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Determinants of Public Acceptance for Traffic-Reducing Policies to Improve Urban Air Quality

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Abstract: Air pollution remains a problem in German cities. In particular, the nitrogen dioxide (NO₂) annual limit-value set by the European Union of 40 µg/m³ was not met at ~40% of roadside monitoring stations across German cities in 2018. In response to this issue, many cities are experimenting with various traffic-reducing measures targeting diesel passenger vehicles so as to reduce emissions of NO₂ and improve air quality. Identifying the determinants of public acceptance for these measures using a systematic approach can help inform policy-makers in other German cities. Survey data generated from a questionnaire in Potsdam, Germany, were used in predictive models to quantify support for investments in traffic-reducing measures generally and to quantify support for a specific traffic-reducing measure implemented in Potsdam in 2017. This exploratory analysis found that general support for investments in such measures was most strongly predicted by environmental and air pollution perception variables, whereas specific support for the actual traffic measure was most strongly predicted by mobility habits and preferences. With such measures becoming more common in German cities and across Europe, these results exemplify the complexity of factors influencing public acceptance of traffic-reducing policies, highlight the contrasting roles environmental beliefs and mobility habits play in determining support for such measures, and emphasize the connections between mobility, air pollution, and human health.

Keywords: public acceptance; transport policy; air quality; urban; transdisciplinary

1. Introduction

Despite improvements in air quality over the past several decades, European cities continue to grapple with the issue of air pollution. Recent lawsuits filed by the European Commission against France, the United Kingdom, Hungary, Italy, Romania, and Germany for infringement of European air quality law attest to the need for further action on this front [1]. In Germany, due to high concentrations of nitrogen dioxide (NO₂) exceeding the EU limit-value of 40 µg/m³ on heavily-trafficked streets in many cities, traffic-reducing measures are being put in place across the country. Following a 2018 ruling by the second-highest German court [2], bans on diesel vehicles are now a legal option aimed at rapidly improving air quality on polluted streets. Such coercive ‘push’ measures are being implemented in many cities, including Düsseldorf, Stuttgart, Hamburg, and Berlin. In 2017 in Potsdam, Germany, a similar trial measure was implemented to improve air quality on a main through street (Zeppelinstrasse), where the NO₂ limit-value was exceeded for 10 years prior. It was less stringent, however, in that it combined several ‘push’ and ‘pull’ measures to both reduce car traffic and encourage

greater use of public transport and cycling on the street. Following a 6-month trial, the measure was implemented permanently on the street due to a measured decrease in NO₂ concentrations from an annual average of 43 µg/m³ in 2016 to 34 µg/m³ in 2017 [3]. The work presented here was carried out in the context of this measure (henceforth referred to as the Potsdam traffic measure).

Alongside the implementation of policies to improve urban air quality across Europe, a discussion regarding sustainable urban mobility has begun to pick up pace at the local, national, and regional level. In 2009, the European Commission presented its action plan on urban mobility that encouraged the uptake of Sustainable Urban Mobility Plans [4]. Since then, there has been considerable research and investment in the development of such plans, though there are still large variations in uptake across Europe [5]. While much research has focused on planning, accessibility, and scenario making, less has elucidated the questions of how to prioritize actions, involve stakeholders, and implement new people-oriented, place-based approaches [6]. Going forward, developing tools used in ex-ante methodologies to help cities identify a priori which measures to prioritize locally to achieve their sustainability goals [7], as well as more concretely understanding citizens' environmental and mobility behaviors and attitudes [8,9], can greatly assist cities in transitioning towards sustainable mobility.

1.1. Acceptability of Environmental Transport Policies

A substantial amount of research has been devoted to understanding factors that influence individuals' acceptability of environmental transport policies, predominantly because public acceptance is a central factor in politicians' decision making on whether to implement a certain policy or not. Such research, however, has focused mainly on the implementation of congestion charging [10–13], environmental and transport taxes [14–16], and road pricing [17–19]. This is likely due to their relative popularity among decision makers as measures for incentivizing reduced car use while generating public funds that can be made available for public transport and alternative transportation infrastructure. Though fewer in number, there are other studies that assess acceptability of various travel demand management (TDM) measures, including both "push" and "pull" measures [20–22]. However, a large portion of these studies were conducted in Scandinavia or the Netherlands, with a few conducted in the United Kingdom. Though there are comprehensive studies examining sustainable transport policy in Germany [23,24] and studies assessing determinants of travel mode choice [25] as well as the impact of road pricing [26], it appears that studies investigating the acceptability of such policies in Germany are lacking in the literature. As such, with the expected increase in stringent environmental transport policies across German cities to improve air quality, assessing their acceptability by the public, as well as factors influencing this acceptability, will provide valuable information for decision-makers involved in implementing such measures.

1.2. Factors Influencing Acceptability of Environmental Transport Policies

In general, there are a few main factors that have been found to influence an individuals' acceptability of environmental transport policies. (1) Personal norm, often underlined by environmental beliefs or biospheric values, appears to be one common predictor of acceptability of car use reduction policies, particularly following the value-belief-norm (VBN) theory [27]. A person's moral obligation, and hence their willingness, to reduce their car use seems to be driven by an awareness that their actions cause harm to the environment [10,12,20,28].

(2) Another important predictor is the individuals' perceived effectiveness of the measures being implemented. Kallbekken et al. [14] assessed three different transport taxes and found perceived effectiveness of the taxes in delivering the promised environmental quality and reduced traffic congestion to be a key determinant of their acceptability. This result has also been found elsewhere [17,29,30].

(3) A third factor is influence on personal freedom of choice [31]. Measures perceived to constrict an individuals' perceived freedom of travel, such as fuel taxes, are considered unfair and unacceptable, whereas measures that increase perceived freedom of travel, such as cheaper public

transport, are evaluated as fair and acceptable [20]. In addition, consumers generally show higher acceptance for measures related to purchase decisions than for measures related to usage behavior [32]. This is because the purchase decision is a one-time decision (e.g., the purchase of an alternatively fueled vehicle), while the change of habitual behavior is more difficult. Measures that target daily usage behavior can be perceived as an intervention in personal lifestyle choices and, thus, a constraint to the individual's personal freedom.

Somewhat separate from these three main factors commonly found to be associated with acceptability of traffic-reducing measures, there are some notable further findings. First, Börjesson et al. [33] found that when assessing changes in acceptance of a congestion charge before and after its implementation, initial status quo bias (a general fear of the unknown and natural resistance in the face of substantial change) was the dominant reason for the measured increase in acceptance. Even after controlling for all determinants in their model, a substantial portion of the change in attitudes towards the charges could not be accounted for. Instead, the authors concluded, the change in acceptance that was seen across all groups (car-drivers, environmentalists, public transport users, etc.) was a general phenomenon; the measure was resisted just because it was a change and was accepted more thereafter simply because it was in place [33].

