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Association of risk perception and transport mode choice during the temporary closure of a major inner-city road bridge: results of a cross-sectional study

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Abstract

Background Since air pollution and physical inactivity pose major public health risks, switching from cars to alternatives like public transport, cycling, and walking is important. Therefore, it is beneficial to identify key events for changes of mode choice.

Methods We examined the association between risk perception and mode choice during the temporary closure of a road bridge between two major German cities in early 2020 using binary and multinomial regression models.

Results 679 people participated in the survey. We found that 22% of car users switched to alternatives. The higher the perceived health risk from traffic-related air pollution, the more likely car users switched to alternatives (odds ratio [OR] = 1.76, 95% CI [1.14, 2.71]).

Discussion Attitude, subjective norm and perceived behavioral control were associated with maintaining but not with switching transport modes. In conclusion, the closure of a main road bridge may present a key event. To explain mode choice, risk perception is a potential extension to the theory of planned behavior.

Keywords Transport mode choice, Health risk perception, Air pollution, Theory of Planned Behavior, Key event

1 Introduction

Greenhouse gases constitute the central cause of global warming [51]. In 2020, road transport still accounts for 77% of all transport greenhouse gas emissions in the European Union [15]. Thus, promoting a modal shift from private cars to alternative modes of transport (public transport, cycling, walking) is an important strategy to reduce greenhouse gas emissions [12]. Reducing air pollution and increasing physical activity by switching to alternative modes of transport lead to additional public health benefits as well [22, 59, 60].

This raises the question of what prevents people from switching to alternative modes of transport. A possible answer may be that transport mode choice is a habit. Habitual behavior is often performed automatically and is therefore unlikely to change without need [58]. According to the Habit Discontinuity Hypothesis, habits are dependent on stable contexts [54]. If the context changes in which people perform mobility behavior, they are more likely to intentionally reflect and (re)consider their mode choice [8]. Context changes that trigger an intentional mode choice are called *key events* [35]. This

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term includes life events (e.g., the birth of a child), long-term mobility decisions (e.g., the purchase of a car), and exogenous events (e.g., road closures).

In mobility research, a popular theoretical framework to explain intentional mode choice is Ajzen's [1] *Theory of Planned Behavior* (TPB). This theory explains a certain behavior by the *behavioral intention*, i.e., the motivation to perform this behavior [18]. A behavioral intention is, in turn, the result of the attitude towards the behavior, subjective norms, and perceived behavioral control [24]. *Attitudes* pertain to the evaluation of people about whether they consider it good or bad to perform a certain behavior. A *subjective norm* represents a person's perceived expectation from relevant people about how that person should behave. *Perceived behavioral control* is defined as a person's expectation of how easy or difficult it is to perform a certain behavior based on one's own abilities on the one hand and in the presence of resources and barriers to action on the other [24]. In a meta-analysis of 58 studies, the TPB constructs were shown to be successful in explaining mode choice, with intention being the main determinant [32].

Since several theories in health psychology take *health-related risk perception* into account when explaining behavior change [41, 42, 47], recent studies extended the TPB with risk perception to explain different behaviors like environmental complaint behavior [55], self-protective behavior [61] or smog reduction behavior [62]. We were interested in whether this construct is also important for transport mode choice and focused on the perceived health risk from traffic-related air pollution. Perceived risk from environmental pollution has previously been identified as a predictor of ecological behaviors [10, 38]. However, studies that have specifically examined the perceived risk of air pollution found inconsistent results: Higher perceived risk was associated with higher intention to reduce car use [56], increased number of bike trips [11], and increased actions to reduce emissions, except for car-related behaviors [49]. However, risk perception was not associated with the intention to switch to public transport [14] and mitigation behavior such as switching to alternative modes of transport [52].

In the present study, we examined the association of risk perception and transport mode choice during the temporary closure of a major inner-city road bridge using a cross-sectional questionnaire. Grounded in the TPB as theoretical framework, we applied descriptive analysis, binary and multinomial regression models, and a non-parametric test for group differences to answer our following research questions. In addition, we underpin our findings with external traffic data. Previously, we measured changes in local air quality related to the bridge closure, reported in [5].

It has already been shown that temporary road closures can be key events that influence mode choice [19, 20, 28]. Accordingly, in our first research question we investigated whether the bridge closure constituted a similar key event. In addition, we looked at psychological associations of mode choice. While the TPB was well studied, the role of health-related risk perception in mode choice during a key event remains unclear. To address this research gap, our second research question arose: What is the contribution of risk perception in explaining mode choice? Finally, it would be of interest if the bridge closure led to more active mobility habits. Although we did not survey mode use after the closure with our questionnaire, we did measure mode use intention. Therefore, our last research question examined whether car users who switched to alternative modes intended to maintain this alternative after the bridge closure.

2 Methods

Approximately 42,000 cars cross the Theodor Heuss Bridge every weekday, making it a central connection over the Rhine River between the cities of Wiesbaden (approx. 280,000 residents) and Mainz (approx. 220,000 residents) in Germany. Apart from four lanes for vehicles, the bridge has a combined pedestrian and cycle path on each side. The bridge was closed to vehicular traffic from 12 January 2020 to 5 February 2020 due to maintenance work, but was still open for walking, cycling, and public transport. The two closest bridges accessible to vehicular traffic are located 7 and 8 km away respectively. Rail traffic between Mainz and Wiesbaden is directed across two railway bridges (Fig. 1). Due to the closure, the monthly ticket for public transport was valid for six weeks instead of four. In addition, a 15 EUR voucher for the bicycle rental service in Mainz was available. We have no information on how often the extended monthly ticket and the voucher were used.

2.1 Sample

We randomly drew a sample (age $\geq$ 18 years) from the resident register in Mainz ($n = 2500$) and three districts of Wiesbaden in the immediate vicinity of the bridge ($n = 500$). Other districts of Wiesbaden should not be affected by the closure because they are too distant from the Theodor Heuss Bridge and have another vehicular bridge within reach. The random sample was proportionally stratified according to age, gender, and zip code. At the third week of the bridge closure (survey period 27 January 2020 to 27 March 2020), we sent a standardized questionnaire to the selected addresses (for the questionnaire see Additional file 1). Study participation was voluntary, i.e., there was no penalty for non-response. Data

