A latent class approach to investigate user preferences and willingness to pay for Smart Technologies. Evidence from five European countries

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SHORT SUMMARY

Despite the potential benefits of smart bicycle technologies in improving cyclists' safety, research on cyclists' attitudes and willingness to pay is missing. This paper is the first to examine cyclists' preferences and willingness to pay for smart bicycle technologies to enhance safety and aims to shed light on their development and adoption. Data from a stated choice survey with 1235 participants from five European countries was analysed. A latent class choice model (LCM) was used to seek random heterogeneity using explanatory variables, such as sociodemographic characteristics, safety-related factors, and geographic areas. Two classes (technology cautious and technology prone) emerged from the LCM. Results indicate that there is a significant heterogeneity in preferences among people, which a number of variables can partially explain. Participants of this study are willing to pay an additional price of up to 200 € for advanced bicycle technologies to increase their safety.

Keywords: Bicycle technologies, Cycling and walking behaviour and design, Discrete choice modelling, Latent class choice model, Willingness to pay

1. INTRODUCTION

Cycling is flourishing worldwide, and its rapid increase is manifest (Buehler & Pucher, 2023). In Europe, the number of people who use bicycles has risen and will continue in the coming years due to the increasing living costs and the climate change-oriented tendency towards more sustainable mobility solutions (Buehler & Pucher, 2021; Schleinitz & Petzoldt, 2023; Shimano, 2022). Electric bicycles (e-bikes) are the new trend, and they overrun the bicycle market in many European countries, encouraging people to ride more and further thanks to motor assistance (Fishman & Cherry, 2016). However, in parallel to the increase in cycling, the number of bicycle crashes also increases, especially those involving e-bikes, although there is an ongoing reducing trend in the number of motor-vehicle crashes (European Transport Safety Council, 2020; Schepers et al., 2020; Swov, 2022).

In an attempt to increase cycling safety, comfort and reliability, a growing stream of research focuses on emerging technologies consisting of sensors, radars and advanced information and communication technologies (ICT) embedded in bicycles, mainly on e-bikes (Kapousizis et al., 2022; Oliveira et al., 2021). Even though safety-enhancing bicycle technologies are rapidly deployed in research environments, such technologies are not commercially available yet. Various reasons can affect their penetration and deployment in the market. The key elements are the users' acceptance and willingness to pay for smart bicycle technologies.

To address the critical knowledge gaps mentioned above, the objectives of this study are three-fold: 1) investigate user preferences and the willingness to pay for smart bicycle technologies enhancing cycling safety, 2) examine the role of different European countries, which vary in cycling culture, on preferences regarding the smart bicycle technologies, and 3) identify the socio-demographic variables that explain the sensitivities among users' preferences. For this purpose, a stated choice survey was conducted in five European countries, Austria, Belgium, Germany, Greece, and the Netherlands, to investigate users' preferences. To the authors' knowledge, this paper is the first study in the literature to investigate user preferences and willingness to pay for smart bicycle technologies with a large-scale European survey.

2. METHODOLOGY

The main core of this study was to capture people's preferences and investigate willingness to pay (WTP) for smart technologies to increase safety on e-bikes. For this purpose, a stated choice (SC) method was used to capture participants' choices among hypothetical alternatives to examine their preferences (Train et al., 2019). A web-based survey was conducted in five European countries-translated in five languages (English, German, Greek, Dutch and French), which was distributed in Austria, Belgium, Germany, Greece and the Netherlands, between November 2022 and January 2023. Countries were not selected randomly; on the contrary, they were chosen due to the varying quality of cycling infrastructure and cycling culture to understand users' perceived safety in different scenarios. The focus group of the survey comprised people who already use an e-bike or are willing to buy one. This group was chosen to collect more realistic results than asking people not interested in cycling. In total, 1235 responses were collected and the sample distribution can be found in Table 1.

Table 1: Sample

Variable	Austria	Belgium	Germany	Greece	Netherlands
Number of respondents	71 (6)	188 (15)	112 (9)	139 (11)	725 (59)
Gender					
Male	51 (72)	99 (53)	78 (70)	100 (72)	342 (47)
Female	17 (24)	87 (46)	33 (29)	38 (27)	371 (51)
Non-binary	2 (3)	0 (0)	0 (0)	0 (0)	4 (1)
Other/prefer not to answer	1 (1)	2 (1)	1 (1)	1 (1)	8 (1)
Age					
18-29	2 (3)	10 (5)	10 (9)	16 (12)	32(4)
30-39	13 (18)	24 (13)	14 (13)	29 (21)	80 (11)
40-49	10 (14)	26 (14)	16 (14)	44 (32)	72 (10)
50-59	23 (32)	35 (19)	36 (32)	34 (24)	153 (21)
60-69	18 (25)	60 (32)	29 (26)	16 (12)	201 (28)
>70	5 (7)	33 (18)	7 (6)	0 (0)	187 (26)
Education					
Low (high school or lower)	25 (35)	49 (26)	35 (31)	37 (27)	363 (50)
High (university or higher)	46 (65)	139 (74)	77 (59)	102 (73)	362 (50)
Average country income					
Below average	33 (46)	79 (42)	52 (46)	70 (50)	468 (65)
Above average	38 (54)	109 (58)	60 (54)	69 (50)	257 (35)

