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Modal Split Perceptions and Preferences for Public Funding

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Abstract

The modal split, an indicator which summarizes the intensity at which different modes are used in a given location (proportion of trips made), is becoming a widely used benchmark in public policy and regional goal-setting. Using data from a 2024 survey among 3,052 participants in Germany, this study looks at the modal split indicator from the perspective of laypersons. This indicator is often used to communicate local mobility goals with the public. We investigate whether people are able to guess the modal split distribution in their locale, which modal split would be ideal in their view, and how these perceptions influence opinions on public spending for transportation. We also examine whether showing examples of real modal splits to a random subset of participants influences accuracy or any of our other markers. Results indicate that participants have some trouble guessing modal split proportions, and that the examples did not significantly improve this. For example, only 17% of participants' guesses for the car share are within 5 percentage points of the real split. However, 85.6% of participants would like the share of car trips to be lower by on average 22.2 percentage points (mean perceived car share is 55.2%). Additionally, introducing people to the concept of the modal split without also giving real world reference points negatively influences the amount of public funds they would like to be assigned to sustainable transportation modes.

Key words: modal split; perception bias; mobility preferences; information treatment; public spending; policy communication

JEL codes: R40; R42

1 Introduction

While overall CO_2 emissions in Germany have decreased by almost 50% between 1990 and 2024, emissions from the transport sector have only decreased by about 11% between 1990 and 2023 (UBA, 2024, 2025). Motorized individual transport also causes additional negative externalities such as air pollution, accidents, noise, and congestion (Adler & van Ommeren, 2016; Schmutzler, 2011; Wilhelm et al., 2012; Zheng et al., 2010). In Germany, 47% of all trips are done by car or other motorized vehicles, with biking and public transport only accounting for 17% and 10%, respectively (Ecke et al., 2023). To facilitate a transition from motorized individual transport towards more sustainable modes such as biking, public transport, and walking, gathering information about the current status quo of transportation behavior is vital. One way in which transportation behavior is studied is via the *modal split*, an indicator that reflects the relative intensity at which different transportation modes are used. The modal split shows how the the sum of total trips in a city or location is distributed between modes, most commonly distinguishing between these four categories: motorized individual transport, bicycle or e-bike, public transport, and walking.

In many German cities the share of trips done by motorized individual transport is substantially larger than the shares of biking, public transport, or walking. Often the share lies above 50% and is hence larger than the three remaining categories combined (Hubrich et al., 2025, pp.132-139). A number of cities have stated mobility transition goals referencing their modal split. The German city of Essen, where cars were used for 55% of trips in 2019, wants to achieve a modal split with 25% for each mode category by 2035, reducing the car share by 30% (Essen, 2025). The city of Bochum wants to raise the proportion of the so-called "environmental alliance" (i.e. biking, walking, and public transport) in the city's modal share to 60% until 2030 and the city of Hamburg wants to raise it to 80% (Stadt Bochum, 2025; Stadt Hamburg, 2025). And German cities are not alone in this trend of formulating modal split goals, as seen for Manchester (2021), Stockholm (2012), and Atlanta (2018).

Shifting to more sustainable transportation requires substantial investments into transport infrastructure with careful adaptation to local conditions and mobility needs. With many cities being short on funding, these investments may result in less investment into, for example, road infrastructure, a trade-off which is rarely communicated to constituents. Additionally, studies have found that people tend to be in favor of increasing funding for public transport infrastructure, as long as it does not mean higher costs for users (Lichtin et al., 2024). And lastly, depending on political orientation, trust in the government is one of the most important factors to ensure the support of constituents (Lim & Moon, 2022), which is why it is vital for communication about goals to be clear and understandable. If indicators such as the modal split are used as a communication tool, it is advantageous to know how these numbers are interpreted and if they are understood by the public.

This is the first study that examines how people perceive modal splits in their immediate surroundings and how accurate their estimations are. It is a survey-based analysis of how participants across Germany estimate what the modal split looks like where they live, how their perceptions measure against real-world numbers, and which changes participants would like to see in their city's or municipality's modal split. Additionally, we investigate people's preferences for public spending by prompting them to distribute hypothetical public funds between the four categories commonly used in the modal split. This is the first study that looks at what people may be picturing when the modal split indicator is used as a tool to communicate with the public, and at whether intuitive perceptions regarding modal splits are biased. It also looks at how showing modal split examples can influence modal split perceptions and wishes, as well as how preferences for funds distribution are influenced differently, depending on whether participants are only prompted to give their guesses of modal split, or whether they are also shown the above-mentioned modal split examples beforehand.

The following section discusses current modal split literature and usage. The study sample and survey setup are laid out in Section 3, Section 4 discusses methodology, followed by the results in Section 5 and conclusions in Section 6.

2 Background

The modal split indicator – sometimes also referred to as "modal share" – most commonly takes into account four mode categories: motorized individual transport (i.e. cars, motorbikes, and similar, including riding as a passenger), biking (including e-bikes and pedelecs), public transport (the subway, buses, streetcars, etc.), and walking. Usually both trip-amount and trip-length are collected and reported on, two dimensions which contain different information but are systematically linked (Kölbl et al., 2024). It was developed in the 1950s and was first used as a technical parameter in highway traffic forecasts (Deen, 1963; Salter, 1974; Vanoutrive & Huyse, 2023), later applied to mode choice models on optimal transport usage (Goodwin, 1977; Tyson, 1977), and in its most recent function became part of the varied discussions around transitioning to more sustainable mobility systems (Banister, 2008; Lee et al., 2022). Here, the focus is often the proportion of motorized individual transport, in comparison with the proportions of the less emissions-intensive alternative modes, and in comparison with 'better' or 'worse' performing cities and regions.

In Germany, modal splits vary widely between cities. Car trips reportedly take up between 17% and 70% of all trips, biking between 2% and 43.5%, public transport between 5% and 40%, and walking between 9% and 35% (Sources in Table A1). It is important to note that current data on modal splits is not available for all cities. The larger a city, the more likely it is to find data, but often this data can be several years old. Regarding more rural areas, reliance on motorized individual transport is reportedly higher than in cities (BMDV, 2020). The "Mobilität in Deutschland" (MiD) survey series 2019 report summarizes the modal split for small cities below 20,000 inhabitants and rural regions as 66-70% cars, 7-8% biking, 5-7% public transport, and 17-18% walking (Nobis & Kuhnimhof, 2018, p.47).

Modal split is most often measured by conducting household surveys comprising mobility journals, in which participants record all trips for a set amount of time (Strommer et al., 2023). Most commonly, participants are assigned one specific weekday date ("Stichtag") within the study's observation window for which to record their trips (Hubrich et al., 2025; Nobis & Kuhnimhof, 2018). Overall however, there are no national or international guidelines on modal split data collection. Hence, while numbers are often compared, they are not always comparable (Strommer et al., 2023; Vanoutrive & Huyse, 2023). On a European scale, the revised regulation on the Trans-European Transport Network (TEN-T), which entered into force in July 2024, requires the 431 cities listed as "urban nodes" to regularly report a number of indicators with the modal split among them (European Commission, 2024). There are some requirements on data collection, but a lot is left up to the respective city. Even if modal split studies have the same general approach (e.g. household surveys), they can differ with regards to their treatment of multimodal trips, whether walking trips to public transport are counted, the timing and duration of the survey, and numerous other aspects (Strommer et al., 2023). Studies that collect data in a large number of different cities following the same methodology are therefore valuable. One such example is the "Mobility in Cities" study series by TU Dresden, which is a mobility survey that is conducted in regular intervals and included 493 cities and municipalities in its 2023 iteration (Hubrich et al., 2025).

Although modal split goals are communicated publicly to signal commitment to a mobility transition, little is known about how members of the public receive and interpret this indicator. The focus of other studies is often on subjective safety, walkability, or attractiveness of the local area rather than on traffic volumes (Anciaes et al., 2019; Ettema & Schekkerman, 2016; Troped et al., 2017). However, if the modal split is to be used effectively as an indicator of goal achievement and as a communication tool, we need to understand how these numbers are received and contextualized by the public.

As it is well-known that humans struggle with accurately estimating numbers when observing large amounts or volumes (Cheyette & Piantadosi, 2020), we can assume that it is no trivial task to translate one's subjective perceptions about traffic into a simple set of percentages.

The contributions of this study lie first and foremost in the novelty of taking a popular traffic indicator and studying how participants intuit its values. We also investigate which factors contribute to the accuracy of perceptions for participants in larger cities, and whether introducing this indicator and showing real-life examples has any bearing on their preferences for public spending on transport infrastructure. We hypothesize that people cannot easily intuit modal split numbers, specifically that the proportion of trips by car is underestimated, that giving them examples will improve their accuracy, and that it will also positively affect their preferences for public spending on sustainable transport modes.

