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AI Applications in Transportation and Equity: A Survey of U.S. Transportation Professionals

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Abstract: This paper reports on a study investigating transportation professionals' perceptions of AI's equity impacts in the transportation sector, focusing on demographic variations in views. A survey conducted among U.S. transportation professionals examined their attitudes toward AI's potential to influence transportation equity and ethics. The findings reveal insights based on gender, employment sector, educational background, and AI knowledge level, with notable differences in confidence towards AI's ability to reduce bias and engage communities. This research highlights a commonly held opinion that there is a limited understanding of AI ethics within the transportation community, emphasizing the need for ongoing education and adaptation to AI technologies. This study contributes valuable perspectives to the discourse on AI, equity, and ethics in transportation, offering a foundation for future policy and strategy development.

Keywords: transportation; AI; equity

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1. Introduction

Artificial intelligence (AI) is increasingly becoming an essential component of our everyday existence, revolutionizing numerous sectors including healthcare, marketing, banking, and transportation. The U.S. Department of Transportation Intelligent Transportation System (ITS) Joint Program Office published a report in July 2020, in which they identified 60 applications that use AI in the field of ITS [1]. These applications are divided into 11 categories, which range from advanced driver assistance systems to asset management and cover different aspects of transportation that have an impact on the lives of nearly all travelers [2]. Furthermore, AI technologies are expected to be capable of effectively handling operational changes and transportation requirements in various practical situations, including metropolitan arterial networks, multimodal corridors, and underprivileged neighborhoods [3].

Due to their relative novelty, the ability of AI systems to enhance transportation objectives and improve outcomes remains uncertain. While AI systems have the potential to enhance overall transportation systems for communities and travelers, there are concerns that AI may worsen current transportation disparities due, for example, to potential bias in training data resulting from human error in data mislabeling (Abduljabbar et al. 2019) [4]. As the transportation sector moves forward, it will be confronted with questions regarding the advantages of AI, the difficulties of its deployment, and the ethical ramifications that emerge. These conversations are currently taking place in other disciplines, such as those utilizing facial recognition, as well as within the wider scientific community. For instance, a recent study carried out by *Nature* among researchers revealed that scientists are experiencing both enthusiasm and apprehension over the growing utilization of AI technologies in research [5]. Over 50% of the participants held the belief that AI has improved the efficiency of data processing and computing speeds, resulting in time and cost savings for researchers. However, more than half of them voiced apprehension about the potential for AI outcomes to perpetuate biases or discriminatory outcomes. The ambivalent sentiments conveyed by scholars in the study suggest that AI can potentially have both positive and negative consequences for the transportation sector. Although the implementation of AI in transportation is seen by some as having significant advantages, these applications can also raise ethical issues and give rise to unforeseen outcomes, such as exacerbating inequality.

While AI holds great potential to make transport safer, cleaner, more reliable, and more efficient, deploying AI to transform current transportation practices faces many challenges. A major concern is the issue of equity and ethics, considering that some existing AI applications such as facial recognition and résumé screening have shown high levels of bias. So far, while extensive research efforts are devoted to incorporating ethical and equity considerations into the design and development of AI systems, limited research has focused on the equity implications of deploying AI technologies across sectors. In the field of transportation, AI-enabled applications may lead to inequitable outcomes despite good intentions. For instance, a data-driven, AI-informed roadway maintenance decision-making procedure can cause the road infrastructure in disadvantaged neighborhoods to receive fewer investments; this happens when a lack of data results in a lower ranking of transportation facilities that are less well maintained, which are more commonly found in marginalized communities. Also, AI-based decision-support systems can lead to policies and decisions that leave out the needs of certain population groups if they are underrepresented in the data used to support decision-making.

The current AI applications in transportation primarily stem from technology developers and early adopters who possess a greater openness to innovation and a keen interest in exploring the capabilities of new technologies. Some recent consumer surveys suggest that over half of Americans harbor skepticism toward autonomous vehicles (e.g., [6]). Given that AI is widely employed in the transportation sector, it can be inferred that certain individuals have reservations regarding its implementation in this field. Nevertheless, there is little empirical research that illustrates the presence and magnitude of diverse perspectives on AI among transportation professionals, as well as the underlying factors contributing to these divergent ideas. A thorough investigation into these discrepancies is necessary for the transportation sector to better understand the obstacles that may arise during the adoption of AI technologies in the transportation industry. Furthermore, there is little evidence about the amount of AI knowledge among transportation professionals, their perspectives on the effects of AI on the transportation system, and their readiness and ability to utilize AI systems to revolutionize existing transportation methods. The implementation of such work is crucial since the perception of AI and its effects on efficiency and equity within the transportation profession will greatly influence the adoption of these technologies by transportation agencies, both in terms of timing and extent. The readiness of the transportation workforce to handle AI systems in real-world scenarios depends on their existing degree of awareness and knowledge about AI technology and applications in transportation.