Second, problem awareness is important in determining acceptability of measures. Respondents who are aware that car use is an environmental problem show more acceptability for traffic-reducing measures, as long as alternative travel options are increased [20]. In a later study, the same connection between problem awareness and acceptability was identified, concluding that increasing problem awareness may increase acceptability of various traffic measures [21]. A more recent study found not only that problem awareness was related to a stronger sense of responsibility to reduce harmful actions, and hence a greater acceptability of traffic-reducing measures, but that environmental concern was the strongest predictor of problem awareness [28]. Here, too, the VBN theory plays an important role, with different values influencing an individual's perception of environmental problems. People with egoistic value orientations will assess their environmentally-oriented behaviors based on perceived costs and benefits to them personally, whereas those with biospheric value orientations will consider the costs and benefits to the biosphere as a whole [34]. As such, endorsement of egoistic values has been found to reduce acceptability of traffic-reducing measures, whereas biospheric values tend to increase it [28,35].

1.3. The Present Study

An avenue of research with less focus in the literature is that of comparing predictors of hypothetical support for traffic-reducing measures with predictors of support for an actual traffic-reducing measure. Many of the aforementioned studies focus on either a set of hypothetical measures or an actual measure, but do not incorporate both. It may very well be the case that people draw upon different beliefs and values when determining their support for investments in hypothetical traffic measures as opposed to when they are directly impacted by such a measure. As such, this exploratory analysis attempts to elucidate on that point. Though not designed to assess any particular behavioral theory (e.g., VBN theory), it seeks to determine predictors of support for hypothetical investments in traffic-reducing measures as well as predictors of support for the Potsdam traffic measure, implemented in 2017. Moreover, it assesses the varying influences of environmental beliefs and mobility habits and preferences on support. The working hypothesis follows that individuals draw upon differing beliefs and values when assessing the hypothetical need for investments in traffic measures versus a measure that impacts them directly.

2. Materials and Methods

2.1. Study Context

This study was conducted in coordination with the implementation of the Potsdam traffic measure that sought to limit individual vehicular traffic so as to improve air quality. From July to December of 2017, the city implemented a series of infrastructure changes on the heavily-trafficked southwestern principal access route (Zeppelinstrasse) intending to constrict traffic volume and encourage car commuters to switch to public transit or bicycle. These included: (i) reducing the street from four to two lanes for two-way traffic, with some sections including a third lane for turn-offs; (ii) allocating the additional space for a right-turn lane, a dedicated bike lane, and as a bus lane at varying points along a stretch of several kilometers; (iii) increasing the frequency of bus service along the street from four to six trips per hour; (iv) constructing pedestrian ‘islands’ to improve safety of pedestrian crossings; and (v) providing more park and ride infrastructure in connection with Potsdam’s tram network. As the Zeppelinstrasse is one of three main entry points to Potsdam, residents as well as commuters from the surrounding region of Brandenburg were affected by these modifications.

2.2. Study Design and Data Collection

Prior to the implementation of the trial measure, we conducted an online survey seeking to assess varying aspects of public perceptions of the traffic measure, air quality, and climate change, as well as individuals’ mobility habits (see Figure 1). The questionnaire was developed in collaboration with the traffic development, city planning, and civic participation departments of the Potsdam city council and was further supported by their mobility campaign “Besser Mobil. Besser Leben.” (English: “Better Mobility. Better Living.”). Furthermore, the design was informed by previous survey research conducted by the Potsdam city council [36], the German Environment Ministry [37], and the European Commission [38]. The questionnaire was an interdisciplinary effort that included social and natural scientists. Following common practice [39], the questionnaire was pre-tested with a group of 55 participants and scrutinized by an interdisciplinary team at the Institute for Advanced Sustainability Studies (IASS), including social and natural scientists, as well as behavioral psychologists, to identify any ambiguous wording, unclear instructions, or irrelevance of item selection and scaling. The questionnaire contained 40 questions in the following thematic areas: (i) perceptions and attitudes regarding the Potsdam traffic measure; (ii) mobility behaviors; (iii) environmental beliefs and public health attitudes; (iv) communication of air quality; and (v) socio-demographics (see Supplementary Information for the complete, translated questionnaire; the original was in German). With the support of the aforementioned Potsdam mobility campaign, it was advertised through several media including websites, press releases, online news platforms, and digital traffic boards around the city. The link was made available for access between June 1 and June 30 of 2017, receiving 4661 total submissions, of which 3553 were fully-completed. As the questionnaire was anonymous and voluntary, the data gathered represent a non-probability convenience sample. For a more in-depth discussion of the study design, see Schmitz et al. [40].

2.3. Statistical Methods

2.3.1. Dependent and Independent Variables

The 40 questions in this questionnaire produced a total of 131 possible variables available for analysis. For the analysis presented here, the dependent variables were produced from the questions of “Do you support investments in traffic-reducing measures?” and “Do you support the traffic measure on the Zeppelinstrasse?”. These will henceforth be referred to by their assigned variable codes of *support_nocars* and *support_measure*, respectively. The initial list of independent variables tested by this study included all remaining variables, with the exception of 21 variables and some variable categories that were removed due to a lack of sufficient responses. If a variable category contained less than 1%

of the total responses to the questionnaire, it was removed. The full questionnaire and a complete list of variables with their codes and categories can be found in the supplementary information (Table S1).

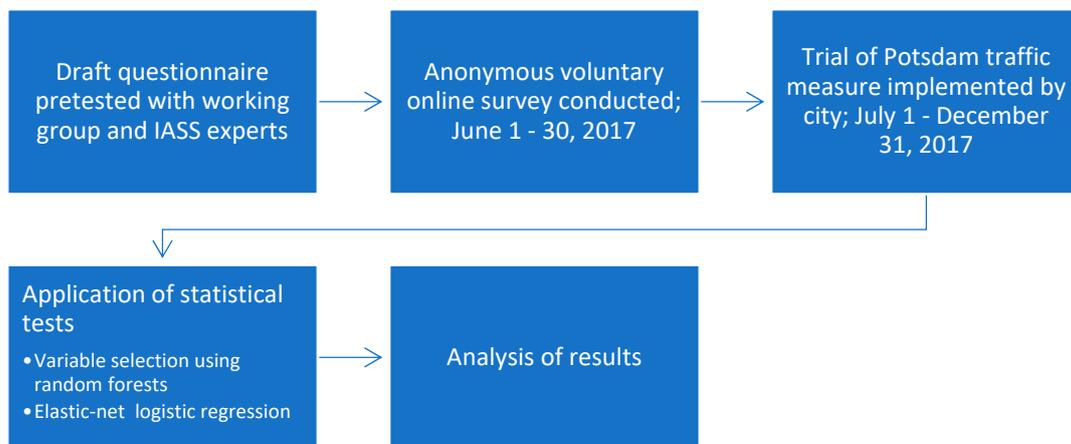


Figure 1. Data flow diagram of the methods used in this study.

2.3.2. Missing Data

When working with questionnaire data, a common and challenging problem is the occurrence of missing responses. This survey was no different, as 5.6% of the cells in the observation by variable matrix produced by this questionnaire contained no data. Rubin [41] identified three mechanisms whereby data may be missing: MCAR (missing completely at random), MAR (missing at random), and MNAR (missing not at random). Determining on a case-by-case basis by which mechanism a single response may be missing is an arduous and lengthy process and is often not possible. To address this issue, various methods for dealing with missing data have been proposed elsewhere and detailed at length [42]. In this study, the regularized iterative multiple correspondence analysis algorithm was used to replace any missing data with the expected values from available variable categories. This was done using the *imputeMCA()* function from the ‘missMDA’ package in R [43]. Descriptions of the algorithm can be found in [44].