3 Data

This study uses data from a household survey conducted between April 24th and May 20th 2024, the full sample of finished surveys comprises 8,257 participants. The survey was part of the "mobility panel" for which the RWI conducted four surveys in the years 2018-2024 and which were all centered around mobility and transport policy. Andor et al., 2024 summarize the results of the general part of the 2024 survey. Of the 8,257 participants in the survey, a random sub-sample of 3,052 participants answered questions centered around the modal split.

The experiment which follows was developed after a similar modal split "guess" question, including an example table, was posed in the 2022 version of the survey, and guesses for car proportions were far lower than expected. It was suspected that the examples that were shown displayed too low of a range of car proportions, biasing the participants' guesses downward. Therefore the example table in the experiment below shows a different set of four cities than in the 2022 survey, with car trip proportions between 25% and 60%. The experiment originally also included a second part which focused on the cities of Essen, Bochum, and Dortmund. This part is mentioned in the registered preanalysis plan. However, due to survey design issues we were not able to use these results as initially planned and therefore focus on the Germany-wide portion of the experiment in this paper.

All participants first answered a number of questions on socioeconomic characteristics as well as their mobility behavior and their living environment. The sample was then split randomly into three groups: Group ″Info″, Group ″No Info″, and the Control Group. The balance table in the Appendix (Table A5) shows that this randomization was successful, as the three groups do not differ from each other significantly in their characteristics.

Group ″Info″ received an example table with current modal split percentages in the cities of Duisburg, Köln, Herne, and Münster (see Appendix, Table A1). We chose four cities that would represent a relatively wide spread of real world trip proportions of car trips, biking, public transport, and walking so that the example table would only serve as an achor point to theoretically realistic numbers, but not prime the participants into any particular direction. We also chose four cities located in Northrhine-Westfalia (NRW) since the same four cities were also used for another experiment in the same survey focused on NRW and we wanted the ″treatment″ to stay comparable between the two designs.

Since participants' zip codes were known, if they lived in one of these four cities they were only shown the other three examples to not reveal the real modal split numbers to them. This information treatment using modal split reference points was hypothesized to increase the accuracy of the participants' stated modal split perceptions. Group ″No Info″ did not receive any additional information before the modal split questions.

Both Group ″Info″ and Group ″No Info″ were then prompted to guess the modal splits in their city or municipality (Question MS2) and to specify their ideal modal split (Question MS3). For both questions, they were asked to give percentages for the

Variable	Details	Mean	Std.D.
Female	(0/1); 1 if female	0.46	0.50
Age	Age at time of survey (Min: 18 years, Max: 90 years)	58	15
Low income	(0/1); 1 if monthly net household income below €2,200)	0.26	0.44
Medium income	(0/1); 1 if monthly net household income between €2,220 and €4,200	0.40	0.49
High income	(0/1); 1 if monthly net household income above €4,200	0.34	0.47
Children	(0/1); 1 if participant has one or more children	0.13	0.34
Household size	Number of individuals living in same household	2.13	1.05
University education	(0/1); 1 if achieved university degree of Bachelor's or equivalent	0.45	0.50
Working	(0/1); 1 if currently (self-)employed or serving in military/civil service	0.50	0.50
Lives in city	(0/1); 1 if lives in (outskirts of) a city > 20,000 inhabitants	0.56	0.50
Car	(0/1); 1 if household has one or more cars	0.90	0.30
Ticket	(0/1); 1 if owns a public transport ticket	0.24	0.43
Bike	(0/1); 1 if household has one or more bicycles	0.67	0.47
E-bike	(0/1); 1 if household has one or more electric bikes/pedelecs	0.32	0.46
Would use car less	(0/1); 1 if could imagine using car significantly less ("(Somewhat) agree")	0.22	0.41
No commute	(0/1); 1 if participant has no regular commute	0.52	0.50
Commute: Car	(0/1); 1 if most often commutes by car	0.31	0.46
Commute: Bike	(0/1); 1 if most often commutes by bike or e-bike	0.07	0.25
Commute: Public Transport	(0/1); 1 if most often commutes by public transport	0.06	0.23
Commute: Other mode	(0/1); 1 if most often commutes by other mode	0.05	0.21
Green	(0/1); 1 if inclinded towards the party "Die Grünen/Bündnis90"	0.18	0.39
SPD	(0/1); 1 if inclinded towards the party SPD	0.19	0.39
CDU	(0/1); 1 if inclinded towards the party CDU	0.21	0.41
Party: Other/None	(0/1); 1 if inclinded towards another political party or none	0.42	0.49
# observations		3052	

Table 1: Summary Statistics

following four categories: 1) Car (and motorbike, scooter, etc.) also as passenger, 2) bike or e-bike, 3) public transport, 4) walking.

All three groups, including the control group, were then asked to distribute hypothetical public funds for transport and mobility infrastructure (Question MS4). This was the only question which the Control group received. They were prompted to imagine that their muni-cipality or city was able to spend a large sum of money, earmarked for transport infrastructure projects, and then asked to divide these funds between the previously mentioned four categories. Lastly, all participants answered a second block of questions on socioeconomic characteristics. The exact wording of all experimental questions can be found in Appendix A. Table 1 shows summary statistics of all relevant variables and Table A4 in the appendix compares our sample to representative statistics of the German population. Our sample is slightly older, more individuals live in households of two persons or more, more individuals have a university education.

Since Group "No Info" was prompted to guess their local modal split, but had to do so without receiving the table of reference modal splits, the group's function is to

	Mean	(Std.D.)	Median	Min	Max
Car	45.5%	(11.2%)	48.4%	17.0%	70.0%
Bike	15.8%	(7.9%)	14.9%	2.0%	43.5%
Public Transport	11.3%	(5.5%)	10.5%	2.7%	40.0%
Walking	27.3%	(5.6%)	27.4%	9.0%	40.5%
City size	219,582.3	(385,542.6)	114,972	16,155	3,596,999

Data: 2015-2023, for sources see Table A2, for details see Table A6

Table 2: Real Modal Split: Summary Statistics for 84 cities

show what role the example table plays in both guess accuracy and further opinions on public spending (see below). Group "No Info" therefore serves as both a control group to the information treatment that Group "Info" received, and as a group to show the effect of receiving the "treatment" of only being prompted to think about the modal split, when comparing its answers to those of the Control Group to the funds distribution question.

In addition to the survey data, we also use data on cities' real modal splits, if available. Fortunately, there were a number of larger studies to draw data from. For 79 cities, data stems from the 2023 "Mobilität in Städten" survey conducted by TU Dresden (Hubrich et al., 2025). For another 13 and 14 cities, respectively, we used data from the Agora Verkehrswende study (Agora Verkehrswende, 2020) and the "Mobilität in Deutschland" study (Bäumer et al., 2019). About 80% of the real modal split data we use in this study therefore stems from three large studies, which makes comparability of data easier, as these three studies also had similar survey approaches. Some detail on the survey approaches is shown in Table A3. We were able to compile current modal proportions for 136 cities, stemming from the years 2016 to 2023, with 85% from 2020 or later. The represented cities have varying sizes, from 16,000 inhabitants to 3.6 million, and include cities from all federal states.

This real modal split data could be matched with the residences of 749 of our participants in Groups "Info" and "No Info", for which perceived and real modal splits could now be compared. With 38.6% and 35.4% respectively, a similar proportion of participants from Groups "Info" and "No Info" were matched with real data. Table 2 summarizes the collected city data, and Table A2 in the Appendix lists all data sources. Since the data stems from a time span of eight years, the comparisons are not representative of the current situation in all cases. This is addressed through robustness tests.

4 Methodology

Since this is the first study looking at how people perceive modal splits in their immediate surroundings and how accurate these perceptions are, there will be a strong focus on descriptive results and comparing outcomes between the three treatment groups via statistical tests.

First, an overview of modal split perceptions is presented, including descriptives separated by location. Then, for those participants for which real world modal split data was available, the "accuracy" of their guesses is calculated by subtracting the real number from the perceived one. We then estimate via ordinary least squares (OLS) how the perception accuracy, specifically of the proportion of car trips, is affected by showing the reference table (Group "Info"):

$$AccuracyCar_i = \alpha_0 + \alpha_T TreatInfo_i + \alpha_v Overest_i + \alpha_u Underest_i + \alpha'_x x_i + \epsilon_i \qquad (1)$$

$$AccuracyCar_i = \left| \frac{GuessShareCar_i - RealShareCar_i}{RealShareCar_i} \right|$$

where $AccuracyCar_i$ is the absolute value of the relative difference between perceived modal split share of car trips and the real number, $TreatInfo_i$ indicates whether a participant belonged to Group "Info" (reference group is group "No Info"), and $Overest_i$ and $Underest_i$ are binary indicators of whether an individual over- or underestimated the real split, respectively, with perfect accuracy as the reference level. x_i designates the set of socio-economic characteristics, attitudes and other control variables and ϵ_i is the error term.

