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Investigating willingness to pay towards shared e-bikes: A comparison of methods ☆

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ABSTRACT

Background: Bike-sharing systems (BSSs) are essential for mitigating carbon emissions associated with individual transportation and for enhancing spatial and mobility efficiency. Nonetheless, the full potential of BSSs remains untapped. The introduction of new services, such as rental e-bikes, presents the challenge of establishing optimal pricing strategies that balance revenue generation and market penetration. Different measurement approaches to find optimal prices exist. Our research addresses the willingness to pay (WTP) towards shared e-bikes among users and non-users of BSSs in order to address user and non-users of BSSs. Furthermore, two separate measurement approaches are utilized for the purpose of a methodological comparison.
Methods: Our research uses quantitative data from three surveys (n = 968) to calculate WTP of users and non-users of BSSs towards shared e-bikes. We employ van Westendorp's Price Sensitivity Meter (PSM) and a multinomial logit (MNL) model based on discrete choice experiments (DCEs) to measure WTP and compare results.
Results: We find a strong price sensitivity towards e-bike rentals among users and non-users of BSSs. WTPs for a 30-minute e-bike rental measured with PSM range from €1.98 to €2.95 for users and from €1.40 to €2.85 for non-users. Comparing users only, MNL measurements broadly correspond to the PSM results, offering revenue-maximizing prices from €2.08 to €2.65 and competitiveness-oriented prices from €1.52 to €2.76 depending on the choice scenario. However, MNL results start to diverge from PSM results when considering more variance in the modal choice share for BSS.
Conclusion: Our findings suggest that users and non-users of BSSs derive utility from e-bike rental and can be addressed at comparable prices. However, pricing depends on strategic goals. Our comparison of methods when measuring WTP suggests an overall comparability of PSM and MNL and highlights possible synergies. We also highlight the need for future research considering alternative choice modelling approaches, optimizing PSM data collection and subgroup comparisons.

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Abbreviations

BDM	Becker, De Groot, Marshak Method
BSS	Bike-Sharing System
CATI	Computer-Assisted Telephone Interview
CBC	Choice-Based Conjoint
CMV	Comparative Method of Valuation
DCE	Discrete Choice Experiment
ES	Electric Scooter
ICBC	Incentive-Aligned Choice-Based Conjoint
IDP	Indifference Price Point
IOE	Incentive-Aligned Open-Ended Questioning
MaaS	Mobility as a Service
MDP	Point of Marginal Cheapness
MEP	Point of Marginal Expensiveness
MNL	Multinomial Logit
MRS	Marginal Rate of Substitution
OE	Open-Ended Questioning
OPP	Optimal Pricing Point
PAPI	Paper-and-Pencil Interview
PLN	Polish Zloty
PSM	Price Sensitivity Meter
PT	Public Transport
RAP	Range of Acceptable Prices
RP	Revealed Preferences
RUM	Random Utility Maximization
SEM	Structural Equation Modelling
SP	Stated Preferences
SPR	Stress Price Range
VTTS	Value of Travel Time Savings
WTP	Willingness To Pay
W	Korean Won

1. Introduction

The roles of individual mobility and mobility services are omnipresent in contemporary discussion about decarbonization (e.g. Gössling, 2020). Transportation is among the sectors with the fastest growing emission rates (+2.5 % CO2 per year) (Rogelj et al., 2018) and responsible for not less than 23 % of the global energy-related CO_2 emissions (Graham-Rowe et al., 2011). This fact has led policymakers to reconsider modes of mobility predominantly based on fossil energy (e.g. cars) (Pucher and Buehler, 2008). Besides simply decreasing the degree of mobility, modal shifts from private cars to cycling are identified to be one way to efficiently reduce CO_2 emissions (Brand et al., 2021a; Brand et al., 2021b). For modal shifts in general, travel costs, travel time and convenience are identified to be the major drivers (e.g. Chen et al., 2020; Grüner et al., 2023c). Especially car users, whose value of travel time savings (VTTS) tends to be higher than for Public Transport (PT) users, are sensitive to travel costs whereas the reduction of travel time and the availability of e-bikes is more relevant for PT users or pedestrians (Teixeira et al., 2023). In addition, cycling infrastructure and aspects of subjective safety are of high relevance for bike trips (Stinson and Bhat, 2003; Sener et al., 2009).

Costs and pricing are critical issues for shared-mobility providers as they compete with established modes of private car-based mobility. Several studies from the shared-mobility sector focus on (cost- and value-based) pricing strategies (for autonomous mobility services see Bösch et al. (2018), for station-based bike-sharing systems (BSSs) see Jara-Díaz et al. (2022) and for optimal pricing strategies of BSSs see Chen et al. (2020)). Cost-based pricing is a strategy that determines prices based on the provider's own costs. However, prices calculated that way cannot be set easily because they are a product of fixed and variable entities. As a result, a price that is based on costs for one specific product or service could actually never be fixed because its value is determined by degrees of capacity utilization of fixed-cost entities (Courcoubetis, 2003) – e.g. the price for a bus ticket would always depend on the number of additional passengers. Value-based pricing, conversely, shifts the focus from internal cost considerations to the perceived value, which customers are willing to pay. Value-based pricing requires service providers to take userś perception of an actual value in relation to a specific price into account (Raja et al., 2020).

Research approaches that incorporate value-based pricing and mode-changing behaviour are closely related to discrete choice experiments (DCEs) and stated preference (SP) studies (Carrone et al., 2020; Tsouros et al., 2021). However, there are other approaches to investigate willingness to pay (WTP), such as perceived value theory and structural equation modelling (SEM) (Song et al., 2021). Another approach to set value-based prices is van Westendorp's Price Sensitivity Meter (PSM). An initial literature review on this technique reveals that – currently – PSM is usually not applied to measure WTP of mobility services. Moreover, there is a research gap on WTP for shared e-bikes among users and non-users of BSSs. This is surprising, as potential for a modal shift of BSSs non-users to e-bikes instead of conventional bikes should be assumed.

The aim of our paper is to address these gaps by applying and evaluating PSM as a measurement of WTP in the domain of mobility. This will be achieved through a methodological comparison of van Westendorp's PSM and DCE analysis using multinomial logit (MNL) models applied within the domain of e-bike-sharing among users and non-users of BSSs. The following questions will be addressed:

1. Which WTP values do users and non-users of BSSs have towards shared e-bikes?
2. How do measurements of WTP (DCE/MNL vs. van Westendorp's PSM) affect reported WTPs.
3. What are the potential benefits and drawbacks of the aforementioned methods and how can they complement or substitute each other in practical applications?

Thus, besides providing an analysis on BSS WTP for BSS users and non-users, our paper contributes a methodological reflection of two different WTP measurement methods on the same data to enable a comparison between the methods and their results and to test whether both methods reliably measure the same or similar WTP. Furthermore, we provide readers with recommendations on when either method can be used and whether the methods can be used to complement or substitute each other.

2. Literature review

In behavioural economics, WTP is a dynamic construct (Bettman, Luce and Payne, 1998; He, Anderson and Rucker, 2024). It depends on personal dispositions (e.g. purchase for personal use vs gift-giving) (Voelckner, 2006), situational factors (like individual versus group consumption or choices between convenience stores and restaurants) (He, Anderson and Rucker, 2024), and contextual variables (e.g. framing or decoy effect). Additionally, it differs across distinct product categories (Thomas, 2023). Earlier measurements of WTP assumed comparisons to be invariant and externally determined. Recent studies consider contextual factors such as the relevant set and subjective perception of specific product/ service features in comparative analyses (He, Anderson and Rucker, 2024). WTP measurements may or may not incorporate contextual factors influencing decision-making. Respondents may be placed in controlled scenarios (personal use versus gifting) or presented with a defined range of options, including variations in product or service attributes. Comparative analysis rests on the premise that perceived discrepancies between options generate quantifiable added value. Within their WTP framework, He, Anderson and Rucker (2024) posit that the WTP for a product (p_x) is the aggregate of its alternative's (r) price (p_r) and its incremental value (v) relative to that alternative (Δv_{xr}), expressed monetarily.

$$WTP_{xr} = p_r + \Delta v_{xr}$$

Multiple measurements for assessing WTP exist, encompassing both direct and indirect, contextualized and non-contextualized as well as hypothetical and actual operationalizations (Miller et al., 2011). Table 1 provides an overview of currently existing measurements, which are briefly explained in the following section.

2.1. Direct WTP measurements

Direct measurements involve directly inquiring about the price respondents are willing to pay for a specific product or service (e.g. "what would you be willing to pay for object x?"). The question is verbalized open-ended (OE) and may encompass both hypothetical and actual purchases. In hypothetical cases, respondents are expected to only assume a purchase without actual consequences arising from their statement. In cases of so called incentive-aligned open-ended questioning (IOE) concrete respondentś action after stating their WTP is required. I.e., respondents are obliged to actually buy the product according to their bid.

A special OE approach is represented by the Price Sensitivity Meter (PSM) created by van Westendorp, (Westendorp, 1976). Respondents are asked four questions openly, i.e. at which price they consider a product or service to be too cheap/implausibly cheap, at which price they consider it to be cheap and a good deal, at which price they consider it to be expensive but still affordable and at which price they consider it to be too expensive. Subsequently, four curves are derived from the answers with intersections indicating a penetration price, an indifference price as well as a minimum and a maximum price (Westendorp, 1976). PSM does not utilize predefined price-ranges and is partially compatible to a limited number of fixed alternative options, when presenting them with reference prices (e.g. "Please note that the price of an alternative product/service is €*x*").

IOE may utilize varying design specifications concerning the likelihood of the investigated object's acquisition (Lipovetsky, Magnan and Zanetti-Polzi, 2011). One possibility are standard auctions, wherein participants are obligated to purchase the object of investigation based on their submitted bid. Alternatively, they can randomly become drawn from a lottery after placing their bid and then have to buy the object of investigation (BDM method according to Becker, DeGroot and Marschak, 1964). Another option are Vickrey auctions, in which the highest bidder is obliged to purchase the product for the second-highest bid's price (Vickrey, 1961). In contrast to OE, IOE approaches endeavour to elicit respondents' genuine willingness to pay. BDM and Vickrey auctions guarantee

Table 1
Classification of recent WTP measurements (Miller et al., 2011).