In light of these research needs, our study primarily focuses on two research questions: (1) How do transportation professionals perceive the equity impacts of AI-enabled technologies in transportation? And (2) to what extent do these perceptions vary by the socioeconomic and demographic characteristics of the transportation professional? In pursuit of this objective, we surveyed transportation professionals in the U.S. We sought to gain insight into their views on the potential effects of AI in the field of transportation. The participants were requested to assess some attitudinal statements regarding fairness and ethical considerations for AI implementations in the field of transportation. In addition, the survey inquires about the respondents' familiarity with, and education related to AI, along with their sociodemographic characteristics. As far as we know, this is one of the first surveys conducted on this topic, and it represents the early phases of AI adoption in the transportation industry.

This paper presents the findings of a survey of transportation professionals regarding the anticipated equity impacts of AI use in transportation. This is a companion paper to an earlier work that applied latent class cluster analysis to segment survey respondents into distinct groups based on their latent attitudes toward AI [7]. In contrast to [7] factor analysis approach, the current paper evaluates responses to each equity-related statement separately to provide a more detailed understanding of transportation professionals' views on various aspects of AI's equity impacts. Specifically, we present a descriptive analysis of survey responses on equity-related statements along with an investigation of the associations between these responses and individual characteristics such as sociodemographics, education level, and AI knowledge level. The results shed light on the sociodemographic traits and attitudes among the professionals' perspectives as well as being helpful for policy and strategy development. These insights are particularly important for dealing with any resistance or uncertainty towards AI within specific sub-groups. Furthermore, the paper illuminates possible changes in views toward AI in the transportation industry as demographic dynamics progress.

1.1. Literature Review

The 21st century has witnessed the rapid development of new technologies across all sectors, with AI emerging as one of the most prominent. The transportation industry is no different, and there is immense potential for the implementation of AI in a wide range of roles. Key applications in transportation encompass several areas such as passenger decision support tools, transportation systems management and operations (TSMO), transit operations and management, and asset management. Traveler decision support solutions utilize AI to gather information about a transportation network [1] to assist travelers in planning itineraries that align with their specific requirements and preferences. Machine learning (ML) is a significant focus of research in this field [8]. ML is applied in several ways, such as enhancing trip time forecasts in Google Maps [9] and being utilized in airports to forecast congestion, analyzing air traffic control voice, and identifying anomalies in flight trajectories and taxiing [10]. TSMO pertains to the upkeep and enhancement of transportation infrastructure and operations, with an emphasis on non-expansion of capacity. On the other hand, transit operations and management is a component of TSMO that specifically concentrates on transit systems. Applications encompass incident localization and tracking, adaptive ramp metering for congestion management, signal synchronization, timetable optimization [11], route optimization [12], and fare enforcement. Asset management involves the maintenance of physical infrastructure to optimize and secure working conditions while managing expenses. Other applications range from the automation of train inspection to the detection of pavement conditions [13]. Table 1 provides a list of the topics mentioned in the literature review to illustrate the range of AI applications currently in transportation.

The utilization of AI in transportation systems represents numerous potential advantages. At the organizational level, advantages may include enhanced efficiency, reduced expenses, and reduced environmental impacts. Efficiency gains can be achieved through the implementation of dynamic scheduling algorithms [14], real-time route optimization [15], and value chain transformation using the physical internet [16]. The utilization of demand forecasting and response [4] as well as infrastructure monitoring [17] holds the capability to decrease operating expenses. Reducing traffic congestion [18] and decreasing the number of vehicles [19] can enhance environmental performance. Travelers can anticipate enhanced safety, improved accessibility, and increased convenience. Utilizing crime predictions [20] and adjusting to the road and traffic circumstances [21] could enhance the safety of public transportation. Computer vision-based collaborative traffic signal assistance [22], LiDAR-based infrastructure assessment [23], and haptic feedback technologies [24] can enhance accessibility. Ultimately, convenience can be improved by reducing waiting periods [25], improving pathways [26], and developing intelligent suggestions and guidance for tourists [27].

Table 1. Example AI in transportation topics.

Publication/Authors	Topics
Walker 2020 [1]	Assist travelers in planning itineraries
Derrow-Pinion et al., 2021 [9]	Enhance trip time forecasts in Google Maps
Tien 2022 [10]	Airport congestion forecasting and air traffic control
Muller-Hannemann et al., 2022 [11]	Incident localization and tracking, congestion management
Ge and Jin 2021 [12]	Route optimization
Tsai 2023 [13]	Detection of pavement conditions
Lv et al., 2021 [14]	Dynamic scheduling algorithms
Iyer 2021 [15]	Real-time route optimization
Nikitas et al., 2020 [16]	Value chain transformation
Abduljabbar et al., 2019 [3]	Utilization of demand forecasting and response
Okrepilov et al., 2022 [17]	Infrastructure monitoring
Hasan et al., 2019 [18]	Traffic congestion
Rigole 2014 [19]	Decreasing vehicle demand
Kouziokas 2017 [20]	Crime predictions
Boukerche et al., 2020 [21]	Adjusting to road and traffic circumstances
Yang et al. 2022 [22]	Computer vision-based collaborative traffic signal assistance
Ai and Tsai 2016 [23]	LiDAR-based infrastructure assessment
Boldini et al., 2021 [24]	Haptic feedback technologies
Yin et al., 2020 [25]	Wait time reductions
Adler and Blue 1998 [26]	Improving pathways
Tsaih and Hsu 2018 [27]	Intelligent suggestions and guidance for tourists