Next, we look at the desired modal splits as stated by the participants, and compare these to the perceived modal splits. To look at participants' wishes for change in the share of car trips specifically, the following two equations are then estimated:

$$WishLessCars_i = \beta_0 + \beta_x' x_i + \beta_T TreatInfo_i + \eta_i \tag{2}$$

$$|\Delta CarShare_i| = \gamma_0 + \gamma_x' x_i + \gamma_T TreatInfo_i + \nu_i \tag{3}$$

where $WishLessCars_i$ is a binary indicator for whether a participant's stated wish for the share of car trips was lower than their perceived share and $|\Delta CarShare_i|$ is the absolute value of the difference between wish and perception. η_i and ν_i are the error terms. Equation 3 is only estimated with data from those participants for whom the desired car proportion was lower than their perceived car proportion.

We additionally want to investigate how a desire for change within the proportion of car trips correlates with acceptance for concrete policies. In the survey, before the section on modal split, participants were also asked to state their acceptance for a large number of measures on a 5-point Likert Scale between (1) "Strongly disapprove" to (5) "Strongly approve". To juxtapose acceptance and desired change in car trip proportion, we recode the stated acceptance into a binary variable which is 1 if a participant "Rather Approves" or "Strongly Approves" of a measure, and then show the correlation of acceptance rates with the desired change in modal split.

The last object of study is the distribution of hypothetical funds between the four mode categories. Specifically, we look at the sum of funds assigned to the "environmental alliance" – i.e. to biking, public transport, and walking. Here, the impacts of the information treatment and of introducing the concept of the modal split in general are estimated through Equation 4:

$$FundsEnvAlliance_i = \delta_0 + \delta_x' x_i + \delta_{info} TreatInfo_i + \delta_{noinfo} TreatNoInfo_i + \upsilon_i \tag{4}$$

where $FundsEnvAlliance_i$ is the sum of funds participant i assigned to modes of the "environmental alliance", $TreatInfo_i$ indicates whether they were assigned to Group "Info", $TreatNoInfo_i$ indicates whether they were assigned to Group "No Info" (reference group here is the Control Group), and v_i is the error term.

The vector of covariates x_i comprises almost the same variables in all four types of models. The covariates used everywhere are gender, age, highest schooling, household income, having kids, household size, employment status, whether the individual owns a car, a bike/e-bike, or a public transport ticket, whether they indicated they would consider using their car significantly less, what their main mode of commuting is (if applicable), and their political party sympathies. The reference group for age is "Age 18-25", the reference group for income is "Low Income", the reference group for the commuting dummies is "Commute: Other mode", and the reference group for the political party inclinations is "Party: Other/None". For equation 4, in a third model the control group is excluded and the difference between participants' perceived car proportion and their wished-for car proportion is also included as a covariate, to see if a stronger wish for change has an effect on the funds they assigned to the environmental alliance.

The average treatment effects, reflected by the coefficients α_T, β_T, γ_T, $\delta_G info$ and $\delta_G noinfo$, can be consistently estimated using standard discrete-choice methods, as the groups were randomly assigned.

5 Results

5.1 Overall Modal split Perceptions

Of our full sample, 2,023 participants were asked to state their perceived modal split shares and of these, 1,812 participants responded. Half of them were in Group "Info" and thus received a reference point via the example table. Table 3 shows the means and standard deviations of the modal split perceptions for the four categories of transport, separately for Group ”No Info” and for Group ”Info”. Table A7 in the Appendix additionally summarizes Medians, Minima and Maxima.

Participants of the Group ”No Info” averaged slightly lower guesses for the bike and walking proportions, and slightly higher guesses for the car and public transport proportions. Based on a Student’s t-test, the differences in mean guesses are statistically significant for the modes of biking, public transport, and walking, meaning that showing the modal splits example table affected guesses for these three modes significantly, although magnitudes are negligible.

Standard deviations tend to be larger for the group which did not see the example table. Indeed, a Kolmogorov-Smirnov test (Feller, 1948) as reported in the last column of Table 3 shows that the distributions of perceptions are significantly different from each other when comparing Group ”No Info” to Group ”Info”, for all four modes. As expected, participants’ guesses without a reference point are spread further. Additionally, the generally wide spreads may indicate that the modal split is not an indicator that people are commonly exposed to. Without a reference point, people’s assumptions about the modal split show higher proportions of car and public transport trips, perhaps because cars and public transport vehicles are overall more visible than bikes and pedestrians.

	Group ”No Info”		Group ”Info”			
Mode	Mean	Std.D.	Mean	Std.D.	T-Test	Kolmogorov-Smirnov Test
Car	55.6%	(18.0%)	55.0%	(16.9%)	t=0.707	D=0.072*
Bike	14.4%	(8.8%)	16.2%	(8.5%)	t=-4.298**	D=0.132**
Public Transport	19.8%	(12.3%)	17.7%	(10.5%)	t=3.953**	D=0.079**
Walking	10.2%	(8.3%)	11.1%	(7.6%)	t=-2.595**	D=0.113**
# observations	870 of 995 (87.4%)		942 of 1,028 (91.6%)			

* p<0.05; ** p<0.01

Table 3: Perceptions of Modal Split - Summary

Of course, perceptions differ by location. Inhabitants of ”urban” areas perceive the car proportion to be on average 14.2 percentage points lower than inhabitants of more ”rural” areas (Table 4). Conversely, perceptions of the proportion of public transport are on average 9 percentage points higher among participants from ”urban” areas.

Mode	All participants		Rural participants		Urban participants	
	Mean	Std.D.	Mean	Std.D.	Mean	Std.D.
Car	55.2%	(17.9%)	63.0%	(16.9%)	48.9%	(16.1%)
Bike	15.4%	(8.7%)	13.7%	(8.4%)	16.8%	(8.7%)
Public Transport	18.7%	(11.5%)	13.8%	(9.4%)	22.8%	(11.4%)
Walking	10.7%	(8.0%)	9.6%	(8.1%)	11.6%	(7.7%)
Total # observations	1,812		816		996	

Note: "Urban" summarizes those participants who stated they live in or on the outskirts of a city above 20,000 inhabitants, "Rural" summarizes the rest.

Table 4: Perceptions of Modal Split - Urban vs. Rural

When looking at these locations separately, the information treatment shows similar effects as on the sample as a whole, with participants from Group "Info" averaging slightly higher proportions of biking and walking and slightly lower proportions of public transport and car driving (Table A8).

5.2 Accuracy of Modal Split Perceptions

Of the 1,812 participants in Groups "Info" and "No Info", 749 individuals (37%) live in the 136 cities for which we have access to reliable real modal split data. For them, we can examine the relative accuracy of their modal split guesses by subtracting the real number from their guesses, and then dividing this by the real number. Table 5 shows the results.

Mode	Group "No Info"			Group "Info"			T-test
	Mean Accuracy	(Std.D.)	Within +/- 5pp of real number	Mean Accuracy	(Std.D.)	Within +/- 5pp of real number	
Car	0.33	(0.60)	17.7%	0.40	(0.57)	19.2%	t=-1.534
Bike	0.08	(0.86)	42.3%	0.13	(0.75)	44.8%	t=-0.882
Public Transport	0.91	(1.31)	22.6%	0.74	(1.24)	28.3%	t=1.710**
Walking	-0.59	(0.30)	7.0%	-0.57	(0.26)	8.0%	t=-1.139
# observations		385			364		

"pp" = percentage points
* p<0.05; ** p<0.01

Table 5: Accuracy of Modal Split Perceptions (Perception - Real Data / Real Data)

Overall, the proportions of car and public transport trips were overestimated and the proportions of walking trips underestimated. Perceptions of the proportion of biking trips were on average closest to the real numbers, where guesses in both treatment groups were off by less than 15% on average. 42.3% and 44.8% of participants managed to state a number within 5 percentage points of the real number, by group respectively. Furthest from the real numbers, on average, were perceptions of public transport proportions, where guesses were off by on average 91% and 74%, respectively. Regarding walking proportions, average accuracy was slightly better than with the public transport proportions, but only 7% and 8% of participants in the two groups guessed within 5 percentage points, respectively.

Despite having seen an example table, Group ”Info” does not show a higher average accuracy. Group ”Info”, however, has consistently more guesses that lie within 5 percentage points of the real numbers, which aligns with the narrower distribution of guesses seen in Table 3.