	Direct	Indirect
Hypothetical WTP	Open-ended question	Gabor Granger
	Van Westendorp (PSM)	Choice-Based-Conjoint (CBC)
Actual WTP	Auctions	Incentive-aligned choice-based conjoin (ICBC)
	Becker, DeGroot, Marschak method (BDM)	
	Comparative method of valuation (CMV)	

incentive compatibility, eliminating any strategic advantage from respondents misrepresenting their willingness to pay (Kaas and Ruprecht, 2006). However, IOE approaches are measurements that are still assumed to be fixed to certain comparisons, although a fixed choice WTP measurement cannot address indirect effects of situations within decisions are made. In order to tackle this issue, He, Anderson and Rucker (2024) developed a *Comparative Method of Valuation* (CMV). The method suggests, to initially present a selection of pertinent alternatives to respondents, each with distinct configurations and prices, excluding the target item. This way, respondents are expected to make a choice from a not fixed set of comparisons. In a second step, the object of investigation is introduced and respondents are asked to level their first choice in terms of price with the target item (e.g. asking: "At what price would your preference for the target item be equal to your preference for the first choice at the given price of the first choice?"). Step three involves a lottery, from which a random number is selected. The object of investigation should be purchased at the stated price only if it is greater than or equal to the randomly generated number. Purchase of the relevant alternative (first choice) is mandatory should the stated WTP fall below the generated random number. This way CMV ensures incentive compatibility in a situational context.

In summary, direct measurements of WTP pursue distinct objectives and exhibit both advantages and limitations. OE serves to determine a directional preference and is characterized by its ease of application and compatibility with novel products and services. PSM elaborates OE WTP estimation by identifying price acceptance thresholds and considering value differentiation. It allows for open-ended answers without predefined ranges and supports fixed alternative options. However, as comparative analysis is typically omitted, the resulting WTP estimates may be equivocal (Lipovetsky, 2006). Furthermore, OE questions lack incentive-compatibility, which may impact the reliability of responses (He, Anderson and Rucker, 2024). Auction-based methods aim to estimate real WTP by leveraging auction mechanisms. While they are relatively straightforward to implement, they necessitate the existence and knowledge of test objects. Additionally, comparative analysis is often absent, a minimum of two bidders is required, and competitive behaviour may distort WTP estimates. BDM is specifically designed to facilitate a realistic measurement of WTP. It is easy to implement and ensures incentive-compatibility, making it a widely recognized approach. Nevertheless, the method is contingent upon the existence and knowledge of test objects, does not explicitly specify relevant alternatives, and may yield ambiguous WTP estimates due to individual comparison assumptions made by respondents. CMV offers a situational, realistic measurement of WTP by explicitly defining comparative options and ensuring incentive-compatibility. Despite these advantages, CMV requires the existence and knowledge of test objects, is relatively time-intensive, and necessitates a comparative selection process, which may increase the methodological complexity of its implementation (He, Anderson and Rucker, 2024).

2.2. Indirect WTP measurements

Indirect measurements may also follow an incentive-based or a hypothetical design. Both, the Gabor-Granger approach (Gabor and Granger, 1966; Gabor and Granger, 1979) and van Westendorp's PSM (Westendorp, 1976) are popular indirect measurements used to estimate hypothetical WTP. Gabor-Granger is commonly used to assess the price sensitivity of established products or services, allowing to identify critical price points at which demand starts to decline drastically (Miller et al., 2011). Having controlled for respondentś interest in the object of investigation, a predetermined set of prices is introduced, and respondents are asked to assess their probability of purchase (via dichotomous or scaled response). Upon acceptance of a proposed price, a superior price is presented. Upon rejection of the subsequently proposed price, a progressively lower price is presented until acceptance is achieved. The procedure iterates until all price suggestions meaningful have been evaluated, thus identifying the optimal price point for each respondent. A demand curve is thus established, allowing for the investigation of optimal pricing and the effects of price variability on demand (Wedel and Leeflang, 1998).

In choice-based conjoint (CBC) experiments, respondents are confronted with several choice alternatives, of which each is made up of several attributes that respondents need to jointly consider to decide which alternative they like best. As the alternatives' attributes can also contain prices, CBC can be used to elicit WTP for the alternatives' attributes (e.g., Carson, 2000). Accordingly, CBC manipulates pricing and alternative configurations to ascertain WTP by observing tipping points, where decisional shifts from purchase intent to refusal occur stochastically. Choice-based methods offer the advantage of facilitating the development of models capable of estimating WTP across diverse choice sets using well-established microeconometric models such as the Logit model (Ortúzar and Willumsen, 2011). Consequently, CBC demonstrates relative efficiency in analyzing the impact of marginal offer variations (He, Anderson and Rucker, 2024). However, as is the case for Gabor Granger and PSM, CBC is not incentive-compatible and also often reports overestimated WTP (Voelckner, 2006; Schmidt and Bijmolt, 2020).

The incentive-aligned mechanism for conjoint analysis (ICBC) addresses the incentive compatibility problem frequently overlooked in other indirect measurement methods. Traditional CBC experiments are combined with a lottery, introducing a probabilistic element to product/service purchase obligations (Ding, 2007). Thus, ICBC provides the advantage that respondents' decision-making among the presented alternatives generates real WTP values.

In conclusion, indirect methods for measuring WTP vary in approach, advantages, and limitations. Gabor-Granger determines a directional preference, offering easy application and compatibility with new products and services. However, it relies on a predefined price range, omits comparative analysis, and lacks incentive-compatibility, which leads to hypothetical and potentially equivocal WTP estimates. CBC measures WTP across varying attribute combinations and choice sets, making it efficient for evaluating multiple product or service variations. It ensures precisely defined comparative options and offers a generalizable measurement model. However, it assumes rational decision-making, is data-intensive, and relies on model-derived estimates, which introduces potential inaccuracies. Additionally, it lacks incentive-compatibility. ICBC enhances CBC by ensuring incentive-compatibility, allowing for the measurement of real WTP across different attribute combinations and choice sets. While it precisely defines comparative options, it requires test object availability, is data-intensive, and involves a comparative selection process, increasing its complexity.

3. Existing research on WTP for bike-sharing

Existing research on WTP for shared bikes predominantly focusses on shared bikes while only few studies also consider shared e-bikes. Furthermore, most studies focus less on estimating WTP values but rather examine the impact of price on BSS demand. Studies on indirect measurements of WTP are dominant as transportation means are often employed habitually and seldomly object to auctions which allow direct WTP measurement. In the following paragraphs, we will disseminate the existing state of research on WTP for shared bikes.

3.1. WTP based on revealed preferences

A common approach to indirectly measure actual WTP in transportation are conjoint models – e.g. mode choice models – based on revealed preference (RP) data, i.e. observations of actual behaviour. While the data obtained in this way is incentive-consistent, researchers often cannot exert any influence on the choice situation, i.e. the available alternatives and their attributes. Such data was analysed by Reck et al. (2021), who collected RP data on the usage of several micromobility modes in Zurich and estimated a model on shifts between the modes.

However, in random utility maximization (RUM)-based discrete choice models, WTP values can only be calculated as marginal rates of substitution (MRS) between alternatives' attributes. Unfortunately, in mode choice models, the transportation modes themselves (including BSS) usually are the choice alternatives. Thus, the mode choice model estimation results cannot be directly used to calculate BSS WTP. However, they can be used to forecast the demand and the demand elasticity w.r.t. price and thus derive pricing recommendations (see e.g. Willumsen (2014); we will further detail how mode choice model results can be used to derive pricing recommendations and WTP values in chapter 3).

Other researchers indirectly survey WTP by analysing changes in BSS demand following price changes or by comparing usage and pricing strategy among BSS systems. For example, Weschke (2024) analysed the impacts of a one-month intervention in Boston, where prices for the urban BSS were reduced from $US2.95 to $US0 by using a difference-in-differences approach. He found that the fare reduction yielded a 55 % rise in BSS demand during the intervention and a lasting rise of 20 % in BSS demand even three months after the intervention ended.

Li, Liu and Song (2019) used a panel data regression model to explain BSS usage behaviour – represented by click data from the apps of ten different bike-sharing brands in Beijing – based on the half-hour price, congestion index and each brand's market share. They did not find any overall effect of price on brand choice, which they attribute to the fact that the BSS operators were undercutting each constantly in a price war.

Goodman and Cheshire (2014) examined the usage of the London BSS from 2010 to 2013, a timeframe which included a system expansion into less affluent areas and a doubling of prices, with one-day prices increasing from £1 to £2. In the 7 months after the price increase, they found that the number of trips by registered users increased by 7 % compared to the equivalent time period in the year before, while the number of trips by non-registered / casual users decreased by 14 %.

Kaviti et al. (2020) analysed the impacts of introducing a single-trip fare of US$2 in Washington, D.C.s Capital Bikeshare system, where previously a 24 h-pass and a 3-day pass were the shortest available "casual" subscriptions, costing US$8 and US$17 respectively. While they found that the number of first-time casual users as well as the daily ridership levels increased after the introduction of the single-trip fare, this effect may also partially be attributed to simultaneous construction and restoration efforts disturbing the D.C. metro's service.

3.2. WTP based on stated preferences

WTP for shared bikes is also frequently measured by using hypothetical choice data. E.g., Tsouros et al. (2021, see also Polydoropoulou et al. (2020)) conducted a SP experiment to determine personalized Mobility as a Service (MaaS) designs for inhabitants of the greater Manchester Area in the UK. For respondents that currently conduct more than five cycling trips per week, they found a WTP of €27 per month to include access to a bike-sharing system in a MaaS package. Bahamonde-Birke et al. (2023) also conducted an SP experiment on MaaS package design in the Netherlands but found a WTP for discounted or unlimited BSS use of €160 per month. However, they consider this WTP to be unreasonably high and attribute this effect to the important role of cycling in their survey area, due to which respondents may feel that MaaS packages have to include BSS.

Kim et al. (2020) found a WTP of ₩1000 per 15 min for an electric BSS in Seoul. For conventional bikes, Spindler, Dehnavi and Wirl (2019) report a WTP of €1.20/ 60 min. of users while dell'Olio, dell'Olio et al. (2011) report a WTP reaching from €0.29 – €3.96 per hour depending on the purpose of the trip (leisure vs. work) for non-users.

Using van Westendorp's PSM, a study by Bieliński et al. (2024) indicates a price range of around 20.1 Polish zloty (PLN) to 29.7 PLN [appx. €4.63 – €6.84] per 45 min for shared e-bikes as acceptable, with 21.8 PLN [appx. €5.02] identified as the optimal price and 24.1 PLN [appx. €5.62] identified as the indifference price.

Several other studies also used experimental SP data to model mode choice between several modes including shared bikes, see e.g. Li and Kamargianni (2020). However, as previously mentioned, if the BSS is considered as an alternative (as in Li and Kamargianni (2020)) and not as an alternative's attribute (as in Tsouros et al. (2021)), WTP values for BSS usage cannot directly be derived from choice model estimation results.

