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Biases in self-reported travel behaviour: effects on self-reported travel distance, travel time and rain prevalence

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Abstract

Travel time and distance are key variables in evaluating transport planning decisions. However, people's perceptions and experiences often differ from objectively measured conditions. Therefore, this paper assesses the effect of different socio-demographic variables, travel habits, and mobility options on self-reported travel distance, travel time, and rain prevalence. Data from a survey on the potential use of e-bikes are analysed using logistic regression models. The most important conclusion from this paper is that travel distances in self-reported surveys are often overestimated, especially when these distances are short. Travel times are better estimated.

Keywords: self-reported behavior; travel distance; travel time; rain prevalence

1. Introduction

Travel time and distance are two related key variables used in travel demand models and travel behaviour analysis (Witlox, 2007; Tenenboim and Shiftan, 2018). Furthermore, they play a crucial role in evaluating transport planning decisions (Tenenboim and Shiftan, 2018). However, people's perceptions and experiences often differ from objectively measured conditions. Therefore, understanding the underlying reasons for these differences is crucial for decision-making (Curl et al., 2015).

This paper assesses the effect of different socio-demographic variables, travel habits, and mobility options on self-reported travel behaviour. In particular, an emphasis is laid on biases on self-reported travel distance, travel time and one weather phenomenon significantly affecting modal choice (see, e.g., Cools et al. (2010) and Creemers et al.

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(2015)), i.e. rain prevalence. As (national household) travel surveys primarily rely on self-reported behaviour, it is imminent to know what type of biases are introduced by the respondents that complete such surveys.

The literature related to the assessment of self-reported travel distances shows that both socio-demographics and characteristics of the trip play a role in the quality of reporting. In terms of socio-demographics, Witlox (2007) and Hess (2012) concluded that older adults report less well the travel distance. In contrast, Soltani et al. (2015) reported that elders were better able to estimate the distance for their routine trips. Concerning gender, Witlox (2007) found no significant effect of gender, whereas McCormack et al. (2008) found that men overestimated the distance to the nearest supermarket to a greater extent than did women. With respect to other significant socio-demographics, Witlox (2007) identified income and professional status as other contributing factors: people with a higher income report more reliably, as do executives and employees.

Regarding trip-related characteristics, the first aspect that significantly affects the quality of reporting is the (objective) distance of the trip itself. Literature is unanimous regarding the fact that longer trips are more accurately reported than shorter trips (Witlox, 2007; McCormack et al., 2008; Soltani et al., 2015). Furthermore, familiarity with an activity location plays a role: more repetitive trips, such as commuting trips, are more accurately reported (Witlox, 2007), and the more frequently an activity location is visited, the more accurate the distance estimation is (Soltani et al., 2015). Besides, also the mode plays a role; e.g., Dewulf et al. (2012) showed that perceived walking distances are often an overestimation of the objective walking distances.

Finally, with respect to the accuracy of self-reported travel distances, the satisfaction of residents with their neighbourhood significantly affects the accuracy: Soltani et al. (2015) showed that the more satisfied residents are with their neighbourhood, the more accurate their distance estimation was.

Concerning the accuracy of self-reported travel times, the literature is unanimous that travel times are generally overestimated (Kelly et al., 2013; Peer et al., 2014; Curl et al., 2015; Tenenboim and Shiftan, 2018). However, Curl et al. (2015) reported that for shopping trips, travel times are, on average, underestimated. The rounding in multiples of five minutes is one of the causes of the inaccuracy and leads to biased estimates for especially short-distance trips (Rietveld et al., 1999). The questionnaire format also plays a role: Gerike et al. (2015) found that travel times are consistently higher using a time-use format compared to a trip diary format.

In terms of socio-demographic factors, education and income do not seem to impact the accuracy of reporting travel times (Peer et al., 2014; Tenenboim and Shiftan, 2018). The role of age, gender and household size are contested: Peer et al. (2014) did not find a significant impact, whereas Tenenboim and Shiftan (2018) reported that females, older persons, and people living in a larger household have a higher subjective travel time.

