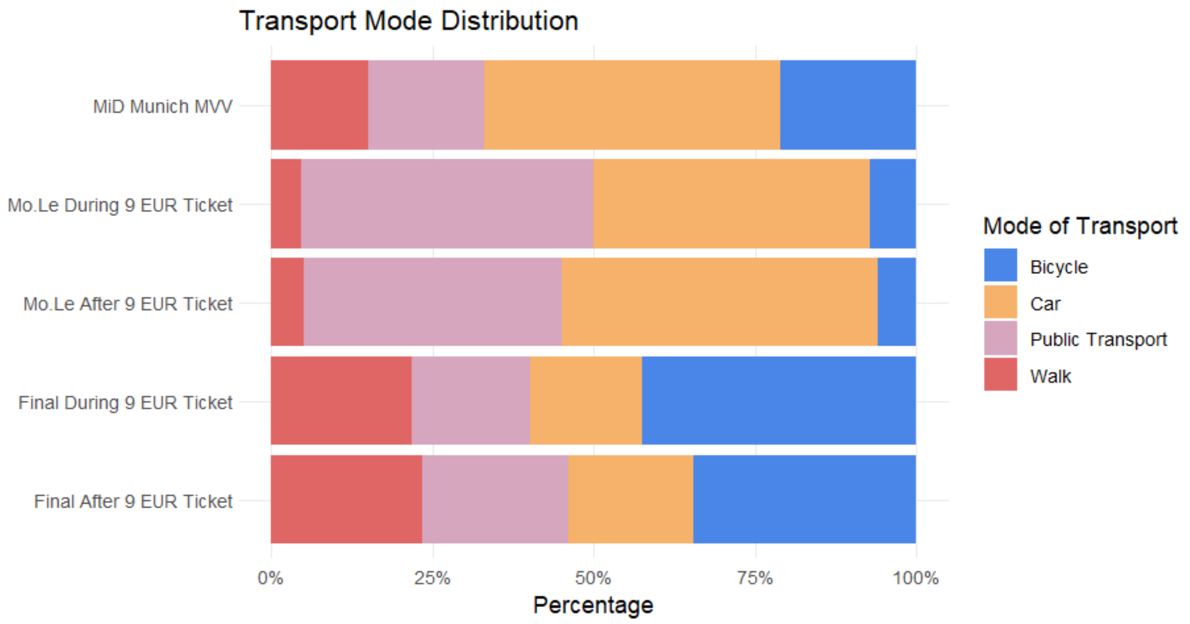
a person travels from work to home and stops by a grocery store for errands, appropriately labeling the trip by its purpose becomes challenging. Therefore, only trips from home or towards home were considered, labeled by the purpose of the unique other stay in the trip. The speed of bike trips in our dataset was capped at 29 km/h, which is a reasonable speed for urban cycling. Walking trips faster than 9 km/h were excluded to eliminate running trips from our analysis. Observed public transportation trips were excluded from the analysis if the waiting time and/or the access time exceeded 60 minutes to exclude disturbances. Car alternatives were included only for respondents who indicated car accessibility in the household survey. Similarly, bike and walk alternatives were considered only within their respective distance thresholds of less than 5 kilometers for walking and less than 20 kilometers for cycling, ensuring they posed viable alternatives. After this extensive data-cleaning process depicted in Figure 3, only 15.80% of the initial trips were left, with 24,593 trips of 353 individuals, including 8,197 trips for July and 16,396 trips for September and October.

3.3 Key Descriptives of the Final Dataset

Interestingly, when examining the mode composition of the final dataset, our comprehensive filtering process resulted in a mode share where only 18.8% of the trips were made by car, 21.1% by public transportation, 22.9% by walking, and a notable 37.1% by cycling. This distribution contrasts sharply with the mode shares reported in the MiD survey data from 2017 (Belz *et al.*, 2020). The proportion of car trips observed in our dataset is remarkably lower than the 46% reported in the MiD 2017 survey for the Munich MVV area (Belz *et al.*, 2020). While the MiD survey indicated that 36% of trips were made by active modes, including walking and cycling, our final sample shows a share of 60% for these modes. It also contrasts with the descriptive analysis of the Mobilität.Leben dataset using raw trip data from June 1, 2022, to September 30, 2022, as illustrated in Figure 4 (Adenaw *et al.*, 2022).