3.3. Studies on other aspects influencing WTP

Another necessary consideration is that price structures of BSS often are rather complex. For example, Hardt and Bogenberger (2016) analysed the pricing systems of different mobility sharing offers (including bike-, scooter- and carsharing) and found that some operators offered both, a payment per unit (bike-use) as well as payment per time period (sometimes also combinations of both). In addition, more complex price-packages, and graduated tariffs, regional and temporal heterogeneous pricing structures, and initial free minutes were available for some BSS services. The authors recommend a demand-based variable pricing framework which requires an accurate, dynamic demand forecast. Li, Liu and Song (2019) recommend a time-of-day-based pricing strategy. Furthermore, prices may not only be determined in order to attract customers, but also to maximize revenue (e.g. Cheng and Gao (2018), or Dong, Fan and Wang (2023)), to incentivize trips from certain origins and to certain destinations to achieve a more balanced distribution of shared bikes across the coverage area (e.g. Pfrommer et al. (2014) or Han, Chong and Huangfu (2018)), to minimize necessary subsidies (e.g. Jara-Diaz et al. (2022)) or to maximize welfare, i.e. increase financial and temporal transportation system efficiency while decreasing energy consumption (e.g. Becker et al. (2020)).

3.4. Literature summary and research gap

In summary, WTP for BSSs is usually measured indirectly, although direct measurement methods are also employed, especially when aiming to calculate WTP with respect to other products. Furthermore, both direct and indirect methods can be applied to measure actual WTP as well as theoretical WTP.

Several studies that indirectly measure or examine actual WTP for shared bike usage analyse changes in the usage of BSSs after changes in the pricing structure occurred. However, in addition to the price changes being out of control of the researchers, these studies can usually only provide an overview of the price elasticities, but do not recommend specific prices.

A frequently used method in transportation mode choice research is to create discrete choice models based on RP and SP data, however there are restrictions regarding the calculation of WTP as an MRS. Other approaches to measure hypothetical WTP for shared bike usage include approaches such as van Westendorp's PSM.

Thus, considering shared bikes, while a number of WTP measurement approaches have been used, there is a research gap regarding direct measurements of actual WTP. While methodologically sound and proven approaches to model reactions to price based on real data (namely discrete choice modelling based on RP data) exist, they do not deliver single WTP values and are difficult to compare to other measurement approaches. Furthermore, many WTP measurement approaches often cannot or hardly be applied to actual choices. However, both discrete choice modelling as well as van Westendorp's PSM can be applied to hypothetical data. Thus, in the following, we want to use hypothetical data derived from surveys on electric shared bikes in Germany to model and compare WTP and price sensitivities using PSM and discrete choice modelling respectively.

4. Method

Our analysis incorporates two distinct measurement methodologies. To estimate WTP among both users and non-users of BSSs for shared e-bikes, we employ DCEs and van Westendorp's PSM. The addressed comparisons between methods and target groups can be retrieved from Table 2.

4.1. Van Westendorp's price sensitivity meter (PSM)

The van Westendorp PSM is a commonly employed method for determining optimal pricing for products and services. The methodology was devised by Dutch economist Peter H. van Westendorp (Westendorp, 1976) and gained widespread popularity due to its heuristic nature in identifying acceptable price ranges. PSM suggests a connection between perceived quality/utility and stated willingness to pay for a product or service (Lipovetsky, Magnan and Zanetti-Polzi, 2011). Hence, PSM is classified as a direct stated-preference measurement. The process of gathering PSM data entails directly inquiring with customers about their perception of the price at which a product or service is deemed too expensive, expensive, cheap, or too cheap. Each of our surveys includes PSM questions to capture WTP. Participants are asked at what price they would perceive a 30-minute rental of an e-bike….

… "to be too expensive so they would not consider renting it."
… *"to be expensive but* still *consider renting it."*
… "*to be fair (cheap) in terms of* pricing *so they would consider renting it because it is good value for money.*"
… "*to be too cheap so they would not* consider *renting it because they have quality/ safety concerns.*"

Answering these questions might not be easy but response burden is rather low, especially when compared to DCE. Analyses of PSM

Table 2
Comparisons of WTP between measurements across users and non-users of BSSs towards shared e-bikes.

	Measurement	Bike-sharing users	Bike-sharing non-users
Willingness to pay (WTP) towards shared e-bikes	Van Westendorp's Price Sensitivity Meter (PSM)	**WTP: € A**	**WTP: € B**
	Discrete Choice Experiment (DCE)	**WTP: € C**	

data predominantly focus on descriptive statistics, often visualized through intersecting plots (Lipovetsky, 2006). Such plots are results of the cumulative frequencies of responses towards participants evaluation at which price a product or service appears too expensive, expensive, cheap or too cheap (see Fig. 1). The intersections of the curves reveal price points, representing: (i) an *optimal pricing point* (OPP) (intersection between the reversed curves "too cheap" and "too expensive"), (ii) an *indifference price point* (IDP) (intersection between the curve "cheap" and the reversed curve "expensive"), (iii) a point of *marginal expensiveness* (MEP) (intersection between the reversed curves "cheap" and "too expensive"), and iv) a point of *marginal cheapness* (MDP) (intersection between reversed curves "too cheap" and "expensive" curve) (Lipovetsky, 2006). The intersections of the curves provide substantial opportunities for analysis. The OPP represents the price at which a product or service is neither too inexpensive nor too expensive, ensuring that subjects are willing and able to purchase it without questioning its value or their ability to afford it. At this price point the resistance towards the purchase product or service is lowest (Westendorp, 1976) and most of the customers can still be addressed without a product or service falling out of their relevant set. OPP therefore can also be seen as penetration price. The IDP is seen as the price that is most accepted in terms of perceived quality, utility and credibility. At the IDP the price for a product or service is acceptable or a good bargain for an equal number of respondents. IDP represents the average price at which a product or service is most accepted in terms of perceived quality, utility and credibility. Pricing beyond IDP either causes a loss of profit or a decrease of sales volume (Çolak and Koşan, 2021). The interval between OPP and IDP can be interpreted as *stress price range* (SPR) Westendorp (1976). OPP and IDP can be identical, but a greater stress price range indicates the presence of price consciousness, characterized by a certain degree of pressure or tension. If OPP is to the left of IDP, it can be inferred that a proportion of customers have a high price consciousness and prefer a lower price. Conversely, an OPP laying to the right of IDP indicates that some customers are willing to accept higher prices, meaning that the willingness to pay has not yet been exhausted. The MEP and MDP define the range of acceptable prices (RAP) to consumers. Prices outside this range will lead to refused offers or substitutional behaviour. MEP represents the price at which customers start to perceive a product to be overpriced relative to its value (Çolak and Koşan, 2021). At this juncture, an equivalent proportion of respondents characterized the price offer as both "very expensive" and "cheap". MEP denotes the highest acceptable price point within the designated price range. Prices surpassing this threshold leads to a decline in perceived value and hence sales volume, rendering competing products more appealing to consumers, and a reduction of sales volume and revenue. On the other hand, no customers are gained through the increase of the price. The MDP represents the point where an equivalent number of participants deem a product or service "too cheap" or "expensive". Customer attrition due to quality issues will occur below this point, rendering price decreases futile in acquiring new customers.

4.2. Discrete choice experiments

DCEs are a type of conjoint analysis that is widely used in mobility research to identify preferences in terms of e.g. mode and route

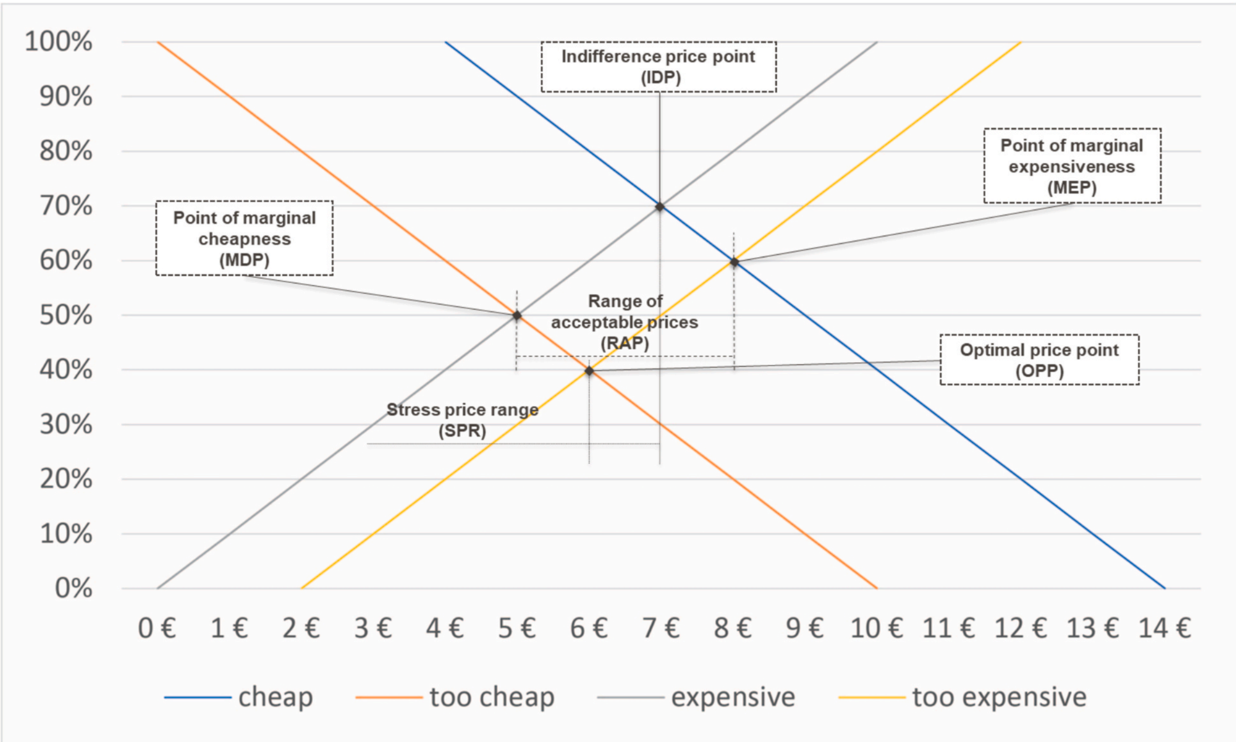

Fig. 1. Exemplified PSM-measurement and outcomes.

choices (Weis et al., 2021; Hartwig, Gühnemann and Hössinger, 2024). Respondents face multiple choice alternatives consisting of attributes such as travel time, access time, travel costs etc. The values of the attributes vary between the situations. While in the case of RP data, the variation in attributes is often correlated both within and between alternatives, the utilization of SP data addresses this challenge of multicollinearity by varying attributes' values based on an experimental design.

