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REVIEW

In the blind spot of AI-based mobility: eye-tracking visual attention to people with reduced mobility in autonomous vehicles and the ethics of inclusive design

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Abstract
As AI systems increasingly shape urban mobility futures, the principles of equity, diversity, and inclusion have become central to responsible design. While race, gender, and age have been extensively studied, people with reduced mobility (PRM) remain underrepresented in empirical research on AI and autonomous vehicles (AVs). This article addresses this critical gap by investigating how disability and intersecting social categories are perceived and attended to in the visual framing of AV from an ethical standpoint. Our aim is to understand how people cognitively perceive PRM in automated decision-making contexts, and what this reveals about inclusive AI-based mobility design. We conducted a large-scale online eye-tracking experiment ($N = 1272$) combined with a survey to assess visual attention toward PRM in AV. Results reveal that PRM are consistently overlooked in visual attention compared to other demographic categories. Cluster analysis identified three distinct profiles of perception: *High Disability Awareness*, *Adaptive Disability Evaluators*, and *Low Disability and Diversity Awareness*, the latter encompassing most respondents. These insights were validated in an in-lab experiment with data science experts. Despite broad endorsement of fairness, justice, and diversity as guiding values in AV development, actual gaze behavior suggests a disconnect between normative commitments and perceptual engagement. We argue that this "blind spot" in AI-based mobility reflects deeper ableist assumptions embedded in algorithmic perceptions and raises ethical concerns. To counter this, we call for inclusive, cross-sectoral advisory boards that include PRM communities, ensuring that algorithmic designs not only reflect diversity but ethically *see* it.

Keywords Disability · Diversity · Autonomous vehicles · Ethics · Inclusion · Eye-tracking

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1 Introduction

The rapid development of autonomous vehicles (AV) promises to revolutionize transportation and social participation for marginalized groups such as people with reduced mobility (Peña Cepeda et al. 2018; Yousfi et al. 2025). Yet, AVs raise profound social justice issues and ethical questions about who benefits and who is left behind in automated transport (Nyholm and Smids 2016; Dubljević and Bauer 2022). Ethics-focused scholarship on AVs has stressed the importance of engaging affected communities, identifying normative trade-offs, and embedding pluralistic societal values into design and policy (Gerdes and Thornton 2016; Jenkins et al. 2022; Cecchini et al. 2025). Despite these calls, disability—a key factor in mobility technology planning—remains overlooked in AI transport ethics. This study strives to fill this gap by mapping how people with reduced mobility (PRM) are perceived alongside other diversity categories

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in the AV context and the ethical implications. The goal is not simply to inform ethical technological development, but to uncover the underlying mechanisms through which social diversity, particularly PRM, is overlooked in automated decision-making, and to show how such mechanisms may support more just and fairer AI-based mobility design.

We approach disability from the social model, viewing barriers in the built environment rather than individual impairments as primary disabling factors. Although we use *people with disabilities* as an umbrella term,[1] our empirical focus is on PRM, specifically wheelchair users. Many studies have identified people with disabilities as a demographic facing significant social exclusion, largely due to mobility constraints (Barnes and Mercer 2005; Aarhaug and Elvebakk 2015; Peña Cepeda et al. 2018). Difficulties in accessing public transport rank among the most critical causes of this exclusion (Stanley et al. 2011; Aarhaug and Elvebakk 2015). While AVs have the potential to reduce these barriers (Hwang et al. 2020; Cordts et al. 2021), the shift to greater automation through artificial intelligence (AI) also risks deepening existing ableist paradigms if disability remains underrepresented in data and design. In addition, the AV perception systems face difficulties in visually recognizing different-sized and shaped objects in real-world environments (Wilson et al. 2019), which makes it even more crucial to understand how PRM are perceived in automated decision contexts.