The changes in mode share from during to after the 9-Euro-Ticket period are notable. Unlike the referenced analysis (Adenaw *et al.*, 2022), which observed an increase in the share of public transportation trips from 45.3% in the intervention period to 45.3% in September, our selected trips do not reflect this trend. The data of this analysis depict an increase of PT usage after the end of the price intervention by 23.1% to 22.55% in September and October. We can not observe an increase in PT trips induced by the drastic price decrease in the final data sample and any additional trips present in other studies appear to have been filtered out (Adenaw *et al.*, 2022; Link *et al.*, 2023). Research suggests the 9-Euro-Ticket increased

Figure 4: Mode Share Comparison of Different Datasets.



public transportation usage for holiday activities and excursions (Nobis *et al.*, 2022), which do not typically fall within regular urban travel patterns. The price intervention does not seem to have increased the demand for public transportation trips used for daily commuting and essential short-distance travel. There is also a noticeable decrease in the share of bike trips in September-October compared to the intervention period, dropping from 42.4% to 34.5%, likely influenced by changing weather conditions. Conversely, car usage slightly increased after the 9-Euro-Ticket period, rising from 17.5% to 19.5%. These trends align with those observed in the referenced analysis (Adenaw *et al.*, 2022).

The variation in mode share observed in the final dataset can be partly attributed to the specific subset of trips analyzed, which were filtered for short, urban distances under 30 km with a high proportion of very short trips (> 15 km) favoring active transport modes, as depicted in Figure 5. In contrast, the references data analysis included a broader dataset encompassing 670,096 trips over different periods and accounted for long-distance trips, including those by airplane (Adenaw *et al.*, 2022). The MiD survey's mode share is also constrained to the MVV area, but the share is calculated for all individual trips. Our study concentrates on a smaller subset of trips made for specific purposes (such as shopping, leisure, and commuting) to and from home. When comparing the trip purposes across the two periods of analysis, as shown in Figure 6, we observe that in September and October, there is a higher percentage of trips made for study and work purposes (30.9%), and fewer trips for leisure activities (34%) compared to 28.6% and 37.4% in July. This could be explained by July being a holiday period and summer weather encouraging more leisure trips. Notably, bike trips for leisure and commuting seem almost entirely supplemented by public transportation trips in September and October. In contrast, the mode shares for walking and driving remain relatively constant for leisure and commuting trips.

Figure 5: Trip Distance by Main Mode

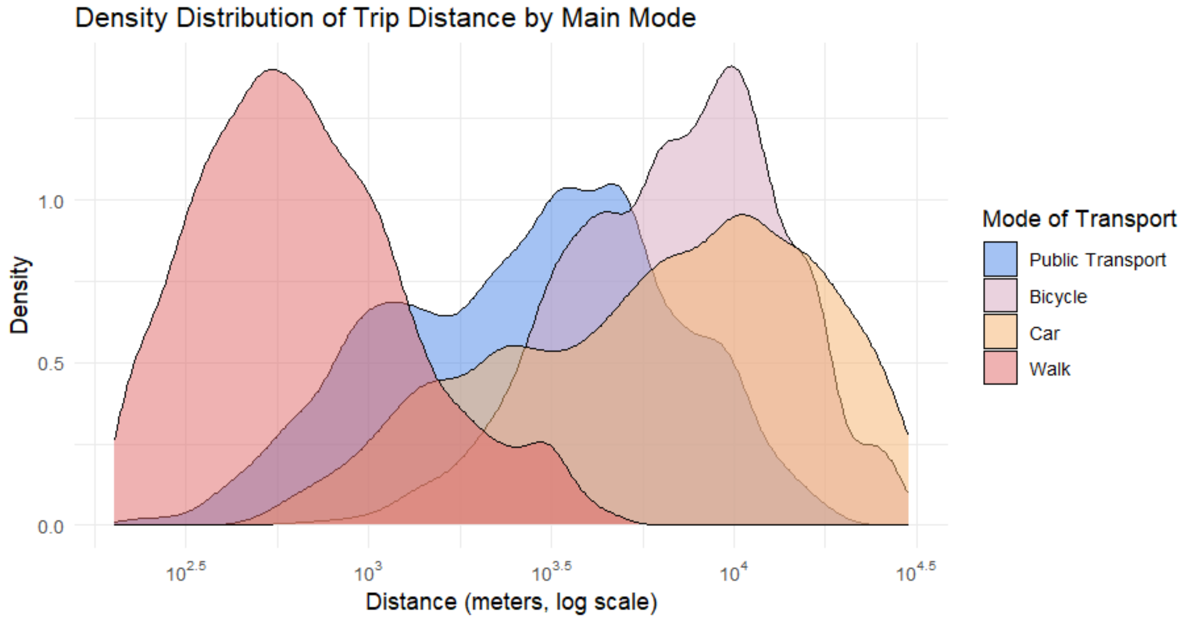
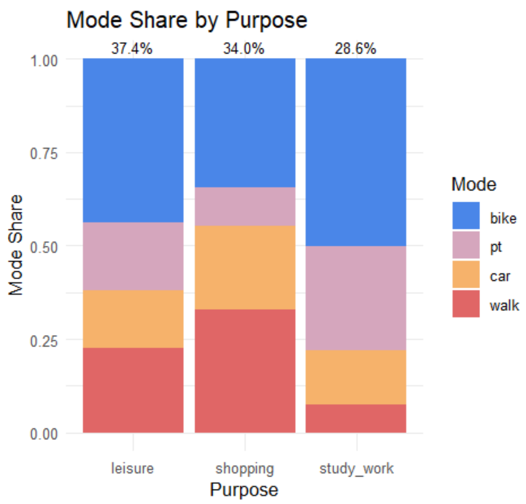
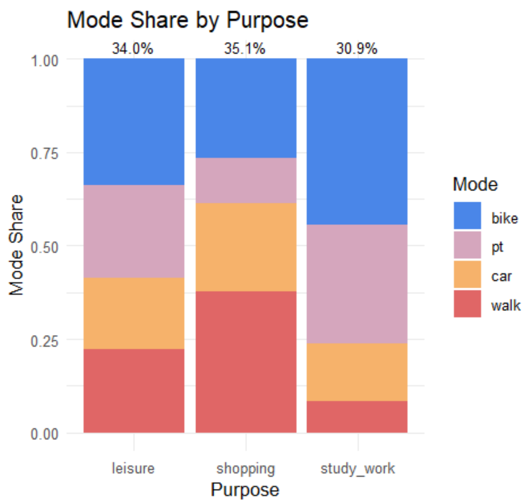