Relative accuracy is displayed here, but there are some additional observations when looking at absolute accuracy (see Table A9). Regarding the unadjusted distance from the real number, it becomes evident that biking trips are also regularly underestimated, even if not by much. Also, while the relative accuracy table seems to show that accuracy is much worse regarding public transport trips than regarding car trips, this is not true when looking at the absolute accuracy, where average distance from the real number was similar for car share and public transport share guesses. A lower share of trips is undertaken by public transport overall, so the same distance from the real number will result in a lower relative accuracy than for modes where the real number is higher (such as for car trips).

The real modal splits we use to compute guess accuracy stem from several different studies from a range of years. To control for the bias from potential differences in study design and from the temporal differences, Table A11 looks at the accuracy of participants from only those cities for which we have data from the newest ”Mobilität in Städten” survey, i.e. from the year 2023 (Hubrich et al., 2025). The accuracy of the car share was slightly lower in this group, while guesses for the bike proportion were slightly better. All in all though, comparing this to the original table, there does not seem to be a significant bias from combining this new data with data from earlier years and different studies.

Since we specifically asked for modal split guesses about the place where participants *live* and not where they most often travel to, another robustness test is evaluating whether those who work in and commute in the same city where they live have a better grasp on modal split. Table A12 shows the accuracy of the subgroup who has a commute of 10 kilometers or less. In this subgroup as well, accuracy for car share is slightly worse while accuracy of bike share is slightly better, but without any meaningful differences from the full sample.

To further investigate guess accuracy specifically of the proportion of cars, an OLS model is estimated, based on equation 1. Here, the relative accuracy – perceived proportion of car trips minus real proportion, divided by real proportion – is used in absolute value terms, and an indicator is included whether an individual over- or underestimated. A negative coefficient signifies an increase in accuracy (since perfect accuracy is equal to the number 0). Results are reported in Table A10 in the Appendix.

Interestingly, the general prevalence of car travel in a participant's city seems to have a strong effect on guess accuracy: Participants from cities with shares of car trips in the first or second quartiles (at 26.5% or lower, and between 26.5% and 34%) show statistically significantly lower guess accuracy. Participants in the former group are on average 50% further away from the real number than those from cities in the reference quartile (car shares between 34% and 48.7%). Those from the second quartile are on average 12% further away. The only other factor with a statistically significant influence on guess accuracy in all model variations is being between 78 and 85 years old. Being in Group "Info" results in a (not statistically significant) negative coefficient. Hence, at least when looking at absolute values of accuracy, showing participants the example table did not raise their perception accuracy to a significant degree.

5.3 Wishes for Modal Split

Next, we investigate what our participants envision in an ideal world, when it comes to the distribution of trips between modes. Table 6 compares perceived modal splits

	Wish		Perception		Difference		Participants for whom wish < perception
Mode	Mean	(Std.D.)	Mean	(Std.D.)	Mean	(Std.D.)	%
Car	32.5%	(19.2%)	55.2%	(17.9%)	-22.2	(17.5)	85.6%
Bike	24.6%	(12.8%)	15.4%	(8.7%)	9.1	(11.4)	8.8%
Public Transport	28.9%	(15.4%)	18.7%	(11.5%)	9.8	(13.3)	11.7%
Walk	14.1%	(9.2%)	10.7%	(8.0%)	3.2	(7.3)	12.9%
Total # observations	1,586		1,586				

Table 6: Wishes for Modal Split vs. Perceptions

with stated ideal modal splits. In this table, we do not differentiate between treatment groups because the outcomes are very similar (see Table A13 and Table A14). Participants almost universally desired the proportion of car trips to be smaller than how they currently perceived it to be and on average desired a reduction by 22.2 percentage points. Only 8.8% of participants wished for a reduction of bike trips, 11.7% of public transport trips, and 12.9% of walking trips.

Figure 1 shows how the modal split shares that participants desire for the different modes are distributed, compared to the distribution of their perceptions. What participants wished for is distributed wider than what they perceived and has more outliers, meaning that there is a large range of opinions on the ideal modal split.

To investigate which other factors may influence opinions on ideal modal splits we estimate two models, based on Equations (2) and (3). In the first model, results reported in Table 7, the dependent variable $WishLessCars_i$ indicates whether participants' ideal car share is lower than their perception of the current car share. Those who received the example table are 5 percentage points more likely to desire a lower car proportion. Higher education, owning a bike or e-bike, considering to use the car less, and leaning towards voting Green also increase the likelihood of desiring a lower car share. Being above the age of 86 decreases the likelihood of desiring a lower proportion of cars, as does owning a car.

The second model (right column of Table 7) serves to understand which factors influence the size of the desired change in car proportion. We use the difference between ideal and perceived car share as the dependent variable and only estimate the model with data from those participants for whom this difference was negative. The dependent variable is used in absolute values to facilitate coefficient interpretation. A positive coefficient thus signifies that a variable increases the size of the desired change in car proportion.

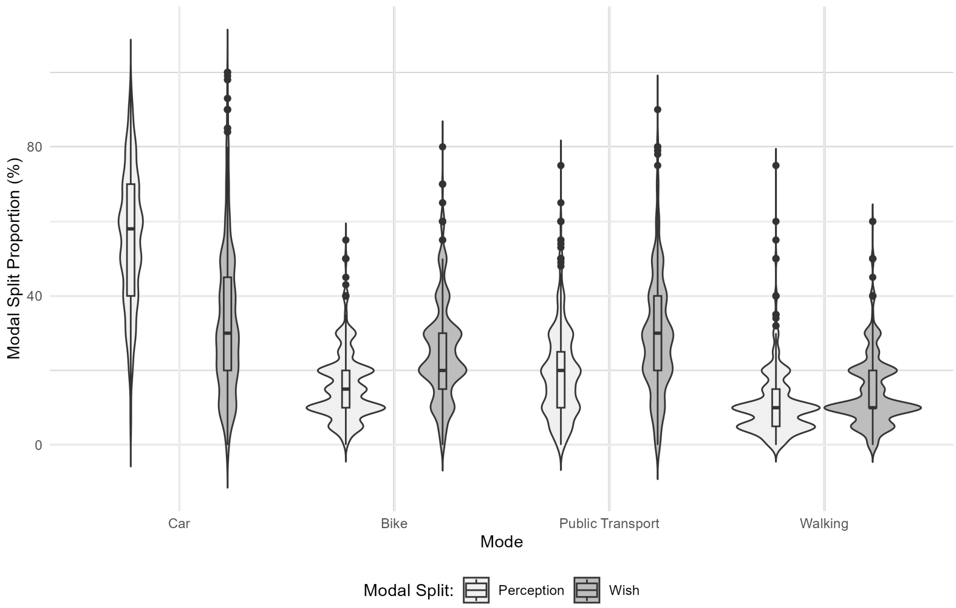

Figure 1: Distributions of Modal Split Perceptions (light gray) vs. Wishes (dark grey)

Results indicate that participants of Group "Info" on average desire a statistically significantly smaller change in car proportion than those of Group "No Info", by about 2 percentage points. It is difficult to say how the treatment of having been shown the info table leads to this small but statistically significant difference. One hypothesis is that seeing real modal split data made the car split proportion which they experience in their city feel more normal, and thus led to a less pronounced desire for change. However, since the difference is rather small it does not warrant substantial investigation at this point.

Larger changes in car proportion are desired by those in the age group 46-55, those with a larger household, with medium income, by those who would be willing to use their car less, and those who lean towards voting Green. More moderate changes are desired when a participant is currently employed, lives in a city, or owns a car.

Dependent variable:	$WishLessCars_i$ (binary)		$\lvert\Delta CarShare_i\rvert$ (Wish-Perception)	
	Coeff.	Std. E.	Coeff.	Std. E.
Group 'Info'	0.052**	(0.017)	-2.050**	(0.793)
Female	0.015	(0.018)	1.467	(0.807)
Age 26-35	-0.113	(0.082)	5.781	(3.645)
Age 36-45	-0.087	(0.082)	5.468	(3.642)
Age 46-55	-0.022	(0.079)	7.038*	(3.488)
Age 56-65	-0.067	(0.077)	5.377	(3.421)
Age 66-75	-0.049	(0.078)	1.876	(3.418)
Age 76-85	-0.069	(0.080)	-0.434	(3.521)
Age 86+	-0.316**	(0.120)	2.088	(6.168)
Medium income	0.027	(0.023)	2.283*	(1.076)
High income	-0.019	(0.027)	0.827	(1.235)
Children	0.016	(0.036)	-0.824	(1.633)
Household size	0.014	(0.012)	1.169*	(0.522)
University education	0.051**	(0.018)	0.068	(0.832)
Working	0.012	(0.068)	-7.129*	(3.154)
Lives in city	-0.017	(0.018)	-3.720**	(0.842)
Car	-0.078*	(0.034)	-5.154**	(1.493)
Ticket	0.061*	(0.024)	1.484	(1.085)
Bike (any)	0.066**	(0.023)	1.525	(1.093)
Would use car less	0.100**	(0.021)	5.426**	(0.934)
No commute	-0.010	(0.077)	-2.116	(3.528)
Commute: Car	-0.017	(0.046)	1.528	(2.110)
Commute: Bike	0.058	(0.053)	2.388	(2.375)
Commute: Public Transport	0.011	(0.056)	1.672	(2.546)
Green	0.125**	(0.024)	5.218**	(1.069)
SPD	0.120**	(0.025)	1.406	(1.131)
CDU	0.039	(0.024)	-1.884	(1.123)
Constant	0.749**	(0.116)	25.270**	(5.185)
# Observations	1,567		1,341	
Adjusted R-Squared	0.09		0.10	

Model 2 (right) only run with those who wish for lower car proportion.
* p<0.05; ** p<0.01

Table 7: LPM/OLS Results on Wish for Change in Car Proportion, Equations (2) and (3)

5.4 Approval for Transport Policies

The above section established that a large majority of people would like the proportion of car trips within the modal split to decrease, with a mean desired reduction by about 22 percentage points. As this would be a substantial change compared to most current modal splits, achieving it would require effective and decisive policymaking.