DCE data is often analysed according to the RUM decision rule, i.e. that each alternative provides the decision-maker with a subjective utility that is composed of a systematic and a random part and that the decision-maker wants to maximize (Ortúzar and Willumsen, 2011). Among other things, the systematic part of the utility usually incorporates the attributes of the alternatives, i.e. travel times, costs etc. Employing a dataset of either RP or SP choices, a range of model specifications, including the MNL model, can be leveraged to determine the influence of each systematic utility component on the systematic utility part.

In RUM models, the utility contributions of the alternatives' attributes can offset each other. Thus, the estimated model coefficients can easily be used to infer MRS between choice alternatives' attributes, such as the WTP for reductions in travel times, increased comfort, etc., but not to infer WTP for alternatives (Ortúzar and Willumsen, 2011).

In this paper, we use data from a SP mode choice experiment to investigate the influence of BSSś attributes on the choice of shared bikes. We offered respondents a choice between three transportation alternatives: BSS, free-floating shared e-scooters (ES), and PT. Prior to the SP experiment, we used respondentś RP BSS trip data (see section 4.4) to create the hypothetical choice situations. Using the experiment plan depicted in Table 3, we created a blocked D-efficient design for a MNL, consisting out of 6 blocks of 10 choice situations each. The design was estimated using the software Ngene (ChoiceMetrics, 2025). An exemplary questionnaire is attached (Appendix, Fig. 7). The experiment plan was created based on other mode choice studies and previous own experiences. The fieldwork has been disseminated in various working papers (Röth et al., 2022a; Röth et al., 2022b; Rutka et al., 2022; Grüner et al., 2023a; Grüner et al., 2023b; Wirtgen et al., 2023; Grüner et al., 2024).

4.3. Comparison between PSM and DCE

We will use two approaches to compare the WTP derived from van Westendorp's PSM to WTP from DCE analyses, both of which rely on the DCE analyses' forecasting capabilities.

To set prices for transportation services based on transport demand modelling (usually based on DCE analyses), common practices recommend selecting the price that maximizes the overall revenue (i.e., the product of the number of users and the revenue per user). This price is equal to the price where the demand elasticity is −1 and the revenue elasticity is 0 (Willumsen, 2014, pp. 160–161). In our study, the revenue-maximizing price is defined as the price which maximizes the product of price and BSS choice probability.

However, as public operators implementing BSS may not only be interested in revenue maximization but also in welfare, i.e. in terms of ecological sustainability and social equity in access, we also implement a second comparison approach. In this approach, we interpret the predicted choice probability of the BSS based on the price as a measure of the attractiveness of the BSS offer. Both approaches are based on the same MNL model, which is based on SP data whose experiment design was described above.

To compare the DCE results to PSM analysis results in this paper, we use a simple MNL model containing only the choice influences from the experiment design to analyse the DCE data. We decided against more complex model designs – e.g. addressing nest effects, interactions with personal attributes and latent variables as well as randomly distributed choice effects to prevent making the method comparison too complex. The MNL was estimated using the packages apollo (Hess and Palma, 2019) and bgw (Bunch et al., 2022) for the statistical software R (The R Foundation, 2025). MNL estimation results are given by Table 7 (Appendix). Utilizing MNL's forecasting capabilities, we investigate the impact of BSSs price variations on user choice. Using MNL for forecasting, however, mandates the precise definition of contextual elements within the choice situations. This includes determining appropriate values for parameters

Table 3
Mode choice experiment plan.

Attribute	Transport mean-specific variation relative to reference values (numerical variables) / variation levels (categorical variables)		
	BSS	Electric Scooter (ES)	PT (Bus)
Access time	−40 %/−10 %/+30 %	3 min/2 min/1 min	−50 %/−10 %/+30 %
Egress time	−40 %/−10 %/+30 %	–	−50 %/−10 %/+30 %
Ride time	−40 %/−10 %/+30 %	−40 %/−10 %/+30 %	−40 %/−10 %/+30 %
ES unlocking fee [€]	–	0/0.5/1/2	
Travel costs	−100 %/+0%/+30 %/+100 %	−100 %/+0%/+50 %/+100 %	−100 %/−50 %/+50 %/+100 %
Additional conveniences	none / smartphone holder / bag holder	none / smartphone holder	–
ES: return policy	–	none/take picture/chain scooter	–
BSS: electric propulsion support	no/yes	–	–
ES: battery charge and distance range [km]	–	4/8/20	–
Bike infrastructure	no infrastructure/bike lane/protected bike lane/bike path	no infrastructure/bike lane/protected bike lane/bike path	–
PT capacity utilization	–	–	middle/high/overloaded
PT service frequency: each [x] minutes	–	–	2/10/20
Number of PT transfers	–	–	0/1

such as BSS, ES, and PT access and egress times, ride time, bike infrastructure etc. For continuous attributes of the choice situations such as ride times and costs, we decided to use the mean values of the RP data. For categorical attributes, we decided to create three scenarios that aim to confront BSSs and the competing transport means ES and PT by varying the quality of infrastructure and the utilized PT capacity. In all scenarios, we will assume that the shared bikes offered in the BSS have electric propulsion support, as the PSM questions were posed with regards to shared e-bikes. Concurrently, we will followingly refer to the BSS choice alternative as e-bikes. In the first scenario, the quality of the categorical e-bike attributes is inferior to that of ES and PT attributes, in the second scenario it is equivalent to them and in the third scenario it is superior.

Given the defined scenarios, we compute the predicted probability of respondents opting for the rental of e-bikes when confronted with a range of prices between €0 and €10. This probability represents the projected market share of e-bikes amongst respondents exposed to the stipulated scenarios, contingent upon the price for e-bike rental. We use the calculation results to calculate the revenue-maximizing price and to compare the probability distribution to the PSM results.

4.4. *Sample and data collection*

Data was collected in three separate survey projects from three German BSSs: Frelo (Freiburg, from February to August 2023), VRNnextbike (Mannheim, Heidelberg, Kaiserslautern, from June 2023 to February 2024), and meinRad (Mainz, from May to September 2024). A total of 1,533 participants, encompassing both BSS-users and non-users, were interviewed using either computer-assisted telephone interviews (CATI) or an online survey. The primary objectives of our surveys were to evaluate the specified BSSs and investigate the behaviors, motivations, as well as social and psychological attributes of users and non-users. Details on the fieldwork and other findings unrelated to this paper have been disseminated in a series of working papers (Grüner et al., 2023a; Grüner et al., 2023b; Grüner et al., 2024; Röth et al., 2022a; Röth et al., 2022b; Rutka, et al., 2022; Wirtgen, et al., 2023). Most of the CATI participants were personally approached with an invitation to participate in our survey at BSS stations when renting or returning a bike. Together with the recruiter an interview appointment was scheduled online. At the time of the scheduled interview, participants were contacted and interviewed. This strategy facilitated the completion of over 50 % of the initially scheduled interviews. Participants in the online survey have been recruited through push notifications or news within their BSS applications, or through social media channels operated by the client and operator of the BSS. They completed the online survey by themselves. A subset of CATI participants (mainly from Frelo) was guided to schedule appointments directly through our landing page without personal assistance.

Data for PSM measurement and DCE were collected at two distinct time points, i.e. using two questionnaires. The first questionnaire gathered revealed preferences of participants together with PSM-data. Subsequently, personalized conjoint questionnaires, tailored to revealed preferences, were disseminated to willing respondents as a follow-up paper and pencil questionnaire to gather DCE data (see Fig. 2). This facilitated the collection of valuable DCE data using a smaller sample size through the implementation of an adaptive conjoint analysis approach, thereby mitigating systematic biases associated with evaluating two measures of willingness to pay within a single survey.

A total of 1,619 complete responses were collected, none of which had missing values for PSM (see Table 4). Data consistency was ensured by eliminating redundant values across the four PSM items (cleaning step 1), verifying logical progression of values, ranging from "too cheap" to "too expensive" (cleaning step 2) and excluding illogical or extreme values (e.g. €-1, €20+) ($n = 1$). A total of 391 records were eliminated, resulting in a cleansed dataset with 1,228 valid responses, 968 from BSS-users and 260 from BSS non-users.

For the SP mode choice experiment, CATI respondents that had reported a BSS trip and indicated willingness to participate in the mode choice experiment were randomly assigned to one of the 6 choice task blocks and choice tasks were created based on their RP trip data. Respondents conducting round trips, i.e. starting and ending their trip at the same BSS station, were excluded from the SP experiment. The mode choice experiment was conducted as a pencil-and-paper interview (PAPI) that was sent to the respondents by Of 415 questionnaires that were sent to CATI respondents, 278 questionnaires – i.e. 67 % of the questionnaires – were returned. Of these questionnaires, 5 were excluded as they did not provide sufficient data or sociodemographic data that did not match their data from the CATI survey. Of the 2.730 choice situations these respondents were confronted with, 2.713 could be used for MNL model creation.

We have encountered census data (RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany, 2023) for the federal states Rhineland Palatinate and Baden-Württemberg, encompassing the observed region. However, accessing

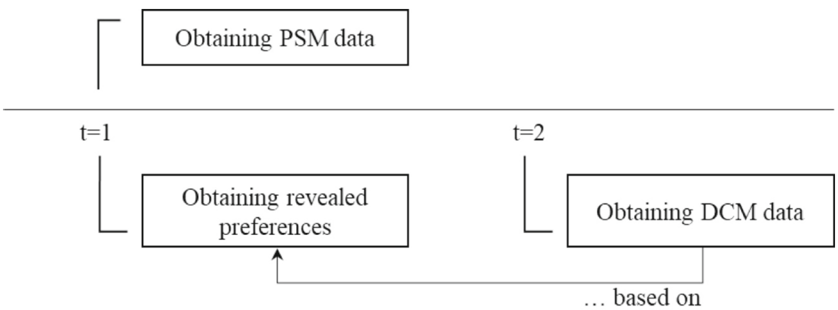

Fig. 2. DCE and PSM data is collected at two points in time.

Table 4
Data base for WTP calculations (PSM and DCE).

