Rethinking Mobility: AI-Based Pricing Systems To Promote Fair Mobility Participation In Cities

Madeleine Neumann
EBS University
Sarah Selinka
Baden-Wuerttemberg Cooperative State University Stuttgart
Vanessa Reit
Cooperative State University Baden-Württemberg (DHBW Stuttgart)
Sinu Thirukketheeswaran
Toulouse School of Management
Marc Kuhn
Baden-Wuerttemberg Cooperative State University Stuttgart

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Abstract

The study examines AI's role in pricing shared mobility services and its potential to promote fair mobility in urban areas. Urbanization exacerbates social inequalities, limiting mobility access for disadvantaged groups. AI-driven systems, such as shared autonomous vehicles (SAVs), are seen as solutions for enhancing accessibility and sustainability. This study explores how socio-demographic factors and social constructs like inclusion and participation influence AI pricing. Survey data from 89 German respondents reveals income, number of children, caregiver status, age, and travel purpose significantly impact pricing, while inclusion and participation have no effect. Higher income and age increase prices, while caregiving and more children reduce fares. These findings indicate AI prioritizes demographic data over nuanced social equity measures. Future research will use simulations to refine AI models and assess public acceptance of socially oriented pricing systems.

Keywords: AI-driven Mobility Pricing, Social Equity, Shared Autonomous Vehicles

Track: Social Responsibility & Ethics

1. Introduction

The ongoing urbanization leads to increasing social segregation and marginalization of certain population groups (Yue et al., 2024). Socio-economically disadvantaged people, who often have less access to mobility services, are particularly affected (Guzman et al., 2017; Hidayati et al., 2021). This unequal participation exacerbates social inequalities in urban areas (Van Ham et al., 2021). The introduction of AI-supported, shared mobility services, such as SAV, is seen as a solution to make mobility more efficient (Garikapati & Shetiya, 2024; Mahrez et al., 2022) and promote sustainability (Munhoz et al., 2020). Research emphasizes that the transformative potential of AI for building a more inclusive and equitable society is significant if we focus on equality, social justice and human welfare in the development and implementation of AI (Farahani & Ghasemi, 2024). On the other hand, there is research that highlights that, the use of AI algorithms may further reinforce social inequalities, for example, by learning and perpetuating existing biases from historical data, applying models inaccurately across different contexts, and lacking standardized ethical evaluations, all of which can unintentionally disadvantage marginalized groups (Ferrer et al., 2021). But how does AI currently make decisions? Do the underlying structures that trained the AI truly ensure that marginalized groups are granted greater participation, for example, through a pricing model for the use of a mobility service adapted to social circumstances? And if so, what characteristics lead to certain groups being offered a lower price for mobility use? The aim of this work is to investigate the relationship between social data and the decisions of AI in urban mobility, as these factors could significantly influence the distribution of mobility services and their pricing. This paper therefore deals with the question of which social characteristics should be given particular importance in the context of AI-controlled pricing for shared mobility services. The theoretical background is therefore first discussed below, with a focus on the exploratory nature of the study. This is followed by a description of the survey method and the presentation of the regression results. Finally, the results are discussed, limitations are pointed out and the need for future research based on this explorative preliminary study is presented.

2. Background

With AI-facilitated mobility, social inclusion and participation become increasingly important, as intelligent technologies could not only enhance access to mobility services but also create opportunities for social engagement and participation across all segments of the population, particularly for disadvantaged and mobility-impaired individuals. Hidayati et al. (2021) highlight how mobility inequalities result from a combination of intrinsic (individual attributes such as income, gender, and age) and extrinsic (socio-cultural) factors. Regarding socio-cultural factors that can influence mobility inequalities, social inclusion and participation appear to be interesting influencing factors.

Social inclusion describes the process by which individuals gain access to essential resources and opportunities for full participation in social, cultural, and economic life (Davlembayeva et al., 2020). Social participation refers to the active involvement of individuals in societal activities, enhancing their sense of belonging, self-efficacy, and self-worth (Berger et al., 2020).

Research on sharing economy platforms has shown that these systems could promote social inclusion by facilitating access to key resources, helping users achieve satisfactory living standards through community integration (Davlembayeva et al., 2020). Curtis et al. (2020) seek to deepen the understanding of how sharing platforms impact society, arguing that while the sharing economy theoretically promotes social inclusion, the actual mechanisms to achieve this goal are not yet fully understood. Although these studies have made significant progress in exploring the general impact of the sharing economy, there remains a gap in understanding how shared mobility services, such as car sharing and ridesharing, specifically address social inequalities and promote broader social equity.

Socio-demographics are generally identified in research as an influencing factor for mobility use and participation (O’Driscoll et al., 2024). This research therefore takes numerous socio-demographic variables into account. Of particular interest are those that can be an indicator of whether a person may be socially disadvantaged. Specifically, these are, for example, the variables household size, age, number of children in the household, income, caregiver status, educational and occupational background.