Regarding travel frequency, Peer et al. (2014) reported that it did not impact the accuracy, whereas Tenenboim and Shiftan (2018) found that less frequent trip makers have higher subjective travel times. However, regular usage of a private car for their trip-making did not influence the accuracy of the perceived travel time. Nonetheless, modal choice does seem to impact the accuracy: pedestrians seem to overestimate their travel times (Dewulf et al., 2012), whereas car possession seems to lead to an underestimation (Tenenboim and Shiftan, 2018).

In terms of methods, most studies reported in the literature compare self-reported travel distances (in most cases to predefined destinations) and times with the ones tabulated using shortest-path estimates using network data (Witlox, 2007; McCormack et al., 2008; Dewulf et al., 2012; Hess, 2012; Soltani et al., 2015) or by comparing the self-reported data with data stemming from route planners or floating car data (Rietveld et al., 1999; Peer et al., 2014; Tenenboim and Shiftan, 2018). Kelly et al. (2013) performed a literature review on studies comparing self-reported travel times with GPS-measured travel times. Gerike et al. (2015) underlined the effect of the travel survey format (time-use survey versus trip-based survey) on the reported travel indices.

With respect to the accuracy of perceived weather, the literature is rather scarce. Notwithstanding, Shao (2016) and Nunley and Sherman-Morris (2020) state that females have a lower self-perceived weather knowledge and are more likely to perceive a strange weather pattern in the recent past. Lower education also results in decreased accuracy (Shao, 2016). Frequent consultation of wheater forecasts enhances the assessed weather knowledge (Nunley and Sherman-Morris, 2020).

2. Data and methods

To assess the effect of different socio-demographic variables, travel habits and mobility options on self-reported travel distance, travel time and rain prevalence, data from an online (Qualtrics) survey on the potential use of e-bikes in the context of the Liège campuses (city centre, Sart-Tilman North and South) of the University of Liège are analysed.

As detailed in Nematchoua et al. (2020), the questionnaire was distributed by email to all ULiège students, doctoral students, and staff members. The survey was opened from 24 March to 17 April 2016. The survey was divided into different parts: *(i)* questions concerning the respondents' profile, *((ii)* questions dealing with the use and satisfaction of different transport modes, and *((iii)* questions concerning the perception of conventional and electric bicycles, and barriers and key conditions to increase bicycle use towards the campus.

In total, data from 1088 respondents completed the survey (corresponding to a response and sampling rate of 5.2%), for which the addresses of 848 respondents could be georeferenced. A basic description of the sample is provided in Table 1.

Table 1. Sample composition

Variable	Distribution/descriptive statistics
Age (years)	Mean: 28.63, Std.Dev.: 10.84
Gender	Male: 41.45%, Female: 58.55%
Status	Student: 58.64%, PhD candidate: 10.20%, Staff: 31.16%
Highest obtained degree	Secondary school: 31.34%, Bachelor: 35.75%, Master: 19.03%, Post-master/PhD: 13.88%
Campus	Sart-Tilman South: 24.82%, Sart-Tilman North: 50.55%, City center: 24.63%
Residence-campus distance (km)	Mean: 12.66, Std.Dev.: 13.65
Car availability	Yes: 72.43%, No: 27.57%
Bike availability	Yes: 74.45%, No: 25.55%
E-bike availabity	Yes: 6.80%, No: 93.20%
Frequent car driver[1,2]	Yes: 56.89%, No: 43.11%
Frequent carpooler[1,3]	Yes: 29.96%, No: 70.04%
Frequent public transport user[1]	Yes: 48.99%, No: 51.01%
Frequent walker (> 10 min)[1]	Yes: 62.04%, No: 37.96%
Frequent cyclist[1]	Yes: 16.54%, No: 83.46%
Recommendation (0-10) of commuting mode[4]	Mean: 6.83, Std.Dev.: 2.22

[1] "Frequent" defined as at least once per week
[2] Driving a car without passengers
[3] Either as driver or passenger
[4] Net promoter score (NPS) question asking respondents to rate the likelihood that they would recommend a service to a friend or colleague.