2.3.3. Variable Selection Using Random Forests

In order to discern which variables from a possible selection of 110 produced by the questionnaire were important for identifying predictors of support for investments in traffic-reducing measures and for support of the Potsdam traffic measure, the random forest machine-learning technique, first introduced by Breiman [45] was used. To this end, the ‘VSURF’ (Variable Selection Using Random Forests) package in R provides a rigorous method for selecting a subset of variables most important for prediction of the dependent variable [46]. These authors first described the methods used in the VSURF package in [47], which follows a basic two-step procedure and uses the *randomForest* package to grow the random forests [48]. The initial step conducts 50 runs of the desired regression or classification formula, each containing 2000 trees and using the default *mtry* parameter ($p/3$ for classification, where p is the number of variables being tested). This first step orders the variables in decreasing order of their variable importance (VI) measure, which is a unique feature of random forests, successively eliminating those of least importance. The second step is designed to create two further subsets of variables, one for interpretation and one for prediction. The distinction between these two is that the interpretation subset contains all variables highly related to the dependent variable, with the possibility for redundancy among them, whereas the prediction subset removes this redundancy, ultimately containing only those variables sufficient for good prediction of the response variable [46]. The interpretation subset is determined by averaging the results from 25 random forests grown with the subset of variables from step 1, with the prediction subset being determined from growing 25

further random forests using the interpretation subset. Further details on the calculations involved in establishing these subsets in step 2 can be found in Genuer et al. [46] and [47].

The VSURF calculation was run three times with slightly different sets of independent variables. The first run included all variables in the dataset, with *support_measure* as the dependent variable, whereas the last two were run with 16 variables directly related to the Potsdam traffic measure removed, with *support_nocars* and *support_measure* as dependent variables in one run each. The removed variables included questions such as ‘What priority do you think the following goals have in the implementation of the traffic measure?’ or ‘In your opinion, what effect will the traffic measure have on the following issues?’. As the question producing the dependent variable *support_nocars* is phrased in a general sense, it was deemed important to also assess the output with a set of independent variables general in nature, disentangled from the local Potsdam traffic measure. The same logic was applied to the second dependent variable *support_measure*, but instead was used to assess differences in identified predictors between the two sets of independent variables.

2.3.4. Regularized Elastic-Net Logistic Regression

Once the subsets of variables most important for interpretation were determined, those variables were then used as predictors in regularized elastic-net logistic regression models. Elastic-net is a form of penalized regression that combines the penalization parameters of ‘ridge’ regression and ‘lasso’ regression into one. Elastic-net regression seeks to reduce the variance of the final model by shrinking the coefficients using the L_1 and L_2 penalization parameters, thus intentionally introducing bias to improve the model fit [49]. The parameter of α determines the extent to which the ridge or the lasso parameter takes precedence in the calculation of coefficients. Variables that are insignificant to the model have their coefficients penalized to zero, effectively removing them from it. Due to this intentional introduction of bias into the model, traditional significance tests are neither meaningful nor accurate [50] and were therefore not calculated in this study. However, the models were trained and tested on separate random stratified subsets of the overall dataset, to assess model predictive accuracy and validity.

2.3.5. Model Selection and Optimization

When conducting exploratory analyses with regression and classification, a crucial step is the model selection process. Stepwise methods, though still commonly used, have been criticized for several key faults, including (but not limited to): (1) they will not necessarily produce the best model if there are collinear predictors; (2) there is an inflated risk that the models will capitalize on chance features of the data; and (3) it produces biased coefficients that are too large [51,52]. To avoid these issues, an alternate approach was taken. First, the dataset was partitioned using stratified random sampling into a test and a training set (20% and 80% of the data, respectively). Each set contained a proportionate amount of responses from the relevant dependent variables being tested. The elastic-net models were then trained with the training set using 10-fold cross-validation with the “glmnet” package in R. The value of α was set to 1, corresponding to lasso regression, because its aggressive feature selection tendencies was preferred to find the best predictive model with the least amount of significant predictors. To optimize the penalization parameter λ , the “glmnet” package automatically tests a series of values. The optimal value produces a model one standard error above the error of the best model (in terms of misclassification rate). This “1 SE rule” is standard practice and exists to select the simplest model with accuracy comparable to that of the best model [53,54]. Using this model, the log-odds coefficients were calculated and the predictive accuracy was tested. To simplify the interpretation of relationships between predictors and response variables, the model log-odds estimates were converted to odds ratios and subsequently to probabilities. Log-odds coefficients were calculated directly by the model in R. Odds ratios (OR) were calculated manually from the coefficients and the probabilities were calculated subsequently using the OR. A probability of $P(\text{sup}) > 0.5$ indicates that selecting that category is associated with a greater likelihood of supporting investments in traffic-reducing

measures (*support_nocars*); $P(\text{sup}) < 0.5$ indicates a greater likelihood not to support these investments (as in Tables 2–4). Additionally, the two ‘yes’ (‘Yes, I strongly support it’ and ‘Yes, I support it’) and two ‘no’ (‘No, I don’t support it at all’ and ‘No, I don’t support it’) categories of *support_nocars* were each combined and the 178 responses (5% of all responses for the question) from the ‘I am undecided’ category were removed in order to create a binary response variable comparable to that of *support_measure*, which was also made binary by removing 125 responses of ‘I don’t know’.

3. Results

3.1. Basic Statistics

The responses to the dependent variables *support_nocars* and *support_measure* were substantially different, as can be seen in Figure 2. Overall, responses to the question on support for investments in traffic reducing measures were spread quite evenly across the four ‘No’ and ‘Yes’ categories (52% and 43% of all responses, respectively). This relatively even distribution lies in stark contrast to the overwhelming rejection of the Potsdam traffic measure (86% selected ‘No’). The few respondents that expressed support for the Potsdam traffic measure also indicated support for investments in traffic-reducing measures. Figure 2 also shows, however, that 1066 respondents (30%) who do not support the Potsdam traffic measure alternatively expressed support or strong support for hypothetical investments in such measures.

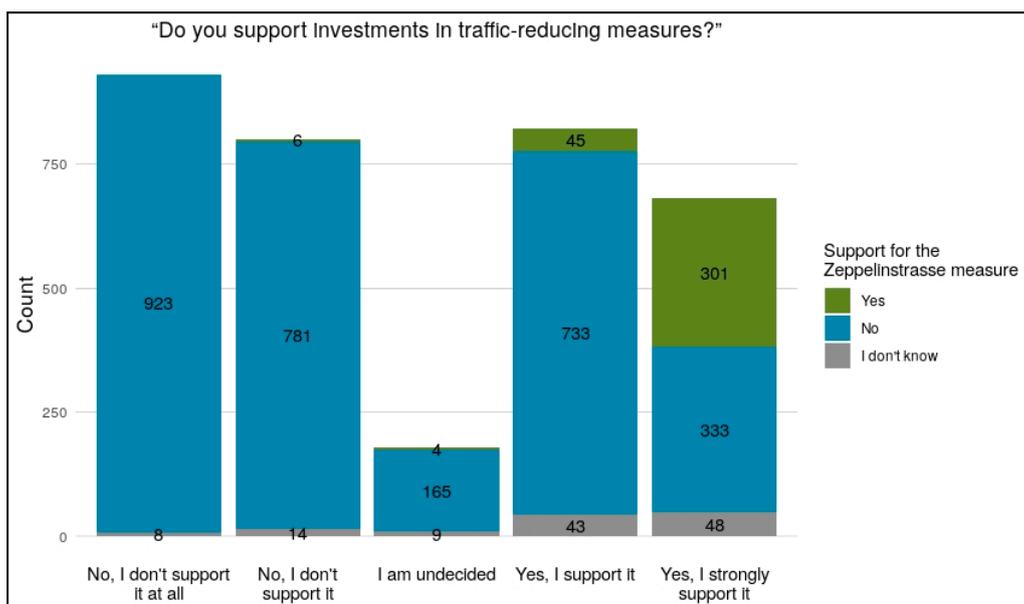


Figure 2. Counts of responses to the dependent variable *support_nocars*, organized by counts of responses to *support_measure*.