1.2. AI's Transportation Equity Concerns

While AI applications may have a wide range of advantages in transportation, there are concerns that they may also give rise to equity considerations. The primary goal of transportation equity is to ensure fair and equal access to social and economic opportunities for all communities and demographic groups [28]. A broad spectrum of socioeconomic disparities in transportation have been identified. Traditionally, transportation policy in the United States has shown a preference for the construction of highways rather than investing in public transit, resulting in a variety of adverse effects. In the 1950s and 1960s, highways were frequently built through minority areas as a means of "slum clearance" and "urban renewal" [29]. These projects caused disturbances in community life and persistently contributed to heightened pollution and compromised health in underprivileged populations. The construction of highways also promotes the expansion of housing in more distant areas from urban centers, hence intensifying residential segregation and income disparities. This resulted in a "spatial mismatch" of employment opportunities since positions located on the periphery of urban areas were unattainable for individuals residing in the city cores [30]. The unequal allocation of funds towards highways compared to public transit, coupled with imbalanced urban development, has resulted in limited alternatives to driving for many individuals [31]. Consequently, transportation expenditures account for a larger portion of low-income households' budgets compared to those with higher incomes. These are just a few examples of the numerous disparities that arise from past expenditures and the ongoing development of transportation policies.

The hope is that AI applications in transportation can improve the accessibility, fairness, dependability, and affordability of transportation services for historically underserved people [2]. Some examples of AI applications are AI-enhanced citizen engagement, AI-enabled routing and wayfinding systems for pedestrians, and AI-powered assistive robots for individuals with disabilities. However, instead of focusing on meeting the requirements of marginalized populations and specific demographic groups, the current AI applications in transportation mostly aim to improve driver assistance systems, reduce traffic congestion, and automate infrastructure assessments [3,15]). Furthermore, the primary focus of these AI applications is to enhance or substitute existing transportation methods, while neglecting the potential ethical consequences of AI implementation. Nevertheless, there is a possibility of discrimination in the development and implementation of AI systems, which poses a risk to specific population groups, particularly ethnic minorities [32]. AI-driven decision-support systems may result in policies and choices that disregard the requirements of individuals with disabilities if they are inadequately reflected in the training data utilized for AI models. Failure to adequately address ethical and equity concerns may result in AI technology meant to enhance transportation procedures and outcomes inadvertently worsening pre-existing inequities.

1.3. Transportation Professionals' Perception of AI

Currently, there is little research on the perceptions of professionals in the transportation industry on the potential and impacts of AI in transportation applications. The primary focus of research lies in understanding the public's perception of autonomous vehicles (AVs), a critical area of study within the field of AI and one of the most well-known AI applications in the transportation sector. [33] conducted a comprehensive analysis of research examining the public's acceptance and perception of autonomous vehicles (AVs). The findings indicate that older adults tend to hold a pessimistic view towards AVs, despite the potential benefits of enhanced accessibility for this demographic group. Additionally, males and individuals with higher levels of education exhibit more favorable attitudes toward AVs compared to females and those with lower educational attainment. A survey study conducted in Taiwan [34] investigated the level of societal readiness for AVs by surveying individuals who are AI experts or have a background in computer science or electrical engineering. While AI professionals acknowledged the beneficial effects of AVs on the mobility of disadvantaged populations, both groups considered social equity concerns to be of lesser importance and urgency compared to cybersecurity and data privacy issues. For example, a survey conducted among residents of Brisbane uncovered notable disparities in perceptions towards the advantages of AVs [35]. Young and middle-aged persons, individuals with impairments, and public transport users had favorable opinions; however, gender did not exhibit a significant association with attitudes toward AVs.

In the field of transportation, current AI applications are mostly utilized by a small number of individuals who were relatively quick to embrace the technology. However, for AI to be widely adopted in the transportation industry, it is necessary for a large share of transportation professionals to actively participate and embrace its use. Hence, it is crucial to comprehend the perception of the transportation profession regarding AI as the adoption increases despite numerous uncertainties. Without a comprehensive understanding of professionals' perspectives on the integration of AI in transportation, it becomes challenging to effectively strategize for shifts in the workforce, fully capitalize on societal benefits, or address equity concerns. To fill these gaps in knowledge, the survey results reported here seek to better understand the perceptions of transportation professionals regarding the possible utilization of AI in transportation, its advantages, and the potential fairness issues that may come from its implementation.

2. Data and Methods

2.1. Survey Design and Participant Recruitment

Our survey collected information on the perceptions of transportation professionals in the U.S. regarding the capabilities and potential consequences of AI. The survey questionnaire was categorized into four sections: respondents' assessment of the influence of AI on transportation, their proficiency and education in AI, their evaluation of the fairness and ethical issues related to AI, and their sociodemographic characteristics. The survey comprised a total of 23 questions, with 18 close-ended multiple-choice questions, 3 matrix table questions, and 2 open-ended questions. The first open-ended question prompted respondents to provide their ideas on the equality and ethics of utilizing AI in transportation, while the second open-ended question allowed for general comments. Given the vast nature of AI and transportation, the survey includes the following definitions to assist with clarity:

- *AI* pertains to procedures that allow systems to supplant or enhance mundane human duties or facilitate novel capabilities that are beyond human capacity. AI facilitates the capability of systems to (1) detect patterns, (2) logically process and evaluate data, (3) acquire knowledge from past encounters and adjust to new circumstances, potentially without human involvement, and (4) make determinations, communicate, and execute actions.
- *Transportation* primarily encompasses the strategic and technical methods employed to enable the efficient and effective transportation of individuals and commodities.