Figure 6: Mode Share by Purpose in the Different Periods



a) Mode Share by Purpose for July

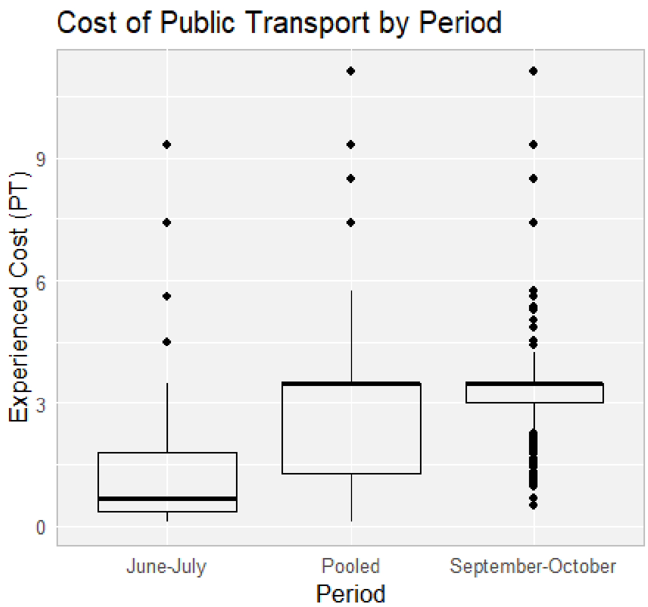


b) Mode Share by Purpose for Sept & Oct

The average cost of a PT trip in July was only 50 cents, compared to an average of €2.60 without the price intervention, which is more than five times the mean price during the 9-Euro-

Ticket period (Figure 7). For car trips, the costs were slightly higher in July, averaging €4.87, compared to €4.65 in September and October, reflecting the slightly longer average distances traveled by car during the intervention period. However, this does not accurately reflect the reality, as our analysis did not account for the concurrent fuel price intervention. Overall, our sample is not representative compared the population in the region, Bavaria, in 2022 (für Statistik, 2024). A substantial proportion of the participants (60%) possess a higher education degree, which is above the representative figure of 20%, and 10% hold a PhD, a considerable over-representation compared to the Bavarian average of 1.6% (für Statistik, 2024). This trend is also reflected in the income levels, with 50% of participants earning €4000 or more per month. Additionally, the sample's age distribution is skewed, with over 50% of participants falling within the 25 to 44-year-old age range. Notably, 89.24% of the sample participants reported having a 9-Euro-Ticket during the intervention period, underscoring its popularity. However, this finding is not generalizable, as a representative survey (Verkehrsunternehmen, 2022) found that 49% of individuals purchased a 9-Euro-Ticket in July.

Figure 7: Cost Distribution of Public Transportation



4 Discrete Choice Modeling of Policy Interventions

4.1 Modeling framework

To measure behavioral changes in mode choice resulting from price interventions such as the 9-Euro-Ticket we use discrete choice modeling. Since the analyst can not directly observe the choice process, the modeling approach utilizes the collected revealed data and is based on random utility theory (McFadden *et al.*, 1973; Hensher *et al.*, 1998). The latent utility U_{int} for an individual n choosing an alternative i among a set of alternatives J in a choice task t is composed of a deterministic component V_{int} and an unobserved disturbance term ϵ_{int} in Eq.2. The deterministic utility is a function of the observed alternative-specific attributes x_{int}, the observed characteristics of the decision-maker z_n, and a vector of corresponding parameters β (Tsoleridis *et al.*, 2022):

$$U_{int} = V_{int} + \epsilon_{int} = f(\,\beta, x_{int}, z_n\,) + \epsilon_{int} \tag{2}$$