While the survey was a convenience sample, the socio-demographic breakdown was similar to that of Potsdam overall. This however does not make the results representative for the city. Overall, 54% of respondents were male and 46% female. 51% were 35–54 years old, with 32% between 18 and 34 years of age and the remaining 17% 55 years old or older. 75% and 13% of the respondents had full-time or part-time jobs, respectively, while the remaining respondents were students, did not work, were retired, or did not specify. 51% had some kind of university degree (Bachelor or higher), 29% had vocational training. For further socio-demographic information, see Weiland et al. [55] or [56].

3.2. Interpretative and Predictive Variables

The VSURF function was run three times with two different dependent variables, *support_nocars* and *support_measure*, the results of which can be found in Table 1. A fourth run with *support_nocars* as dependent variable and all other variables as predictors was not included, because including the 16 variables specifically related to the Potsdam traffic measure was deemed irrelevant for predicting the hypothetical *support_nocars*. For interpretation of *support_nocars* 37 variables were found to be important, the top 4 of which were most important for prediction: *measure_aq_limit_traffic*, *use_car*, *decision_env*, and *future_public*. For *support_measure*, eight variables were identified in the initial interpretation subset from all available variables, five of which composed the prediction subset: *effect_mobility*, *effect_lifequal*, *effect_health*, *measure_aq_limit_traffic*, and *effect_smell*. As the set of perceived effectiveness variables specific to the Potsdam traffic measure were found to be dominant in predicting and interpreting *support_measure* to the detriment of most other variables, they were removed and then the analysis was run once more. With this smaller set of general variables not linked to perceptions of the Potsdam traffic measure, 31 variables were identified in the interpretation subset, 7 of which composed the prediction subset: *measure_aq_limit_traffic*, *use_car*, *decision_env*, *use_bike*, *air_transportation*, *future_foot*, and *use_carshare*. Though the two sets with no Potsdam traffic measure variables are somewhat similar in composition, *support_measure* has a greater share of mobility variables in its interpretation subset than *support_nocars*, whose subset contains more sociodemographic and environmental perception variables.

Table 1. Lists of the variables found to be most important for interpretation of the dependent variables *support_nocars* and *support_measure*, ordered by decreasing variable importance. The bolded and italicized variables in each list are those found to be most important for prediction.

Support_Nocars		Support_Measure	
No Potsdam Traffic Measure Variables		All Variables	No Potsdam Traffic Measure Variables
<i>measure_aq_limit_traffic</i>	cc_concern	<i>effect_mobility</i>	<i>measure_aq_limit_traffic</i>
<i>use_car</i>	measure_aq_car	<i>effect_lifequal</i>	<i>use_car</i>
<i>decision_env</i>	zep_freq_work_car	<i>effect_health</i>	<i>decision_env</i>
<i>future_public</i>	income	<i>effect_aq</i>	<i>use_bike</i>
<i>future_bike</i>	zep_freq_work_public	support_nocars	<i>future_bike</i>
<i>health_air_poll</i>	zep_freq_work_bike	<i>measure_aq_limit_traffic</i>	access_bike
<i>budget_env</i>	filter_km_studyarea	<i>effect_cc</i>	zep_freq_work_car
<i>air_transportation</i>	zep_freq_priv_foot	<i>effect_smell</i>	zep_freq_priv_bike
cc_affected	future_carpool		use_public
use_public	future_carshare		<i>future_public</i>
use_bike	person_house		zep_freq_work_foot
zep_freq_priv_bike	informed_wishes		<i>future_carshare</i>
qualification	measure_aq_indus_energy		filter_km_studyarea
zep_freq_priv_car	resident_location		<i>air_transportation</i>
access_bike	future_foot		zep_freq_priv_foot
env_pollution	use_foot		env_deforest
aq_concern	informed_aq		
access_public	age		
zep_freq_priv_public			
			zep_freq_work_bike
			zep_freq_priv_public
			<i>future_foot</i>
			budget_env
			access_public
			health_air_poll
			measure_aq_indus_energy
			aq_concern
			qualification
			zep_freq_work_public
			access_foot
			<i>use_carshare</i>
			zep_freq_work_foot
			person_house
			kids_house

3.3. Regularized Elastic-Net Logistic Regression

Using the three separate variable subsets from the three VSURF runs, three elastic-net logistic models were built, the results of which can be seen in Table 2, Table 3, and Table 4. In the *support_nocars* regression model (Table 2), the categories of ‘yes’ from *future_public* and *measure_aq_limit_traffic* are both associated with a high probability ($P(\text{sup}) = 0.71$ and $P(\text{sup}) = 0.79$, respectively) of supporting investments in traffic-reducing measures. The lowest probabilities of support, or alternatively, highest likelihoods of not supporting traffic-reducing measures, belong to the categories of ‘very low priority’ from *budget_env* ($P(\text{sup}) = 0.28$), ‘daily or almost daily’ from *use_car* ($P(\text{sup}) = 0.37$), and ‘6 = not at all important’ from *decision_env*. Quite a few variable categories are associated with a somewhat higher probability of supporting investments in these measures, including environmental and air quality perception variables such as *air_transportation* (‘yes’), *health_air_poll* (‘yes’), and *cc_concern* (‘6 = very concerned’), as well as transport variables such as *future_bike* (‘yes’), *future_carpool* (‘yes’), and *use_bike* (‘daily or almost daily’). The predictive accuracy of this model on the test subset of data was 76.9%.

Table 2. Output from the regularized elastic-net regression model using the interpretation subset found from the first VSURF run with *support_nocars* and no Potsdam traffic measure variables. The variable categories are organized in descending order of the absolute value of the log-odds coefficients. Variable categories either penalized to zero or with a log-odds coefficient less than the absolute value of ± 0.2 are not shown. The full Table S2 can be found in Supplementary Information.