Numbers in parenthesis indicate percentage (%)

Stated choice design

The survey's main core was the SC experiment. Participants initially received a short introductory text for the aim of the survey. The survey was divided into three parts: 1) screening questions and mobility habits, 2) a short explanation and illustration of how an e-bike with smart technologies looks like with explanatory questions and the six hypothetical choice tasks, and 3) sociodemographic questions at the end of the survey.

This SC aimed to examine the trade-off among smart bicycle technologies investigated by Kapousizis et al. (2022). Since this study aimed to calculate the WTP for smart technologies enhancing cycling safety, we used four attributes with three levels each, except the cost, which had four levels. We consulted bicycle experts to set a realistic price range for these systems. Hence, the price scale used in this design ranged from 400 € to 1000 €.

An orthogonal experimental design was developed using the Lighthouse studio (Sawtooth Software, 2022). Each respondent received six choice tasks, consisting of two alternatives each and the opt-out choice (no choice). Table 2 presents the SC attributes and attribute levels.

Table 2: Attribute level for the CE

Attributes	Attribute levels
Assistance systems	Call emergency unit Automated call to the emergency unit in case of an accident.
	Automated call to your emergency contacts in case of an accident
	Smart navigation system (safe/comfortable routes)
Automatic speed adjustment systems	In busy streets, cycle paths, near schools, etc
	In high crash-risk locations (e.g. dangerous locations)
	To keep a safe distance from a vehicle ahead
Collision avoidance (warnings)	Vehicles/obstacles in front side
	Vehicles behind you (approaching dangerously)
	Blind Spot detector (left and right assist)
Cost	400 €
	600 €
	800 €
	1000 €

3. RESULTS AND DISCUSSION

The Apollo package (Hess & Palma, 2019) in R (R Core Team, 2023) was used to estimate the LCM. Table 3 presents the results LCM.

Class 1: Technology cautious. This class has a negative cost-utility of -0.0072, and most attributes are negative. This means that this class includes more cost-sensitive participants and a low preference for smart bicycle technologies. In detail, we found only two positive coefficients, smart routes, and collision avoidance blind spot, with the former attribute level having a higher coefficient (0.7450) and a significant t-ratio (4.5496) compared to the latter (collision avoidance blindspot) with a coefficient of 0.0093. The rest of the attribute levels have negative coefficients, with the automatic speed limit system being negative and significant at a high confidence interval level. This means the latter is the least preferred option among the other attribute levels.

Class 2: Technology prone. This class includes less cost-sensitive participants (-0.0013) and shows that all attributes have positive utilities, meaning participants in this class have a positive attitude toward smart bicycle technologies. In general, participants in this class have a higher preference for the technologies than participants in Class 1. In detail, we see that smart routes, collision avoidance rear-side, and blind spots have positive and significant t-ratios. Both collision avoidance systems have the highest utility in this class (0.2626 and 0.2627), while the assistance smart routes have a utility of (0.2446). Emergency call system, automatic speed limit and automatic speed risky areas systems are still positive but with insignificant t-ratio (below 1.96). Moreover, the cost is the only negative coefficient in this class with a high and significant t-ratio (-7.8445).

Table 3: Model estimation

	LCM Class 1			**LCM Class 2**		
	Coeff.	Rob. Std.err.	Rob. t-ratio	Coeff.	Rob. Std.err.	Rob. t-ratio
Assistance emergency unit	0 (ref.)		NA	0 (ref.)		NA
Assistance emergency call	-0.1329	0.0993	-1.3382	0.0328	0.0489	0.6716
Assistance smart routes	0.7454	0.1657	4.5496	0.2446	0.0629	3.8951
Automatic speed safe distance	0 (ref.)	NA	NA	0 (ref.)	NA	NA
Automatic speed limit	-0.3187	0.1386	-2.2990	0.0296	0.0553	0.5352
Automatic speed risky areas	-0.2391	0.1399	-1.7085	0.0805	0.0577	1.4450
Collision front side	0 (ref.)	NA	NA	0 (ref.)	NA	NA
Collision rear side	-0.0148	0.1055	-0.1408	0.0519	0.0511	5.1549
Collision blind spot	0.0093	0.1156	0.0808	0.2627	0.0565	4.6450
Cost	-0.0072	0.0004	-20.1834	-0.0013	0.0002	-7.7380
Choice component*Variables						
Constant	Reference Class 1			0.8857	0.4813	1.8403
Country level						
Austria				-0.2143	0.2717	-0.7889
Belgium				-0.0598	0.1781	-0.3357
Germany				-0.1390	0.2237	-0.6215
Greece				0.9906	0.2416	4.0994
Netherlands (ref.)				0 (fixed)	NA	NA
Sociodemographic						
Education (high)				-0.4863	0.1347	-3.6099
Income (high)				0.5472	0.1343	4.0739
Other variables						
Technology friendly				0.3224	0.1370	2.3528
Crash				-1.1207	0.4731	-2.3690
Class weight	52%			48%		
Parameters						25
Final Loglikelihood						-5815.76
Rho-square						0.285