Among the questions concerning the stimuli and barriers for (e-)cycling, a particular subsection was dedicated to the perceptions of key determinants, in particular travel distance and travel time, and rail prevalence. It is important to highlight the following instruction was provided to the respondents: "*IMPORTANT: No calculations or research is required! Without thinking too hard, just give your personal estimate or an order of magnitude if you have no idea of a precise number*." Following this instruction, the respondents were asked about (*i*) the travel distance (in km) between the residence and the main location where they follow lectures, (*ii*) the travel distance (in km) between two well-known anchor points, i.e. the city centre (Pont d'Avroy) and the Sart-Tilman campus (Grands Amphis), (*iii*) the travel time (in min) between the city centre and the Sart-Tilman (Grands Amphis) by car, and (*iii*) the travel time (in min) between the city centre and the Sart-Tilman (Grands Amphis) by bus. Besides, also the rain prevalence was queried. First, the respondents were asked to indicate this prevalence in percentage of time: "*According to you, in Belgium it rains: (i) 0 to 25% of the time, (ii) 25 to 50% of the time, (iii) 50 to 75% of the time, or (iv) 75 to 100% of the time*". On a separate screen, the respondents were then asked to indicate the number of days it rains on average in Belgium, as well as the number of hours it rains on average on a rainy day.

To tabulate the differences between reported and actual behaviour, the distances and travel times retrieved from shortest path calculations using Google Maps were considered as the true values. Concerning the prevalence of rain, the average number of days with rainfall was set to 200, in line with the reports from the Royal Meteorological Institute. Concerning the prevalence of rain in terms of the percentage of time it rains, in the popular press, 7% is indicated as the "true" value (Freys, 2015). For all the variables of interest, we consider the estimation as correct if they are within 10% of the true value.

Different logistic regression models are constructed to assess the effect of the explanatory variables (described in Table) on the correctness of the different travel indicators and rain prevalence. In particular, the probability of having an inaccurate estimation is predicted (correct estimates are used as the baseline reference).

3. Results

3.1. Descriptive results

In terms of descriptive statistics, we could see from Table 2 that the respondents generally overestimate the travel distance between their residence and the campus by 23.17%. The vast majority (74.17%) either under- or overestimates the distance. From Figure 1, one could clearly depict that the relative errors are considerably larger in the case of small distances compared to long distances. This can be partially accounted for by the fact for longer distances, the use of navigation tools will be more frequent. Furthermore, this finding is in line with the literature that is unanimous about this finding (Witlox, 2007; McCormack et al., 2008; Soltani et al., 2015).

Table 2. Description of the variables of interest

Variable of interest	Mean	Std.Dev.	Correct[1]
Relative error distance between residence and campus [DIST_RC]	23.17%	50.19%	25.83%
Relative error distance between the city center and Sart-Tilman[2] [DIST_CCST]	28.34%	66.83%	3.15%
Relative error travel time by car between the city center and Sart-Tilman[2] [TIME_CAR]	12.71%	43.38%	37.06%
Relative error travel time by bus between the city center and Sart-Tilman[2] [TIME_BUS]	-1.31%	31.92%	26.54%
Relative error percentage of time raining (real = 7%) [RAIN]	38.85%	137.67%	7.93%

[1] Less than 10% smaller or larger than the true value
[2] City center: Pont d'Avroy, Liège; Start-Tilman: Les Grands Amphis

Besides the distance between the residence and the campus, also the perceived distance between the city centre, defined by a well-known landmark, i.e. Pont d'Avroy, and a precisely defined location at the campus was queried, 9km representing the real value. On average, this distance was overestimated by 28.34%, with only 3.15% of the respondents estimating this distance more or less correctly. Compared to the distance between their residence and the campus, the respondents thus reported the distance less accurately. This is in line with Witlox (2007) and Soltani et al. (2015), which state that the more habitual a trip becomes, the higher the accuracy of the self-reported distance.

In terms of the perception of travel times, the perceived travel time of the trajectory between Pont d'Avroy and the campus was queried for both car travel as well as bus travel. Concerning the travel times by car, respondents overestimated the travel time by car by 12.71% on average. With regard to the travel time by bus, on average, there is an underestimation of 1.31%. The fact that, on average, the absolute value of the error is much smaller for the travel time by bus in comparison to the travel time by car, does not imply that these reported travel times are more correctly reported. After all, 37.06% of the respondents evaluated the travel time by car correctly, in comparison to 26.52% that assessed the travel time by bus more or less correct. The consensus in the literature that travel times are generally overestimated (Kelly et al., 2013; Peer et al., 2014; Curl et al., 2015; Tenenboim and Shiftan, 2018) seems to be validated for car travel, but is not supported for bus travel.