For this initial exploratory analysis, the Multinomial Logit model (MNL) is employed. The MNL model is chosen due to its simplicity, effectiveness, and widespread use in identifying mode choice in travel behavior analysis (Ben-Akiva and Lerman, 1985). The MNL model is based on the assumption that each ϵ_{int} is independently and identically distributed (iid) according to the type-I (Gumbel) Extreme Value distribution (Train, 1993). This unobserved utility component distribution allows the MNL model's probabilities to be derived from the following equation (Tsoleridis *et al.*, 2022):

$$P_{int} = \frac{e^{V_{int}}}{\sum_{j=1}^{J} e^{V_{jnt}}} \tag{3}$$

4.2 Value of Travel Time

An important indicator for assessing policy interventions in transportation is the value of travel time (VTT) (Tveter, 2023). It quantifies the willingness to pay to achieve a specific travel time reduction, thereby measuring travelers' trade-off between travel cost and travel time. Equation 4 calculates the relative importance of one unit (hour) of change in time relative to one unit (euro) of change in cost for a MNL model.

$$VTT = 60 \times \frac{\frac{\partial V_i}{\partial tt_i}}{\frac{\partial V_i}{\partial tc_i}} = 60 \times \frac{\beta_{tt}}{\beta_{tc}} \tag{4}$$

The utility functions of the MNL model were specified for the four travel modes: car, public transport, walking, and cycling. Each mode is associated with an alternative-specific constant (ASC), with the ASC for car set to zero. The basic MNL specification assumes uniform sensitivity to the specified parameters among individuals. However, MNL models can account for taste variation to a limited extent when such variations systematically correlate with observed variables (Train, 1993). In this study, such deterministic taste variation was captured by specifying shifts from the base level of the ASCs for specific socio-demographic and environmental attributes. Additionally, shifts were included for travel time based on trip purposes. We tested the model using both public transportation cost estimations, *experienced cost* and *single trip costs*. Due to a better model fit, we chose to include experienced costs as the cost approximation for PT in the final models.

To account for sensitivities related to continuous variables such as income, we initially included an income elasticity as an interaction with cost. However, since income elasticity consistently showed statistical insignificance and produced anomalous results, it was excluded from the final analysis. We also tested distance elasticity for both travel time and cost. Only the distance elasticity for cost yielded viable results in the two separate models, leading us to include it in the analysis. Distance elasticity for travel time was excluded. Despite filtering data to include only trips shorter than 30 kilometers, the heteroscedasticity of the choice tasks can still vary based on trip distance. To address this, we followed the methodology proposed by Tsoleridis *et al.* (2022), integrating scale parameters, ϕ_l, corresponding to various distance quartiles l within the dataset. These scale parameters were applied to the utility function, with the shortest distance scale parameter, ϕ_1, set at 1.0.

In the modeling literature, there is no universally accepted approach to effectively model policy interventions within discrete choice models based on revealed data. There are three main approaches to modeling such interventions: Firstly, two separate models are estimated, and their post-estimation results are compared. Secondly, shifts are used to measure the intervention. Thirdly, a pooled model with a scale variable is calculated to account for sample heterogeneity (Swait and Louviere, 1993). However, a major drawback of using such a scale to measure the effect of an intervention is that the scale is canceled out when calculating the VTTS. Apart from indicating randomness in the model, the scale does not measure the intervention's effect. Our study employed a pooled model and included an ASC shift for July. We chose to include a shift for the entire month rather than for 9-Euro-Ticket ownership because the price effect is captured in the cost variable, and nearly 90% of our sample had the ticket. We opted not to include a shift for the value of the travel time variable, as an ASC shift can capture broader effects associated with the ticket. Previous research has found that the intervention led to changes in perception, such as increased trust in PT (Krämer *et al.*, 2022; Verkehrsunternehmen, 2022; Bissel, 2023) or had negative aspects, such as increased congestion and bottlenecks (Suckow and George, 2023).

Therefore, we estimated three preliminary MNL models: two separate models (one for each period) and a pooled model with an ASC shift for July. These models serve as an initial insight into the potential effects of the intervention.

Table 2: Estimation Results for Three MNL Models

Reference Car	**July MNL**		**September-October MNL**		**Pooled MNL**	
	Est.	**Rob. t-ratio**	**Est.**	**Rob. t-ratio**	**Est.**	**Rob. t-ratio**
ASC						
PT (α_{pt})	-1.693	(-0.772)	9.624	(3.635)	7.979	(3.537)
PT shift female (α_{pt})	-0.079	(-0.170)	0.399	(0.826)	0.356	(0.762)
PT shift age (α_{pt})	0.009	(0.104)	-0.168	(-1.546)	-0.099	(-0.991)
PT shift age sq. (α_{pt})	0.000	(-0.437)	0.001	(0.958)	0.000	(0.383)
PT shift education (α_{pt})	-0.268	(-0.554)	0.059	(0.112)	0.045	(0.088)
PT shift july (α_{pt})					-3.167	(-5.534)
Walk (α_{walk})	-2.783	(-1.117)	3.561	(1.863)	2.937	(1.595)
Walk shift female (α_{walk})	-0.448	(-1.104)	-0.066	(-0.166)	-0.105	(-0.282)