AIC	11681.52
BIC	11854.29
Individuals	1235
Observations	7410

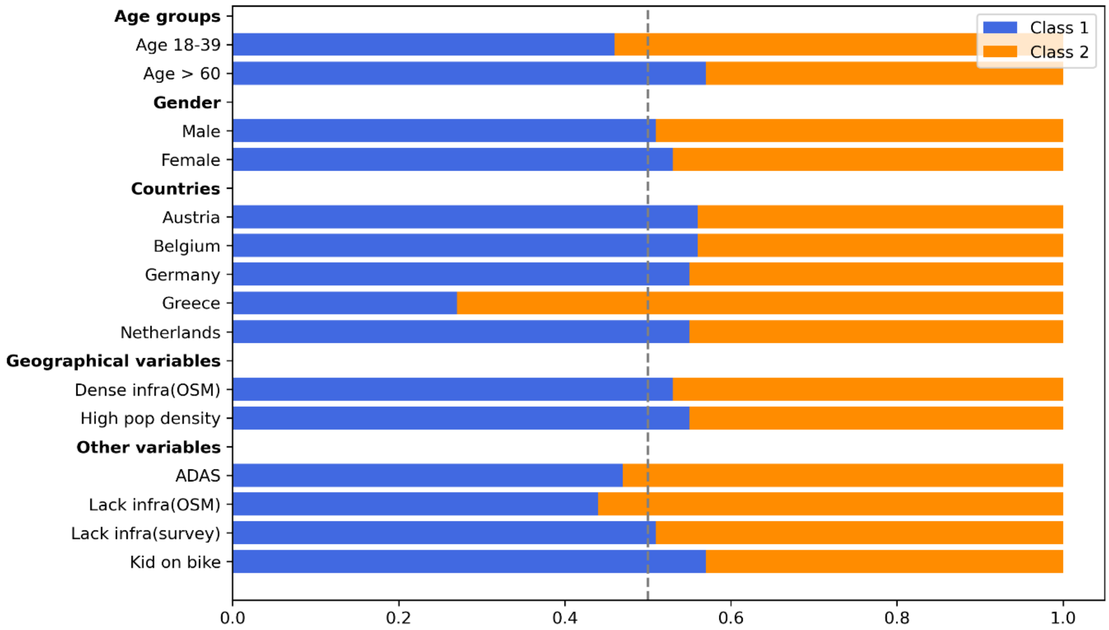
Furthermore, we calculated the posterior class analysis, which derived from the choices participants made and the sample- (Amaris et al., 2021; Greene & Hensher, 2003; Hess, 2014) and revealed further insights into the probability that a person belongs to a specific class. Figure 1 shows the posterior analysis and illustrates variations in the class allocation.

The posterior class allocation shows that 56% of the participants who belong to the age group between 18-39 fall in Class 2 – Technology prone, while the age group older than 60 falls by 57% in Class 1 – Technology cautious. This shows that the latter age group is more neutral toward new technologies. Regarding the gender effect on the posterior class analysis, we analysed males and females due to the low number of the other genders; we found that males and females have a higher concentration of Class 1 (51% and 53%, respectively).

Participants living in high-density areas are more likely to fall in class 1 by 52%. We also found that participants living in areas with the absent of cycling infrastructure are more likely to fall into Class 2 (56%), while those living in areas with dense cycling infrastructure are more likely to fall into Class 1 (53%). Note that we were able to estimate the level of cycling infrastructure based on the OSM network data since we asked participants for their 4-digit postal code.