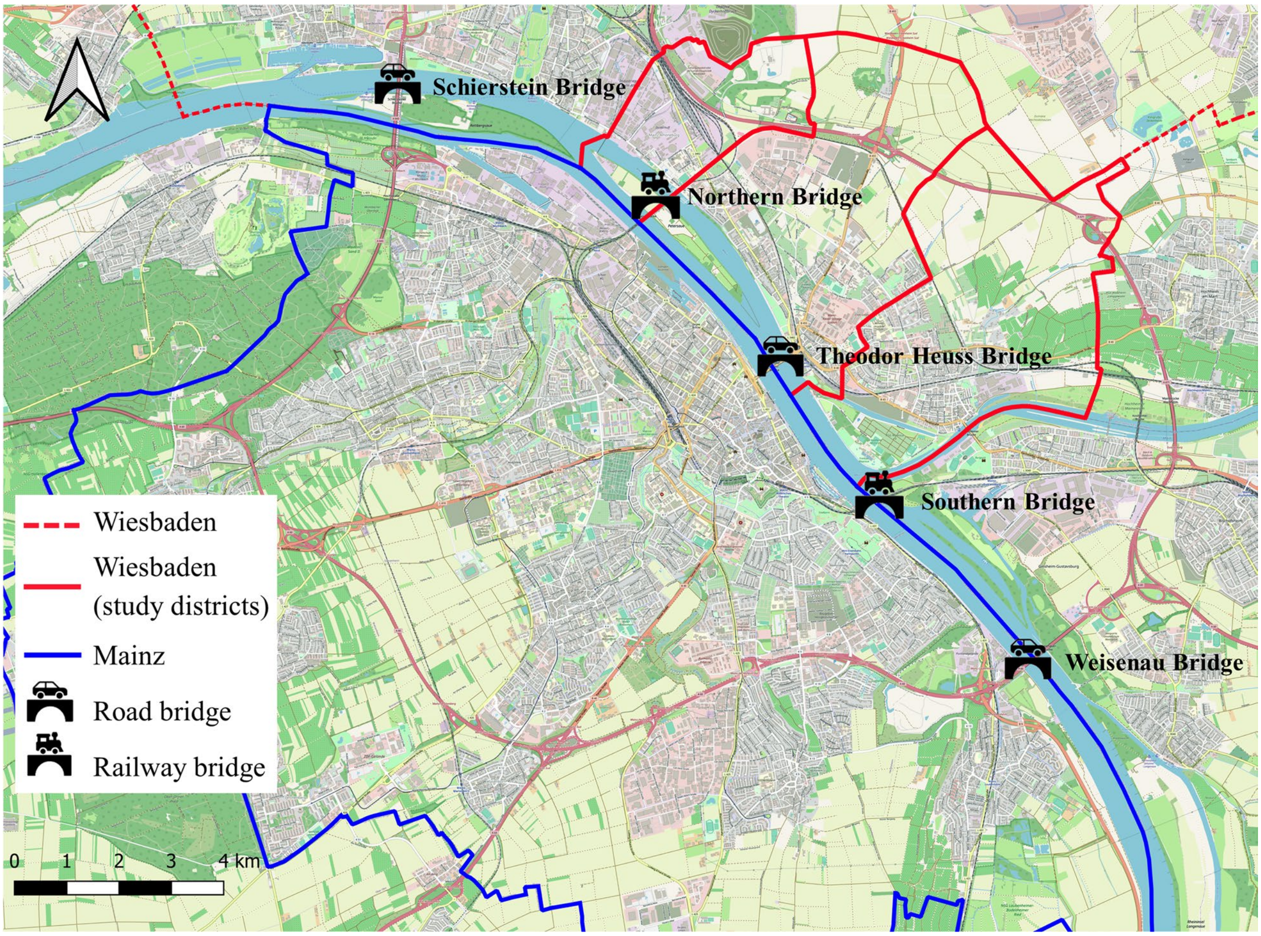

Fig. 1 Location of the Theodor Heuss Bridge, road bridges and railway bridges across the Rhine between the cities of Mainz and Wiesbaden, Germany. OSM Carto map style and map data from OpenStreetMap (openstreetmap.org/copyright). Coordinate system is EPSG:3857-WGS 84/Pseudo-Mercator. Edited with QGIS (version 3.20) and Microsoft PowerPoint (version 2105)

were collected anonymously, meaning that returned questionnaires did not contain any information associated with participants' names or addresses.

Over the survey period, 721 of the contacted residents returned a questionnaire while 157 letters were undeliverable. Based on the number of eligible addresses, a response of 27% was achieved (Fig. 2). To improve data quality, we performed several plausibility checks (see Additional file 2: Table s1). We corrected implausible data, if possible, and otherwise treated them as missing values. We excluded 42 questionnaires from the sample. Of these, eight respondents were younger than 18 years and 34 questionnaires contained $\geq$ 30% missing values. Thus, the final sample size is $N = 679$. Figure 3 (and Additional file 2: Table s2) shows the sample characteristics.

2.1.1 Representativity

We compared the age and gender structure of the achieved sample with the population (Additional file 2: Figure s1). This showed that 18 to 29 year-old men were underrepresented (–4 percentage points) and 60 to 74 year-old women were overrepresented (+3 percentage points) in the sample. To adjust for differences between the population and our sample, we used sampling weights. To this end, we calculated the sampling fraction for each combination of gender and age group [29]. To determine normalized weights, we multiplied the inverted sampling fractions of these combinations by the sampling fraction of the total sample [26] (Additional file 2: Table s3).

The sample characteristics show that high education was common among participants. However, it was not possible to weight the sample for education because respective population data were not available. Compared to the distribution of education in the federal state of Rhineland-Palatinate (Fig. 4), of which Mainz is the capital, people with low and medium education were underrepresented in all age groups.

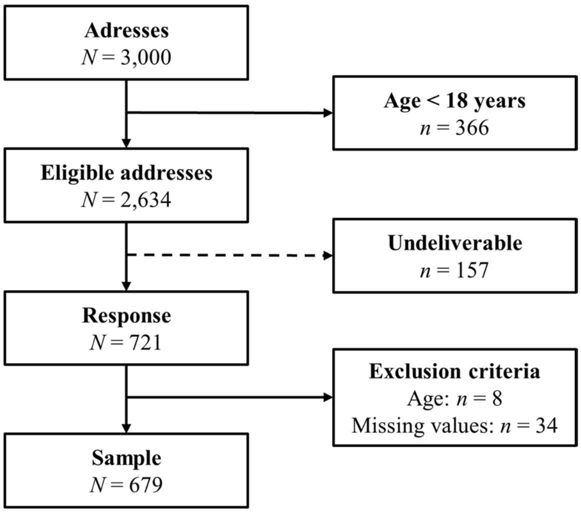

Fig. 2 Flow of the survey in Mainz and Wiesbaden, Germany (27 January 2020–27 March 2020). By mistake, the random sample from the resident register in Mainz ($N=2500$) included persons under the age of 18. Estimated by the age distribution of Mainz, this corresponds to approximately $n=366$ persons (15%). Thus, there were presumably $N=2634$ suitable addresses in the total random sample from Mainz and Wiesbaden

2.2 Questionnaire

2.2.1 Mode choice

In the questionnaire, respondents stated the modes of transport they mainly used to cross the river. They were asked to specify their main mode for the period during the bridge closure as well as for the period before the closure. Answer options were "car", "cycling", "walking", and "public transport". Based on these answers, we formed three groups of mode choice for the statistical analysis: We assigned respondents with persistent car use, i.e., those who mainly used cars before and during the closure, to the *car* group. The *alternative* group included respondents with persistent use of alternative modes, i.e., those who mainly used cycling, walking, or public transport in both time periods. The *switch* group refers to respondents who switched from cars to alternative modes of transport during the bridge closure. Since only four participants switched from alternative modes to cars, we did not assign them to any group of mode choice. We similarly did not assign participants who did not travel the route. Accordingly, we excluded non-assigned participants from all analyses related to groups of mode choice.