Data and Data cleaning		
PSM		
Data sample (no missing values)	n = 1.619	
Data sample (cleaned)	User: n = 968	Non-user n = 260
Frelo	n = 77	n = 72
meinRad	n = 571	n = 188
VRNnextbike	n = 320	
DCEs		
PAPI surveys sent	n = 415	
Suitable for MNL modeling	User: n = 273	Situations: n = 2.713
Frelo	n = 48	n = 480
meinRad	n = 35	n = 349
VRNnextbike	n = 190	n = 1884

census data for comparative analysis of our sample is complicated by the geographic scope of the observed BSS. Our sample exhibits partial comparability with census data from both federal states, mostly in terms of non-users of BSSs. Still, since the distribution and density of the BSS are neither uniform across the observed area nor representative of both federal states, the provision of census data specifically for the observed area is difficult. However, the observed sample's characteristics of BSS users largely align with typical characteristics as reported in the literature. Research indicates that the typical bike-sharing user is a younger, full- or part-time employed male with above-average income (Fishman, 2016; Soltani et al., 2022). Our sample is 31.2 % female and 68.4 % male (0.4 % diverse). The predominance of male users can also be found in other European cities such as Zurich (Reck and Axhausen, 2021). By contrast, the non-user sample presents a more equitable distribution, consisting of 45.5 % female, 53.6 % male, and 0.9 % diverse gender participants. The major age group of our BSS user sample is 25–39 years old with a 52.4 % share. 68.7 are younger than 40 years old while the sample's mean age is 35.4 years. In accordance with research conducted by Friedrich et al. (2015) and Reck and Axhausen (2021), it is observed that younger individuals constitute a higher proportion of bike rental users compared to the general population. Specifically, in Nuremberg and Zurich, more than 30 % of users are under 31 years old, whereas in Kassel, this percentage exceeds 50 %. Conversely, the non-user sample's mean age is 47.9 years, with 66.3 % falling within the 40 + years age group. Finally,

Table 5
Sociodemographic sample characteristics.

Sociodemographic			
Gender	User	Non-user	Census
Female	31.2 %	45.5 %	49.2 %
Male	68.40 %	53.5 %	50.8 %
Divers	0.4 %	0.9 %	No data available
Age	User	Non-user	Census
18–24	16.3 %	7.2 %	7.7 %
25–39	52.4 %	26.5 %	22.1 %
40–59	25.8 %	34.9 %	31.8 %
60+	5.5 %	31.3 %	33.0 %
Education	User	Non-user (no data collected)	Census
BSc, MSc or higher	51.0 %		20.2 %
High school diploma (12th grade)	42.4 %		34.9 %
Intermediate/ secondary school certificate (10th grade)	5.5 %		25.7 %
Intermediate/ secondary school certificate (8th grade)	0.8 %		27.8 %
Other	0.3 %		7.4 %
Profession	User	Non-user	Census (no aggregated data available)
Employed 30 h/week +	44.6 %	53.5 %	
Employed < 30 h/week	5.5 %	11.2 %	
Self-employed	0.0 %	0.00 %	
Student (college/university)	41.3 %	8.7 %	
Student (high school)/ Apprenticeship	3.2 %	5.0 %	
Pensioner	2.4 %	17.8 %	
Job seeking	1.3 %	1.7 %	
Other	1.7 %	2.1 %	

Source: Authors, RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany (2023).

also our BSS user sample is well educated, i.e. most respondents have education corresponding to a high school diploma (12th grade) (42.4 %) or higher (BSc, MSc or higher) (51.0 %), and are mainly employed full time (44.6 %) or enrolled as students (41.3 %). The non-user sample shows more diverse professions. The majority of individuals within it are fully employed (53.53 %), alongside pensioners (17.8 %) and a smaller percentage of students (8.7 %). The complete sociodemographic characteristics of the sample and the census are listed in Table 5. As a subpopulation of the entire sample, the SP mode choice sample is more similar to the user sample containing mainly male respondents (67.5 %) and respondents enrolled as students (58.3 %).

5. Results

The results chapter delineates the findings of the applied methods, PSM and DCE, initially presented independently before concluding with a comparative analysis. Section 5.1 presents WTP estimates derived through PSM for users and non-users of BSS. Section 5.2 outlines the price sensitivity of BSS users regarding e-bikes, derived from the DCEs via MNL modelling. Section 5.3 contrasts the findings derived from both methods.

5.1. PSM-based WTP calculation for users and non– users of BSS

Our analysis indicates a SPR from €1,99 to €2.90 for a 30-minute e-bike rental among BSS users. The price discrepancy between OPP (€1.99) and IDP (€2.90) suggests a considerable sensitivity to pricing within the market. A 30-minute e-bike rental priced at €1.99 is accepted by 94 % of the target user base. In total the remaining 6 % of potential customers are not likely to accept the price, due to their perception of the €1.99 being too expensive or the presence of doubts towards the quality of the service (i.e. the BSS is perceived as too cheap). The price point of €2.90 (IPD) is associated with the most favorable relationship between revenue and user acceptance. At this point 32 % of respondents perceive the offer to be a good deal and neither significantly cheap or expensive. It is significant to note that the SPR for users of BSS closely aligns with the RAP. The latter exhibits a price range between €1.98 (MDP) and €2.95 (MEP), thus supporting the conclusion of a high price sensitivity. Beyond these limits neither additional users can be attracted or higher revenues realized because the users perceive the offer either as being too cheap or too expensive while others consider it already expensive or still cheap. The PSM results concerning users‧ WTP for a 30-minute e-bike rental are depicted in Fig. 3.

Among non-users of BSS we find a SPR from €1.88 to €2.42 for a 30-minute e-bike rental. At €1.88 (OPP) the maximum of 90.6 % of the non-users accept the price. A price point above or below the threshold leads to a decrease in acceptance due to the non-users' perception of the offer as being either prohibitively expensive or suspiciously inexpensive. The WTP of non-users (31.5 %) is highest at €2.42 (IDP). An equal number of users at this intersection perceives the price as either cheap or expensive, thereby indicating willingness to go for the service. The RAP of non-users towards a shared e-bike ranges from €1.40 (MDP) to €2.85 (MEP). Beyond this, user

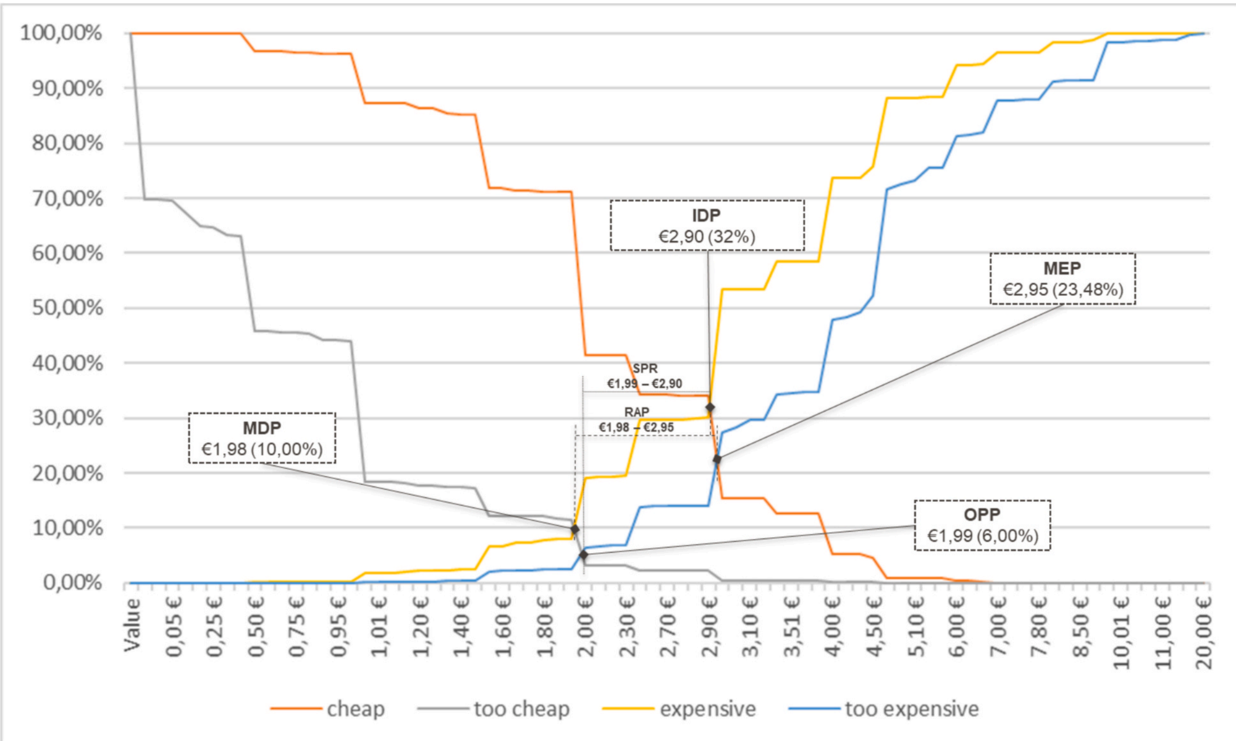

Fig. 3. WTP of BSS-users towards 30 min rental of an e-bike (PSM measurement).

erosion can occur when rentals are priced too low (MDP) or too high (MEP), ultimately hindering revenue generation instead of maximizing revenue at a price point where perceptions intersect. While the SPR of €1.88 to €2.42 suggests price sensitivity, the disparity between it and the RAP implies that an increase in revenue is still possible. Prices below €1.88 (OPP) may attract fewer non-users. However, higher revenues could be achieved as the higher price is still acceptable albeit expensive for a smaller proportion of non-users. The same principle applies to the IDP of €2.42. Non-users who perceive the price of a 30-minute e-bike rental as expensive may be less inclined to choose this option in case of inclining prices. Conversely, non-users who consider the price as “cheap” are even more likely to select it in case of rising prices. The PSM results of non-users for a 30-minute e-bike rental can be retrieved from Fig. 4.

A comparison of the WTP for a 30-minute e-bike rental among users and non-users of BSSs reveals a marginal difference, with users demonstrating a slightly higher WTP compared to non-users (MEP: €2.95 versus €2.85). Nevertheless, the range of acceptable prices for non-users (RAP: €1.40 – €2.85) is broader than for users (€1.98 – €2.95). Additionally, the lower price boundary, defined as the MDP, is lower for non-users (€1.40) than for users (€1.98). Variations also exist with respect to the OPP and the IDP. Users of BSSs exhibit a greater level of IDP compared to non-users. While 32 % of the users perceive a price of €2.90 as a fair deal, an equivalent share of non-users (31.5 %) perceive a price of only €2.42 as a fair deal. The same effect is observed for the OPP. At a price of €1.99, an estimated 94.0 % of existing users are likely to accept the price, whereas for non-users (90.6 %) to accept the price it would need to be lowered to €1.88. It is noteworthy that both users and non-users exhibit price sensitivity towards a 30-minute e-bike rental, albeit within differing price ranges. Table 6 presents a summary of the data obtained from the PSM measurement of BSS users and non-users for a 30-minute e-bike rental.