Despite extensive work on algorithmic bias, a few studies examine PRM perceptions within AI-based mobility and the ethical implications of their exclusion. This study uses the term *AI-based mobility* to refer to the use of artificial intelligence in mobility infrastructure and mobility-system development, including, but not limited to, autonomous vehicles. The term is used to emphasize that contemporary mobility is increasingly mediated by AI-based infrastructures, data flows, and decision systems, which together shape how people move, interact, and are represented in automated environments (Kitchin 2014). Studies have revealed that AV control systems often struggle to recognize wheelchair users and individuals with characteristics that are underrepresented in training datasets (Whittaker et al. 2019). This lack of data diversity not only undermines the safety and reliability of AV systems but also reflects broader issues of exclusion that have long plagued urban design and infrastructure. Moreover, machine vision systems used in pedestrian detection have demonstrated biases—exhibiting lower accuracy when confronted with darker skin tones and female subjects (Buolamwini and Gebru 2018). These findings resonate with a persistent history of urban environments that overlook the needs of people with reduced mobility and marginalized communities (Kapsalis et al. 2024).

Beyond automated decision-making, AV deployment raises additional accessibility and equity concerns for people with disabilities. Questions remain about whether autonomous shuttles will provide adequate boarding assistance or wheelchair securement features that human drivers currently offer (Harper et al. 2016; Golbabaei et al. 2024). AV-oriented urban development may reduce walkability, active transport, and social interaction (Gehl 2001; Fishman et al. 2015). Scholars have also cautioned that the rise of AV systems may divert investment away from accessible public transit and create mobility systems that privilege individualized, automated travel over collective infrastructure (Wu et al. 2021; Stilgoe and Mladenović 2022). Furthermore, as AV systems increasingly rely on large-scale data infrastructures to regulate movement and allocate risk, questions of whose mobility is rendered visible, legible, and worth protecting become central to mobility data justice (Behrendt and Sheller 2024). These challenges are not only infrastructural but also stem from how social groups are perceived, as such perceptions influence both user behavior and the development of AI systems that mediate mobility.

Behrendt and Sheller (2024) underscore the need to consider the intersectionality of race, gender, sex, and disability in discussions of *mobility data justice* to ensure fair and inclusive technological design and policy, yet empirical research is scarce. We bridge this gap with a semi-experimental method—combining large-scale online eye-tracking with a survey (Author 1 et al. 2025), to assess how people visually and cognitively engage with PRM and intersectional diversity in the AV. As AV technologies become increasingly central to public infrastructure, it is crucial to examine how people perceive that their data, and its unique attributes, are reshaping our understanding of diversity, especially regarding the representation and experience of vulnerable groups like PRM in AI contexts.

Building on *mobile risk society* theory (Kesselring 2024) and calls on *ethical sociotechnical systems* (Dubljevic et al. 2021), we show that AV systems can both enhance accessibility and entrench new uncertainties for PRM by embedding ableist assumptions if not explicitly designed for diverse mobilities. By focusing on data subjects (Dalmer et al. 2024), individuals whose data feed AI systems and whose experiences and needs are directly impacted by AI-based

[1] We acknowledge varying terminology, some prefer identity-first ("disabled people"), but we follow person-first usage ("people with disabilities") as standard in major international and academic texts (e.g., UN Convention on the Rights of Persons with Disabilities; WHO ICF; Equity, Diversity & Inclusion discussions). In the experiment and data outputs, we retained the label "Disability" for the scenario category to ensure consistency across stimuli, variable names, and analysis files. However, conceptually, the manuscript refers to people with reduced mobility to more precisely capture mobility-specific constraints. Thus, "Disability" appears only as the operational label in the experimental materials and in the figures and tables derived directly from those data.

systems, our results provide empirical insights into how public perceptions and expectations must be reconciled to develop inclusive and ethical AI-based mobility. Our study shows the importance of embedding diverse perspectives throughout the AI lifecycle. This is critical not only for mitigating bias but also for ensuring that emerging technologies like AV systems are developed in ethical ways that truly serve the needs of all societal groups.