Continued on next page

Table 2: Estimation Results for Three MNL Models (Continued)

Walk shift age (α_{walk})	0.108	(1.265)	-0.004	(-0.052)	0.031	(0.388)
Walk shift age sq. (α_{walk})	-0.002	(-1.919)	-0.001	-(0.717)	-0.001	(-1.195)
Walk shift education (α_{walk})	-0.094	(-0.182)	0.356	(0.765)	0.315	(0.718)
Walk shift july (α_{walk})					0.075	(0.312)
Bike (α_{bike})	-6.418	(-2.647)	0.173	(0.091)	-0.856	(-0.465)
Bike shift female (α_{bike})	0.021	(0.055)	0.286	(0.674)	0.293	(0.733)
Bike shift age (α_{bike})	0.085	(1.107)	0.000	(0.001)	0.032	(0.375)
Bike shift age sq. (α_{bike})	-0.001	(-1.381)	-0.001	(-0.578)	-0.001	(-0.881)
Bike shift education (α_{bike})	0.076	(0.153)	0.236	(0.438)	0.312	(0.616)
Bike shift july (α_{bike})					0.334	(1.426)
Daily Weather						
PT shift rain (α_{PT})	0.198	(1.073)	0.413	(2.409)	0.418	(2.944)
PT shift temperature (α_{PT})	-0.051	(-1.419)	-0.033	(-1.197)	-0.051	(-2.119)
Walk shift rain (α_{walk})	-0.454	(-2.219)	-0.346	(-2.957)	-0.396	(-3.770)
Walk shift temperature (α_{walk})	0.029	(0.986)	0.040	(1.976)	0.040	(2.384)
Bike shift rain (α_{bike})	-0.425	(-2.098)	-0.383	(-3.193)	-0.411	(-3.796)
Bike shift temperature (α_{bike})	0.068	(2.379)	0.064	(3.439)	0.070	(4.334)
Bike shift wind (α_{bike})	-0.027	(-2.196)	-0.014	(-1.279)	-0.018	(-1.936)
Parameters						
Travel time (β_{car})	-0.237	(-1.387)	-0.246	(-3.167)	-0.308	(-3.904)
Travel time (β_{pt})	-0.071	(-1.024)	-0.240	(-4.013)	-0.246	(-4.313)
Access time (β_{pt})	-0.098	(-1.288)	-0.217	(-5.055)	-0.231	(-6.242)
Waiting time (β_{pt})	-0.134	(-1.477)	-0.167	(-3.596)	-0.220	(-4.779)
Travel time (β_{walk})	-0.230	(-3.012)	-0.317	(-6.444)	-0.339	(-7.482)
Travel time (β_{bike})	-0.095	(-1.143)	-0.249	(-4.406)	-0.281	(-5.606)
Travel Cost (β_{cost})	-1.642	(-3.477)	-1.498	(-6.254)	-1.552	(-7.360)
Distance cost elasticity (λ)	-1.121	[-22.954]	-0.496	[18.573]	-0.477	[-21.484]
Purpose						

Continued on next page

Table 2: Estimation Results for Three MNL Models (Continued)

TT shift $shopping_{\text{pt}}$	-0.022	(-0.591)	-0.064	(-1.451)	-0.062	(-1.384)
TT shift $leisure_{\text{pt}}$	-0.010	(-0.323)	0.022	(0.516)	0.010	(0.232)
TT shift $shopping_{\text{car}}$	0.028	(0.503)	0.038	(0.686)	0.054	(0.931)
TT shift $leisure_{\text{car}}$	-0.002	(-0.043)	0.054	(1.004)	0.042	(0.764)
TT shift $shopping_{\text{walk}}$	-0.067	(-1.880)	-0.040	(-1.320)	-0.051	(-1.669)
TT shift $leisure_{\text{walk}}$	0.002	(0.048)	0.035	(1.120)	0.026	(0.832)
TT shift $shopping_{\text{bike}}$	-0.072	(-1.416)	-0.124	(-3.649)	-0.136	(-4.273)
TT shift $leisure_{\text{bike}}$	-0.026	(-1.007)	-0.026	(-0.971)	-0.040	(-1.453)
Scale Parameter						
Scale ϕ_0 short	1.00	[-]	1.00	[-]	1.00	[-]
Scale ϕ_1 medium	0.92	[-2.725]	0.90	[-4.677]	0.90	[-5.834]
Scale ϕ_1 long	0.97	[-0.554]	0.94	[-2.935]	0.93	[-4.753]
Scale ϕ_1 very long	0.97	[-0.330]	0.88	[-4.525]	0.86	[-6.450]
Model Fit						
Log-likelihood (0)	-8492.83		-17250.95		-25743.79	
Log-likelihood (model)	-5930.73		-12375.57		-18575.55	
Adj.ρ^2) equal shares	0.2969		0.2826		0.2805	
Adj.$\rho 2$) observed shares	0.2871		0.2788		0.2780	
AIC	11943.47		24833.15		37043.48	
BIC	12230.94		25149.05		37400.33	
Observations	8197		16396		24593	
Respondents	329		337		353	
Parameters	41		41		44	

Note: We report the Rob t-ratio against 0 in round brackets and the Rob t-ratios against 1 in square brackets.The units of the temporal variables are minutes while those related to costs are Euros.