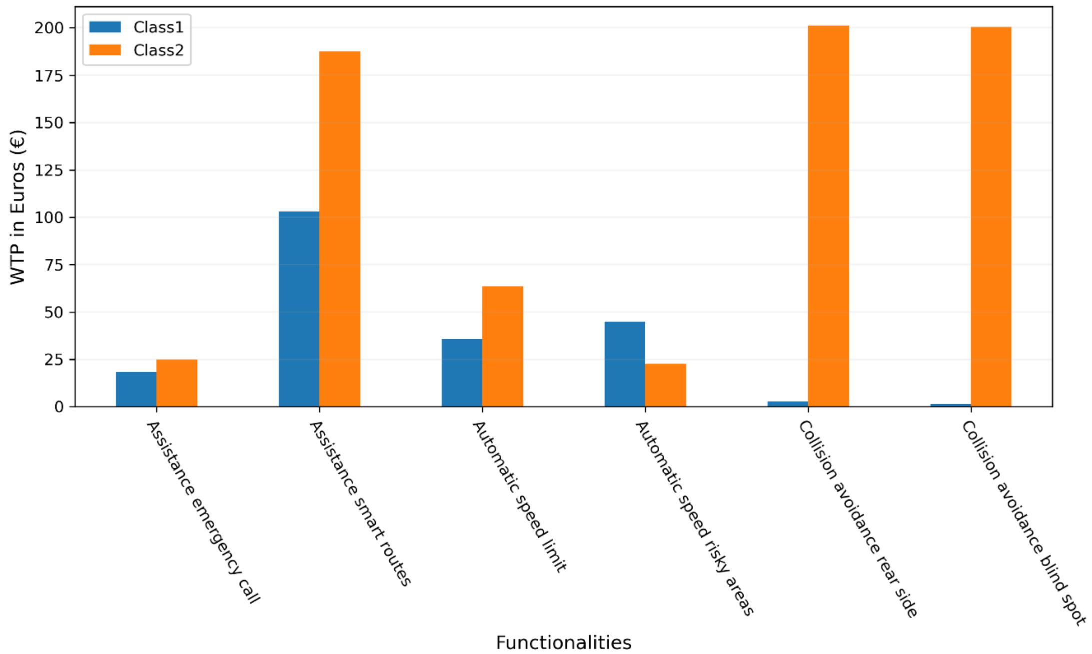
In addition, we calculated the posterior probability for other variables that were obtained from the survey. In detail, based on a Likert scale question, we asked participants to state whether they live in areas lacking cycling infrastructure, "Lack infra (survey)" and thus we estimated the perceived level of cycling infrastructure as well as the objective as we mentioned above, based on the OSM data. However, we found that participants' responses on this variable are almost equally distributed among classes, with a favour over Class 1 (51%). Participants who have used Advanced Driving Assistance Systems (ADAS) are more likely to fall into Class 2 (53%); participants who carry their children on a bicycle are more likely to fall into Class 1 (57%). Class 1 is considered cost-sensitive and less likely to favour advanced technologies since only smart routes show a high utility.

Figure 1: Posterior class analysis



It is apparent that Class 2 – Technology prone has mainly higher utilities, which is reflected in higher WTP for all functionalities compared to Class 1 – Technology cautious; thus, Class 2 has a higher expected WTP. More specifically, people who fall in Class 2 are willing to pay around 187 € for the assistance smart routes compared to only 25 € for the assistance emergency call. People in Class 1 are more likely to pay around 104 € for a smart route system and around 18 € for an emergency call system. Regarding the collision avoidance system, Class 2 has a higher WTP for the collision avoidance rear side and collision avoidance blind spot. Participants in this class are willing to pay around 201 € for each of those systems. However, participants in Class 1 are willing to pay around 2 € for a collision avoidance rear-side system and 1 € for a collision avoidance blind-spot system.

Figure 2: Willingness to pay



4. CONCLUSIONS

With the current trend towards sustainable mobility, cycling usage grows and more people are expected to use e-bikes for transportation. This will increase the kilometres ridden per person and lead to more crashes since people are unfamiliar, for instance, with the high speed of e-bikes. This study delves into the potential of cycling technologies to enhance e-bike safety and explores e-bike users' preferences and willingness to adopt such technologies. Notably, it presents novel findings regarding e-bike user preferences for safety-enhancing technologies, providing valuable insights for improving e-bike safety.

We estimated a latent-class model using a stated choice survey's data from five European countries with varying cycling rates, cycling behaviour, and cycling infrastructure. The results of this study contribute to the literature regarding bicycle technologies that can reduce crash risk. The main findings of this paper are summarised as follows:

- This study investigated people's opinions of smart bicycle technologies and found that there are indicators that smart bicycle technologies are perceived positively by an important portion of participants in this study.

- The Latent Class Model indicates two classes: Class 1 - Technology cautious, participants who do not have a positive attitude toward advanced technologies, and Class 2 - Technology prone, participants with a higher preference for advanced technologies.
- WTP for smart bicycle technologies showed significant differences between the two classes, with participants falling in Class 1 willing to pay up to 100 € and participants falling in Class 2 up to 200 €.
- Heterogeneity can partially be explained by linking sociodemographic, geographical, and other variables, such as the participants' technology friendliness and safety-related questions, to the class allocation.

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