Bridging the Attitude–Behaviour Gap

An Explanation of Travel Mode Choice through Analytical Sociology

Proposal for

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Topic

- Discrete choice modelling ***or***
- Activity-based modelling

1 Introduction

Understanding mode choice remains a key challenge in mobility research. Individual mobility behaviour is shaped by various factors, such as attitudes, social norms, infrastructure and institutional frameworks. Numerous statistical approaches – ranging from regression models to structural equation modelling – have been developed to explain these influences. However, review studies report inconsistent and, in some cases, contradictory results. This is problematic, as private motorised transport contributes significantly to greenhouse gas emissions and traffic congestion in cities. Improving explanatory models is therefore not merely an academic exercise, but a prerequisite for effective transport policy.

Two strands dominate the field: attitude-related models (e.g., Theory of Planned Behaviour, Technology Acceptance Model) and choice models rooted in rational utility theory. Hybrid choice models attempt to combine both traditions. While each approach offers important insights, none fully resolves a persistent empirical puzzle: the attitude–behaviour gap. Many individuals express pro-environmental attitudes yet continue to rely on private cars. Conversely, some who prefer sustainable modes do not use them in practice.

This paper introduces the *Extended Model of Mobility Behaviour (xMooBe)*, a sociological model grounded in analytical sociology. xMooBe integrates subjective expected utility (SEU) theory with contextual factors such as car

ownership and the accessibility of public transport. We argue that incorporating these factors significantly improves explanatory power and helps bridge the attitude–behaviour gap.

Using survey data from over 10,000 university members – students as well as employees – in the Ruhr region (Germany), we first apply the standard SEU model and then gradually expand it to include contextual variables. The results show that prediction accuracy increases from approximately 70% to nearly 80% when contextual factors are included. Furthermore, the model enables thought experiments through which starting points for behavioural change can be identified and empirically tested.

2 Theoretical Framework

2.1 Attitude-Related Models

Attitude-based approaches such as the Theory of Planned Behaviour (TPB) assume that behaviour is determined by behavioural intentions, which in turn depend on attitudes, subjective norms, and perceived behavioural control. Technology-focused adaptations (e.g., TAM) focus on perceived usefulness and ease of use.

Although widely applied in mobility research, these models face several limitations (cf. Turner et al., 2010):

1. They often rely on self-reported behavioural intentions rather than actual behaviour.
2. They typically examine a single behavioural alternative instead of modelling trade-offs between competing modes.
3. They struggle to explain discrepancies between stated attitudes and observed actions.

Empirical evidence suggests that behaviour can influence attitudes as strongly as the reverse (cf. Kroesen et al., 2017). Furthermore, contextual constraints are often not sufficiently taken into account in theoretical models, leading to inconsistent results across different studies (cf. Javaid et al., 2020).

2.2 Choice Models and Hybrid Approaches

Choice models assume that individuals choose the option that offers the greatest utility. Utility functions typically take into account travel time and costs, as well as socio-demographic variables, to estimate transport demand (Horni et al., 2016). These models often treat social factors as residual variance and partially resolve the ‘problem’ of human individuality by introducing a certain degree of randomness, for example through the random utility theory (Walker & Ben-Akiva, 2002).

Although hybrid choice models attempt to integrate latent attitudes into utility functions, they frequently rely on explicitly stated preferences, producing rather tautological results (e.g., those who prefer cycling are more likely to cycle). Most importantly, traditional choice models often extrapolate future behaviour from past patterns without analysing the underlying decision mechanisms in depth (Chorus & Kroesen, 2014).

2.3 Analytical Sociology and the SEU Model

Analytical sociology offers a mechanism-based model of decision-making that makes it possible to model individual behaviour based on subjective preferences and goals (Coleman, 1990; Esser, 1993; Gërxhani et al., 2022; Hedström & Ylikoski, 2010; Manzo, 2021). It is generally assumed that, when faced with a choice between alternatives (A1, A2 …), individuals will choose the alternative that – from their own perspective – best meets their needs.