The survey was piloted with a small group of transportation experts, whose feedback refined the questions. We targeted transportation professionals from both public and private sectors. Specifically, we contacted state and local Departments of Transportation (DOTs), Metropolitan Planning Organizations (MPOs), and transit agencies across 48 U.S. states, focusing on leaders in research, planning, and civil rights, asking them to participate and share the survey. The survey was also promoted through the Travel Model Improvement Program (TMIP) listserv, Institute of Transportation Engineers (ITE) chapters, Transportation Research Board (TRB) committees, and the American Planning Association (APA). Notably, to promote broader participation, we reached out to all chapters of the Conference of Minority Transportation Officials (COMTO) and requested them to help with survey distribution. The survey ran from January to May 2023, collecting 359 responses, with 253 fully completed. Due to convenience sampling, a response rate could not be calculated, but the goal was to reach a diverse range of professionals.

2.2. Analytical Approach

Data preparation involved handling missing values and addressing responses such as "prefer not to answer" and "other, please specify" by either treating them as missing values or, occasionally, merging them with existing response options. We then recoded the survey responses to construct eight variables used to characterize each respondent: gender, age, race, knowledge level of AI concepts and technologies, household income, employment sector, educational background, and education level. All of the variables except for educational background are derived from multiple-choice questions.

Gender and educational attainment are binary variables. Age, knowledge level of AI concepts, and knowledge level of AI technologies are continuous variables. Respondents' AI knowledge was gauged by asking about their level of familiarity with a variety of AI concepts (including machine learning, deep learning, neural networks, and reinforcement learning) and AI technologies (including computer vision, natural language processing, robotic systems, and predictive analytics). The race variable was collapsed to include three categories: White, Asian, and other. Regarding the respondents' employment sector, we obtained three categories: for-profit private sector, government or public agencies, and other. The other category includes students, people working in non-profit organizations, and academia, which are grouped due to their small sample sizes. Finally, the educational background variable was obtained from an open-ended question: "What is the field of study for your academic degree(s) (e.g., Civil/Transportation Engineering, Urban Planning, Geography, etc.)?" Based on these responses, an "educational background" variable was constructed with three categories: urban planning, engineering (including civil/transportation engineering and other engineering degrees), and other (e.g., business, geography, and economics).

The first step in the data analysis examined the sociodemographic profile of survey respondents to represent the sample characteristics. Following this was a descriptive analysis of statements related to equity to investigate respondents' attitudes regarding various aspects of AI's equity implications. Finally, an ordered logit model was used to examine the relationship between socioeconomic and demographic factors and respondents' attitudes toward different aspects of AI's equity impacts. The dependent variables in the ordered logit model are the levels of agreement with ten statements (one model for each statement—see Figure 1). The level of agreement was rated on a scale from 1 to 5, with a score of 1 indicating strong disagreement, and a score of 5 signifying strong agreement. The nine variables discussed in the previous paragraph are used as independent variables in all models (the categorical variables were converted to binary variables first before model-fitting).

3. Findings

3.1. Sociodemographic Profile of Survey Respondents

Table 2 presents the sociodemographic profile of the survey respondents. About 66% of the respondents are male, and about 30% of the respondents are 30–39 years old, the largest age group in our sample, followed by people who are 40–49 years old (18%) and 50–59 years old (16%). The household income of the respondents in our survey sample is higher than the general population. Most respondents have a household income of $75,000 or more, and those having a household income of $150,000 or more constitute the largest income group. This likely results from our survey recruitment method as previously discussed which included individuals in leadership positions when reaching out to state and local transportation agencies. Most respondents are White or Asian, with White respondents comprising 59% of the sample. While extensive effort was devoted to engaging minority professionals (e.g., reaching out to all local chapters of COMTO), they remained underrepresented in our sample. The majority of respondents have a Bachelor's degree or above, with about 73% of respondents having a post-graduate degree (e.g., M.A., M.S., Ph.D., M.D., J.D.). Most respondents reported having low to moderate levels of knowledge of AI concepts and technologies. The respondents predominantly work in government or public agencies, representing 48% of the sample, followed by those employed in the for-profit private sector (26% of the sample). The primary educational backgrounds of the respondents are in engineering, comprising 59%, and urban planning, at 31%.

Table 2. Sociodemographic profile of survey respondents.