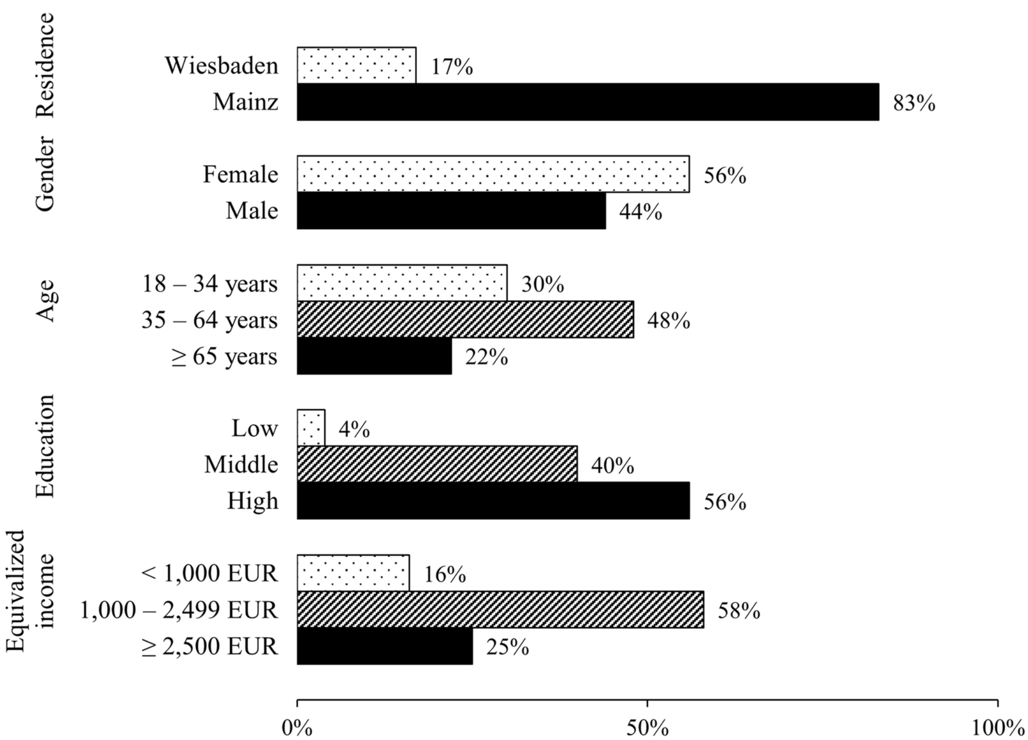

Fig. 3 Characteristics of the sample ($N=679$) in percent. Due to rounding, percentages sometimes do not sum to 100%

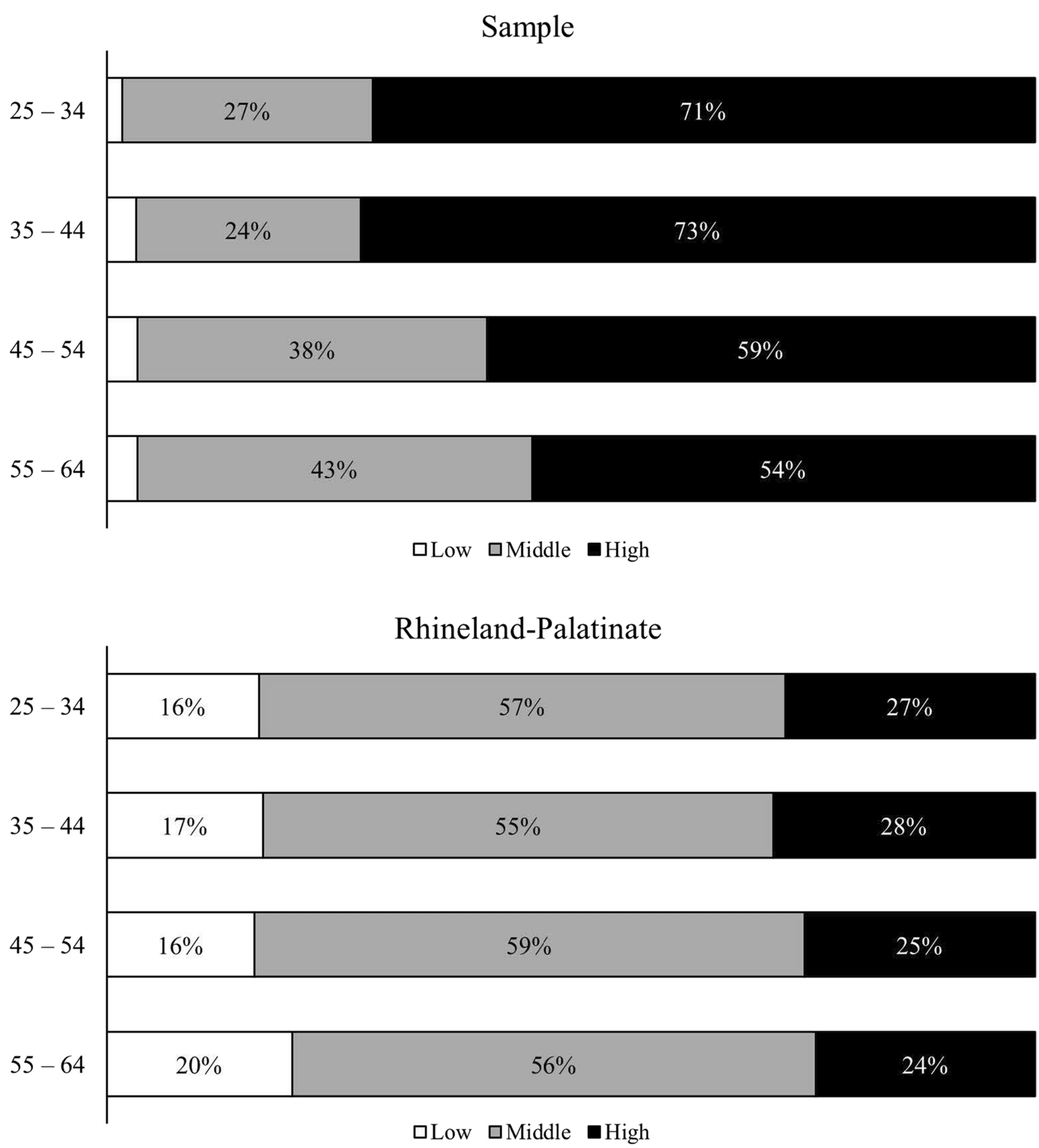

Fig. 4 Distribution of the educational level (x-axis) in specific age groups (y-axis) in the federal state of Rhineland-Palatinate (Mainz is the capital city of this state) from Schröder [46] and the sample from Mainz and Wiesbaden in percent ($n=437$)