Each individual's options for action are calculated using the following equation:

$$SEU\ (A_i) = \sum_{j=1}^{n} p_{ij} * U(O)_j$$

Equation 1: Subjective expected utility calculation

Subjectively expected utility (SEU) is based on two factors:

- Individually preferred (U) objectives (O), such as fast, environmentally friendly, comfortable, safe, reliable or cost-effective travel;
- the subjectively perceived probability (p) of achieving a desired objective by choosing one of several courses of action.

The latter variable is an important component of the sociological decision-making model, which is not considered in other, purely preference-based models.

The SEU framework is a powerful tool for explaining individual behaviour, taking into account the subjectivity of individual perceptions, for example in relation to contextual conditions such as the availability of public transport. However, because it focuses on subjective factors, it tends to underestimate the objectivity of contextual constraints.

3 The Extended Model of Mobility Behaviour (xMooBe)

To address this limitation, we extend the SEU framework by incorporating contextual factors (Cf) such as car ownership, distance to destination, and public transport quality, which may influence the perceived probabilities. The modified utility function is:

$$SEU\ (A_i) = \sum_{j=1}^{n} (p * \boldsymbol{Cf})_{ij} * U(O)_j$$

Equation 2: Modified SEU formula for utility calculation

The resulting *Extended Model of Mobility Behaviour (xMooBe)* can be represented as follows (Weyer & Hoffmann, 2025):

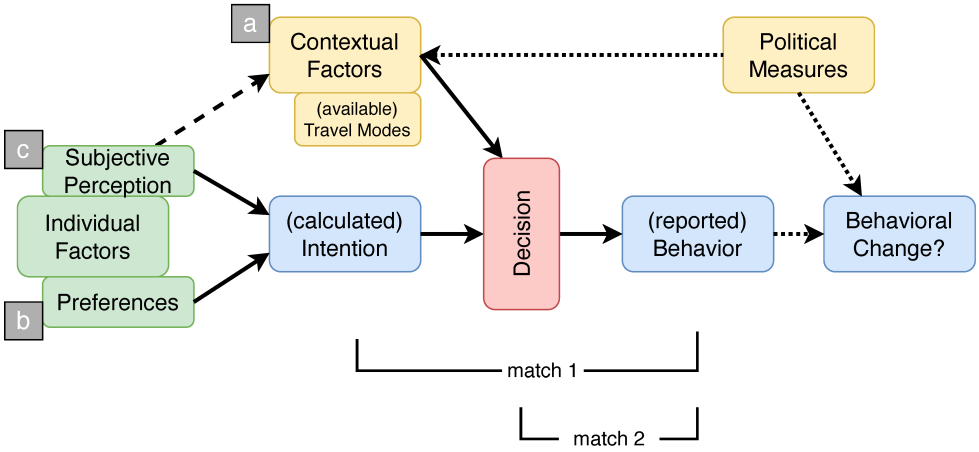


Fig 1: The Extended Model of Mobility Behaviour (xMooBe)

The model complements the purely SEU-based model, which calculates intentions (blue box on the left) by taking into account individual factors such as latent, mode-specific preferences (b) and subjectively perceived probabilities (c), which reflect the subjective definition of the contextual situation (dotted arrow from c to a). Since reported behaviour (blue box further to the right) does not perfectly match intentions (match 1), objective contextual factors (a) are used as an additional factor that increases the explanatory power of individual decisions (pink box) and helps to bridge the attitude-behaviour gap (match 2).

Policy measures to promote more sustainable transport could therefore aim to influence all three factors (a to c; see below for details) in order to bring about behaviour change (blue box on the far right). Our approach of modelling individual decision-making processes – rather than relying on stated preferences – enables us to conduct experiments, whether in the form of simulation experiments or thought experiments, in which various parameters can be adjusted in line with policy strategies to investigate the effects on mobility behaviour.