A large number of diverse transport policies are being discussed in political and public spheres. They differ in effectiveness – i.e. the size of their potential impact on decreasing carbon-intensive transportation – but also in their desirability for the public. For example, a congestion charge (a fee for entering a city by car) has been proven to be effective in decreasing traffic and air pollution (Börjesson & Kristoffersson, 2015; Börjesson et al., 2012; Croci, 2016; Green et al., 2016; Leape, 2006; Li & Hensher, 2012) but also frequently struggles to garner public support (Frondel et al., 2025; Fürst & Dieplinger, 2014; Schuitema et al., 2010).

It is therefore of great interest to see whether the strong desire for lower car traffic, as it is clearly indicated by many of our participants, translates into approval for different transport policies. Table 8 lists a few of the policies for which approval was elicited in our survey and compares approval rates (i.e. which proportion of participants responded ”Approve somewhat” or ”Strongly approve”) by the desired change in car proportion. Results for a larger set of policies can be found in the Appendix (Figures A1 and A2).

	Desired Δ car proportion (Wish - Perception)					
Transport measure	+10 to 0	-1 to -10	-11 to -20	-21 to -30	-31 to -40	$\leq$ -41
Stop sale of combustion vehicles by 2035	0.07	0.18	0.24	0.36	0.39	0.46
Congestion Charge	0.08	0.16	0.25	0.36	0.40	0.41
Higher parking fees	0.13	0.19	0.31	0.44	0.50	0.50
Repurposed parking	0.14	0.21	0.34	0.52	0.51	0.62
Deutschlandticket[1]	0.50	0.67	0.74	0.84	0.81	0.84
Better/more bike paths	0.51	0.68	0.80	0.88	0.88	0.89
Mean funds to env. alliance	59.2%	71.5%	77.8%	83.8%	86.2%	89.9%
Total # observations	228	272	398	317	182	189

Note: Values are proportions of active approval – (4) ”Rather approve” and (5) ”Highly approve”
[1]: 49 EUR/month ticket for using any short-distance public transport in Germany, introduced in spring 2023

Table 8: Policy approval and desire for change

As is commonly the case, approval rates vary widely between the most restrictive policies (”Stop sale of new combustion vehicles by 2035”) and the more positively-phrased, additive policies (”Better/more bike paths”). In the group which desired no reduction of car proportion at all or even an increase, 7% of participants stated approval for the former policy and 51% for the latter. Also unsurprisingly, acceptance rises with the reduction in car share desired. Between those who desire no change and those who desire a decrease in the car share of more than 40 percentage points, the difference in approval rate lies between 33 and 48 percentage points.

However, even among those who desire a decrease of the share of cars by 41 percentage points or more, the three least popular policies still do not garner approval rates of more than 50%. This points to an interesting dissonance between a strong wish for a greener, more sustainable transport environment and a lack of support for more restrictive but effective policies.

5.5 Funds Assigned to Environmental Alliance

	Socioec. vars		Full model		Incl. desired change[1]	
	Coeff.	Std. E.	Coeff.	Std. E.	Coeff.	Std. E.
Group "Info"	-0.014	(0.926)	-0.634	(0.844)		
Group "No Info"	-3.614**	(0.934)	-4.021**	(0.850)	-2.310**	(0.822)
Female	5.900**	(0.780)	4.321**	(0.717)	4.265**	(0.837)
Age 26-35	-1.124	(3.305)	-0.618	(3.019)	-1.095	(3.801)
Age 36-45	-1.902	(3.239)	1.877	(2.968)	-0.791	(3.796)
Age 46-55	-4.044	(3.068)	0.888	(2.811)	-1.286	(3.638)
Age 56-65	-6.817*	(2.994)	-1.410	(2.756)	-3.362	(3.573)
Age 66-75	-6.690*	(3.008)	-1.236	(2.775)	-3.868	(3.563)
Age 76-85	-5.804	(3.105)	0.760	(2.869)	-2.941	(3.668)
Age 86+	-2.391	(4.869)	6.025	(4.474)	2.826	(6.316)
Medium income	1.293	(1.003)	1.114	(0.920)	2.006	(1.116)
High income	0.267	(1.152)	-0.004	(1.060)	2.080	(1.276)
Children	-2.230	(1.622)	-2.115	(1.478)	-3.511*	(1.701)
Household size	0.835	(0.516)	0.898	(0.479)	0.876	(0.545)
University education	4.942**	(0.803)	3.176**	(0.736)	2.973**	(0.861)
Working	-1.127	(1.277)	0.675	(2.598)	3.378	(3.282)
Lives in city	3.492**	(0.779)	0.014	(0.737)	1.398	(0.877)
Car			-9.975**	(1.368)	-5.971**	(1.553)
Ticket			4.795**	(0.979)	3.558**	(1.121)
Bike (any)			5.403**	(0.916)	3.054**	(1.154)
Would use car less			8.706**	(0.872)	3.804**	(0.972)
No commute			2.152	(2.887)	4.696	(3.658)
Commute: Car			-1.527	(1.739)	1.501	(2.185)
Commute: Bike			5.268*	(2.085)	3.749	(2.458)
Commute: Public Transport			3.512	(2.245)	3.112	(2.618)
Green			10.039**	(0.999)	4.183**	(1.113)
SPD			5.079**	(0.998)	2.856*	(1.170)
CDU			-1.752	(0.948)	-3.693**	(1.164)
$\lvert \Delta CarShare_i \rvert$					0.293**	(0.029)
Constant	74.821**	(3.314)	70.685**	(4.363)	63.965**	(5.450)
# Observations	2,687		2,687		1,291	
Adjusted R-Squared	0.05		0.22		0.25	

Dep. variable is % of public funds assigned to env. alliance (biking, public transport, walking)
[1]: Sub-sample of participants wishing for lower car proportion
* p<0.05; ** p<0.01

Table 9: OLS Results on % Funds Assigned to Environmental Alliance, Equation (4)

The last part of the survey asked all participants to state how they would distribute a large sum of funds between the four mode categories, assuming the money had to be used for transport infrastructure. We will be looking at the proportion of funds assigned to the "environmental alliance" in sum (i.e. biking, public transport, walking).

Running models with this proportion as dependent variable, based on Equation 4, we find an interesting pattern regarding the influence of the information treatment (Table 9). While participants from Group "Info" do not differ significantly from the control group in how they assign the funds, Group "No Info" assigns a statistically significantly lower proportion of funds to the environmental alliance, of 3.6 percentage points on average and 4 percentage points in the full model.

The following tentative conclusion can be drawn: The combination of introducing participants to the modal split, showing them the example table, and then asking them to estimate it did not have a significant effect on their preferences for public spending. However, only introducing the concept of modal split and asking for their modal split guesses *without* a reference point seems to have led to some uncertainty about how necessary funds are for the more sustainable modes.

One reason for this could be that the questions on modal split perceptions and wishes made people more aware of what they experience day-to-day when traveling. And since a majority of trips are likely done with cars, this general awareness may have resulted in a specific awareness of where local roads and car infrastructure are lacking on a participant's regular routes, and therefore inspired them to assign more funds to car infrastructure compared to the rest of the sample. This hypothesis is supported by the observation that owning a car also leads to statistically significantly fewer funds assigned to the environmental alliance, with car ownership showing the largest coefficients in our models (-9.98% and -5.97%).

Further observations are that women assign statistically significantly more funds to the environmental alliance, as do those with a university degree, those who own a public transport ticket or bike, commute by bike, or have stated to be willing to use their car much less. Both an affinity for the Green party and an affinity for the SPD are significantly correlated with assigning more funds to the environmental alliance. Statistically significantly fewer funds went to sustainable modes by those aged 56-75.