5 Results

The model estimates of the three behavioral models are presented in Table 2. The July-MNL model demonstrates the best model fit, with an adjusted ρ^2 of 0.287, indicating that the model explains a substantial portion of the variation in the data. The model fit for the September-October (Sep-Oct) MNL is reasonably good, with the pooled model showing a satisfactory fit, albeit the least fitting among the three. This can be partially attributed to the loss of nearly half of the degrees of freedom in the pooled model. One possible explanation for the superior fit of the July-model is the reduced uncertainty and fewer assumptions required in the calculation of the experienced PT costs during the intervention period. The cost calculation was straightforward, with nearly all respondents owning a 9-Euro-Ticket travel pass. In contrast, for the September-October period, the type of travel pass had to be inferred from the data, increasing the uncertainty in the cost parameter for the Sep-Oct MNL model. ASCs reflect the inherent preference for a mode not captured by other model variables. We had anticipated positive ASCs for all modes compared to the car in the July-model, given perceived favorable attitudes towards PT during the intervention period and favorable weather conditions typically promoting the use of active modes. But in the July-model ASCs are all negative. The unexpected negative ASCs may be attributed to not accounting for the fuel tax cut in our car price calculation, possibly shifting the perceived utility differences to the ASCs. This indicates that factors not explicitly modeled, such as such changes in fuel costs or avoidance of PT due to COVID-19 concerns or overcrowding during that period, might have influenced the relative attractiveness of the car. Thereby affecting the utility differences captured by the ASCs. Such an surprising effect is also evident in the pooled model's highly significant, strongly negative ASC shift (-3.167) for July. Future research should focus on more elaborate modeling strategies to better understand these effects. Most socio-demographic variables are not significantly different from zero, except for the squared age variable for walking (-0.002) in July. This indicates that overall utility for walking—ceteris paribus—increases with age but decreases beyond a certain point. We tested various weather measurements using likelihood ratio tests and ultimately included only daily weather metrics: mean temperature, a dummy variable for rain, and maximum wind speed for cycling. Incorporating daily weather metrics led to a better model fit than hourly or aggregated weather statistics. This suggests that individuals might plan their trips by incorporating daily weather information into their decision-making process. The weather-related variables showed expected trends when contrasted to car usage. For active modes such as cycling and walking, significant outcomes on the one-% level were observed, with a decrease in utility when it rains. We can observe a positive estimate for active modes with increasing temperature in all models, although not significant. For cycling, strong winds (-0.027) significantly decreased the utility in July holding all other factors fixed. The cost coefficient consistently exhibited a significant negative effect at the one%-level across all models. The distance elasticity on cost is also significantly different from one and has the expected negative sign in all models. This indicates that cost sensitivity decreases as distances increase, which is behaviorally sensible. Purpose shifts for travel time were fixed for work and study trips and were mostly non-significant. Lastly, we expected the scale parameters ϕ_l to decrease with increased trip distance, aligning with the findings of (Tsoleridis *et al.*, 2022). Such an diminishing scale would indicating greater uncertainty and variability in trips over longer distances. However, in our model, this expected pattern is not consistently observed. While we do observe a diminishing scale for the longest distances, this behavior is not as evident for medium and long trips. A closer analysis using more advanced models would be necessary to fully understand these discrepancies.