4 Data and Methods

4.1 Survey Data

As part of the InnaMoRuhr project (Weyer, 2025), data on modes of transport used, individual preferences, subjective probabilities and contextual conditions were collected in spring 2021. All members of three universities in the Ruhr region (approx. 130,000 people) were invited to take part in an online survey. After data cleansing, 10,782 responses remained, the majority of which came from students (68.0%), but also from academic (18.4%) and administrative staff (13.5%). The latter group had the highest response rate (26.7%), compared with a low response rate among students (6.2%). Surprisingly, the general attitudes of students and staff (explanans) do not differ particularly, apart from the single item 'assessment of the costs of cars', whilst mobility behaviour (explanandum) differs significantly, as students use public transport considerably more frequently.

Although the dataset is not representative of the general population, two conclusions can be drawn from it: student participation does not compromise data quality (at least not the data required for behavioural modelling), and mobility behaviour should be explained by taking into account factors other than just attitudes.

4.2 Methodological Approach

We adopted a mixed-methods approach combining statistical analysis, behavioural modelling, and thought experiments – a method that is widely used in the natural sciences, but rarely applied in the social sciences (Betta & Swedberg, 2021).

Our approach comprised five steps:

1. Statistical analysis of survey data;
2. Behavioural modelling to identify the best rated mode of transport;
3. Comparison of best rated mode of transport and the one actually used (attitude-behaviour gap);
4. Regression analysis to identify those factors that are responsible for the 'non-utilization' of the preferred mode of transport;
5. Thought experiments involving fictious characters to assess options for behavioural change.

Below, we will briefly report on the findings relating to points 2, 4 and 5. At the hEART conference in Paris, these findings may be supplemented by the results of a second study, based on a survey conducted in the Munich area in 2024, the aim of which was to test the applicability of xMooBe to a different dataset (Weyer et al., 2026). In addition, the presentation may cover current research into extending xMooBe to the new transport mode of autonomous shuttles, as well as the results of a simulation of the introduction of these shuttles in the Paderborn area.

5 Results

5.1 Standard SEU Model

Based on the stated preferences and estimated probabilities, SEU values were calculated in a first step for the car, the bicycle and public transport. Almost half of the respondents (48.6%) rated the bicycle highest, closely followed by the car (42.6%); public transport lagged far behind (8.8%). When comparing predicted behaviour with actual behaviour, the model correctly classified up to 73.7% of cases (in the case of public transport).

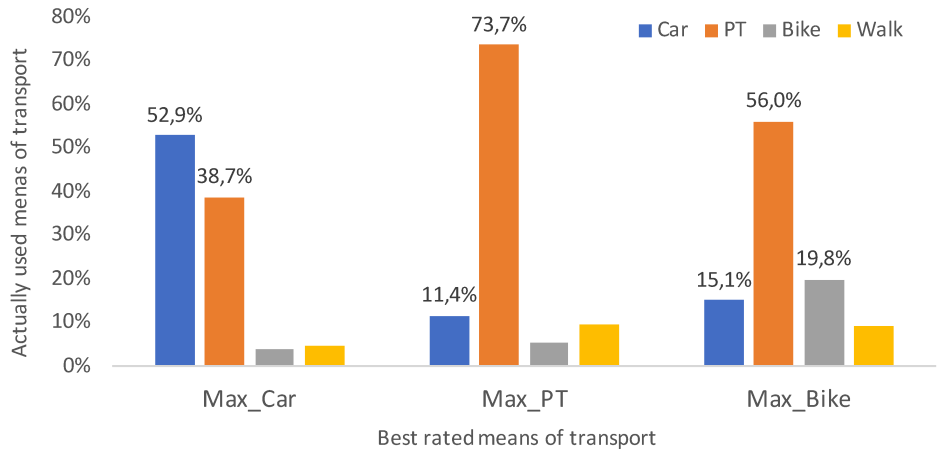


Fig 2: Actually used and highest rated modes of transport (own illustration)

However, as shown in Figure 2, there were significant discrepancies:

- Only 19.8% of respondents who rated cycling highest actually used a bicycle for getting around (grey bar).
- A significant proportion of those who preferred the car used public transport (38.7%, orange bar).