Variable Category	Log-Odds Coefficient	Odds Ratio	Probability $P(\text{sup})$
X-Intercept	-1.33		
measure_aq_limit_traffic <i>yes</i>	1.33	3.80	0.79
budget_env <i>very low priority</i>	-0.94	0.39	0.28
future_public <i>yes</i>	0.90	2.45	0.71
use_car <i>daily or almost daily</i>	-0.54	0.58	0.37
air_transportation <i>yes</i>	0.42	1.52	0.60
decision_env 6 = <i>not at all important</i>	-0.37	0.69	0.41
health_air_poll <i>yes</i>	0.31	1.37	0.58
cc_concern 6 = <i>very concerned</i>	0.31	1.36	0.58
measure_aq_car <i>yes</i>	0.30	1.35	0.57
budget_env <i>very high priority</i>	0.30	1.35	0.57
future_bike <i>yes</i>	0.28	1.33	0.57
future_carpool <i>yes</i>	0.28	1.33	0.57
future_public <i>maybe</i>	0.26	1.29	0.56
income 60 to 69,999 EUR	0.25	1.28	0.56
env_pollution <i>yes</i>	0.23	1.26	0.56
use_bike <i>daily or almost daily</i>	0.22	1.25	0.56
measure_aq_indus_energy <i>yes</i>	-0.21	0.81	0.45

Table 3. Output from the regularized elastic-net logistic regression model using the interpretation subset found from the second VSURF run with *support_measure* and all variables. Results calculated as in Table 2. The full Table S3 can be found in Supplementary Information.

Variable Category	Log-Odds Coefficient	Odds Ratio	Probability $P(\text{sup})$
X-Intercept	-3.46		
effect_lifequal <i>greatly improve</i>	2.22	9.17	0.90
effect_lifequal <i>improve</i>	1.53	4.63	0.82
measure_aq_limit_traffic <i>yes</i>	1.12	3.07	0.75
support_nocars <i>yes, I strongly support it</i>	1.02	2.78	0.74
effect_mobility <i>greatly worsen</i>	-0.84	0.43	0.30
effect_mobility <i>greatly improve</i>	0.74	2.09	0.68
effect_health <i>improve</i>	0.63	1.87	0.65
effect_mobility <i>improve</i>	0.61	1.84	0.65
effect_aq <i>improve</i>	0.53	1.70	0.63
effect_aq <i>greatly improve</i>	0.45	1.56	0.61

Table 4. Output from the regularized elastic-net logistic regression model using the interpretation subset found from the VSURF run with *support_measure* without Potsdam traffic measure variables. Results calculated as in Table 2. The full Table S4 can be found in Supplementary Information.

Variable Category	Log-Odds Coefficient	Odds Ratio	Probability $P(\text{sup})$
X-Intercept	-3.65		
measure_aq_limit_traffic <i>yes</i>	2.29	9.90	0.91
use_car <i>daily or almost daily</i>	-0.85	0.43	0.30
future_carshare <i>yes</i>	0.63	1.88	0.65
budget_env <i>very high priority</i>	0.58	1.79	0.64
use_bike <i>daily or almost daily</i>	0.48	1.62	0.62
future_bike <i>yes</i>	0.45	1.56	0.61
use_public <i>on 1 to 3 days a week</i>	0.42	1.52	0.60
decision_env 3	-0.39	0.68	0.40
env_deforest <i>yes</i>	-0.38	0.68	0.41
future_public <i>yes</i>	0.37	1.44	0.59
measure_aq_indus_energy <i>yes</i>	-0.30	0.74	0.42
access_public <i>good</i>	0.26	1.30	0.56
zep_freq_work_bike <i>daily or almost daily</i>	0.26	1.29	0.56
qualification <i>master's degree</i>	0.22	1.25	0.56

The regression model run including all variables with *support_measure* as the dependent variable (Table 3) resulted in a substantially smaller list of variable categories that were not penalized to

zero. Of these, the categories of ‘greatly improve’ and ‘improve’ from *effect_lifequal* ($P(\text{sup}) = 0.90$ and $P(\text{sup}) = 0.82$, respectively) as well as ‘yes’ from *measure_aq_limit_traffic* ($P(\text{sup}) = 0.75$) and ‘yes, I strongly support it’ from *support_nocars* ($P(\text{sup}) = 0.74$) were found to be the strongest predictors of *support_measure*. The only variable category found to be associated with a much lower probability of supporting the Potsdam traffic measure was ‘greatly worsen’ from *effect_mobility*. All other categories of ‘worsen’ or ‘greatly worsen’ from variables of perceived effectiveness were penalized to zero, leaving only categories of ‘improve’ or ‘greatly improve’ as important predictors of support for the Potsdam traffic measure. The predictive accuracy of this model on the test subset of data was 96.3%.

The regression model for *support_measure* without Zeppelinstrasse variables (Table 4) contains results somewhat similar to that of the *support_nocars* model, though there are some noticeable differences. The highest probabilities in this model belong to the categories of ‘yes’ from *measure_aq_limit_traffic* and *future_carshare* ($P(\text{sup}) = 0.91$ and $P(\text{sup}) = 0.65$, respectively). The lowest probability of support for the Potsdam traffic measure belongs to the category ‘daily or almost daily’ from *use_car* ($P(\text{sup}) = 0.30$). Here too, many variable categories are associated with higher probabilities of supporting the Potsdam traffic measure. Some notable categories include *budget_env* (‘very high priority’), as well as the transport variables *use_bike* (‘daily or almost daily’), *future_bike* (‘yes’), and *use_public* (‘1 to 3 days a week’), all with $P(\text{sup}) > 0.6$. Additionally, the environmental perception variables *decision_env* (‘3’) and *env_deforest* (‘Yes’) are associated with a lower probability of support ($P(\text{sup}) = 0.40$ and $P(\text{sup}) = 0.41$, respectively). The predictive accuracy of this model on a test subset of data was 93.1%.

4. Discussion

In this study, we empirically investigated the predicting factors for hypothetical versus actual support for traffic-reducing measures. The results show that there appears to be a stark contrast between respondents’ hypothetical support for investments in traffic-reducing measures versus support for a specific implementation of such measures. Even at a surface level this distinction is clear, as can be seen in Figure 2; there is moderate support for these investments, but more than 1000 respondents who indicated as much also rejected the Potsdam traffic measure. A clear distinction does arise, though, between predictors of support for investments in traffic-reducing measures compared with for the Potsdam traffic measure. Variables measuring environmental beliefs and awareness of air quality were more prevalent as predictors of the hypothetical case, whereas variables assessing mobility habits and preferences, as well as expected outcomes of the measure, were more important for predicting the concrete case. These results show that environmental beliefs are indeed important for determining a person’s support for investing public money in these traffic measures, as outlined by VBN theory and as found previously in the literature [34]. This support, as well as the role environmental beliefs play in determining it, appears to remain hypothetical, diminishing significantly once the same people are faced with a measure that has real impacts on their daily routines and perceived mobility freedom. Thus, when deciding their support for the Potsdam traffic measure, respondents’ environmental beliefs no longer hold the same weight. Instead, respondents’ rating of the measure’s effectiveness and their willingness to change their mobility habits influence their attitudes towards the Potsdam traffic measure.