5.2. DCE-based WTP calculation of BSS users

As outlined previously, we employed the data collected from the SP experiment to estimate a MNL mode choice model. For the sake of a simpler method comparison, this model contains only the attributes from the experiment design as well as alternative-specific constants. Using this model, we constructed representative mode choice scenarios for calculating the revenue-maximizing price as well as the e-bike market share contingent on its corresponding rental price. The result of these calculations is displayed in Fig. 5 and Fig. 6 respectively.

In scenario 1, the categorical attributes of the e-bike are worse than those of PT and ES. I.e., if the e-bike alternative is chosen, no cycling infrastructure will be available, while a favourable cycling infrastructure could be used if the ES is chosen and PT is only lightly used by other travelers and thus not crowded. In this scenario, the maximum revenue per traveller, i.e. per BSS-user faced with the choice between e-bike, ES and PT, is equal to 0.82€ and achieved at a price of 2.08€ (see Fig. 5). Both price increases and reductions will reduce the revenue per traveller, although the revenue function is right-tailed, which can be attributed to the probabilistic nature of the logit model in which the probability to choose a certain alternative (and thus, the revenue per traveller for prices >0€) will never

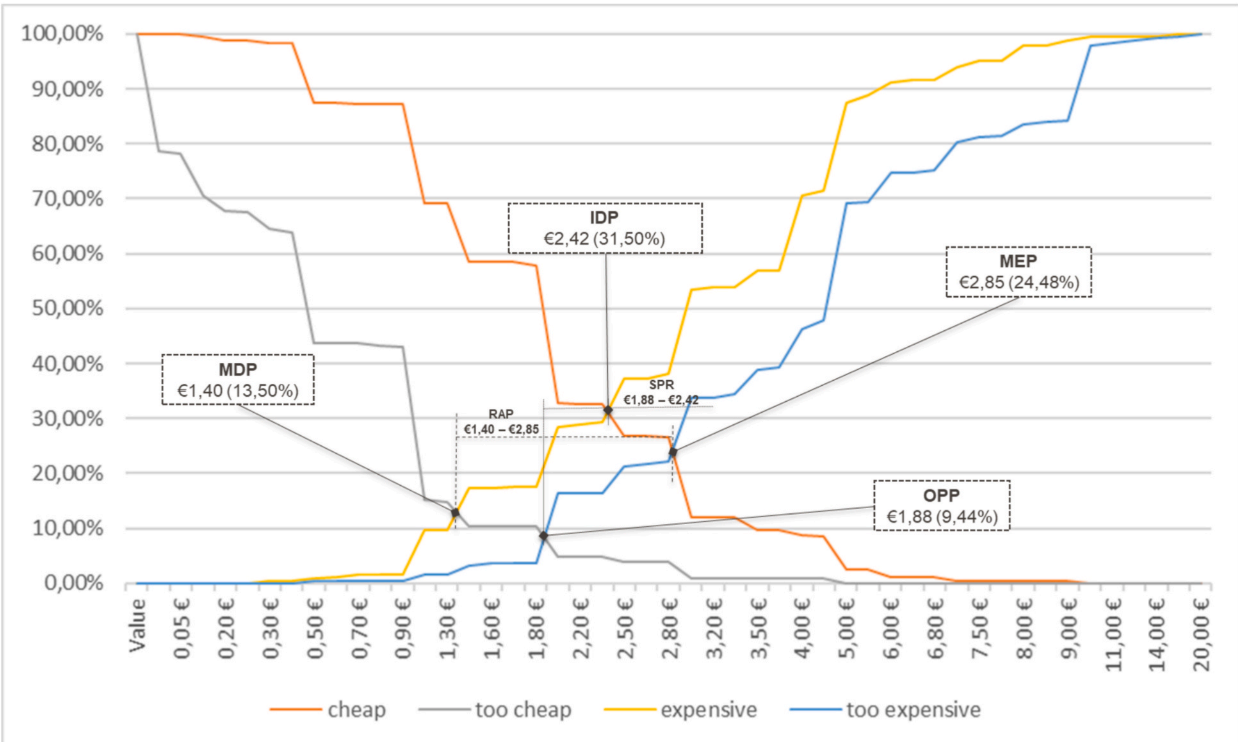

Fig. 4. WTP of non-users of BSSs towards 30 min rental of an e-bike (PSM measurement).

Table 6
WTP of BSS-user & non-user towards 30 min rental of an e-bike (PSM measurement).

	Optimal price (OPP)	Indifference price (IDP)	Stress price range (SPR)	Point of marginal cheapness (MDP)	Point of marginal expensiveness (MEP)	Range of acceptable prices (RAP)
User	€1.99 (6.0 %)	€2.90 (32.0 %)	€1.99 to €2.90	€ 1.98 (10.0 %)	€2.95 (23.5 %)	€1.98 to €2.95
Non-user	€1.88 (9.4 %)	€2.42 (31.5 %)	€1.88 to €2.42	€1.40 (13.5 %)	€ 2.85 (24.5 %)	€1.40 to €2.85

Source: Authors.

be zero. The probability of choosing the e-bike, dependent on an e-bike price between €0 and €10 as depicted in Fig. 6, follows the s-curve typically observed in logit models. Travelers appear to react most sensitively to price changes in the price range between €0 and roughly €4. Given an e-bike price of €0, roughly 75 % of travellers will choose the e-bike, although this share decreases to 50 % if the price increases to €1.5. The e-bike share further decreases to 25 % if the price doubles again and is reduced to 10 % for a price of roughly €4. Going from this point, the e-bike share keeps decreasing towards 0 % with increases in price, although the functional form of the decrease and the ever-remaining choice likelihood are shaped by the mathematical formulation of the logit model.

In scenario 2, meanwhile, the e-bike is also provided with a favourable cycling infrastructure, while ES also offers a favourable cycling infrastructure and PT is only lightly used by other travellers. In this scenario, the maximum revenue per traveller, 1.05€, is achieved at a price of 2.31€ per ride. Given a price of €0, roughly 80 % to 85 % of travellers tend to choose the e-bike. This share decreases to 75 % percent for prices of €0.70. The strongest price sensitivity seems to be present for prices between €0.70 and €5. Going from €0.70 to €2,1, the e-bike share decreases from 75 % to 50 %, and further to 25 % for prices of €3.50. For prices of €5, the share is decreased to 10 %, further decreasing towards 0 from there on.

In scenario 3, only the e-bike is provided with a favourable cycling infrastructure, while ES is not provided with any cycling infrastructure and PT is crowded. In this case, the optimal revenue per traveller, 1.38€, is achieved at a price of 2.65€ / ride. An e-bike price of €0 will lead to a predicted share of 90 % of users. If the price is increased to €1.40, the e-bike share will only decrease to 75 %. Further doubling of the price leads to an e-bike share reduction of another 25 percentage points, finally arriving at a share of 25 % percent given a price of €4.20. The e-bike-share falls under 10 % only for prices of €5.50 and above.

Comparing the scenarios, it is apparent that, in each scenario, the price points of the 25 %, 50 % and 75 % shares always seem to be apart roughly €1.40. However, the baseline is shifted, with accepted price differences of €0.60 between scenarios 1 and 2 and €0.70 between scenarios 2 and 3. As expected, the scenario in which the quality of e-biking is superior to that of using PT or ES consistently offers the highest user shares for the e-bike, while the other scenarios offer lower user shares.

5.3. Comparison of PSM- and DCE-based calculations

To enable a comparison between PSM and DCE WTP measurements, we posit that respondents in both approaches make their choices among alternatives based on a utility function that incorporates factors beyond price alone. WTP derived from PSM asks respondents to specify a particular price point that, when combined with the remaining, implicit utility of the alternative, would result in their perceiving the alternative as too cheap, expensive, or otherwise. In DCEs, however, the relevant attributes of the alternatives – including price – are specified explicitly, leading to the choice of a specific alternative based on their combination. WTP derived from MNL models represents MRS, indicating the amount of attribute A (such as monetary value) that equates in utility to a corresponding amount of attribute B. Nevertheless, these values do not provide information about the perceived worth of an alternative solely based on its price attribute.

When examining the optimal e-bike price points calculated based on the revenue forecast by the MNL, all optimal price points fall within the stress-price range as determined by the PSM. This may reflect the circumstance that the PSM leaves the assumption of infrastructural quality and similar attributes of the considered product up to the imagination of the respondent – leading to variation in stated price preferences – while the DCE is based on explicitly specifies the alternatives' attributes. As the PSM does not specify a revenue-maximizing price point, it unfortunately cannot be directly compared to the revenue-maximizing price forecast by the MNL. However, the overlap with the stress price range allows the assumption that the stress price range provides a good indication of the range that the revenue-maximizing price should be situated in.

An examination of the e-bike market share distributions derived from the MNL modelling and the PSM measurement results (among users of BSSs) reveals intriguing parallels between the OPP and the price point corresponding to a 50 % BSS market share in the equal quality scenario. As per the PSM, the OPP can be interpreted as a penetration pricing strategy, aiming to reach the largest possible user audience. Based on the price sensitivity derived from the stress price range within the PSM measurement for BSS users, 94 % of respondents would be willing to pay a price of €1.99 for BSS usage. The MNL model demonstrates that market share experiences a sharp decline as prices rise. In the equal quality scenario, a market share or choice probability of 50 % for choosing or not choosing the e-bike is given at a price of €2.07. This indicates that, at the specified price, respondents are as likely to choose the e-bike as they are to choose an alternative mode of transportation. MNL model results also show the probability of choosing an e-bike in the equal scenario lays between 25 % and 50 % for a pricing range of €3.46 – €2.07. The conclusiveness of this range is evident through its correspondence with the IDP of €2.90, which 32 % of BSS-using respondents would be willing to pay.