The third model in Table 9 was estimated using only those participants whose desired share of car trips was lower than their perceived share of car trips, and included the desired change in car share as an additional variable. Results show that each percentage point of reduction desired in the share of cars is associated with about 0.3 percentage points more funds assigned to the environmental alliance, showing some congruency in attitudes. Overall, correlations and significance of the remaining covariates are similar to the other two models, except that a medium level of income now also has a statistically significantly positive impact on the funds assigned to the environmental alliance, and having children a significant negative impact.

6 Conclusions

The modal split - summarizing relative trip intensity by mode - is an indicator that is often used to discuss the status of the urban mobility transition. It is also often used to communicate transformation goals to the wider public. However, it is unclear how well the public is able to contextualize these numbers. In this study, we used data from a large-scale survey in Germany to investigate the population's modal split perceptions and wishes, and how these are influenced by receiving reference points of real modal split data. In addition, we looked at how the reference points influenced the allocation of hypothetical funds between different transport modes, allowing some conclusions about preferences for public funds distribution.

The results show that modal split numbers can be difficult to pinpoint intuitively since our participants' estimates of the modal split in their place of residence were spread across a rather wide range. Based on our results, accuracy was also quite low. The proportion of trips made by car, for example, was overestimated by about 10 percentage points, and only about 18-19% of participants gave guesses within 5 percent of the real number. Guessing the proportion of trips by bike seemed easiest for the participants - here people were only off by less than 1.5 percentage points, and almost half guessed within 5 percentage points of the real splits. Giving a treatment group examples of real modal splits narrows the distribution of their guesses but has little further effects on accuracy.

A large majority of 85.6% of the participants desire the proportion of car trips in their city or municipality to be lower than they currently perceive it to be, by 22.2 percentage points on average. This shift should, according to the participants, go along with increases in the shares of bike and public transport trips and to a lesser extent of walking trips. While people generally wish the share of car trips to be lower, the average magnitude decreases for the group that received the modal splits example table. Participants who desire a larger reduction of the proportion of car trips also generally show higher approval of transport policies and measures. However, even among those who want rather extreme changes (i.e. a decrease in the proportion of car trips by 41% or more), approval for effective but controversial policies such as congestion charges did not surpass 50%.

Examining how participants allocated funds between the environmental alliance (biking, public transport, walking) and motorized individual transport, we see no difference between the control group and Group "Info" which received modal split reference points. Group "No Info", however, who were prompted to think about the modal split and state their perceptions and wishes, but did not receive the reference points, assigned about 3.5 percentage points fewer funds to modes of the environmental alliance. This shows that using an indicator in policy communication without adding context to anchor it to real world data could backfire and lead to lower acceptance for investments into greener modes.

Overall, the results show that it may be beneficial, from a policymaking perspective, to familiarize inhabitants of a city with the concept of the modal split. This applies especially in places where the local government has officially announced transportation policy goals which reference this measure. Making people aware of the real split in their city may also make them more likely to accept increased public spending to modes that are not motorized individual transport. While the modal split is not a holistic measure and additional indicators are vital for getting a full picture of the transportation environment and infrastructure, it can help to keep this rather straightforward measure up to date, to track changes in behavior resulting from policy adjustments and to communicate progress to the wider public.

Appendix

A Wording of the Experiment

MS_Info: Mode proportions of total trips (only Group "Info"))

How do you think the total trips made by the residents of your city are distributed between different transport modes? If you do not live in a city, please think of the municipality in which you live.

The four categories listed below account for the majority of mobility in cities. Other means of transportation, such as e-scooters, skateboards or tractors, are therefore not included here or below.

To give you a point of reference, below you can see the shares in a few other cities:

	Duisburg[1]	Köln[2]	Herne[3]	Münster[4]
Car (and motorbike, scooter, etc.) also as passenger	58%	25%	60%	34%
Bike or e-bike	11%	25%	10%	44%
Public transport	15%	17%	13%	10%
On foot	16%	33%	16%	12%

As info box with clickable links:
[1]Duisburg (2022), p. 15; [2]Köln (2022), p.38; [3]Herne (2016), p.62; [4]Münster (2019), p. 6

Table A1: Real modal split examples

Question MS2: Proportion of trips by mode of transportation (Group "Info" and Group "No Info")

How do you think the total trips made by the residents of your city are distributed between different transport modes? If you do not live in a city, please think of the municipality in which you live.

Share of trips by mode of transportation in your city:

- Car (and motorbike, scooter, etc.) also as passenger [NUM: 0-100] %
- Bike or e-bike [NUM: 0-100] %
- Public transport [NUM: 0-100] %
- On foot [NUM: 0-100] %
- Don't know/no response

[NUM: Percentages must sum up to 100%]

Question MS3: Desired shares of trips by mode (Group "Info" and Group "No Info")

What proportion of different modes of transport would you like to see in the total number of trips made by residents in your city?

Desired share of mode of transportation in your city:

- Car (and motorbike, scooter, etc.) also as passenger [NUM: 0-100] %
- Bike or e-bike [NUM: 0-100] %

- Public transport [NUM: 0-100] %
- On foot [NUM: 0-100] %
- Don't know/no response

[NUM: Percentages must sum up to 100%]

Question MS4: Distribution of public funds between modes of transportation

Please assume your city (or municipality) had received additional funds for the current year (e.g. in the form of EU grants earmarked for transportation), which may only be used for transportation infrastructure. Please also assume, that this sum is large enough to undertake significant investments.

If you were able to decide how these funds are used for the expansion or improvement of the transportation infrastructure in your city (or municipality), how would you distribute them?

The funds earmarked for transportation in my city (or municipality) should be distributed thusly:

- Car (and motorbike, scooter, etc.) also as passenger [NUM: 0-100] %
- Bike or e-bike [NUM: 0-100] %
- Public transport [NUM: 0-100] %
- On foot [NUM: 0-100] %
- Don't know/no response

[NUM: Percentages must sum up to 100%]

B Tables

City	Year	Source
Augsburg, Bautzen, Berlin, Bochum, Braunschweig, Bremen, Bruchsal, Böblingen, Chemnitz, Cottbus, Crailsheim, Darmstadt, Dessau, Dormagen, Dresden, Duisburg, Düsseldorf, Eberswalde, Eilenburg, Eisenach, Erfurt, Erkrath, Falkensee, Frankfurt am Main, Freital, Fulda, Gera, Gießen, Gifhorn, Greifswald, Grevenbroich, Grimma, Großenhain, Görlitz, Halle, Hanau, Heidelberg, Heilbronn, Hennigsdorf, Hilden, Jena, Kaarst, Kaiserslautern, Karlsruhe, Kassel, Kiel, Konstanz, Krefeld, Langenfeld, Leipzig, Ludwigshafen am Rhein, Magdeburg, Mannheim, Mönchengladbach, Monheim am Rhein, München, Neuss, Oldenburg (Oldenburg), Osnabrück, Paderborn, Pforzheim, Potsdam, Regensburg, Rostock, Salzgitter, Solingen, Tübingen, Ulm, Wiesbaden, Wittenberg	2023	Hubrich et al., 2025
Aachen, Bonn, Erlangen, Freiburg im Breisgau, Fürth, Hannover, Koblenz, Lübeck, Ludwigsburg, Offenbach, Stuttgart, Wuppertal, Würzburg	2020	Agora Verkehrswende, 2020
Bottrop, Bremerhaven, Flensburg, Gelsenkirchen, Hagen, Herne, Hildesheim, Ingolstadt, Leverkusen, Oberhausen, Recklinghausen, Reutlingen, Saarbrücken, Siegen	2017	Bäumer et al., 2019
Trier	2018	TU Dresden, 2021
Bergisch Gladbach	2016	Bergisch-Gladb. Mobik Befragung 2016.pdf
Bielefeld	2022	HHB Bielefeld Kurzbericht.pdf
Dortmund	2019	Mobilitätsbefragung Dortmund 2019
Essen	2019	HHB Mobilität Essen Kurzbericht 2019.pdf
Göttingen	2022	HHB zum Mobilitätsverhalten 2022
Gütersloh	2023	HHB Mobilitätsverhalten Gütersloh 2023
Hamburg	2022	Mobilitätsstudie Hamburg 2022
Hamm	2018	Modal Split Hamm.pdf
Mainz	2023	Mobilitätsbefragung 2023 Mainz.pdf
Moers	2023	Umfrage Mobilität in Moers 2023
Mülheim an der Ruhr	2022	HHB Mühlheim 2022.pdf
Nürnberg	2023	Daten und Fakten zur Mobilität Nürnberg
Remscheid	2021	Modal Split Remscheid 2021.pdf
Wolfsburg	2019	Mobilität in Zahlen Raum Braunschweig