A closer look at this general result reveals that awareness of the issue of air pollution as well as its sources and solutions is particularly important to predicting support. Whether or not respondents believe reducing traffic is an effective measure for improving air quality (*measure_aq_limit_traffic*) is either the most significant predictor or one of the most significant in all three regression models. This indicates that support for traffic-reducing measures is most strongly predicted by an individuals’ belief that such policies are inherently successful at improving air quality. This connection between problem awareness and support plays an even stronger role in predicting hypothetical support, as beliefs that (i) transportation is a major source of air pollutants (*air_transportation*); (ii) air pollution is a significant environmental issue affecting health of the residents of Potsdam (*health_air_poll*); and

iii) stricter controls on emissions from cars are effective in improving air quality (*measure_aq_car*), are all important predictors of *support_nocars* (see Table 5). Responses of ‘yes’ to these four questions lead to a higher probability that a respondent will support investments in traffic-reducing measures. Conversely, the belief that stricter controls on industry and energy production are an effective way to improve air quality (*measure_aq_indus_energy*) is associated with a lower probability of supporting both investments in traffic-reducing measures and the Potsdam traffic measure. As there is minimal industry in Potsdam which contributes only 15% to total NO_x emissions, such stricter controls would be ineffective in minimizing local air pollution of NO₂, especially since 70% of emissions come from car traffic [57]. This misconception of the sources of air pollution may play a role in the acceptability of traffic-reducing measures, but is not conclusive based on the data collected here. Since problem awareness is connected to positive support for the Potsdam traffic measure and hypothetical investments in such measures, a greater emphasis on increasing problem awareness could increase acceptability of these transport policies.

Table 5. Summary of the determinants of support for investments in traffic-reducing measures (‘hypothetical’), support for the Potsdam traffic measure (‘actual’), and for both variables

Hypothetical Support	Both	Actual Support
<ul style="list-style-type: none"> • Perception that transportation is a major source of air pollution. • Perception that air pollution is a local health problem in Potsdam. • A high level of concern for climate change. • Perception that stricter control on vehicle emissions is a viable measure for improving air quality. 	<ul style="list-style-type: none"> • Perception that restricting traffic is a viable measure for improving air quality. • Frequency of use of car and bike. • Perceived future use of car sharing, bike, and public transport. 	<ul style="list-style-type: none"> • Perception that stricter control on industry and energy production is a viable measure for improving air quality. • Perceived effect of the Potsdam traffic measure on personal life-quality. • Perceived effect of the Potsdam traffic measure on personal mobility. • Perceived effect of the Potsdam traffic measure on air quality.

Another set of predictor variables important to both dependent variables, but particularly to predicting support for the Potsdam traffic measure, are those measuring mobility habits and willingness to change mobility modes. Daily use of the car is associated with a lower probability of supporting traffic-reducing measures and the Potsdam traffic measure, whereas daily bicycle use and frequent use of public transport are associated with higher probabilities of support. This is understandable as daily car users were the most negatively affected by the Potsdam traffic measure, with the number of lanes available for car traffic being cut in half on the street. The extra space was converted into a lane dedicated for bicycles and partially for busses. As such, car owners likely perceive these measures negatively due to the perceived constriction of their mobility freedom, whereas users of alternative modes perceive an increase in their mobility freedom, fostering positive feelings towards traffic-reducing measures. Furthermore, respondents that perceived themselves as using public transport (*future_public*), the bicycle (*future_bike*), car sharing services (*future_carshare*), or carpooling (*future_carpool*) more often in the future were more likely to support both the Potsdam traffic measure and hypothetical investments in such measures. This is in line with previous research showing that multimodal travelers are more inclined to support sustainable transport policies than single mode car drivers [58].

The willingness to change is crucial in the context of traffic-reducing measures, as it indicates that support is dependent on an individual’s inclination to switch to alternative modes of transport. Therefore, coupling traffic-reducing measures with policies that ease the use of public transport, the bicycle, and car sharing services would likely increase support for such measures. This conclusion aligns with a 2016 German Environment Agency study that found substantial willingness to switch from the car to alternative travel modes among a representative sample of Germans. Two-thirds of regular car drivers would cycle more often and half would use public transport more. Such willingness, however, is crucially dependent on the caveats of greater provision of alternative mobility options and enhanced alternative mobility infrastructure, enabling people to complete their daily routines without cars [37]. Considering that bans on diesel vehicles, among other traffic-restricting measures,

are currently being enacted in cities across Germany to improve air quality, low support for those measures may be improved by easing and incentivizing a switch to alternative modes of transport.

Particularly important to predicting support for the Potsdam traffic measure are variables measuring expected effects of the measure on people's lives. Respondents that believe this measure will 'improve' or 'greatly improve' their quality of life have a very high probability of supporting it. This trend, though lessened in strength, is the same for perceived effects of the measure on personal mobility, health of Potsdam residents, and local air quality. It is clear that when determining their support for this measure, respondents focus on the consequences it will have on their personal lives, often referred to as 'personal outcome expectation', as well as those of other local residents, known as 'perceived effectiveness' of the measure in terms of general positive effects. This relationship is further strengthened by the fact that, from a dataset of all possible independent variables, these *effect_[xxx]* variables dominate in prediction at the expense of all others. Only once these were removed from the dataset and the analysis was run again could the aforementioned connections between mobility habits and preferences and support for the Potsdam traffic measure be discerned. This result supports previous findings in the literature of a connection between expected effects of traffic policies and their acceptability.

Limitations of the Study

While the results of this study serve as interesting benchmarks for further research to advance upon, there are some key limitations. First, this study used a convenience sample that is not representative of the city of Potsdam. While the demographics of the respondents to this survey are quite similar to those of the city of Potsdam, the generalizability of the results remains limited. Furthermore, it may be the case that a majority of respondents took part in the survey to voice their discontent with the Potsdam traffic measure. This is seen as a limitation because the similar motivation of participants (dissatisfaction with the traffic measure) to participate in the survey may mean that respondents had similar responses to certain questions in the questionnaire, potentially skewing the proportions of responses for the Likert-type questions. Second, the research was not developed using a specific behavioral or psychological theory. Instead, this study is exploratory by design and sought to broadly assess predictors of support, from which the aforementioned results were ascertained. Last, significance tests for the lasso regression model were not conducted, as they are inappropriate for penalized regression methods which intentionally introduce bias into the model. This does not impact the model's accuracy, it rather improves it. However, this is an atypical method for this type of research and is therefore not comparable to similar research using alternative statistical methods.

5. Conclusions

Though traffic-reducing measures are crucial for improving air quality in polluted German cities, they are, more often than not, deemed unacceptable by the public. We find in this study that although there is relatively high support for hypothetically diverting public funds towards such measures, it dissipates substantially when the same individuals experience an actual measure that impacts them directly. Furthermore, whereas environmental beliefs are indeed important to predicting hypothetical support for investments in such measures, they are set aside when predicting support for concrete traffic-reducing measures with locally specific designs. Instead, mobility habits and preferences, perceived outcome expectations, and perceived effectiveness appear to be the main determinants of an individual's support. Another key finding is that while willingness to shift from passenger vehicles to alternative modes of transport is a moderate determinant of hypothetical support for investments in traffic-measures, it is central to support for actual traffic measures. The most important predictor of support, however, is an individual's problem awareness, in this case regarding air pollution. Knowledge of its local sources and viable solutions are directly connected to support for traffic policies that reduce car traffic in an effort to improve air quality. As such, emphasizing the major role fossil-fuel

cars play in producing poor local air quality is vital to ensuring both greater understanding of air pollution and support for restrictive measures.