These and the previously described constructs of social inclusion (Davlembayeva et al., 2020) and social participation (Berger et al., 2020) serve as key factors for us to investigate the current decisions of an AI in relation to the pricing of shared mobility services.

3. Methodology

The research was designed as an exploratory, impact orientated analysis. A questionnaire was developed and distributed online to a sample of the German population. In addition to the socio-demographic aspects, the constructs of social inclusion (Davlembayeva et al., 2020) and social participation (Berger et al., 2020) were operationalized using 12 and 5 corresponding items respectively. An overall index was then calculated for each construct based on the individual assessment of the items using a 5-point Likert scale (see Appendix).

After the completion of the field phase, the dependent variable of the potential mobility price was generated by using a two way approach in python. First, the data from the online survey, containing each respondents' data was automatically extracted, decoded and transformed and stored in an initial prompt file. A prompt is a text-based query, especially used for the communication with large language models, such as GPT-4 (Ekin, 2023). We followed the current best practices for prompt engineering for creating the prompts (Ekin, 2023). After the first step, the initial prompt file was then processed through the GPT-4 API to analyze the social profile of each respondent through the AI. GPT-4 was chosen as a large language model due to its extensive language understanding capabilities for psychological constructs (Demszky et al., 2023). Afterwards the potential mobility price was determined. This price represents the dependent variable of the experiment and is analyzed and evaluated in the further course of the study.

4. Results

The quantitative data was analyzed with Jamovi 2.3. The basis of the data analysis is a sample of 89 test persons (78.8% female, 21.2% male). The average age is 36.31 years.

A linear regression was used to evaluate the research question (s. Table 1). The regression is based on 80 data sets. All requirements of the regression were tested (outlier analysis, multicolinearity, normal distribution, linearity, autocorrelation) and are fulfilled. The model test with total price of a shared autonomous shuttle as dependent variable and different sociodemografic factors as predictors is significant with $F(33, 46) = 6.823$, $p < 0.001$, the adjusted R^2 is = 0.709.

As assumed, there is a significant influence on pricing by AI for some influencing factors. Interestingly, the social constructs entered have no influence on the AI's price decision. The factors income, number of children, reason for mobility, caregiver and age are the factors that appear to have a significant influence on the AI's price decision, in order of strength of influence.

The higher the income of the test person, the more expensive the journey. The more children a person has, the cheaper the ride is offered by the AI. For important and urgent reasons, the journey is more expensive than for normal appointments or reasons. The effect is particularly interesting for people who care for another person. These people have to pay less for the journey than people who are not carers. The older the person, the more the AI charges for the journey.

Predictor	Est.	SE	t	p	Stand. Est.
Intercept	-7.483	5.810	-1.288	0.204	
Gender:					
male - female	0.808	0.876	0.922	0.361	0.181
Formal School Graduation:					
Secondary School - Basic School	3.320	2.914	1.139	0.260	0.743
High School Diploma - Basic School	2.391	2.730	0.876	0.386	0.535
Formal Vocational Training:					
Vocational Training - No vocational train.	3.553	2.783	1.277	0.208	0.795
University Degree - No vocational train.	0.980	2.873	0.341	0.734	0.219
PhD - No vocational train.	-1.132	3.152	-0.359	0.721	-0.253
Current Occupational Status:					
Part-time - In Education	-0.676	3.125	-0.216	0.830	-0.151
Full-time/Self-employed - In Education	-2.211	3.192	-0.693	0.492	-0.495
Unemployed - In Education	-0.819	3.835	-0.213	0.832	-0.183
Retired - In Education	-2.296	4.283	-0.536	0.594	-0.514
Marital Status:					
Married/Registered Partnership - Single	0.614	1.008	0.609	0.546	0.137
Widowed - Single	-5.633	3.170	-1.777	0.082	-1.261
Divorced - Single	-2.940	3.014	-0.976	0.334	-0.658
People in Household:					
2 - 1	1.406	1.142	1.231	0.225	0.315
3 - 1	0.643	2.560	0.251	0.803	0.144
4 - 1	2.762	2.324	1.188	0.241	0.618
5 or more - 1	3.343	2.962	1.129	0.265	0.748