	N	Pct
Gender	271	
Male	178	65.68%
Female	77	28.41%
Race	282	100%
White	165	58.51%
Asian	49	17.38%
Hispanic or Latino	20	7.09%
Black	15	5.32%
Age	272	
18–24	7	2.57%
25–29	30	11.03%
30–39	81	29.78%
40–49	50	18.38%
50–59	43	15.81%
60–69	30	11.03%
70 or over	15	5.51%

Table 2. *Cont.*

	N	Pct
Household income	271	
Less than $25,000	9	3.32%
$25,000–$49,999	13	4.80%
$50,000–$74,999	19	7.01%
$75,000–$99,999	38	14.02%
$100,000–$124,999	43	15.87%
$125,000–$149,999	37	13.65%
$150,000 or more	73	26.94%
Knowledge of AI concepts (5 indicates the highest level)	279	
1	57	20.43%
2	84	30.11%
3	86	30.82%
4	39	13.98%
5	13	4.66%
Knowledge of AI technologies (5 indicates the highest level)	279	
1	84	30.11%
2	88	31.54%
3	69	24.73%
4	27	9.68%
5	11	3.94%
Employment sector	284	
Student	18	6.34%
Academia	36	12.68%
Government or public agency	136	47.89%
For-profit private sector	74	26.06%
Non-profit organization	11	3.87%
Educational background	258	
Urban planning	79	30.62%
Engineering majors	151	58.53%
Graduate degree	270	
Yes	196	72.59%
No	74	27.41%

3.2. Descriptive Results

As previously discussed, the survey contained 10 statements related to AI's expected equity implications (see Figure 1). Respondents were asked to indicate their opinion for each statement on a Likert scale ("strongly agree", "somewhat agree", "neither agree nor disagree", "somewhat disagree", and "strongly agree"). Statements S1 through S5 assessed the perceived equity impacts on transport, and statements S6 through S10 focused on ethical concerns regarding AI applications in transportation from the perspective of transportation professionals.

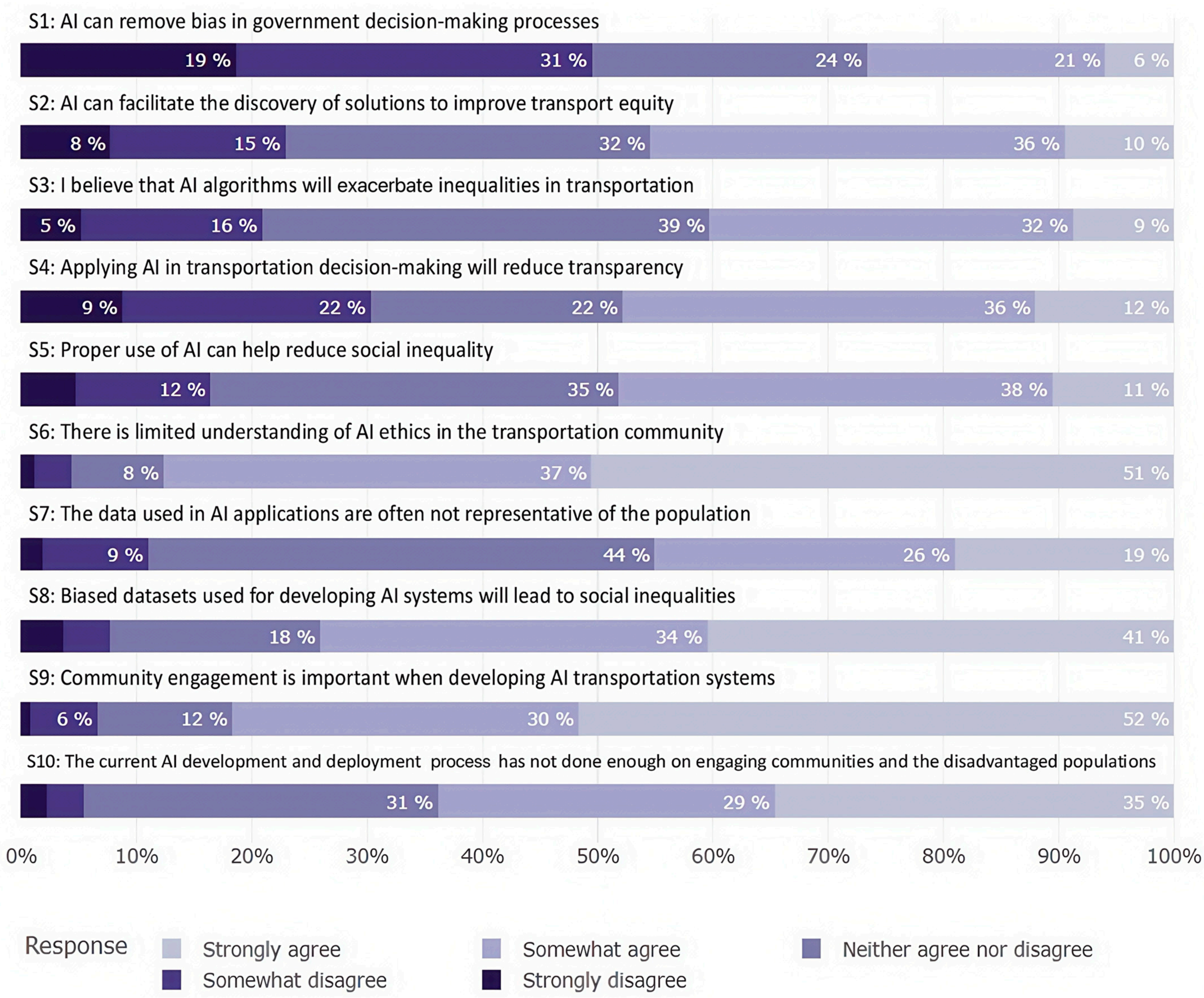

Figure 1. Survey responses on equity-related statements.