While individual measures such as the Potsdam traffic measure may achieve short-term goals of improving air quality, they struggle to address underlying mobility patterns among citizens and commuters. Considering the lingering issue of air pollution in German cities, local administrations should ensure their plans for improving air quality focus on a holistic approach to mobility infrastructure, so as to ease the mobility transition for their citizens, as opposed to implementing targeted measures to improve air quality mainly at hot spots. Such an approach represents a significant shift away from traditional transport planning, one that steers towards development of integrated, sustainable urban mobility plans. Previous research has shown that characteristics of such plans include (1) a long-term vision (20–30 years); (2) a high level of citizen and stakeholder involvement; (3) the integration of different policy sectors, both geographically across the greater urban region and institutionally across hierarchies of government; and (4) a shift in thematic focus towards greater emphasis of alternative forms of transport such as walking, cycling, and public transit [59]. This study shows that the implementation of targeted transport policies in the absence of an over-arching plan can be received with substantial opposition, even from an audience that predominantly shares the environmental goals of such measures. As such, a more holistic and sustainable approach to transport planning is recommended.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2071-1050/11/14/3991/s1>, Table S1: Codes, questions, and answer categories of the questionnaire. Table S2: Full version of Table 2, Table S3: Full version of Table 3, and Table S4: Full version of Table 4.

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References

1. European Commission. *Air Quality: Commission Takes Action to Protect Citizens from Air Pollution (Press Release)*; European Commission: Brussels, Belgium, 2018.
2. Bundesverwaltungsgericht Luftreinhaltepläne Düsseldorf und Stuttgart: Diesel-Verkehrsverbote Ausnahmsweise Möglich. Available online: <https://www.bverwg.de/pm/2018/9> (accessed on 28 January 2019).
3. Landesamt für Umwelt. *Luftqualität in Brandenburg: Jahresbericht*; Ministerium für Ländliche Entwicklung, Umwelt und Landwirtschaft (MLUL): Potsdam, Germany, 2017.
4. *Action Plan on Urban Mobility*; European Commission DG Energy and Transport: Brussels, Belgium, 2009.
5. Chinellato, M.; Staelens, P.; Wennberg, H.; Sundberg, R.; Böhler, S.; Brand, L.; Adams, R.; Dragutescu, A.; Gertheis, A. *Users’ Needs Analysis on SUMP Take Up*; CIVITAS SUMPS-UP: Brussels, Belgium, 2017.
6. Nikulina, V.; Simon, D.; Ny, H.; Baumann, H. Context-Adapted Urban Planning for Rapid Transitioning of Personal Mobility towards Sustainability: A Systematic Literature Review. *Sustainability* **2019**, *11*, 1007. [[CrossRef](#)]
7. Russo, F.; Comi, A. Urban freight transport planning towards green goals: Synthetic environmental evidence from tested results. *Sustainability* **2016**, *8*, 381. [[CrossRef](#)]
8. García, J.; Arroyo, R.; Mars, L.; Ruiz, T. The influence of attitudes towards cycling and walking on travel intentions and actual behavior. *Sustainability* **2019**, *11*, 2554. [[CrossRef](#)]

9. Suchanek, M.; Szmelter-Jarosz, A. Environmental aspects of generation Y's sustainable mobility. *Sustainability* **2019**, *11*, 3204. [[CrossRef](#)]
10. Nilsson, A.; Hansla, A.; Heiling, J.M.; Bergstad, C.J.; Martinsson, J. Public acceptability towards environmental policy measures: Value-matching appeals. *Environ. Sci. Policy* **2016**, *61*, 176–184. [[CrossRef](#)]
11. Kottenhoff, K.; Brundell Freij, K. The role of public transport for feasibility and acceptability of congestion charging - The case of Stockholm. *Transp. Res. Part A Policy Pract.* **2009**, *43*, 297–305. [[CrossRef](#)]
12. Börjesson, M.; Hamilton, C.J.; Näsman, P.; Papaix, C. Factors driving public support for road congestion reduction policies: Congestion charging, free public transport and more roads in Stockholm, Helsinki and Lyon. *Transp. Res. Part A Policy Pract.* **2015**, *78*, 452–462. [[CrossRef](#)]
13. Schuitema, G.; Steg, L.; Forward, S. Explaining differences in acceptability before and acceptance after the implementation of a congestion charge in Stockholm. *Transp. Res. Part A* **2010**, *44*, 99–109. [[CrossRef](#)]
14. Kallbekken, S.; Garcia, J.H.; Korneliusson, K. Determinants of public support for transport taxes. *Transp. Res. Part A Policy Pract.* **2013**, *58*, 67–78. [[CrossRef](#)]
15. Cherry, T.L.; Kallbekken, S.; Kroll, S. The impact of trial runs on the acceptability of environmental taxes: Experimental evidence. *Resour. Energy Econ.* **2014**, *38*, 84–95. [[CrossRef](#)]
16. Kallbekken, S.; Sælen, H. Public acceptance for environmental taxes: Self-interest, environmental and distributional concerns. *Energy Policy* **2011**, *39*, 2966–2973. [[CrossRef](#)]
17. Dieplinger, M.; Fürst, E. The acceptability of road pricing: Evidence from two studies in Vienna and four other European cities. *Transp. Policy* **2014**, *36*, 10–18. [[CrossRef](#)]
18. Sørensen, C.H.; Isaksson, K.; Macmillan, J.; Åkerman, J.; Kressler, F. Strategies to manage barriers in policy formation and implementation of road pricing packages. *Transp. Res. Part A Policy Pract.* **2014**, *60*, 40–52. [[CrossRef](#)]
19. Tretvik, T. Urban Road Pricing in Norway: Public Acceptability and Travel Behaviour. In *Acceptability of Transport Pricing Strategies*; Emerald Group Publishing Limited: Bingley, UK, 2003; pp. 77–92.
20. Eriksson, L.; Garvill, J.; Nordlund, A.M. Acceptability of travel demand management measures: The importance of problem awareness, personal norm, freedom, and fairness. *J. Environ. Psychol.* **2006**, *26*, 15–26. [[CrossRef](#)]
21. Eriksson, L.; Garvill, J.; Nordlund, A.M. Acceptability of single and combined transport policy measures: The importance of environmental and policy specific beliefs. *Transp. Res. Part A Policy Pract.* **2008**, *42*, 1117–1128. [[CrossRef](#)]
22. Gärling, T.; Schuitema, G. Travel Demand Management Targeting Reduced Private Car Use: Effectiveness, Public Acceptability and Political Feasibility. *J. Soc. Issues* **2007**, *63*, 139–153. [[CrossRef](#)]
23. Schöller-Schwedes, O. The failure of integrated transport policy in Germany: A historical perspective. *J. Transp. Geogr.* **2010**, *18*, 85–96. [[CrossRef](#)]
24. Buehler, R. Transport policies, automobile use, and sustainable transport: A comparison of Germany and the United States. *J. Plan. Educ. Res.* **2010**, *30*, 76–93. [[CrossRef](#)]
25. Buehler, R. Determinants of transport mode choice: A comparison of Germany and the USA. *J. Transp. Geogr.* **2011**, *19*, 644–657. [[CrossRef](#)]
26. Gawel, E. Road pricing in Germany: A behavioral economics perspective. In *New Perspectives for Environmental Policies Through Behavioral Economics2*; Beckenbach, F., Kahlenborn, W., Eds.; Springer International Publishing Switzerland: Basel, Switzerland, 2016.
27. Stern, P.C.; Dietz, T.; Abel, T.; Guagnano, G.A.; Kalof, L. A value-belief-norm theory of support for social movements: The case of environmentalism. *Hum. Ecol. Rev.* **1999**, *6*, 81–97.
28. Ünal, A.B.; Steg, L.; Granskaya, J. "To support or not to support, that is the question". Testing the VBN theory in predicting support for car use reduction policies in Russia. *Transp. Res. Part A Policy Pract.* **2019**, *119*, 73–81. [[CrossRef](#)]
29. Schuitema, G.; Steg, L.; Rothengatter, J.A. The acceptability, personal outcome expectations, and expected effects of transport pricing policies. *J. Environ. Psychol.* **2010**, *30*, 587–593. [[CrossRef](#)]
30. Krupnick, A.; Harrington, W.; Alberini, A. Public Support for Pollution Fee Policies for Motor Vehicles: Survey Results. *Reg. Sci. Urban Econ.* **2001**, *31*, 505–522. [[CrossRef](#)]