Number of Children:					
1 - 0	-2.845	2.791	-1.019	0.313	-0.637
2 - 0	-6.738	2.990	-2.254	0.029	-1.509
3 or more children - 0	-8.960	3.627	-2.471	0.017	-2.006
Children Living in Household:					
yes - no	3.469	2.834	1.224	0.227	0.777
Caregiver:					
yes - no	-3.305	1.130	-2.925	0.005	-0.740
Disability:					
yes - no	0.987	2.191	0.450	0.655	0.221
Member of a (non-profit) association:					
yes - no	-0.081	0.728	-0.112	0.912	-0.018
Travel Reason:					
Important reason - normal reason	3.067	0.974	3.150	0.003	0.687
Urgent reason - normal reason	5.127	0.985	5.205	< .001	1.148
Income:					
25.001-50.000 € - up to 25.000 €	4.727	1.657	2.853	0.006	1.058
50.001-75.000 € - up to 25.000 €	6.038	1.523	3.965	< .001	1.352
75.001-100.000 € - up to 25.000 €	10.881	1.853	5.873	< .001	2.436
over 100.000 € - up to 25.000 €	12.198	2.186	5.580	< .001	2.731
Age (years)	0.228	0.074	3.068	0.004	0.549
social_participation_avg	0.426	0.749	0.569	0.572	0.063
social_inclusion_avg	-0.263	0.605	-0.436	0.665	-0.045

Table 1*: Results of regression with the total price of a shared autonomous shuttle as dependent variable and different (sociodemografic) factors as predictors.*

5. Discussion

The primary aim of this study was to find out which or whether social participation and social inclusion, in addition to classic socio-demographic factors, have an influence on AI-driven pricing of shared mobility services. Interestingly, the two theoretical constructs, which are intended to give an impression of the social situation or the respondents' own perception of it, show no significant influence. This finding suggests that the AI may prioritize quantifiable and structured data, such as income levels and household composition, over subjective measures. This raises the question of the extent to which current AI systems are able to integrate softer, more nuanced indicators of social context. The situation is different for some socio-demographic variables, which can also be seen as indicators of social circumstances. The issue of having children seems to be of particular importance for AI. Interestingly, however, it does not matter whether the children also live in the same household. The pure size of the household, which is presumably related to the number of children in many cases, does not appear to be a decisive factor either. Caring for relatives, on the other hand, again has a significant effect on the price model. The implicit idea of 'taking care' in the case of having children and caring for relatives seems to be a factor for AI that entitles users to be offered a socially assisted ride more favorably than others. Existing income, on the other hand, is perceived as a clear factor by the AI that a person has to pay more the more he or she actually earn. Age is also a highly significant influencing factor on price modeling by AI, suggesting that it recognizes financial capacity as a justification for differential pricing. This reinforces the perception of the AI as a tool for progressive pricing, which might aim to balance affordability and revenue optimization. According to the model, the prices demanded rise with increasing age. This is interesting, because from a social perspective it could have been assumed that lower prices would be offered for older people, e.g. with regard to being a pensioner.

6. Conclusions and further research

The present work is a preliminary study. It has been shown that some influencing factors have a significant impact on the AI-generated pricing of the mobility offer of interest. Contrary to expectations, factors social participation and inclusion do not appear to make a significant contribution to the pricing of a mobility service by AI. For the further process, it must be examined which other factors could be significant in addition to socio-demographics. It must also be evaluated whether the measurement methodology for social participation and inclusion may have been decisive for their non-significance. Based on the knowledge gained, the influencing factors will be investigated further as part of a simulation study. The aim is to make a socially oriented mobility offer tangible with the help of a driving simulator and to research the acceptance of AI-generated pricing by the test subjects. This step is important because the existing landscape is mainly based on pure surveys or scenarios that are to be evaluated by test persons (Cloarec et al., 2022; Yigitcanlar et al., 2019). However, it has already been shown that direct experience is important to consider the barriers to acceptance in AI technologies (Hong, Nam und Kim 2020). To overcome these barriers, comprehensive simulation environments can be used to investigate the holistic perspective of AI in a wide variety of fields of action, such as

AI-driven pricing of shared mobility services. Compared to this preliminary study, even greater attention must be paid to ensuring that the sample is as representative as possible of the German population. For this case men are over-represented in the sample. A balanced relation between women and men is desirable for future research. Furthermore, the characteristics of age and income should also be better addressed in further work.

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Appendix

Table 1: Constructs and Items

Construct	**Items (5-point Likert scale)**
Social Inclusion (Davlembayeva et al., 2020)	I have more than enough money to always afford enough food.
	I have unrestricted access to high-quality childcare and general care facilities.
	I can easily take out a loan of any amount at any time.
	I have unrestricted access to all public services at all times.
	I have full access to first-class healthcare.
	I can get any medical help I need immediately and without waiting.
	I can easily afford all transportation costs at any time.
	I have unrestricted access to all community facilities.
	I am fully and completely economically active.
	I have unrestricted access to all financial services at all times.
	I have unrestricted access to all available educational opportunities.
	I have access to all available transportation at all times and everywhere.
Social Participation (Berger et al., 2020)	I have the feeling that I am part of our society.
	I have an influence on how our society develops.
	I make a valuable contribution to our society.
	I feel well integrated in the social environment outside my family.
	I feel connected to the region in which I live.