Table A2: Data Sources Real Modal Split

	SrV 2023[a]	MiD 2017[b]	Agora Verkehrswende 2019[c]
Mobility Journal for 1 day ("Stichtag")	✓	✓	✓
Randomized "Stichtag" within study period	✓	✓	✓
"Stichtag" on a Tuesday, Wednesday, or Thursday	✓	✓	✓
Count both away and return trip as "trips"	✓	✓	✓
If multimodal trip: count all modes as separate trip	✓	✓	✓

[a](Hubrich et al., 2025); [b](Nobis & Kuhnimhof, 2018); [c](Agora Verkehrswende, 2020)

Table A3: Methodology of three mobility surveys procuring modal split data

Variable	Mikrozensus 2024		This Study	
Age[a]	15 - under 25 years	12%	15 - under 26 years	2%
	25 - under 35 years	14%	26 - under 36 years	7%
	35 - under 45 years	15%	36 - under 46 years	12%
	45 - under 55 years	15%	46 - under 56 years	18%
	55 - under 65 years	18%	56 - under 66 years	24%
	65 - under 75 years	13%	66 - under 76 years	24%
	75 years and more	12%	76 years and more	14%
Income[b]	< €2,000	29%	< €2,200	26%
	€2,000 - under €4,000	39%	€2,200 - €4,200	40%
	$\geq$ €4,000	32%	> €4,200	34%
Has children[c,d]		32%		34%
Houeshold size[b]	1 person	42%		28%
	2 persons	33%		47%
	3 persons	12%		13%
	4 persons	10%		10%
	more than 5 persons	4%		7%
University educ. or equiv.[e]		21%		50%
Working[a]		52%		50%

Sources:
[a] https://www-genesis.destatis.de/datenbank/online/statistic/12211/table/12211-0001
[b] https://www-genesis.destatis.de/datenbank/online/statistic/12211/table/12211-0300
[c] https://www-genesis.destatis.de/datenbank/online/statistic/12211/table/12211-0402
[d] https://www-genesis.destatis.de/datenbank/online/statistic/12211/table/12211-0402
[e] https://www-genesis.destatis.de/datenbank/online/statistic/12211/table/12211-0206

Table A4: Summary Statistics compared to general German population

	Control group	Group "Info"	Group "No Info"	P-values
Female	45.2%	46.7%	47.1%	0.65
Age	58.5	58.6	58.1	0.85
Low Income	25.4%	25.6%	27.6%	0.44
Medium income	39.0%	41.9%	39.9%	0.38
High income	35.7%	32.5%	32.5%	0.21
Children	13.1%	13.7%	12.1%	0.53
Household size	2.2	2.1	2.1	0.39
University education	44.9%	44.6%	46.6%	0.62
Working	51.0%	49.5%	50.1%	0.79
Lives in city	57.7%	53.1%	56.9%	0.081
Car	90.6%	89.5%	90.5%	0.67
Ticket	24.8%	23.2%	25.2%	0.55
Bike (any)	76.2%	76.8%	77.2%	0.87
Would use car less	21.8%	21.7%	22.3%	0.94
Commute: Car	30.6%	31.4%	31.1%	0.92
Commute: Bike	6.4%	6.9%	7.1%	0.80
Commute: Public Transport	5.5%	6.3%	5.4%	0.64
Green	17.4%	18.7%	18.9%	0.64
SPD	17.9%	19.5%	18.6%	0.66
CDU	21.0%	19.6%	21.7%	0.47
# observations	1029	1028	995	

Note: To test differences between groups, we employed Pearson's chi-squared test for binary variables and the Kruskal-Wallis test for continuous variables, p-values are reported in the last column.

Table A5: Balance Table: Means across Treatment Groups

	Mean	(Std.D.)	Median	Min		Max	
Car	45.6%	(11.3%)	48.6%	17.0%	(Bonn)	70.0%	(Remscheid)
Bike	15.6%	(7.7%)	14.6%	2.0%	(Wuppertal)	43.5%	(Münster)
Public Transport	11.45%	(5.5%)	10.7%	2.7%	(Gifhorn)	40.0%	(Bonn)
Walking	27.3%	(5.7%)	27.4%	9.0%	(Gütersloh)	40.5%	(Jena)
City size	223,825.5	(390,484.2)	116,408	16,155		3,596,999	

Table A6: Real Modal Split: Summary Statistics for 84 cities (Data Range 2015 - 2023)

	Group "No Info"					Group "Info"				
Mode	Mean	Std.D.	Min	Max	Median	Mean	Std.D.	Min	Max	Median
Car	55.6%	(19.0%)	5.0%	98.0%	60.0%	55.0%	(16.9%)	5.0%	96.0%	55.0%
Bike	14.4%	(8.8%)	0.0%	50.0%	10.0%	16.2%	(8.5%)	0.0%	55.0%	15.0%
Public Transport	19.8%	(12.3%)	0.0%	75.0%	20.0%	17.7%	(10.5%)	0.0%	65.0%	15.0%
Walking	10.2%	(8.3%)	0.0%	60.0%	10.0%	11.1%	(7.6%)	0.0%	75.0%	10.0%

Table A7: Perceptions of Modal Split - Summary (Detail)

	Rural Participants			Urban Participants		
	Group "No Info"	Group "Info"		Group "No Info"	Group "Info"	
	Mean	Mean	T-Test	Mean	Mean	T-test
Car	63.66	62.5	t=0.975	49.4	48.3	t=1.074
Bike	12.63	14.53	t=-3.226**	15.82	17.67	t=-3.365**
Public Transport	14.62	13.03	t=2.364*	23.8	21.82	t=2.748**
Walking	9.088	9.937	t=-1.489	10.99	12.21	t=-2.488*
# observations	375	441		495	501	

* p<0.05; ** p<0.01

Table A8: Perceptions of Modal Split - Urban vs. Rural (Group Diff.)

	Group "No Info"			Group "Info"			
Mode	Mean Accuracy	(Std.D.)	Within +/- 5pp of real number	Mean Accuracy	(Std.D.)	Within +/- 5pp of real number	T-test
Car	8.48	(17.13)	17.7%	9.89	(15.67)	19.2%	t=-1.116
Bike	-1.49	(8.65)	42.3%	-0.47	(8.17)	44.8%	t=-1.572
Public Transport	10.62	(10.99)	22.6%	7.60	(10.38)	28.3%	t=3.662**
Walking	-17.55	(9.51)	7.0%	-16.97	(8.38)	8.0%	t=-0.844
# observations		385			364		

"pp" = percentage points
* p<0.05; ** p<0.01

Table A9: ABSOLUTE Accuracy of Modal Split Perceptions (Perception - Real Data)

	Basic model		Socioec. vars		Full model	
	Coeff.	Std. E.	Coeff.	Std. E.	Coeff.	Std. E.
Group 'Info'	-0.026	(0.029)	-0.020	(0.029)	-0.016	(0.030)
Car: overestimated	0.362	(0.216)	0.305	(0.219)	0.331	(0.221)
Car: underestimated	0.175	(0.216)	0.108	(0.220)	0.144	(0.222)
Real car share <= 26.5%	0.573**	(0.042)	0.574**	(0.042)	0.577**	(0.044)
Real car share > 26.5% and <= 34%	0.121**	(0.040)	0.131**	(0.041)	0.131**	(0.042)
Real car share > 48.7%	-0.089*	(0.042)	-0.091*	(0.044)	-0.085	(0.045)
Female			-0.012	(0.030)	-0.015	(0.031)
Age 26-35			-0.187	(0.120)	-0.152	(0.121)
Age 36-45			-0.206	(0.122)	-0.170	(0.123)
Age 46-55			-0.243*	(0.116)	-0.208	(0.118)
Age 56-65			-0.144	(0.112)	-0.104	(0.114)
Age 66-75			-0.179	(0.110)	-0.154	(0.112)
Age 76-85			-0.261*	(0.113)	-0.239*	(0.115)
Age 86+			0.130	(0.165)	0.142	(0.169)
Medium income			0.027	(0.038)	0.029	(0.038)
High income			0.003	(0.045)	-0.002	(0.046)
Children			0.045	(0.066)	0.037	(0.067)
Household size			-0.015	(0.020)	-0.009	(0.021)
University education			-0.015	(0.031)	-0.017	(0.031)
Working			0.007	(0.050)	-0.104	(0.113)
Car					-0.033	(0.048)
Ticket					0.038	(0.038)
Bike (any)					-0.024	(0.036)
Would use car less					0.041	(0.038)
No commute					-0.122	(0.128)
Commute: Car					0.002	(0.081)
Commute: Bike					0.024	(0.086)
Commute: Public Transport					-0.090	(0.089)
Green					0.058	(0.040)
SPD					0.026	(0.042)
CDU					0.035	(0.045)
Constant	0.047	(0.216)	0.313	(0.246)	0.360	(0.281)
# Observations	672		659		659	
Adjusted R-Squared	0.38		0.38		0.38	