2.2.2 Bridge use and bridge use frequency

Participants reported which bridges they usually used to cross the Rhine before and during the closure of the Theodor Heuss Bridge. They could choose the Theodor Heuss Bridge, the two other road bridges (Schierstein Bridge, Weisenau Bridge) and both railway bridges (Northern Bridge, Southern Bridge) with multiple answers possible.

Next, participants specified how frequent they used the Theodor Heuss Bridge per week, firstly before the closure and secondly during the closure. We differentiated between *regular* bridge use (at least once a week) and *occasional* bridge use (less than once a week).

2.2.3 Mode intention

Participants estimated to what degree they intended to maintain the mode of transport they chose during the closure after the bridge reopened. Following the instructions of Schwarzer [48] for operationalizing the TPB, we measured mode intention with a 6-point rating scale ranging from *very unlikely* (0) to *very likely* (5). It was also possible to select the option *not applicable*.

2.2.4 Attitude, subjective norm, and perceived behavioral control

In operationalizing these constructs, we developed a total of 12 items again using the instructions of Schwarzer [48]: For each mode of transport, we measured attitude by how respondents rated their own mode of transport use (e.g., "I think that me driving a car is ...") using a 6-point rating scale ranging from *very bad* (0) to *very good* (5). We operationalized subjective norm as the perceived expectation of a relevant person ("Of the people I care about, most think…"). Participants rated their perceived expectation on a 6-point scale from *I should not* (0) to *I should* (5) regarding their own mode use (e.g., "… use the car"). To measure perceived behavioral control, we asked participants how difficult it was to reach a destination on the other side of the river by a particular mode of transport (e.g., car) during the bridge closure. Participants could rate this on a 6-point scale ranging from *very difficult* (0) to *very easy* (5). We summarized the items regarding public transport, cycling, and walking for each construct by calculating the mean. Therefore, attitude, subjective norm, and perceived behavioral control can be differentiated by self-related mode use (i.e., labeled as car use or alternative use).

2.2.5 Health-related risk perception

To operationalize health-related risk perception, we used three items from the questionnaire developed by Okokon et al. [37] and translated them into German with minor changes in wording. Respondents rated their (a) personal burden, (b) perceived symptoms, and (c) personal health risk from traffic emissions on a 5-point scale ranging from *not at all* (0) to *very much* (4) or from *very low* (0) to *very high* (4). Respondents could select *not applicable* in each case. The mean value of these three items served as the indicator for health-related risk perception.

2.2.6 Sociodemographic characteristics

We collected data about the age of participants using 13 age groups (age 18 to 24, age 25 to 29, age 30 to 34, age 35 to 39, … age 80 and above), which we classified into early adulthood (age 18 to 34), middle adulthood (age 35 to 64), and late adulthood to old age (age 65 and above). Participants reported their monthly total net household income based on eight income groups. Using the OECD-modified equivalence scale [25], we adjusted the monthly total net household income for the number of household members. Then, we grouped the sample according to the equivalized income into low income (below 1000 EUR), middle income (1000 EUR–2499 EUR) and high income (2500 EUR and above). By choosing these income groups, each contained an appropriate number of participants. According to the International Standard Classification of Education [16], we determined the education of the participants from their highest degree.

2.2.7 Missing values

To reduce bias, we excluded all participants with $\geq 30\%$ missing values from the data set [57]. Analyzing the missing values of the final sample showed a proportion of only 4% missings among all values, but also revealed that 36% of the participants ($n=245$) had at least one missing value. Little's test [33] indicated that the missing completely at random assumption was violated. As listwise and pairwise deletion would bias the results [23], we applied multiple imputation using the iterative Markov Chain Monte Carlo method [27]. In the imputation model, we included all items that later became the explanatory, dependent, and control variables [23, 31]. Since the proportion of missing values was rather small and a substantial improvement in conclusions is not expected by increasing above five imputations [9], we settled on $m=5$ imputations. In order to avoid imputing *not applicable* responses, we applied dummy variable adjustment [4]. Since *not applicable* responses do not constitute useful information, we had to remove respective participants from certain analyses after the imputation process by pairwise deletion.

2.3 Traffic data

The city of Mainz provided traffic data for the Theodor Heuss Bridge for the period of 1 November 2019 to 31 March 2020. The data were collected by a permanently installed traffic counter and show the number of vehicles on the bridge per day not differentiated between vehicle types (car, bus, motorcycle etc.). As mobility in Germany was reduced during the first COVID-19 wave in March 2020 [44], we excluded all traffic data within the first lockdown in Germany, i.e., from 22 March 2020 onwards.

2.4 Statistical modeling

2.4.1 Bridge use frequency as predictor of switching from car to alternatives

Here, we search for evidence that the bridge closure was a key event, i.e., a context change which triggered an intentional mode choice. Since relevant context changes are more likely to be found among car users who regularly crossed the bridge before the closure, we tested the hypothesis whether switching from car to alternatives is more likely when the bridge use frequency is regular instead of occasional. Considering that binary logistic regression is used to predict a dichotomous dependent variable, we applied a binary logistic regression model in