5.2 Extended Model

When applying the standard SEU model, a discrepancy remains between attitude and behaviour. We have therefore used regression analysis to calculate three separate models for each of the three modes of transport under consideration. Future studies will aim to combine these into a single model.

We included various contextual variables in our analysis, which were relevant to varying degrees – although, unfortunately, the bicycle model did not perform as well as expected (cf. Table 1).

Other contextual variables such as children in household or population density did not yield meaningful results. As the cycling model did not produce the expected results, we looked for additional auxiliary variables and found two: the functional group and the expressed desire for a better cycle path network. In the follow-up study, we managed to achieve significantly better results for the bicycle model (Weyer et al., 2026).

		Odds ratio		
Variable	**Scaling**	**Car**	**PT**	**Bike**
Car [or PT or bike] rated best (SEU)	1 yes, 0 no	5.032	2.591	4.809
Car ownership	1 yes, 0 no	70.598	0.431	
Age group	1-7	1.476	0.608	1.254
Gender	1 woman, 0 man			0.560
PT index	1-5	0.722	1.271	
Mental availability of alternatives	0-10	0.871	1.078	
Distance to destination	km		1.039	0.917
Function group	1 empl., 0 student			2.189
Desire for better cycling network	1 yes, 0 no			1.557
	Adj. R2 (Nagelkerke)	.487	.251	.280
	Chi^2	1,895.99	764.302	774.876
	Correctly classified	79.2%	68.9%	86.6%
	N=	4.439	3,657	4,611

Table 1: Binary logistic regression models with the dependent variable 'car [or PT or bicycle] as main mode of transport' (dummy: 1 = car [or PT or bike], 0 = other)

In summary, by switching from Standard-SEU to xMooBe, we were able to improve the explanatory power of the car model from 71.4% of correctly classified cases to 79.2%, and that of the PT model from 53.9% to 68.9%, whilst the bicycle model yielded less satisfactory results (from 88.3% to 86.6%).

5.3 Short analysis

As the car model shows, car ownership had by far the strongest influence on car use, followed by older age, whilst the quality of public transport and the mental availability of alternatives reduced the likelihood of car use. With the PT model, the opposite is true: car ownership and older age reduce the likelihood of car use, whilst the quality of public transport and the perceived availability of alternatives increase it. In contrast to those who rate the car or bicycle most highly (and therefore use them), the low SEU score for public transport again suggests a weaker attachment to this mode of transport.

Ultimately, the cycling model showed significantly fewer contextual factors that could be influenced by policy measures. Cyclists tend to be slightly older men who do not need to travel particularly long distances. There are more students among them than working people, and many would like to see better conditions for cycling.

Although some of these findings are not particularly surprising, they can now be used as parameters for thought experiments involving fictional characters. Gradually varying these parameters can help us better understand which policy measures can bring about behavioural changes that contribute to a sustainable transport transition. To anticipate the conclusion: it is not the shift in attitudes that politicians repeatedly call for; it is much more trivial, for in an ideal world, if people could, most would cycle (see above).

6 Thought Experiments

6.1 Car Use

The regression coefficients were used to calculate the probabilities of car use by two fictitious persons (cf. Table 2).

Person 1 rates the car best (1), owns a car (1), is between 50 and 59 years old (6), rates the PT as unsatisfactory (1), and has never been interested in alternatives (0). Hence, the probability of car use is 95.3 percent.

Person 2 rates another mode of transport best (0), does not own a car (0), is 25 to 29 years of age (3), rates the PT as quite good (4), and has already looked into various alternatives (3). In this case, the probability of car use is 0.2 percent.