31. Jakobsson, C.; Fujii, S.; Gärling, T. Determinants of private car users' acceptance of road pricing. *Transp. Policy* **2000**, *7*, 153–158. [CrossRef]
32. Poortinga, W.; Steg, L.; Vlek, C.; Wiersma, G. Household preferences for energy-saving measures: A conjoint analysis. *J. Econ. Psychol.* **2003**, *24*, 49–64. [CrossRef]
33. Börjesson, M.; Eliasson, J.; Hamilton, C. Why experience changes attitudes to congestion pricing: The case of Gothenburg. *Transp. Res. Part A Policy Pract.* **2016**, *85*, 1–16. [CrossRef]
34. De Groot, J.I.M.; Steg, L. Value Orientations to explain beliefs related to environmental significant behavior. *Environ. Behav.* **2008**, *40*, 330–354. [CrossRef]
35. De Groot, J.I.M.; Steg, L.; Dicke, M. Transportation trends from a moral perspective: Value orientations, norms, and reducing car use. In *New Transportation Research Progress*; Nova Science Publishers, Inc.: Hauppauge, NY, USA, 2007; ISBN 978-1-60456-032-9.
36. Landeshauptstadt Potsdam. *Potsdam als Wissenschaftsstadt Bürgerumfrage*; Landeshauptstadt Potsdam: Potsdam, Germany, 2015.
37. Benthin, R.; Gellrich, A.; Scholl, G.; Holzhauer, B.; Schipperges, M. *Umweltbewusstsein in Deutschland*; Umweltbundesamt: Dessau-Roßlau, Germany, 2016.
38. European Commission Attitudes of Europeans towards air quality. *Flash Eurobarom.* **2013**, *360*, 167.
39. Draugalis, J.R.; Coons, S.J.; Plaza, C.M. Best practices for survey research reports: A synopsis for authors and reviewers. *Am. J. Pharm. Educ.* **2008**, *72*, 11. [CrossRef] [PubMed]
40. Schmitz, S.; Weiland, L.; Becker, S.; Niehoff, N.; Schwartzbach, F.; von Schneidmesser, E. An assessment of perceptions of air quality surrounding the implementation of a traffic-reduction measure in a local urban environment. *Sustain. Cities Soc.* **2018**, *41*, 525–537. [CrossRef]
41. Rubin, D. Inference and missing data. *Biometrika* **1976**, *63*, 581–592. [CrossRef]
42. Van der Heijden, P.G.; Escofier, B. Multiple Correspondence Analysis with missing data. In *Analyse des Correspondances*; Presses de Rennes: Rennes, France, 2003.
43. Josse, J.; Husson, F. missMDA: A Package for Handling Missing Values in Multivariate Data Analysis. *J. Stat. Softw.* **2016**, *70*, 1–31. [CrossRef]
44. Josse, J.; Chavent, M.; Liquet, B.; Husson, F. Handling missing values with regularized iterative multiple correspondence analysis. *J. Classif.* **2012**, *29*, 91–116. [CrossRef]
45. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
46. Genuer, R.; Poggi, J.-M.; Tuleau-Malot, C. VSURF: An R Package for Variable Selection Using Random Forests. *R J.* **2015**, *7*, 19–33. [CrossRef]
47. Genuer, R.; Poggi, J.-M.; Tuleau-Malot, C. Variable selection using random forests. *Pattern Recognit. Lett.* **2010**, *31*, 2225–2236. [CrossRef]
48. Liaw, A.; Wiener, M. Classification and Regression with Random Forest. *R News* **2002**, *2*, 18–22.
49. Zou, H.; Hastie, T. Regularization and variable selection via the elastic net. *J. R. Stat. Soc. Ser. B* **2005**, *67*, 301–320. [CrossRef]
50. Goeman, J.; Meijer, R.; Chaturvedi, N. L1 and L2 Penalized Regression Models. Available online: <http://cran.nedmirror.nl/web/packages/penalized/vignettes/penalized.pdf> (accessed on 15 February 2019).
51. Judd, C.M.; McClelland, G.H.; Ryan, C. *Data Analysis: A Model Comparison Approach*; Harcourt Brace Jovanovich: San Diego, CA, USA, 1989.
52. Tibshirani, R. Regression Shrinkage and Selection via the Lasso. *J. R. Stat. Soc. Ser. B* **1996**, *58*, 267–288. [CrossRef]
53. Krstajic, D.; Buturovic, L.J.; Leahy, D.E.; Thomas, S. Cross-validation pitfalls when selecting and assessing regression and classification models. *J. Cheminformatics* **2014**, *6*, 10. [CrossRef]
54. Friedman, J.; Hastie, T.; Tibshirani, R. Regularization Paths for Generalized Linear Models via Coordinate Descent. *J. Stat. Softw.* **2010**, *33*, 1. [CrossRef] [PubMed]
55. Weiland, L.; Schmitz, S.; Becker, S.; Niehoff, N.; Schwartzbach, F.; Von Schneidmesser, E. Climate change and air pollution: The connection between traffic intervention policies and public acceptance in a local context. *Environ. Res. Lett.* **2019**, in press. [CrossRef]
56. Weiland, L.; Schmitz, S.; von Schneidmesser, E. *Mobilität, Luftqualität und Nachhaltige Städte: Sichtweisen der Öffentlichkeit*; Institute for Advanced Sustainability Studies (IASS) e.V.: Potsdam, Germany, 2018.

57. Land Brandenburg. *Luftreinhalteplan für die Landeshauptstadt Potsdam Fortschreibung 2015/2016 Abschlussbericht*; Ministerium für Ländliche Entwicklung, Umwelt und Landwirtschaft: Potsdam, Germany, 2016.
58. Steg, L. Can Public Transport Compete With the Private Car? *IATSS Res.* **2003**, *27*, 27–35. [[CrossRef](#)]
59. ELTISplus. *The State-of-the-Art of Sustainable Urban Mobility Plans in Europe*; Rupprecht Consult—Forschung und Beratung GmbH: Cologne, Germany, 2012.



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