Nevertheless, the findings from MNL modelling and PSM diverge, particularly when examining lower price boundaries. Whereas

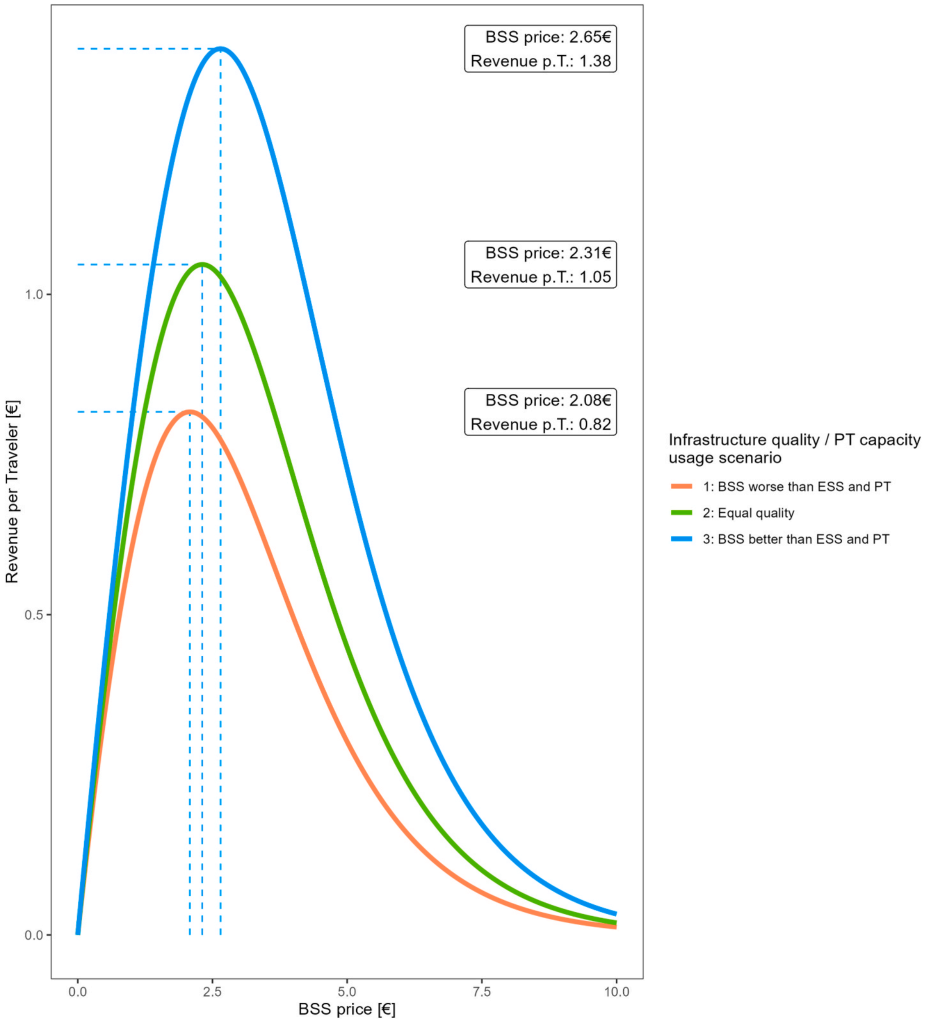

Fig. 5. Revenue-maximizing price points predicted by the MNL model.

PSM indicates a price acceptance rate of 90 % at €1.98, MNL modelling posits a lower probability (75 %) to choose an e-bike rental at much lower prices (€0.68 in the equal quality scenario). This might be due to the linear modelling of the influence of price in the MNL model, whereas PSM explicitly considers non-linear thresholds like prices being "too cheap", but also due to the fact that accepting a price is not necessarily equal to perceiving BSS as the best alternative. When considering other facets of PSM or the allocation of market shares, comparisons become even more indirect. Given that the PSM OPP corresponds to the location of a point of "maximal competitiveness" within the MNL model, it is plausible to expect that the PSM RAP will align with the range encompassing varying market shares (e.g. 25 % to 75 %) in the equal quality scenario. This does not hold true, however, as the PSM RAP for BSS users (€1.98 – €2.95) can roughly be compared to the price range in which shared e-bikes have a market share of 55 % to 35 % in the MNL equal quality scenario. PSM estimates price acceptance rates from 90 % at €1.98 to 23.48 % at €2.95.

These mismatches may be both a result of a lack of similarity between the behaviour measured by the PSM and by the MNL model or due to the nature and the constraints of the MNL model and of the PSM. In fact, decision making always depends on processed information (Grüner, 2024), which is different for PSM and DCE measurements. Further methodological differences between PSM and DCE will be discussed in section 7.

6. Discussion

This research explored the willingness to pay for shared e-bikes as an emerging mode of transportation. We have assessed WTP of users and non-users of BSSs in order to enable addressing different segments with our findings. We employed two distinct methodologies to assess WTP: Van Westendorp's PSM and DCEs, whose results we analysed using an MNL model. This approach aimed to investigate the influence of WTP measurement techniques on reported WTP values. Furthermore, we sought to identify the potential advantages and disadvantages of the aforementioned methods.

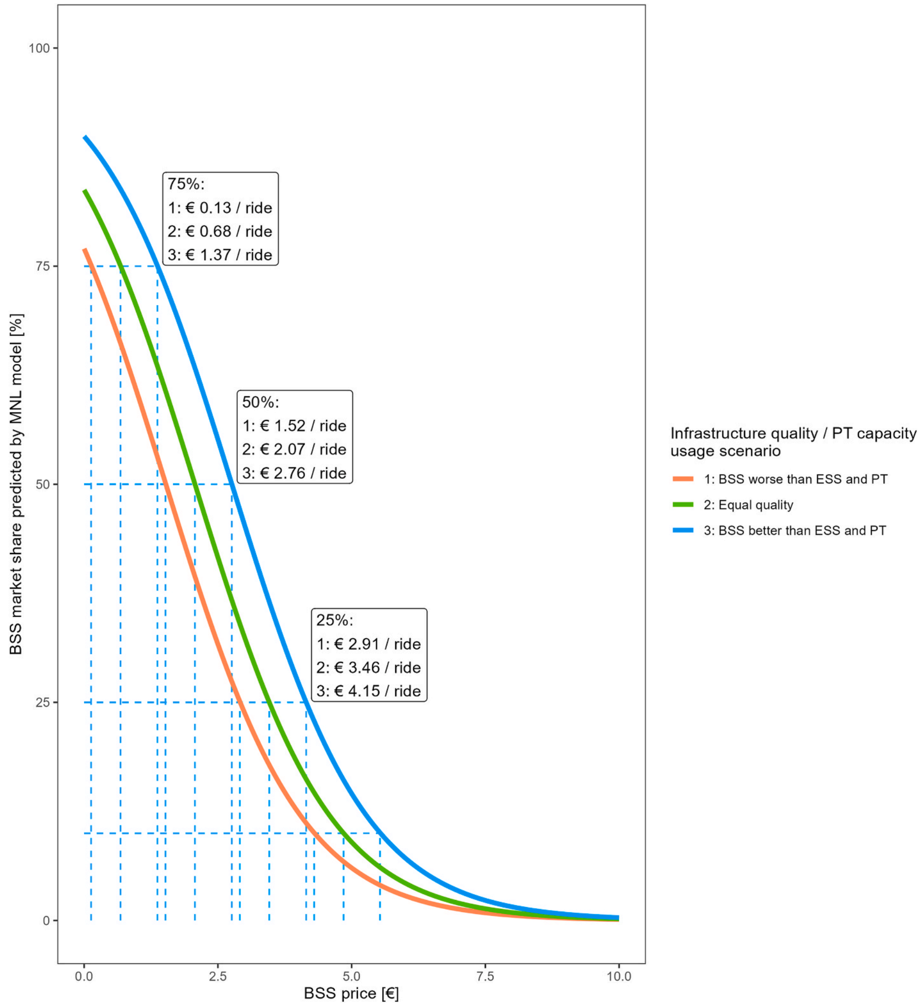

Fig. 6. BSS market shares depending on BSS price predicted by the MNL model.

Given the available data, the investigation of WTP for a 30-minute e-bike rental among both users and non-users of BSSs was conducted solely using PSM. Our measurements indicate a minor disparity, with users exhibiting a slightly greater WTP than non-users (MEP: €2.95 compared to €2.85). Nonetheless, a wider spectrum of prices is acceptable for non-users (RAP: €1.40 – €2.85) compared to users (RAP: €1.98 – €2.95), whereas the lower price boundary (MDP) is lower for non-users (€1.40) than for users (€1.98). Especially the latter finding reveals a disparity in evaluations of shared e-bike programs. Users who have prior experience with BSSs tend to express concerns regarding its assumed reliability and quality (based on how low the price is) sooner than non-users, potentially due to their awareness of existing shared bike pricing models. Variations are also present concerning the OPP and the IDP. Users of BSSs demonstrate a higher IDP than non-users. A price of €2.90 is accepted by 32 % of users, while a similar proportion (31.5 %) of non-users is likely to accept only a lower price of €2.42. The OPP exhibits a similar effect. An estimated 94 % of users are likely to accept a price of €1.99, whereas 90.6 %of non-users would require a lower price of €1.88.

After defining several market scenarios, we used a MNL model created on the basis of SP DCE data to predict e-bike market shares relative to e-bike prices and to predict revenue-maximizing price points. Of the three utilized scenarios, one assumed that e-bikes were inferior in quality compared to ES and PT, one scenario assumed equal quality and one scenario assumed that e-bikes were superior in quality. In the inferior scenario, maximum revenue was achieved at a price of €2.08 per ride, while the revenue-maximizing price points in the equal and superior quality scenario were €2.31 and €2.65 respectively. Analyzing the results, we found that, in each scenario, there is a price difference of roughly €1,4 between the points where the e-bike has market shares of 25 %, 50 % and 75 %. Further, we found shifts of the market share distributions of roughly €0.60 between the scenario in which e-bikes are inferior and the equal quality scenario and €0.70 between the equal quality scenario and the scenario where e-bikes are superior. All market share distributions followed the s-curve functional form typically observed in MNL models. The MNL modelling results show a strong sensitivity of the users to the e-bike price, leading to strong changes in the e-bike market share. Furthermore, the market share of shared e-bikes is higher than the market share of conventional shared bikes.

Considering the available data, the compared WTP estimates derived from the PSM and DCEs (analysed using MNL models) included solely users of BSSs. Our investigation revealed both similarities and disparities. Measurements are essentially the same regarding the OPP (PSM) and an estimated market share of 50 % or a point of maximum competition (MNL models, given that e-bike sharing is equal in quality to other modes of transportation, i.e. equal quality scenario). Findings indicate that 23.5 % to 94 % of current BSS users accept prices between €2.95 and €1.99. MNL modelling results also indicate that the probability of renting an e-bike falls within the range of 50 % to 25 % for a pricing range of €3.46 to €2.07 in the equal quality scenario. The correspondence of this range with the IDP of €2.90 appears conclusive although the mode share (expectably) differs from the price acceptance rate. Nevertheless, comparing other price points and the RAP presents a greater challenge. We observe notable differences for lower mode share/price acceptance thresholds, spanning from €0.68 (75 % mode share in the equal quality MNL scenario) to €1.98 (90 % price acceptance according to PSM). Additionally, the RAP is difficult to compare. PSM calculates a price acceptance rate from 23.5 % to 90 % within the price range of €2.95 to €1.98. The market share calculated by the MNL model derived from our DCE ranges from 55 % to 35 % for similar price points in the equal scenario. However, it is apparent that the revenue-maximizing prices of all three MNL scenarios lie within the SPR derived from the PSM.