Survey results in Figure 1 show limited trust in AI's ability to remove bias in government decisions, with only 27% agreeing. Opinions on AI's role in improving transport equity are mixed: 36% somewhat agree, while 32% are neutral. Similarly, 41% believe AI will worsen inequalities, with 39% being neutral. Concerns over transparency also surfaced, as 48% agree AI could reduce it, while 30% disagree. Most respondents (over 80%) support community engagement in AI development, but 64% feel the current approach lacks sufficient input from disadvantaged communities. Additionally, 88% believe there is a lack of understanding of AI ethics, calling for more education. Data bias is a major issue, with 45% stating AI data are not representative, and 75% agreeing biased datasets could increase social inequalities. These findings highlight a cautious view on AI's potential, with strong calls for ethical use, community involvement, and better data practices to ensure fairness.

3.3. Modeling Results

In addition to the descriptive survey results, this analysis examined the role of demographic characteristics in attitudes towards AI in transportation equity. Table 3 shows the results of ordered logistic regression analysis. In our modeling, the dependent variable is the value assigned to each statement, which ranges from 1 to 5, representing a scale from "strongly disagree" to "strongly agree". Gender, employment sector, graduate degree status, race, and educational background are used as categorical or binary variables. Age and income are coded as numerical variables, starting from 1, with the number of levels consistent with those outlined in Table 2. The variable representing AI knowledge level is derived by summing the scores of 'knowledge of AI concepts' and 'knowledge of AI technologies', which is also treated as a numerical variable. The number of observations for the 10 models (each model corresponds to 1 of the 10 statements) ranged from 208 to 210 due to missing data in the dependent variable. In the analysis below, we will mainly focus on estimates at the 95% significance level (**), with estimates at the 90% significance level (*) serving as a reference.

Table 3. Outputs of ordered logit models.

Statement	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
Sample size	209	208	209	210	209	210	209	210	209	210
Female	0.713 **	0.488	0.074	0.016	0.337	0.0916	−0.297	0.168	0.78 **	0.044
Age	0.107	−0.145	0.037	0.077	−0.171	−0.004	−0.073	−0.16	0.080	0.104
Income	−0.002	0.030	0.024	0.098	0.036	0.070	0.070	−0.015	−0.078	0.024
Graduate degree	−0.790 **	−0.441	0.516	−0.016	−0.265	0.276	0.619 *	0.67 **	−0.212	0.665 **
AI knowledge level	−0.112	0.003	0.114	−0.060	0.247 **	0.043	0.122	0.042	0.075	0.085
Work: For-profit private sector	0.785 **	1.28 **	−0.365	−0.832 **	0.563	0.503	−0.706	0.115	0.13	−0.406
Work: Government or public agency	0.835 **	1.17 **	−0.458	−0.817 **	0.586	−0.066	−0.277	0.0144	−0.287	−0.455
White	−0.663	−0.59	0.435	1.12 **	−0.484	−0.308	−0.262	−0.211	−0.42	−0.403
Asian	0.253	0.156	0.576	1.44 **	−0.192	−0.666	−0.24	0.248	−0.278	0.688
Urban planning	0.262	0.082	−0.000	0.090	0.671 *	0.41	−0.184	0.504	0.372	0.496
Engineering	0.779 **	0.34	−0.504	0.212	0.473	−0.069	−0.164	0.0812	−0.326	−0.454

Note: * Significance at the 0.1 level, ** significance at the 0.05 level.

Apart from income and age, all other variables were significant in at least one statement. It is somewhat surprising that age has no significant influence on people's attitudes towards AI's equity impacts. Other analyses suggest that those with positive or neutral attitudes toward AI are, on average, younger than those with negative attitudes [7]. However, it is noteworthy that [7] examined not only respondents' attitudes towards AI's equity impacts but also their attitudes towards AI's efficiency impacts. Through further data analysis and modeling exercises, we found that age was significant in all statements about AI's efficiency impacts (see [7]) with negative coefficient estimates. Considered together, these results indicate that older adults tend to have more doubts about AI's efficiency impacts and their concerns for AI's equity impacts are not significantly different from other age groups.

The results of the survey also suggest that gender was significant in the two models. Females exhibited greater confidence in AI's ability to remove bias in government decision-making processes (S1). Moreover, females placed more emphasis on the importance of community engagement than males (S9). Interestingly, compared to other racial/ethnic groups, White and Asian respondents strongly believed that applying AI in transportation decision-making will reduce transportation (S4) compared to "other" respondents.

The two binary variables indicating those working in the for-profit private sector, government positions, or public agencies were statistically significant in three overlapping statements (S1, S2, S4), with consistent signs for the coefficient estimates. This means that individuals employed in the for-profit private sector and those working in the government or public agencies have similar attitudes toward the equity implications of AI use in transportation. Moreover, the signs of the three statistically significant coefficients further indicate that compared to students and people working in non-profit organizations or academic institutions, individuals working in the for-profit private sector or public agencies tend to hold more positive attitudes towards AI's equity impacts.