Variable	Scale	Person 1	Person 2	Person 1a	Person 1b	Person 1c
Car rated best	1 = yes 0 = no	1	0	1	0	1
Car ownership	1 = yes 0 = no	1	0	~~1~~	~~1~~	0
Age group	1-7	6	3	~~6~~	~~6~~	~~6~~
PT index	1-5	1	4	4	4	4
Mental availability	0-10	0	3	3	3	3
	Probability	**91.4 %**	**0.2 %**	**72.6 %**	**34.5 %**	**3.6 %**

Table 2: Probability of car use for two fictitious persons (cells crossed out: variable cannot be changed)

Policy measures aimed at persuading Person 1 to use other modes of transport could initially involve improving local public transport (the number increases from 1 to 4) and/or providing better information about alternatives, e.g. via an intermodal mobility app (from 0 to 3). If both measures are implemented, the probability that Person 1 will use a car drops to 72.6% (now Person 1a). Perhaps they have a positive experience using other modes of transport and get used to, for example, the bike-share scheme, so that their rating of the car (SEU value) could also fall (Person 1b, 35.4%). Or, although he/she continues to prefer the car, he/she learns

to travel without a car of his/her own (Person 1c), and the probability of car use drops to as low as 3.6%.

6.2 Public Transport Use

Since age, car ownership or place of residence cannot or should not be altered by policy measures, the two variables 'quality of public transport' and 'mental availability' – much like in the case of the car model – once again prove to be effective factors through which mobility behaviour can be effectively influenced.

Variable	Scaling	Person 1	Person 2	Person 2a	Person 2b	Person 2c
PT rated best	1 = yes 0 = no	1	0	0	1	1
Car ownership	1 = yes 0 = no	0	1	~~1~~	~~1~~	0
Age group	1-7	2	5	~~5~~	~~5~~	~~5~~
PT index	1-5	4	1	4	5	5
Mental availability	0-10	3	0	3	3	3
Distance university	km	10	10	~~10~~	~~10~~	~~10~~
	Probability	**90.1%**	**11.7%**	**25.3%**	**52.8%**	**72.2 %**

Table 3: Probability of using public transport by two fictitious persons (cells crossed out: variable cannot be changed)

Here too, Person 2, who is older, owns a car and has no affinity for other modes of transport (11.7% probability of using public transport), can be persuaded to change their behaviour and become a regular user of public transport (72.2%). As can also be seen, improving the contextual conditions (Person 2a, 25.3%) alone is not sufficient; higher figures can only be achieved if the rating of public transport also improves (Persons 2b and c).

7 Discussion

The results confirm that incorporating contextual factors significantly enhances the explanatory power of our model of human decision-making. The extended xMooBe model can, at least in part, bridge the attitude-behaviour gap and highlight the factors that might prevent people from behaving as they would if preferences alone were at play.

The xMooBe concept also makes it possible to propose various strategies for policy measures that

1. either aim to change long-term preferences ('shift in values' towards sustainability);
2. or to change the framework conditions (e.g. expansion of cycling infrastructure, improvement of local public transport);

3. or influence individual perceptions (e.g. via mobility apps, targeted information).

As the 'shift in values' is a long-term process and many people already wish to travel in an environmentally friendly manner, strategies 2 and 3 appear to be more suitable and effective than strategy 1. Our thought experiments have shown that targeted measures can achieve a remarkable impact.

8 Limitations and Outlook

Several limitations remain:

- The dataset is not representative but limited to a university population.
- Bicycle-specific contextual variables were insufficiently captured.
- Separate binary models were estimated instead of a multinomial framework.

Future research should validate xMooBe using other datasets, as has already been done for Munich (Weyer et al., 2026). Thought experiments should be supplemented by simulation experiments using agent-based models that focus on system dynamics, which are determined by a multitude of individual decisions and the non-linear effects resulting from their interactions.

Furthermore, autonomous systems, such as driverless on-demand shuttles, should be integrated as new modes of transport. Modelling human decision-making using xMooBe can help to better assess the impacts and benefits of introducing these systems before they are put into practice.

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