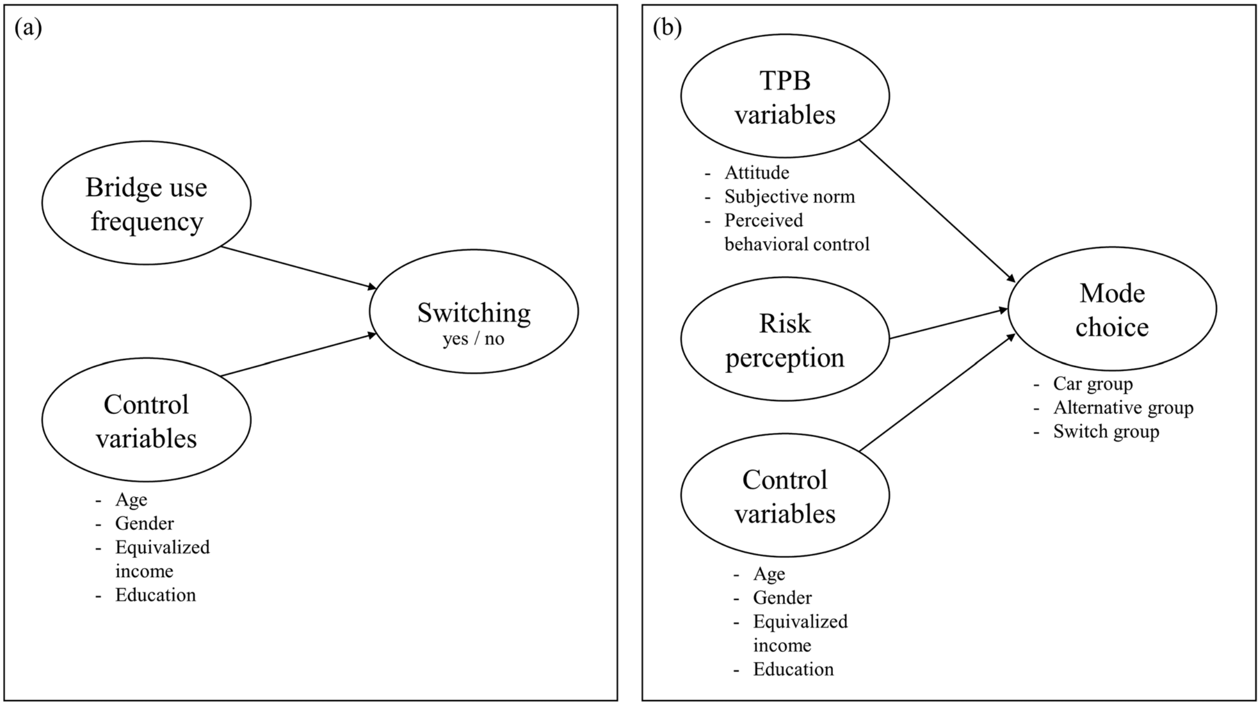

Fig. 5 Graphical representation of the binary regression model (**a**) and multinomial regression model (**b**). *TPB* theory of planned behavior

which we contrasted the switch group with the car group (Fig. 5a). As age, gender, equivalized income, and education may have an effect on mode choice [6, 7], we added these variables to account for possible effects. The binary regression model can be expressed as follows:

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_1 + b_2 X_2 + \ldots + b_5 X_5)}}$$

where Y is the dependent variable (switching from car to alternatives), $P(Y)$ is the probability of Y occurring, b_0 is the constant, b_1 to b_5 are regression coefficients, X_1 is the independent variable (bridge use frequency), X_2 to X_5 are control variables (age, gender, equivalized income, education).

2.4.2 Psychological variables and mode choice

Multinomial regression can be applied to dependent variables with more than two categories. Therefore, we used a multinomial regression model (Fig. 5b) to examine the hypothesis whether risk perception, in addition to TPB variables, explains mode choice. The model contained attitude, subjective norm, perceived behavioral control, and risk perception as explanatory variables (in the additional analyses section of the supplementary file, we compare this model with smaller models where we stepwise removed risk perception and the TPB variables). Further, we controlled the model for the effect of age, gender, equivalized income, and education. For each k, the multinomial regression model can be expressed as follows:

$$\ln\left(\frac{P(Y=k)}{P(Y=K)}\right) = b_{0k} + b_{1k}X_1 + \ldots + b_{8k}X_8$$

where Y is the dependent variable (mode choice), K is the reference category of Y (car group), k is one of the remaining categories (alternative group, switch group), $P(Y)$ is the probability of Y occurring, b_0 is the constant, b_1 to b_8 are regression coefficients, X_1 to X_4 are the independent variables (attitude, subjective norm, perceived behavioral control, risk perception), X_5 to X_8 are control variables (age, gender, equivalized income, education).

As the mobility contexts of participants with occasional bridge use before the closure barely changed, it cannot be assumed that the mobility habits of these participants were broken by the closure. Since the TPB accounts for intentional behavior only, we excluded individuals with occasional bridge use from this analysis. We checked the linearity assumption using the Box-Tidwell procedure, i.e., we tested whether the interactions between the continuous predictors and the log of them were statistically significant when included in the model [17]. In case of violation of the assumption, we transformed the concerned variables using the natural logarithm [45].

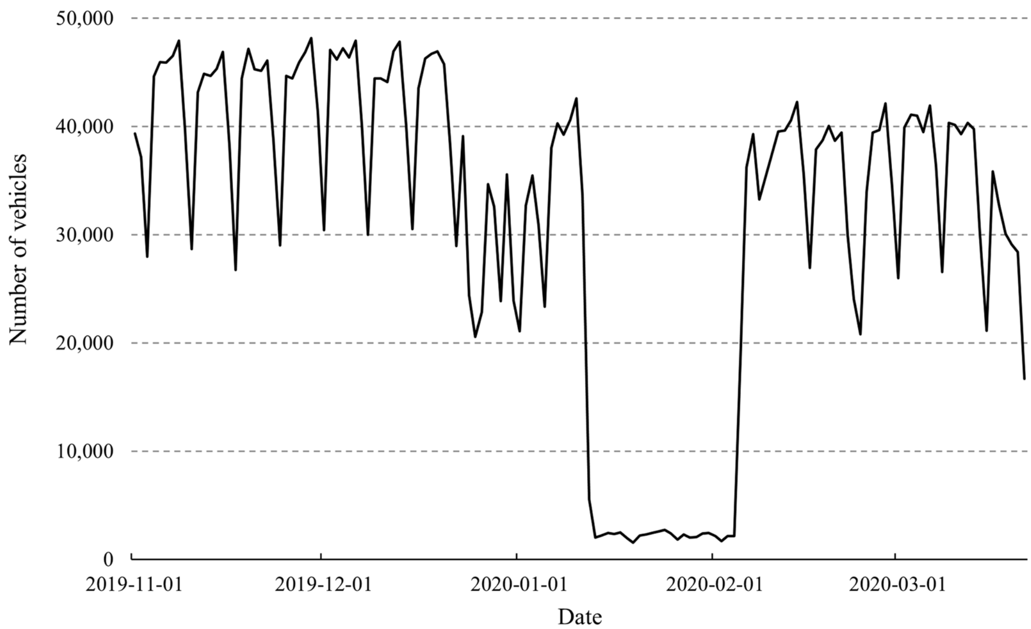

Fig. 6 Number of vehicles on the Theodor Heuss Bridge per day from 1 November 2019 to 21 March 2020. Traffic data was provided by the city of Mainz. Data for 09 and 10 February 2020 are missing

2.4.3 *Differences in mode intention*

To examine the hypothesis whether mode intention differed across the three groups of mode choice, we conducted a Kruskal–Wallis test. This non-parametric test is used for comparing two or more groups in ordinal data. Subsequently, we conducted pairwise Dunn-Bonferroni post-hoc tests to determine which of the group pairs differed in mode intention. Since the groups differed in sample size, which may lead to bias in Pearson's *r*, we chose Cohen's *d* as effect size for pairwise comparisons. Again, we excluded participants with occasional bridge use from the analysis.