Moreover, those with graduate degrees had less confidence in AI's ability to remove bias in government decision-making processes (S1) and held a broad spectrum of ethical concerns (S7, S8, S10). One possible explanation could be that individuals with graduate degrees may have more exposure to the complexities of AI, which could lead to a more cautious perspective. Individuals with a higher AI knowledge level tend to have a stronger belief that the proper use of AI can help reduce social inequality (S5). Regarding educational background, the survey results suggest that those with an urban planning degree were more likely to believe that the proper use of AI could help reduce social inequality compared to other majors (S5). By contrast, those with an engineering background had more faith in AI's ability to remove bias in government decision-making processes (S1).

Finally, we find that no variables were significant in S3 (the belief that AI algorithms will exaggerate inequalities in transportation) and S6 (there is limited understanding of AI ethics in the transportation community), suggesting no significant differences in opinions across population groups. The results for S3 suggest that different population groups, on average, share similar degrees of concern for AI to exaggerate existing inequalities in transportation. For S6, it appears that there is a general consensus among survey respondents that the transportation community has a limited understanding of AI ethics.

Overall, the survey of transportation professionals revealed several key themes regarding their perspectives on AI, particularly in relation to equity and ethics in transportation. Respondents exhibited limited trust in AI's ability to eliminate bias in government decision-making, with only 27% agreeing. There was also a mixed response regarding AI's potential to address transportation equity: while about one-third of respondents expressed optimism, a similar proportion remained neutral or skeptical. A notable concern was that 41% of respondents believed AI algorithms might exacerbate existing inequalities in transportation. The survey highlighted a widespread belief that AI could reduce transparency in decision-making (48% agreed), but interestingly, about half believed that the proper use of AI could help reduce social inequality. Another important theme was the overwhelming support (over 80%) for community engagement in AI development, with 64% stating that current efforts are insufficient in engaging disadvantaged populations. Additionally, there was a consensus that the transportation community has a limited understanding of AI ethics, with 88% agreeing on the need for education and training. These findings suggest a general wariness about AI's equity impacts, emphasizing that the technology's outcomes are highly dependent on how it is developed and implemented, especially in terms of engaging communities and addressing data biases.

3.4. Qualitative Analysis of Open-Ended Survey Responses

The open-ended survey responses complement the quantitative results, offering a clearer view of how participants perceive the impact of AI on equity. The derived qualitative insights can help to contextualize and expand upon the core issues related to AI's development, implementation, and broader societal effects. The following key themes were identified from these responses:

- Lack of Preparedness and Technology Misuse: Respondents believe that the transportation community is not adequately prepared to properly apply artificial intelligence (AI). The use of AI in transportation systems should be approached with caution and should not be implemented solely for the sake of technology.
- Human Factors and Bias: AI systems are developed and designed by humans, which means they may carry the biases of their creators. This could reinforce inequality, particularly among vulnerable groups. AI developers and users need to be aware

of these biases, and work to remove them from the data and algorithms through enhanced engagement with underserved communities.

- Transparency and Data Integrity: AI applications require a high level of transparency and third-party auditing to ensure data integrity and reduce the risk of undesirable outcomes. Quality data input is crucial for generating fair and accurate outputs.
- Social Impact and Workforce Development: The introduction of AI may lead to job losses and wage stagnation, among other societal challenges. It is important to address the social consequences of widespread AI use, including how to help the transportation workforce adapt to a new AI era.
- Privacy Concerns: The use of AI may raise privacy and ethical concerns, especially when individuals feel they are being monitored or have lost control over the technology. Vulnerable groups may feel unsafe as a result.
- Public Oversight and Accountability: AI systems should be subject to public oversight to ensure they are not misused and do not harm the public interest.

4. Discussion

The survey results presented here examine transportation professionals' attitudes toward AI's potential equity. Surprisingly, age was not significant in influencing attitudes about AI's equity impacts, contradicting other analyses showing younger individuals generally have more positive or neutral attitudes. Gender differences were noted, with females showing greater confidence in AI's ability to reduce bias and valuing community engagement more than males. Ethnic differences revealed White and Asian respondents had stronger beliefs in AI's potential to improve transportation decision-making. Employment sector and educational background also influenced attitudes, with those in the for-profit and public sectors, and individuals with specific educational backgrounds, showing distinct perspectives on AI's ability to address equity and bias. Notably, no significant differences were found in concerns about AI exaggerating transportation inequalities or in the transportation community's understanding of AI ethics, indicating a consensus across groups on these issues.

In terms of what can be learned from the survey results, it is important to further explore the underlying reasons for the observed differences in attitudes toward AI, particularly along gender, ethnicity, employment sector, and educational lines. The gender differences, for instance, may stem from societal influences or differing experiences with technology in professional settings, while the ethnic differences could reflect broader patterns in technology adoption or historical disparities in access to resources. Additionally, the distinction between employment sectors and educational backgrounds may be driven by varying levels of exposure to AI applications or organizational priorities that either emphasize or downplay innovation and equity concerns. Understanding these dynamics could help transportation professionals tailor AI tools to better meet the needs of diverse stakeholders.