In terms of the prevalence of rain, the phrasing of the questions is essential. If an overall estimation of rain frequency is asked, in categories of 0-25%, 25-50% of, 50-75%, and 75-100% of the time, 69.41% of respondents indicate the upper three categories (Table 3), whereas the real value is around 7% of the time. In contrast, if the percentage is derived by asking the number of days it rains and the number of hours per day, the estimations are considerable better, albeit respondents still overestimate the rain prevalence by 38.8%.

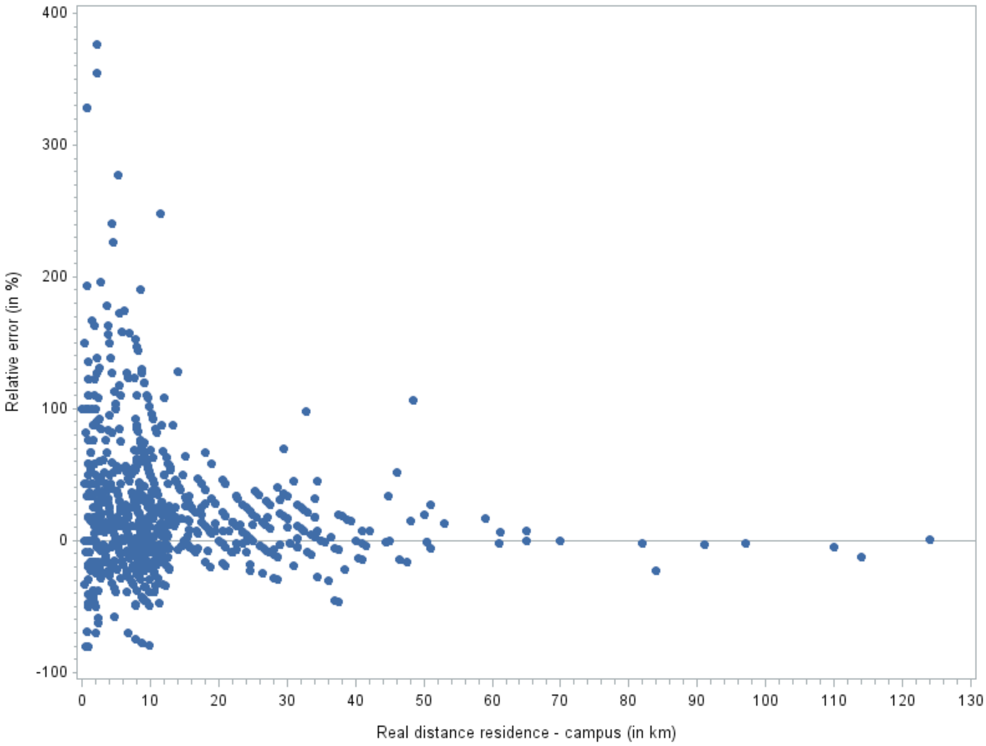

Fig. 1. Relative error self-reported distance in comparison to real distance

Table 3. Perceived rainfall frequency based on two questioning methods

Calculation method	0-25% of the time	25-50% of the time	50-75% of the time	75-100% of the time
Perceived frequency of raining (categorical)[1]	30.51%	48.35%	19.67%	1.47%
Calculated rain percentage[2]	93.66%	5.50%	0.75%	0.09%

[1] Operationalized as follows: “How much % of the time do you think it rains? 0-25%, 25-50%, 50-75% or 75-100% of the time?”
[2] Calculation: perceived number of days it rains/365 $*$ perceived number of hours it rains per day/24

3.2. Model results

Different logistic regression models were tabulated to assess the effect of a series of explanatory variables to assess the correctness of the different travel indicators and rain prevalence. These variables include age, gender, professional status, travel habits (frequency of use of different transport modes), travel options (car possession, bike possession), as well as image-related variables to the different modes.