For the regression models, we calculated odds ratios (ORs) and 95% confidence intervals (CI). We found no evidence for multicollinearity, using a tolerance < 0.10 [34] and a variance inflation factor > 10 [36] as criteria. We performed all calculations using IBM SPSS Statistics (version 27).

3 Results

3.1 Descriptive analysis

3.1.1 *Traffic data*

Figure 6 shows the number of vehicles on the Theodor Heuss Bridge in a time course. When looking on weekdays, the mean number of vehicles was lower after the closure than before the closure (Table 1). Weekends showed no difference.

3.1.2 *Mode choice*

The frequency distribution of the main modes of transport before and during the bridge closure can be found

Table 1 Mean number of vehicles per day on the Theodor Heuss bridge before (01 November 2019–11 January 2020) and after (6 February 2020–21 March 2020) its closure

	Before the bridge closure				After the bridge closure			
	number of days	Mean number of vehicles	95% CI		number of days	Mean number of vehicles	95% CI	
			Lower	Upper			Lower	Upper
Weekday	51	41,878	39,790	43,965	31	37,660	35,890	39,430
Weekend	21	32,847	30,281	35,413	12	28,382	24,559	32,205
Total	72	39,244	37,352	41,136	43	35,071	33,033	37,109

Traffic data was provided by the city of Mainz. Data for 09 and 10 February 2020 are missing

CI confidence interval

Table 2 Frequency distribution of the main modes of transport before and during the bridge closure between Mainz and Wiesbaden, Germany ($N=679$)

Main mode of transport	Before the bridge closure		During the bridge closure	
	n	%	*n*	%
Car	364	54	270	40
Public transport	198	29	232	34
Cycling	75	11	85	12
Walking	24	4	44	7
Route not traveled	17	3	48	7
Total	679	100	679	100

Due to rounding, percentages sometimes do not sum to 100%

in Table 2. From the data on main mode of transport, we were able to classify $n=625$ respondents to a group of mode choice. The majority of respondents did not adapt their mode choice to the closure: We found that 45% ($n=281$) of the respondents mainly used alternative modes of transport before and during the closure. In addition, 43% of respondents mainly crossed the bridge by car before and during the closure. A smaller proportion of respondents ($n=78$, 13%) switched from car to alternative modes of transport. This accounts for 22% of the respondents who reported car as their main mode of transport before the closure.

3.1.3 Bridge use and bridge use frequency

While fewer respondents used the Theodor Heuss Bridge during the bridge closure, more respondents used the other road bridges. The number of respondents who used the railway bridges was consistent during the closure compared to before (Table 3). In addition, before the closure, the majority of respondents ($n=457$, 67%) reported regular use of the Theodor Heuss Bridge. The opposite appeared for the period during the bridge closure: Here, the majority of respondents ($n=419$, 62%) showed an occasional bridge use. Comparing the groups of mode choice, this tendency is most evident in the car group (Table 4).

Table 3 Number of participants who used the Rhine bridges before and during the closure of the Theodor Heuss Bridge between Mainz and Wiesbaden, Germany ($N=679$)

	Before the closure	During the closure
Theodor Heuss Bridge	436	168
Other road bridges		
Schierstein Bridge	208	258
Weisenau Bridge	206	295
Total	414	553
Railway bridges		
Northern Bridge	42	43
Southern Bridge	60	59
Total	102	102

3.1.4 Mode intention

With median scale levels of 5 (scale from 0 = *very unlikely* to 5 = *very likely*), both the car group and the alternative group showed a very high intention to maintain the mode of transport they chose during the closure after the bridge was reopened. While the median scale level of 3 in the switch group is lower compared to the other groups, it still indicates an intention to maintain their mode of transport.

Table 4 Distribution of bridge use frequency by group of mode choice before and during the bridge closure between Mainz and Wiesbaden, Germany

Bridge use frequency	Group of mode choice						Total	
	Car		Alternative		Switch			
	n	%	*n*	%	*n*	%	*n*	%
Before the closure								
Regular	169	164	199	171	65	184	433	169
Occasional	096	136	082	129	13	116	191	131
Total	266	100	281	100	78	100	625	100
During the closure								
Regular	059	122	153	155	40	152	253	140
Occasional	207	178	128	145	38	148	372	160
Total	266	100	281	100	78	100	625	100

Regular = at least once a week. Occasional = less than once a week. Due to multiple imputation, frequencies are rounded. Therefore, certain frequencies do not cumulate to the correct size of some subsamples