Table 3: Estimation Results for Three MNL Models

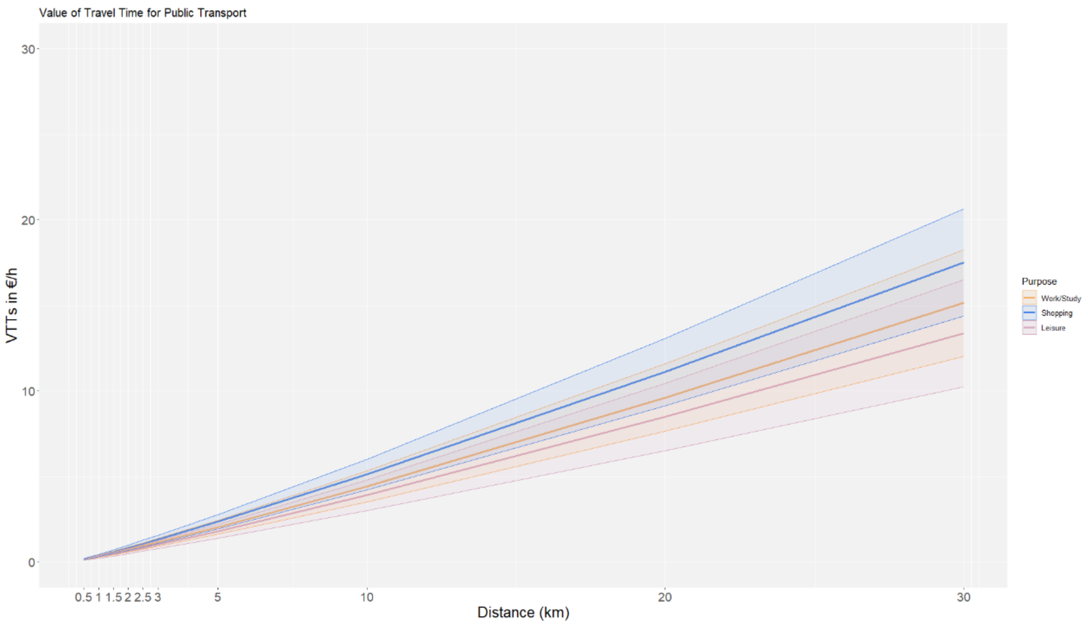
	July MNL		**September-October MNL**		**Pooled MNL**	
Value of Travel Time	**Est.**	**Rob. t-ratio**	**Est.**	**Rob. t-ratio**	**Est.**	**Rob. t-ratio**
VTT hour $work\ /\ study_{\text{car}}$	8.65	(1.45)	9.86	(3.36)	11.89	(3.93)
VTT hour $shopping_{\text{car}}$	7.62	(1.56)	8.32	(3.35)	9.80	(3.98)
VTT hour $leisure_{\text{car}}$	8.71	(1.49)	7.71	(3.01)	10.62	(3.90)
VTT hour $work\ /\ study_{\text{pt}}$	2.61	(1.06)	9.62	(5.03)	9.50	(4.87)
VTT hour $shopping_{\text{pt}}$	3.42	(1.17)	12.18	(6.93)	11.91	(7.18)
VTT hour $leisure_{\text{pt}}$	2.96	(1.15)	8.73	(5.87)	9.10	(6.38)
VTT hour $waiting\ time_{\text{pt}}$	4.89	(1.57)	6.68	(4.05)	8.51	(5.23)
VTT hour $work\ /\ study_{\text{walk}}$	8.40	(2.95)	12.70	(7.77)	13.10	(7.80)
VTT hour $shopping_{\text{walk}}$	10.85	(3.36)	14.30	(9.22)	15.07	(9.59)
VTT hour $leisure_{\text{walk}}$	8.34	(3.24)	11.31	(9.05)	12.11	(9.68)
VTT hour $work\ /\ study_{\text{bike}}$	3.47	(1.18)	9.98	(5.58)	10.87	(6.54)
VTT hour $shopping_{\text{bike}}$	6.09	(1.36)	14.94	(6.97)	16.13	(8.09)
VTT hour $leisure_{\text{bike}}$	4.43	(1.24)	11.01	(5.89)	12.40	(7.14)

The results for the value of travel time, presented in Table 3, align with our expectations, indicating substantially lower VTTS for PT in July, with only 2.61 €/h for commuting trips compared to 9.62 €/h in September and October. The pattern holds true for other purposes as well, with VTTS in September-October being approximately three times higher than during the price intervention period. The models reveal consistent ratios between the VTTS for each mode compared to work and study trips. For car travel, VTTS for shopping trips are generally lower than for commuting, with the lowest values observed for leisure activities in the Sept-Oct model. For active modes such as walking and cycling, the VTTS for shopping trips are higher compared to commuting trips, likely due to the logistical challenges of transporting goods. The pooled model exhibits slightly elevated VTTS across all modes compared to the separate models. We believe this may be due to the higher range of PT costs in the pooled model. Previous SP research has demonstrated that experimental design and the range of cost values can influence VTTS calculations (David A. Hensher, 2006; Ojeda-Cabral *et al.*, 2018). We hypothesize that this effect may also apply to RP data. The deviation between minimum and maximum costs in the pooled model is approximately 20% greater than in the individual models (Figure 7), which could partially explain the inflated VTTS observed. To further understand the changes in VTTS for PT due to the intervention, we plotted the values over various distances. Figure 8 demonstrates that VTTS increase with longer distances, accompanied by larger standard errors at extended distances. This effect is consistent with research by Schatzmann (2023), which reports similar VTTs and increasing values with distance. The significant price reduction offered by the 9-Euro-Ticket notably decreased VTTS for public transportation, compared to the Sep-Oct model and in contrast to the generally higher VTTS reported in the literature for public transportation (Lukas Hartwig *et al.*, 2024).