From Table 4, one can depict that only a limited number of the considered explanatory factors play a role and that the effect is strongly dependent on which travel indicator is assessed. Furthermore, it should be underlined that not a single indicator was significant in the model predicting inaccuracies in rail prevalence. Thus the accuracy of rain prevalence seems to be a purely random process providing counter-evidence against the findings of Shao (2016) and Nunley and Sherman-Morris (2020) that gender is a contributing factor.

Regarding the model predicting inaccuracies in self-reported travel distance between the residence and the university campus, gender, the image of the main commuting mode and the real travel distance are identified as significant factors. From Table 5, one can see that females have a higher likelihood to inaccurately report travel distance in comparison to males. This refutes literature that states that gender has no effect (Witlox, 2007) or that males are more likely to be erroneous (McCormack et al., 2008). The likelihood of making errors decreases when the real travel distance

Table 4. Type 3 analysis of effects*

Explanatory factor	DF	DIST_RC Chi^2	DIST_RC p-value	DIST_CCST Chi^2	DIST_CCST p-value	TIME_CAR Chi^2	TIME_CAR p-value	TIME_BUS Chi^2	TIME_BUS p-value
Age	1	– – –	– – –	– – –	– – –	– – –	– – –	6.25	0.012
Gender	1	6.54	0.011	8.84	0.003	– – –	– – –	– – –	– – –
Status	2	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
Highest obtained degree	3	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
Campus	2	– – –	– – –	– – –	– – –	– – –	– – –	6.16	0.046
Residence-campus distance (km)	1	38.24	<0.001	4.86	0.027	– – –	– – –	– – –	– – –
Car availability	1	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
Bike availability	1	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
E-bike availability	1	– – –	– – –	4.26	0.039	– – –	– – –	– – –	– – –
Frequent car driver[1,2]	1	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
Frequent carpooler[1,3]	1	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
Frequent public transport user[1]	1	– – –	– – –	– – –	– – –	– – –	– – –	6.61	0.010
Frequent walker (> 10 min)[1]	1	– – –	– – –	– – –	– – –	9.25	0.002	– – –	– – –
Frequent cyclist[1]	1	– – –	– – –	– – –	– – –	– – –	– – –	– – –	– – –
Recommendation (0-10) of commuting mode	1	5.75	0.016	– – –	– – –	– – –	– – –	– – –	– – –
AIC		922.1		219.5		1108.6		958.2	
ROC		0.665		0.745		0.553		0.592	

*: No variable was significant in the [RAIN]-model
– – –: not retained in the final model (p-value > 0.05)
[1] "Frequent" defined as at least once per week
[2] Driving a car without passengers
[3] Either as driver or passenger

becomes longer, which again supports the unanimous finding of literature that the quality of reporting improves with longer distances. Besides, the more likely one recommends his/her commuting mode, the more accurate the reporting. The role of satisfaction is in line with Soltani et al. (2015).

Table 5. Maximum Likelihood Parameter Estimates of the DIST_RC-model

Parameter	Est.	Std. Err.	p-value
Intercept	2.001	0.320	<0.001
Gender: Female	0.417	0.163	0.011
Residence-campus distance (km)	-0.039	0.006	<0.001
Recommendation (0-10) of commuting mode	-0.094	0.039	0.016

With respect to the distance between the city centre and the campus (Table 6), gender has a similar effect as for the travel distance between the residence and the campus. In contrast, the effect of the distance between the residence and the campus is different: the longer the distance between the residence and the campus, the higher the probability of reporting the distance inaccurately. The distance between the residence and the campus is the trip the students perform on a nearly daily basis, whereas the distance estimation between the city centre and Sart-Tilman campus does not necessarily concern the daily commute of the respondent. Therefore, the contrast can be partially accounted for by the finding in the literature that more habitual trips such as commuting trips are more accurately reported (Witlox, 2007; Soltani et al., 2015). Besides, the "true" distance between the residence and the campus varies per respondent, whereas the true distance between the city centre and the campus is a fixed value. In addition to gender and the residence-campus distance, the availability of an e-bike played a role: persons with an e-bike at their disposal are more likely to report the travel distance correctly.