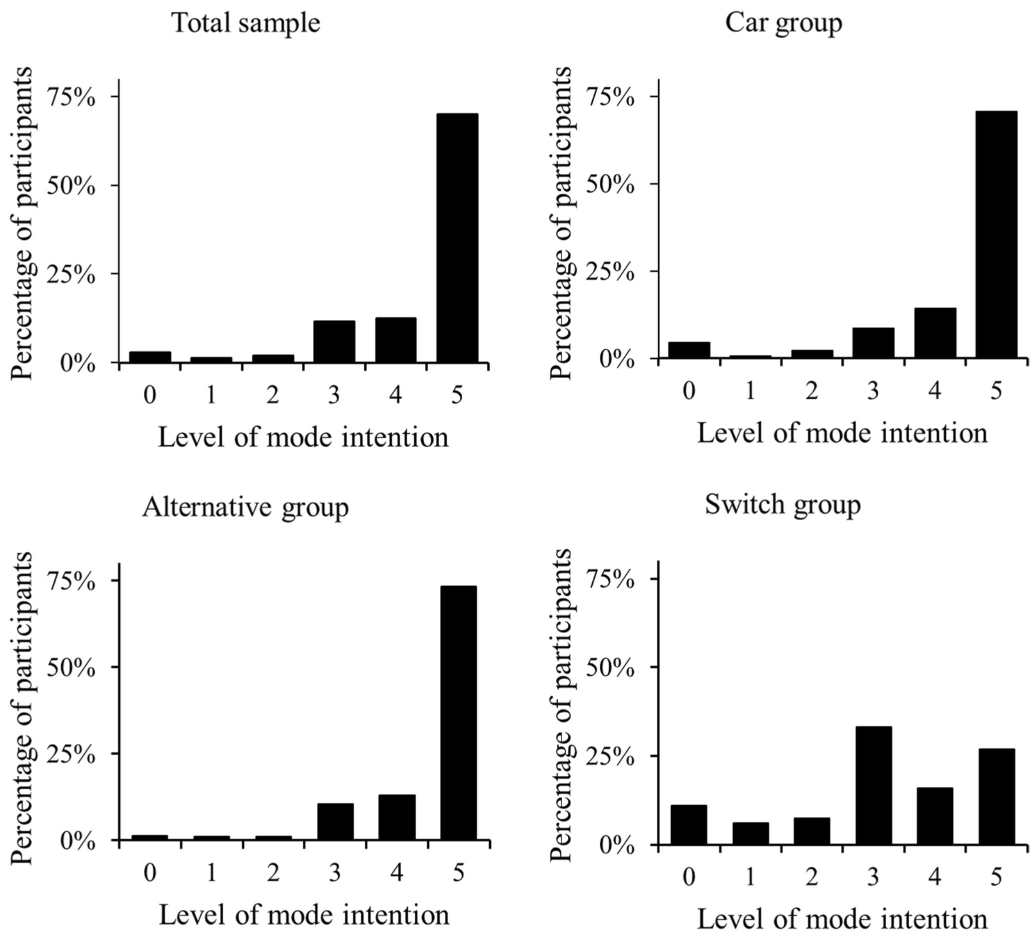

Fig. 7 Number of participants in percent per scale level of mode intention (0 to 5) for total sample ($N = 679$), car group ($n = 169$), alternative group ($n = 199$) and switch group ($n = 66$). Scale from *very unlikely* (0) to *very likely* (5)

Figure 7 shows frequency distributions of the mode intention data.

3.1.5 Psychological variables

Reliability analysis revealed low internal consistency for attitude (alternative use) and subjective norm (alternative use), Cronbach's $\alpha = 0.64$ and $\alpha = 0.63$ respectively [53]. In contrast, internal consistency for perceived behavioral control (alternative use) and risk perception was acceptable ($\alpha = 0.86$ and $\alpha = 0.82$ respectively). Correlation coefficients between the psychological variables are reported in Additional file 2: Table s4.

3.2 Statistical modeling

3.2.1 Bridge use frequency as predictor of switching from car to alternatives

The binary regression model (Table 5) proved statistically significant with $\chi^2(8) = 30.23$ ($p < 0.001$) and explained 13% (Nagelkerke's R^2) of the variance. Bridge use frequency appeared to be an important predictor of mode choice in the regression model. Car users with regular bridge use were 3.76 times more likely to switch than car users with occasional bridge use frequency. Among the control variables, only age was associated with the dependent variable.

3.2.2 Psychological variables and mode choice

The multinomial regression model (Table 6) explained with 37% (Nagelkerke's R^2) a statistically significant amount of the variance, $\chi^2(28) = 105.94$, $p < 0.001$. Attitude (car use), subjective norm (car use), and perceived behavioral control (alternative use) predicted whether a participant was in the alternative group (i.e., used alternative modes before and during the closure) or the car group. In contrast, there was no evidence that risk perception is a relevant predictor for this. None of the TPB variables could predict whether a person switched to an alternative mode. However, risk perception predicted switching to an alternative during the closure.

Table 5 Binary regression model with switch group (reference: car group) as dependent variable among participants who used cars before the bridge closure ($n = 357$)

	OR	95% CI		*p*	*B*	*SE*
		Lower	Upper			
Bridge use frequency						
Regular	3.76	1.66	8.47	0.002	1.32	0.41
Occasional (reference)	1.00					
Gender						
Male	0.65	0.38	1.13	0.126	−0.43	0.28
Female (reference)	1.00					
Age						
18–34 years	0.25	0.11	0.59	0.001	−1.37	0.43
35–64 years	0.39	0.20	0.75	0.005	−0.95	0.34
≥65 years (reference)	1.00					
Education						
Low	0.35	0.05	2.50	0.294	−1.05	1.00
Middle	0.73	0.40	1.31	0.291	−0.32	0.30
High (reference)	1.00					
Equivalized income						
<1000 EUR	1.55	0.47	5.12	0.468	0.44	0.60
1000 EUR–2499 EUR	1.41	0.73	2.72	0.311	0.34	0.34
≥2500 EUR (reference)	1.00					

B = regression coefficient, SE = standard error, CI = confidence interval, OR = odds ratio. $R^2 = 0.13$ (Nagelkerke). Model $\chi^2(8) = 30.23$, $p < 0.001$

3.2.3 Differences in mode intention

Mode intention differed depending on mode choice ($p < 0.001$, $n = 462$). Participants who used cars before and during the closure had a higher mode intention than participants who switched to alternative modes ($z = 7.08$, $p < 0.001$, $d = 0.92$). Similarly, participants who used alternative modes had higher mode intention values than people who switched ($z = 7.51$, $p < 0.001$, $d = 1.18$). In contrast, participants in the car group did not differ from people in the alternative group ($z = -0.42$, $p = 1.000$, $d = 0.12$).

4 Discussion

Our study provides evidence that a temporary bridge (or road) closure is a key event for transport mode choice. This is suggested by our finding that more than one fifth of car users switched to alternative modes during the closure. Moreover, the binary regression model showed that primarily those car users who presumably were more affected by the bridge closure (i.e., used the bridge regularly before the closure) switched to alternative modes. Considering that interventions that discourage car use often do not receive public acceptance, temporary interventions might be an effective option. However, since most car users persisted in using cars during the closure and persistent car users either did not travel the route or used the other road bridges (i.e., they were not influenced by the closure), temporary interventions that only discourage car use are unlikely to be sufficient to cause a modal shift to alternative modes of transport. Likewise, Piatkowski et al. [39] concluded that interventions that discourage car use as well as encourage alternative modes of transport are most effective.

Furthermore, our findings indicate that risk perception provides a useful addition to the TPB in explaining intentional mode choice during a key event. The multinomial regression model showed that people with higher health-related risk perception were more likely to switch from cars to alternative modes during the closure. The TPB constructs were not associated with switching. However, they predicted whether people persisted in using either alternative modes or cars before and during the bridge closure. Health-related risk perception could not explain whether a person persisted in using either alternative modes or the car. According to the TPB, the evaluation of behavioral consequences, including risk perception, is part of developing an attitude [40]. In accordance, the correlation analysis in the present study showed an association between risk perception and attitude. Thus, a possible effect of risk perception on whether persisting in using either alternative modes or the car probably was explained via attitude. Since attitude did not sufficiently differentiate between persistent car use and switching to alternative modes, attitude could not explain the effect of

Table 6 Multinomial regression model with group of mode choice as dependent variable among participants with regular bridge use frequency before the bridge closure ($n = 273$)