7. Conclusion, policy implications and outlook

In conclusion, a direct comparison of WTP values derived from a MNL model and those obtained using the van Westendorp PSM is not readily apparent. Within the PSM framework, participants face a hypothetical scenario where most attributes of the proposed product or service are unspecified. They are solely prompted to indicate price thresholds at which they would perceive the product as too cheap, cheap, expensive, or too expensive. Consequently, it is assumed that respondents have a genuine desire to consume the product (or, in the context of transportation, use the specific mode of transport), and that price is the only determinant of their willingness to do so. Within the context of DCEs, participants typically encounter multiple scenarios where they must select from a range of alternatives with multiple clearly defined attributes. The attributes of the alternatives can be offsetting and are not the only factors influencing the choice, as additional random variation is assumed. Moreover, the attributes of the alternative options differ across various scenarios. Thus, differences in WTP estimates may be caused by differences in the assumed choice behaviour applied by both techniques, including the choice situations respondents are confronted with. Furthermore, differences may also be ascribed to the mathematical properties of the different methodologies. For example, MNL models using simple, i.e. linear-in-parameters utility formulations are not able to reproduce nonlinearities such as alternatives being perceived as “too cheap”.

However, even though there are notable differences between the approaches and the results of both methodologies, the WTP values or price recommendations extracted from each method are similar enough to assume that both methods are broadly measuring the same WTP. Thus, the PSM approach, which is much simpler than the DCE approach and thus much less costly to execute, may be used both to substitute DCE approaches for quick recommendations for transportation pricing or to provide an additional perspective into the pricing of large transportation projects.

Optimal pricing for shared e-bikes based on the PSM should be guided by strategic goals. When aiming for market penetration, a price between €1.88 and €1.99 should be selected. Nevertheless, at a price of €1.88, the primary target audience for BSSs consists of non-users, while current users might be hesitant to transition to e-bikes due to concerns regarding quality. To maximize revenue, a price between €2.42 and €2.90 (IDPs) should be selected. The selection criteria are influenced by the target audience, as the IDP for non-users is lower than for users. Given the existing user base, recruiting non-users as users could yield greater long-term profitability, based on whether the new users’ price perception changes over time. A higher pricing strategy is generally recommended to reflect the distinction between standard shared bikes and shared e-bikes. As indicated by the IDPs and the MEPs, shared e-bikes demonstrate the potential to enhance utility and generate willingness to pay.

Future research should consider confounding variables influencing WTP to facilitate a more nuanced understanding and enable targeted outreach to specific groups. Such variables may include sociodemographic factors like age and gender. Research indicates that the predominant user base for BSSs comprises younger males (Wang, Huang and Dunford, 2019; Reilly, Noyes and Crossa, 2020; Reilly, Wang and Crossa, 2022), suggesting a market opportunity to target new demographic groups, including females and older users, with e-bikes. This potential arises from the prospect of e-bikes offering specific value propositions to those currently not using BSSs. The resolution of distinct reservations held by non-users regarding the shortcomings they perceive regarding simplicity of system use, successful path accomplishment, straightforwardness and non-bindingness, and flexibility (Grüner and Kowald, 2025) has the potential to shift their WTPs further towards the WTPs of users and their corresponding market shares. Additional moderating or mediating variables may include individual characteristics, such as car ownership, spatial considerations, or sociopsychological factors, such as environmental attitudes or self-efficacy. Given that users of BSSs exhibit greater environmental consciousness and self-efficacy than non-users (Chen, 2019), an examination of the moderating role of pricing in this context is warranted. Research focusing on non-users of BSSs holds paramount importance, given that they constitute the majority of the population.

Alongside data-based analyses, methodological advancements for investigating WTP are recommended as well. The elimination of 24.2 % of responses, owing to their lack of logical coherence, suggests potential difficulties among respondents in addressing the PSM questions. One reason for this may be that the distinctions between some items are not consistently clear. A significant number of records dropped out of the survey due to the equal rating assigned to "expensive" and "too expensive". This suggests that respondents had already indicated their maximum willingness to pay for the item "expensive", and logically, anything beyond that should be considered "too expensive". Research endeavors should consider a potential attrition rate of 25 % when determining sample size. Future studies may enhance the questioning technique employed in PSM by deducing certain values rather than acquiring them directly. A potential approach involves exclusively inquiring the items "too expensive" and "too cheap", while calculating intermediate values as the means of the intermediate quantiles.

Considering DCE WTP, the circumstance that nonlinearities such as prices being "too cheap" suggests further experimentation using choice models with different error and utility formulations to further explore similarities between choice modelling and PSM. This experimentation should also include introducing both deterministic (i.e. interactions) and random (i.e. coefficients modelled as realizations of a random distribution) heterogeneity into the MNL model utility formulation, although the result comparison will inevitably become more complicated if more complex MNL model specifications are employed.

Besides considering alternative choice modelling approaches, future research should also consider alternative approaches to compare choice modelling results to PSM analysis results. Such studies could transform the abstract utility of alternatives into price equivalents (i.e. rescale the utility using the price parameter) and analyse the difference in monetarized utilities between situations where e-bikes were chosen and situations where e-bikes where not chosen.

8. Institutional review board statement

The studies were conducted in accordance with the Declaration of Helsinki, and the survey was approved by the data security official of RheinMain University of Applied Sciences

9. Informed consent statement

Informed consent was obtained from all subjects involved in the study.

CRediT authorship contribution statement

Hauke Reckermann: Writing – original draft, Visualization, Methodology, Formal analysis, Writing – review & editing, Conceptualization, Data curation, Investigation. **Sebastian L. Grüner:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – review & editing. **Matthias Kowald:** Writing – review & editing, Investigation, Conceptualization, Methodology, Funding acquisition, Supervision, Formal analysis.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

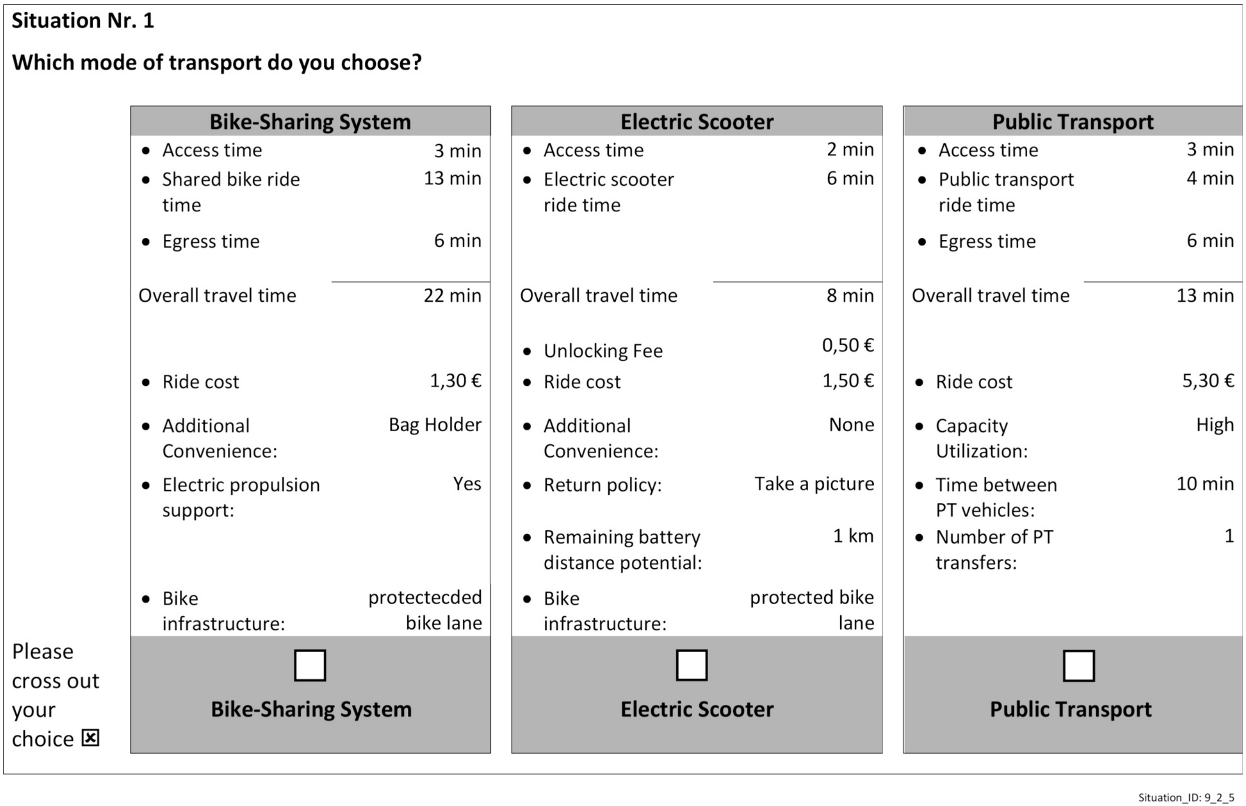

Fig. 7. Exemplary questionnaire DCE

Table 7
. Choice model estimation results.

Attribute/Interaction	Coefficient (robust t-ratio)		
	BSS	**ES**	**PT**
ASC	0 (NA)	0.164 (0.364)	−0.429 (−0.932)
Access/egress time [min]	−0.114 (−3.453)	−0.285 (−4.087)	−0.038 (−1.198)
Ride time [min]	−0.110 (−7.651)	−0.146 (−7.018)	−0.086 (−6.394)
Trip cost [€]	−0.791 (−8.861)	−0.741 (−11.348)	−0.599 (−12.014)
Additional conveniences (ref.: none)			
Smartphone holder	−0.095 (−0.839)	0.055 (0.48)	–
Bag holder	0.104 (0.851)	–	–
ES return policy (ref.: none)			
Take a picture	–	−0.029 (−0.206)	–
Chain the ES	–	−0.352 (−2.194)	–
Electric propulsion support	0.333 (3.393)	–	–
ES remaining range [km]	–	0.001 (0.902)	–
Cycling infrastructure (ref.: none)			
Bike lane	0.609 (2.892)	0.223 (0.863)	–
Protected bike lane	0.43 (2.374)	0.132 (0.601)	–
Bike path	0.453 (2.491)	0.412 (1.757)	–
Utilized PT vehicle capacity (ref.: medium)			
High	–	–	−0.305 (−1.687)

(*continued on next page*)

Table 7 (*continued*)

Attribute/Interaction	Coefficient (robust t-ratio)		
	BSS	ES	PT
Overloaded	–	–	−0.582 (−3.057)
PT service each [x] minutes [min.]	–	–	−0.031 (−3.476)
Number of PT transfers	–	–	−0.109 (−0.881)

Data availability

Data will be made available on request.

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