Dependent variable is $|PerceivedCarShare_i - RealCarShare_i|$
* p<0.05; ** p<0.01

Table A10: OLS results on perception accuracy of car trip proportion, equation (1)

Mode	Group "No Info"			Group "Info"			T-test
	Mean Accuracy (0 = perfect)	(Std.D.)	Within +/- 5pp of real number	Mean Accuracy (0 = perfect)	(Std.D.)	Within +/- 5pp of real number	
Car	0.39	(0.62)	16.6%	0.47	(0.60)	14.3%	t=-1.385
Bike	-0.02	(0.71)	40.4%	0.05	(0.58)	43.0%	t=-1.087
Public Transport	1.03	(1.48)	21.5%	0.89	(1.42)	24.7%	t=1.054
Walking	-0.63	(0.27)	5.7%	-0.61	(0.22)	4.4%	t=-0.847
# observations		265			251		

"pp" = percentage points
* p<0.05; ** p<0.01

Table A11: Relative Accuracy of Modal Split Perceptions, only for real data from 2023

Mode	Group "No Info" Mean Accuracy (0 = perfect)	(Std.D.)	Within +/- 5pp of real number	Group "Info" Mean Accuracy (0 = perfect)	(Std.D.)	Within +/- 5pp of real number	T-test
Car	0.39	(0.59)	13.3%	0.39	(0.54)	15.3%	t=0.004
Bike	-0.00	(0.83)	48.3%	0.05	(0.52)	43.9%	t=-0.530
Public Transport	0.81	(0.82)	25.8%	0.71	(0.88)	31.6%	t=0.812
Walking	-0.62	(0.28)	7.5%	-0.59	(0.24)	9.2%	t=-0.876
# observations		120			98		

"pp" = percentage points
* p<0.05; ** p<0.01

Table A12: Relative Accuracy of Modal Split Perceptions, only for those commuting 10km or less

	Wish		Perception		Difference		Participants for whom wish < perception
Mode	Mean	(Std.D.)	Mean	(Std.D.)	Mean	(Std.D.)	%
Car	32.48%	(20.38%)	55.55%	(18.98%)	-22.3	(18.44)	83.2%
Bike	24.32%	(13.06%)	14.44%	(8.83%)	9.6	(11.98)	8.2%
Public Transport	29.4%	(16.22%)	19.84%	(12.28%)	9.4	(13.82)	12.7%
Walk	13.81%	(9.65%)	10.17%	(8.28%)	3.4	(7.56)	11.9%
Total # observations	754		754				

Table A13: Wish for modal split vs. Perception (Group "No Info")

	Wish		Perception		Difference		Participants for whom wish < perception
Mode	Mean	(Std.D.)	Mean	(Std.D.)	Mean	(Std.D.)	%
Car	32.49%	(18.02%)	54.95%	(16.86%)	-22.0	(16.6)	87.9%
Bike	24.81%	(12.6%)	16.2%	(8.54%)	8.7	(10.86)	9.4%
Public Transport	28.39%	(14.61%)	17.71%	(10.53%)	10.3	(12.86)	10.8%
Walk	14.31%	(8.79%)	11.14%	(7.63%)	3.1	(7.14)	13.7%
Total # observations	832		832				

Table A14: Wish for modal split vs. Perception (Group "Info")

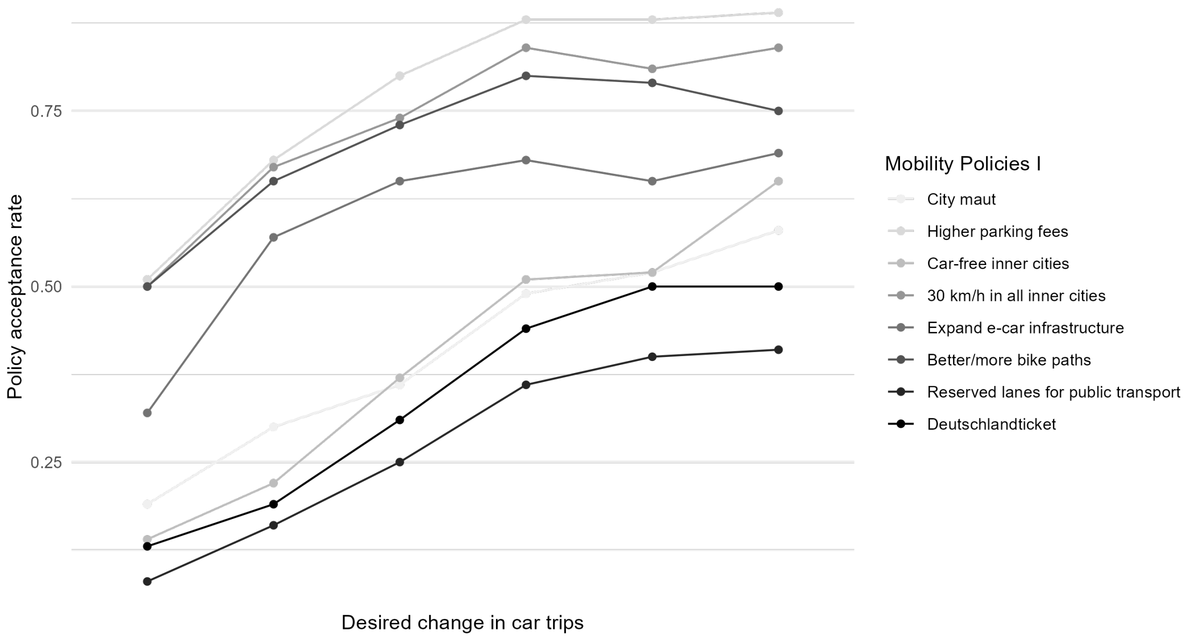

Figure A1: Acceptance rates for different mobility policies by desired change in car proportion in modal split (I)

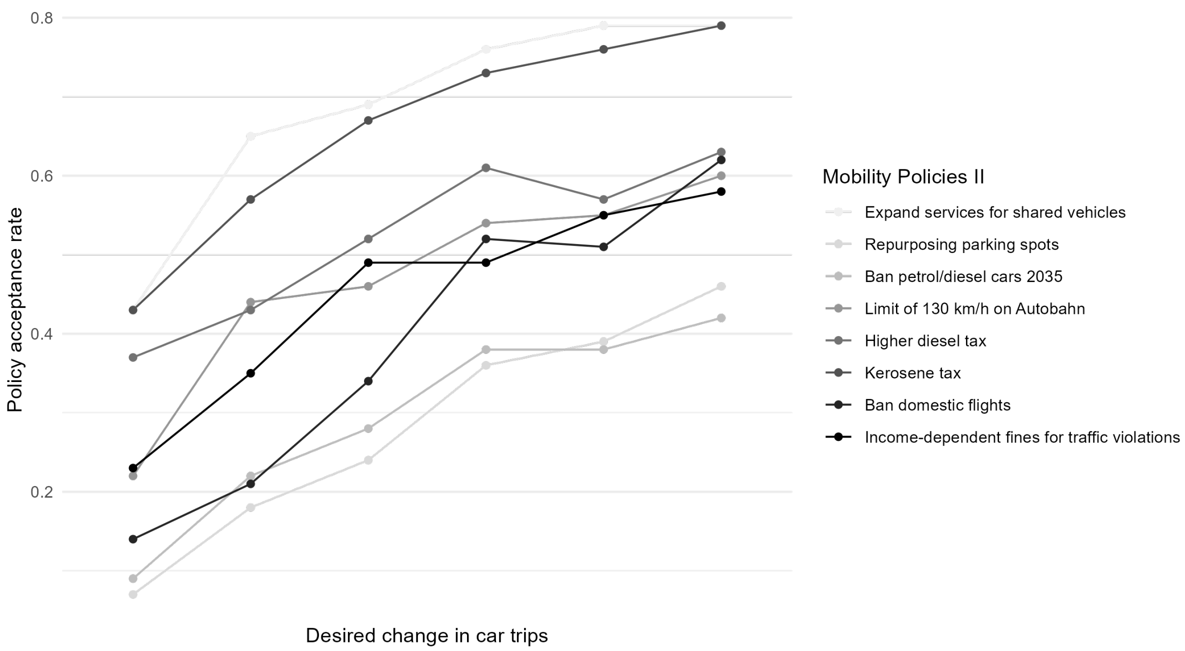

Figure A2: Acceptance rates for different mobility policies by desired change in car proportion in modal split (II)

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