	OR	95% CI		*p*	*B*	*SE*
		Lower	Upper			
Alternative group						
Car group (reference)	1.00					
Attitude (car use)	0.65	0.49	0.87	0.003	−0.43	0.14
Attitude (alternative use)	0.93	0.63	1.39	0.732	−0.07	0.20
Subjective norm (car use)	0.74	0.57	0.97	0.027	−0.30	0.13
Subjective norm (alternative use)	1.45	0.99	2.13	0.055	0.37	0.19
Ln PBC (car use)	0.60	0.33	1.10	0.097	−0.51	0.31
Ln PBC (alternative use)	3.94	1.91	8.13	< 0.001	1.37	0.37
Gender						
Male	0.58	0.29	1.13	0.106	−0.55	0.34
Female (reference)	1.00					
Age						
18–34 years	0.48	0.17	1.34	0.159	−0.74	0.53
35–64 years	0.65	0.25	1.70	0.378	−0.43	0.49
≥ 65 years (reference)	1.00					
Education						
Low	1.74	0.30	10.04	0.532	0.55	0.88
Middle	1.98	0.90	4.35	0.087	0.69	0.40
High (reference)	1.00					
Equivalized income						
< 1000 EUR	3.30	1.00	10.89	0.050	1.19	0.61
1000–2499 EUR	1.01	0.48	2.13	0.976	0.01	0.38
≥ 2,500 EUR (reference)	1.00					
Health-related risk perception	1.17	0.78	1.76	0.436	0.16	0.21
Switch group						
Car group (reference)	1.00					
Attitude (car use)	0.86	0.63	1.17	0.334	−0.15	0.16
Attitude (alternative use)	0.92	0.61	1.39	0.690	−0.08	0.21
Subjective norm (car use)	1.10	0.82	1.47	0.537	0.09	0.15
Subjective norm (alternative use)	1.30	0.90	1.89	0.162	0.26	0.19
Ln PBC (car use)	0.56	0.29	1.08	0.083	−0.57	0.33
Ln PBC (alternative use)	1.52	0.79	2.92	0.206	0.42	0.33
Gender (ref: female)						
Male	0.50	0.25	1.02	0.056	−0.69	0.36
Female (reference)	1.00					
Age (ref: ≥ 65 years)						
18–34 years	0.12	0.04	0.37	< 0.001	−2.16	0.60
35–64 years	0.63	0.26	1.53	0.309	−0.46	0.45
≥ 65 years (reference)	1.00					
Education (ref: high)						
Low	0.34	0.03	3.86	0.386	−1.07	1.23
Middle	1.17	0.55	2.49	0.683	0.16	0.38
High (reference)	1.00					
Equivalized income						
< 1000 EUR	2.11	0.47	9.50	0.331	0.75	0.77
1000 EUR–2499 EUR	1.14	0.53	2.48	0.740	0.13	0.40
≥ 2500 EUR (reference)	1.00					
Health-related risk perception	1.76	1.14	2.71	0.010	0.56	0.22

B = regression coefficient, SE = standard error, CI = confidence interval, OR = odds ratio, Ln = natural logarithm, PBC = perceived behavioral control. $R^2 = 0.37$ (Nagelkerke). Model $\chi^2(28) = 105.94$, $p < 0.001$

risk perception on switching. In accordance, descriptive analysis revealed that participants with persistent car use differed in their attitudes from participants with persistent use of alternative modes and were similar to participants who switched to alternative modes.

Finally, our data suggest that a temporary bridge (or road) closure may lead to more active mobility habits. Therefore, long term improvements in air quality and physical activity are to be expected. Although we found using a Kruskal–Wallis test that participants with persistent mode choice showed the highest intention to maintain their chosen mode of transport, descriptive analysis showed that even those participants who switched to alternative modes generally intended to maintain their chosen alternative after the closure. Traffic data supported this finding by showing that fewer vehicles used the bridge after the closure than before the closure.

4.1 Strengths

Using the closure of the Theodor Heuss Bridge as a case study allowed us to examine mobility behavior and associations with psychological variables under natural conditions. In contrast to studies under laboratory conditions, our study therefore benefits from high external validity [2]. A further strength of our study is the theoretical foundation of the questionnaire. This offers a high comparability with other studies, since the TPB is well established. In addition, this study provides a large and heterogeneous sample. Despite limitations regarding education, the study sample is representative of the age and gender structure of the population.

4.2 Limitations

We collected data at a single measuring time only and did not assign study participants to an intervention and control group. Thus, the results must be considered as correlative rather than causal [21]. Therefore, not only do we lack information about the direction of statistical associations but also effects of unknown confounders could not be controlled.

Although the sample size was comparable to similar studies [3, 20], most analyses relied on smaller subsamples, which yielded statistically non-significant results in several cases. However, the effect sizes of these results indicated the possibility of statistical significance with a larger sample size [13]. A reliable estimation of the required sample size by an a priori power analysis was not feasible, as this depended on many unknown parameters (e.g., response rate, number of respondents meeting criteria for particular subsamples).

Literature indicates that particularly people with higher education are willing to participate in questionnaire studies [30]. In the present study as well, people with higher education were probably overrepresented. Since education is associated with mode choice [43], differences between the sample and the population could not be excluded. This limits the generalizability of our results.

Although we included traffic data from the city of Mainz in our analysis, most of our data are based on a self-report questionnaire. Response biases like extreme responding or socially desirable responding may have impacted our results.

5 Conclusion

In a nutshell, temporary bridge (or road) closures may be considered as key events. TPB constructs may not explain whether people switch from cars to alternative modes during a key event. In contrast, car users who perceive their health risk from traffic-related air pollution to be high, probably are more likely to switch to alternative modes. Therefore, risk perception provides a useful addition to the TPB in explaining intentional mode choice. In addition, our data indicates that car users who switch to alternative modes during a key event generally intend to maintain this mode of transport. These people may establish more active mobility habits.

Further research should examine the association between mode choice and other facets of health-related risk perception, such as perceived risk from accidents, from physical inactivity or from using public transport during and after the pandemic. In addition, the association between risk perception and mode choice suggests that health psychology models that integrated risk perception as a predictor of behavior change are appropriate theoretical frameworks for explaining mode choice as well. Furthermore, we could only support a correlative association between risk perception and mode choice. To examine causality, a randomized controlled trial or a quasi-experimental design are more suitable approaches [50].

The association between risk perception and mode choice suggests that strategies of health-related risk communication before and during the temporary closure of a major road bridge may motivate people switching to alternative modes of transport. Since road closures due to construction are commonplace, this could prove to be an economical measure to reduce traffic-related emissions and promote physical activity.

Abbreviations

CI Confidence interval
OR Odds ratio
TPB Theory of Planned Behavior

Supplementary Information

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Additional file 1. English translation of the questionnaire.

Additional file 2. Additional tables, analyses and one figure.

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Author contributions

EG conceived work. PK performed statistical analyses and wrote the draft. BB, TK, SS, and EG revised the manuscript and wrote individual parts of it. All authors read and approved the final manuscript.

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Availability of data and materials

Data can be provided upon request.

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