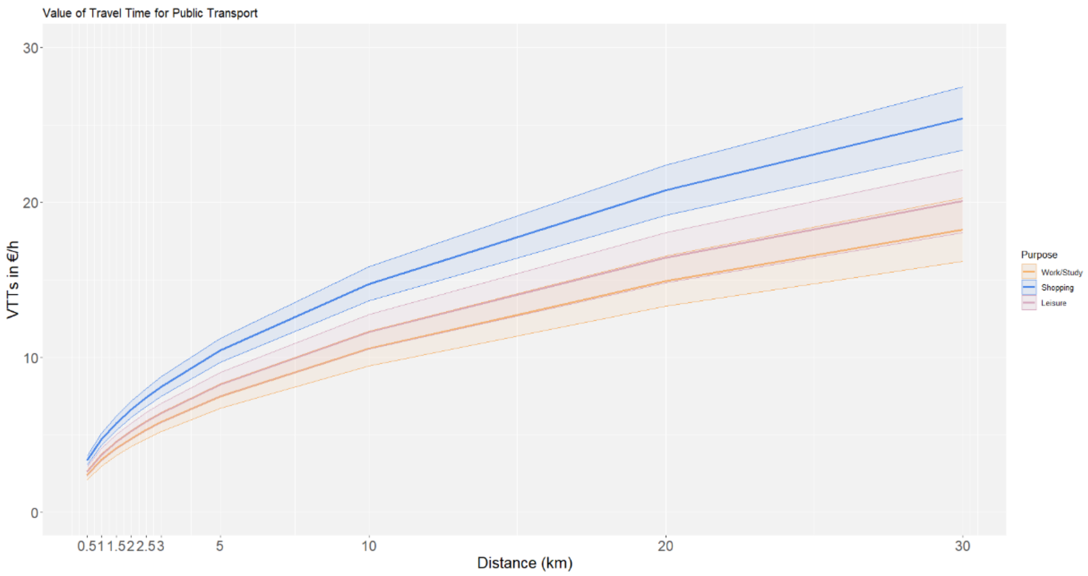
6 Discussion

For future research, enhancing data processing by incorporating supervised machine learning techniques in the data filtering process could significantly refine the selection of trips. One could train an algorithm on a subset of labeled trips and use such an approach on the whole dataset to automatically identify trips that align with our theoretical framework. Another advancement could be the inclusion of more tour-based information in the filtering process. Trip-chaining information could make the final availabilities more realistic since overall travel context of trips matter in decision making. A critical area of uncertainty in our analysis is the cost calculation for public transportation, given the abundance of ticket options and the difficulty in determining the actual ticket used by individuals. Developing a separate model to estimate the latent variable of travel pass ownership based on a broader range of variables could provide a more accurate cost assessment. We also believe that sophisticated approaches to make VTTS comparable across studies and time periods are needed to further increase the robustness of the measures. Research should be conducted on how to incorporate not only observed heterogeneity through shifts and elasticities, but also random heterogeneity into the calculation of VTTs, as well as developing approaches to account for study context and variable distribution in VTTs based on RP. Utilizing advanced modeling techniques such as Mixed Multinomial Logit models would allow for a deeper understanding of heterogeneity in travel behavior, capturing random taste variations. These advancements would lead to more accurate estimates and richer data interpretations, enabling more precise policy recommendations for future research.

Figure 8: VTTS by Distance and by Accounting for Distance Cost Elasticity



a) VTTs for PT in July



b) VTTs for PT in September-October

a

[a] *Note:* VTTS were calculated while accounting for distance cost elasticity.

7 Conclusion

Our analysis aimed to compare the results of two separate models with those of a pooled model to assess the impact of the 9-Euro-Ticket intervention. The findings indicate that the pooled model was inadequate for this purpose. It produced anomalous results, such as a positive distance elasticity (0.403), poorer model fit, and elevated VTTS values. The pooled model's inability to precisely measure the intervention's effect made it challenging to draw definitive conclusions. The contextual differences between the two periods are too remarkable to be accurately captured within a single model, underscoring the necessity of using separate models to effectively evaluate the intervention's impact. By comparing the two separate models, our study successfully demonstrated that the VTTS for PT during the 9-Euro-Ticket intervention in July are remarkably lower than in the September-October period. This finding highlights the substantial influence of the 9-Euro-Ticket on travel behavior. Our detailed data filtering and preparation approach proved effective, allowing us to derive meaningful insights and contribute to the research field.

In closing, one main learning during our analysis is that, even when new technologies serve us with high-accuracy (semi-)automated travel diaries, the collected dataset consists of a large part *messy trips*, which Jennifer L. Kent and Corinne Mulley (2023) characterized as spatially and temporally complex, often deviating from assumed planning behaviors, and being emotionally or physically loaded. This underscores the importance of continually testing and refining nuanced methodologies for processing and modeling GPS-based revealed-preference data.

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9 Authors Contribution

The authors confirm their contribution to the paper as follows: funding acquisition: AL, KB; study conception and design: SAO, FB, AL, KB; data collection: AL, processing and analysis: SAO, FB, AL; manuscript: SAO, FB, AL. All authors reviewed the results and approved the final manuscript.

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