The consensus on concerns regarding AI exacerbating transportation inequalities and the shared understanding of AI ethics is also noteworthy. This indicates a baseline awareness of ethical issues in AI, which should serve as a foundation for the development of ethical frameworks within transportation. Expanding on AI's role in community engagement is equally crucial. Involving marginalized communities in AI decision-making can prevent reinforcing existing inequalities and ensure that the benefits of AI are distributed equitably. This approach requires a focus on organizational culture, as it plays a key role in fostering innovation and openness to AI integration. Organizations that promote a culture of continuous learning and openness may be better positioned to adopt AI effectively, which underscores the need for ongoing AI education and training. By addressing these elements, transportation professionals can better leverage AI to address equity challenges while fostering a more inclusive approach to technology adoption.

Additionally, an intriguing finding is that traditionally defined vulnerable groups, such as low-income and elderly populations, did not express greater concerns for AI's equity impacts compared to other groups. However, in the responses to open-ended questions, there is widespread concern for these groups. A plausible explanation is that traditional vulnerable groups may not yet be fully aware of the potential inequities to be brought about by widespread AI, possibly due to limited access to information or lack of knowledge. Thus, enhancing awareness of AI's broad impacts across sectors and across population groups is crucial for promoting broader participation in AI governance and inclusive AI deployment practices in transportation.

5. Conclusions

While there have not been extensive discussions on AI ethical frameworks in the transportation sector, the ongoing conversations about transportation equity and justice can inform how the transportation community should view AI applications. Historically, transportation investments in the U.S. have prioritized driving over alternative travel modes, and the goal of enhancing mobility (e.g., congestion mitigation) is often prioritized over enhancing access to destinations. Moreover, the transportation benefits and transportation-caused harms (e.g., air pollution) are not equitably distributed, with marginalized communities and population groups bearing disproportionate harms while enjoying fewer benefits. We believe that it is crucial to bring these perspectives into the development, design, and deployment of AI applications in transportation.

Second, identify potential AI applications that can address community transportation needs. Existing AI applications in transportation are mostly motivated by intentions such as improving existing data collection and modeling practices, reducing costs, and improving efficiency. AI technologies also have the potential to improve transportation equity by addressing pressing community needs. At present, however, few studies have conducted in-depth community engagement to examine what essential transportation needs can be fulfilled by AI technologies; to the best of our knowledge, the closest studies are those that focus on how autonomous vehicles can improve accessibility for disadvantaged communities and the public attitudes toward AI technologies.

Third, keep track of transportation professionals' knowledge of and attitudes toward AI applications in transportation. How the transportation community as a whole perceives AI and its efficiency and equity impacts will significantly affect whether and how fast these technologies are adopted by transportation agencies around the world. Building on this project, future research should seek to understand the factors influencing respondent attitudes toward AI beyond demographics and basic knowledge. Using qualitative methods like interviews or focus groups can reveal insights into skepticism or neutrality toward AI in transportation. Also, it is crucial to explore how different AI education programs may impact these attitudes and the role of organizational culture. Comparative analyses of transportation professionals from diverse backgrounds can uncover regional variations. As the transportation sector evolves, understanding how organizations can foster innovation while addressing employee concerns is vital. Experimental design can assess the impact of interventions like workshops on AI literacy. A comprehensive approach considering psychological, organizational, and cultural dimensions is essential for fully understanding AI acceptance in transportation and developing effective integration strategies.

The results presented here underscore the need for continued AI training and education in the transportation industry. The survey results also identify several important future research directions, including investigating data biases in transportation AI applications, identifying AI solutions for community transportation needs, and developing a practical guide for transportation professionals regarding using AI systems in transportation.

In comparing our study's findings with other research on AI adoption, several key patterns emerge. Consistent with studies by [36,37], we found that higher levels of AI knowledge led to more positive attitudes toward its adoption. Our survey results align with their findings, showing that transportation professionals with greater AI knowledge expressed higher confidence in its ability to reduce bias and improve decision-making. Gender differences were also evident, with women showing more skepticism toward AI, a pattern also reported by Horowitz and Kahn, who noted concerns about control and safety. Additionally, sector-specific attitudes were consistent with Zhang and Dafoe's findings, as public sector professionals in our study expressed different views on AI's equity potential compared to those in for-profit sectors.

Unique to our research, however, is the variation in AI perceptions based on ethnicity, with White and Asian respondents expressing more optimism about AI's potential in transportation decision-making. This distinction is less explored in other studies. Moreover, our emphasis on community engagement as a key factor in AI deployment sets our findings apart from prior research, such as that by [38], who focused more on technical aspects of AI implementation. These comparisons highlight the importance of sector-specific dynamics and demographic factors in shaping attitudes toward AI adoption in transportation.

Finally, future research can benefit from addressing several areas that may not have been fully captured in this survey. For instance, expanding the demographic and professional diversity of respondents could provide a broader understanding of perspectives on AI's equity impacts in transportation. The current survey, which focused on individuals from higher-income brackets and leadership roles, might be complemented by engaging a wider range of professionals, particularly those from underrepresented racial and ethnic groups, to gain more inclusive insights. Additionally, future studies could incorporate additional qualitative methods, such as interviews or focus groups, to further explore the reasons behind respondents' skepticism or neutrality toward AI. Exploring the role of psychological, organizational, and cultural factors in shaping attitudes toward AI could also be valuable. Finally, refining the assessment of respondents' AI knowledge, possibly through objective measures rather than self-reporting, could enhance the accuracy of findings. These directions would enrich our understanding and guide the effective integration of AI in the transportation sector.

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