In terms of inaccuracies with respect to the travel time by car, almost no variables were significant, which support the findings in the literature (Peer et al., 2014; Tenenboim and Shiftan, 2018) that socio-demographics only play a limited role in explaining inaccuracies in reporting travel times. The only factor influencing the accuracy of the

Table 6. Maximum Likelihood Parameter Estimates of the DIST_CCST-model

Parameter	Est.	Std. Err.	p-value
Intercept	2.339	0.365	<0.001
Gender: Female	1.347	0.453	0.003
E-bike availability: Yes	-1.096	0.531	0.039
Residence-campus distance (km)	0.072	0.032	0.027

reported travel time is people who regularly walk for at least 10 minutes. They are more likely to inaccurately report the travel time (Table 7). This is in line with Dewulf et al. (2012), who highlighted that pedestrians seem to overestimate their travel times. A possible explanation is that frequent walkers are also frequent public transport users and, therefore, they have difficulties in estimating car travel times.

Table 7. Maximum Likelihood Parameter Estimates of the TIME_CAR-model

Parameter	Est.	Std. Err.	p-value
Intercept	0.266	0.113	0.019
Frequent walker > 10 min): Yes	0.445	0.146	0.002

Concerning the accuracy of the reported travel time by bus, age, the campus, and the frequency of using public transport significantly affect the likelihood of inaccurate reporting. From Table 8, one can observe that older people are less likely to report travel times inaccurately. Frequent public transport users report the travel times more accurately, providing evidence that a higher travel frequency results in better estimates in line with Tenenboim and Shiftan (2018). Besides, commuters that primarily commute to the Sart-Tilman north campus (where the largest lecture rooms “Les Grands Amphis” are located) more accurately estimate bus travel times.

Table 8. Maximum Likelihood Parameter Estimates of the TIME_BUS-model

Parameter	Est.	Std. Err.	p-value
Intercept	1.704	0.293	<0.001
Age	-0.019	0.008	0.012
Campus: city center	0.103	0.190	0.587
Campus: Sart-Tilman South	0.513	0.207	0.013
Frequent public transport user: Yes	-0.448	0.174	0.010

4. Conclusion

This paper assessed the effect of different socio-demographic variables, travel habits and mobility options on self-reported travel distance, travel time and rain prevalence. The most important conclusion to be drawn from this paper is that travel distances in self-reported surveys are often overestimated, especially when these distances are short. Travel times are better estimated (average errors are smaller), especially when fixed time schedules aid the users to have a clear idea of the travel times.

With respect to the scientific literature, the paper both validated and contrasted findings reported in the literature. The main lesson that can be drawn from this is that we have to be extremely careful when using self-reported travel indices. The ambiguity with respect to the contributing factors underlines the context specificity that in itself influences the accuracy of self-reported diaries. Nonetheless, the results also show that the phrasing of questions can be crucial in avoiding errors. For instance, the different formulations on rain prevalence showed that the disentanglement of rail prevalence in the number of perceived days it rains and the number of hours it rains per day improve the reporting by a factor 3.6. Given the importance meteorological factors play in explaining variations in travel behaviour, the inclusion of pertinent questions on weather parameters, such as precipitation, is essential in better understanding the switch to active travel modes (see, e.g. Creemers et al. (2015)).

The insights from this paper can help to revise travel surveys and adopt the necessary level of precaution when interpreting the absolute values of self-reported travel indices. As underlined by Tenenboim and Shiftan (2018) the systematic investigation of self-reported travel indices is the first step for a sensible integration of perceptions of these indices in the modelling process, potentially yielding a substantial improvement in the prediction of travel behaviour. This is in line with Srinivasan et al. (2007), who highlighted that the actual choice of transport mode is based on the subjective perception of reported mode characteristics and less on the objectively measurable mode characteristics.

The data stem from an online survey, where respondents were recruited by email. Therefore, it was hard to distinguish between refusals to participate and non-contacts. However, a total of 5.2% of the target population participated in the survey. When generalizing results from a survey, prudence is always needed, especially in light of non-response bias. In contrast to national household surveys, the respondent burden in our survey did not increase with the variable of interest.

More research is needed to further understand under which conditions the accuracy can be improved and how different question formats help to this. Augmentation with other types of data (e.g. GPS data) can correct certain data, but research on improving the instrument itself is strongly recommended.

References

Cools, M., Moons, E., Creemers, L., Wets, G., 2010. Changes in travel behavior in response to weather conditions: Do type of weather and trip purpose matter? Transportation Research Record: Journal of the Transportation Research Board 2157, 22–28. doi:10.3141/2157-03.

Creemers, L., Wets, G., Cools, M., 2015. Meteorological variation in daily travel behaviour: evidence from revealed preference data from the netherlands. Theoretical and Applied Climatology 120, 183–194. doi:10.1007/s00704-014-1169-0.

Curl, A., Nelson, J.D., Anable, J., 2015. Same question, different answer: A comparison of gis-based journey time accessibility with self-reported measures from the national travel survey in england. Computers, Environment and Urban Systems 49, 86–97. doi:10.1016/j.compenvurbsys.2013.10.006.

Dewulf, B., Neutens, T., Van Dyck, D., de Bourdeaudhuij, I., Van de Weghe, N., 2012. Correspondence between objective and perceived walking times to urban destinations: Influence of physical activity, neighbourhood walkability, and socio-demographics. International Journal of Health Geographics 11, 43. doi:10.1186/1476-072X-11-43.

Freys, J., 2015. Hoezo, regenland? het druppelt maar 7 procent van de tijd. Het Laatste Nieuws , 5.

Gerike, R., Gehlert, T., Leisch, F., 2015. Time use in travel surveys and time use surveys – two sides of the same coin? Transportation Research Part A: Policy and Practice 76, 4–24. doi:10.1016/j.tra.2015.03.030.

Hess, D.B., 2012. Walking to the bus: perceived versus actual walking distance to bus stops for older adults. Transportation 39, 247–266. doi:10.1007/s11116-011-9341-1.

Kelly, P., Krenn, P., Titze, S., Stopher, P., Foster, C., 2013. Quantifying the difference between self-reported and global positioning systems-measured journey durations: A systematic review. Transport Reviews 33, 443–459. doi:10.1080/01441647.2013.815288.

McCormack, G.R., Cerin, E., Leslie, E., Du Toit, L., Owen, N., 2008. Objective versus perceived walking distances to destinations: Correspondence and predictive validity. Environment and Behavior 40, 401–425. doi:10.1177/0013916507300560.

Nematchoua, M.K., Deuse, C., Cools, M., Reiter, S., 2020. Evaluation of the potential of classic and electric bicycle commuting as an impetus for the transition towards environmentally sustainable cities: A case study of the university campuses in liege, belgium. Renewable and Sustainable Energy Reviews 119, 109544. doi:10.1016/j.rser.2019.109544.

Nunley, C., Sherman-Morris, K., 2020. What people know about the weather. Bulletin of the American Meteorological Society 101, E1225–E1240. doi:10.1175/BAMS-D-19-0081.1.

Peer, S., Knockaert, J., Koster, P., Verhoef, E.T., 2014. Over-reporting vs. overreacting: Commuters' perceptions of travel times. Transportation Research Part A: Policy and Practice 69, 476–494. doi:10.1016/j.tra.2014.07.005.

Rietveld, P., Zwart, B., van Wee, B., van den Hoorn, T., 1999. On the relationship between travel time and travel distance of commuters. The Annals of Regional Science 33, 269–287. doi:10.1007/s001680050105.

Shao, W., 2016. Are actual weather and perceived weather the same? understanding perceptions of local weather and their effects on risk perceptions of global warming. Journal of Risk Research 19, 722–742. doi:10.1080/13669877.2014.1003956.

Soltani, A., Hoseini, S.H., Talebi, O., 2015. Walking to local destinations; perceived versus actual distance. Theoretical and Empirical Researches in Urban Management 10, 38–48.

Srinivasan, K.K., Pradhan, G.N., Naidu, G.M., 2007. Commute mode choice in a developing country: Role of subjective factors and variations in responsiveness across captive, semicaptive, and choice segments. Transportation Research Record 2038, 53–61. doi:10.3141/2038-07.

Tenenboim, E., Shiftan, Y., 2018. Accuracy and bias of subjective travel time estimates. Transportation 45, 945–969. doi:10.1007/s11116-016-9757-8.

Witlox, F., 2007. Evaluating the reliability of reported distance data in urban travel behaviour analysis. Journal of Transport Geography 15, 172–183. doi:10.1016/j.jtrangeo.2006.02.012.