2 Disability, ethics, and AI-based mobility

2.1 Disability and mobility data justice in transport systems

The increasing datafication of mobility introduces further dimensions of injustice. Recent work on *mobility data justice* (Behrendt and Sheller 2024) demonstrated that the ways in which mobility-related data are collected, processed, and applied can either mitigate or reinforce existing inequalities (Verlinghieri and Schwanen 2020). Data-driven mobility governance often reproduces structural exclusions, particularly when marginalized populations, including people with disabilities, are underrepresented in transport datasets (Whittaker et al. 2019). However, this emerging stream remains largely theoretical, with few empirical studies to date. This perspective underscores the need for an inclusive mobility paradigm that accounts for diverse embodied experiences and challenges the normative assumptions underpinning mobility infrastructures.

Building on this data-justice perspective, disability has been increasingly examined in mobility studies through the lens of accessibility, exclusion, and the socio-material constraints that shape movement (Sheller and Urry 2006; Cresswell 2010). Scholars highlight how transportation systems, urban infrastructures, and digital mobility technologies often reinforce structural inequalities, limiting the autonomy and participation of people with disabilities in public space (Imrie 2012; Kwan 2016). Critical mobility studies emphasize the interrelation between mobility and power, arguing that disability is not merely an individual impairment but a product of systemic barriers embedded in mobility regimes (Hansen and Philo 2007; Bissell 2018).

Mobility data justice serves as a critical framework for understanding who has access to movement, under what conditions, and how mobility-related exclusions disproportionately affect marginalized populations, particularly people with disabilities (Harvey 2010; Sheller 2018). Transport infrastructures are often designed based on able-bodied norms, reinforcing structural barriers that limit the mobility of people with disabilities and restrict their access to economic and social participation. For example, data from the United States highlight the disproportionate impact of transport inaccessibility, with 34% of people with disabilities reporting inadequate access to transportation, compared to only 16% of non-disabled individuals (Schur et al. 2013).

Kesselring's *mobile risk society* framework (2008) highlights how global mobility not only fosters economic and social participation but also intensifies exclusion, uncertainty, and vulnerability (Kesselring 2008). People with disabilities, often structurally excluded from dominant mobility infrastructures, face heightened risks of restricted access and systemic marginalization. Expanding on this, Kesselring's (2015) *corporate mobilities regimes* concept critiques how mobility is shaped by institutional and economic priorities, privileging efficiency and profitability over inclusivity (Kesselring 2015). As a result, transport systems remain inadequate for users with disability, perpetuating barriers to essential services, employment, and social life.

Methodologically, mobility research has often centered on able-bodied perspectives and relied on qualitative accounts without addressing the cognitive processes that shape decision-making. Parent's (2016) *wheeling interview* method challenges this bias by foregrounding people with disabilities' experiences, demonstrating how urban environments systematically fail to accommodate diverse mobility needs. These insights underscore the necessity of disability-centered methodologies and inclusive planning in both mobility research and policy (Parent 2016). Therefore, new methodological approaches and perspectives are needed to better understand the underlying mechanisms of inclusion and equity in mobility design, particularly concerning marginalized groups such as people with disabilities. More recently, virtual-reality methods have been adopted to recreate immersive moral and mobility scenarios for participants, enabling the study of real-time decision behaviors and perceptual engagement with diverse road users (Patil et al. 2014; Sütfeld et al. 2017; Cecchini et al. 2025). Studying cognitive processes is vital, because it reveals the biases and heuristics that shape interactions with mobility systems, addressing the call for *cognitive data justice* (de Souza 2025) and providing essential insights for designing inclusive and equitable transport solutions.

Addressing these disparities requires a fundamental rethinking of transport policies, mobility infrastructures, and research methodologies. Ensuring equitable and inclusive mobility for people with disabilities necessitates intentional policy interventions, the integration of disability perspectives in transport governance, and a critical examination of the sociotechnical dimensions of AI-based mobility systems.

2.2 Ethics at the intersection of disability and autonomous vehicles

AI's integration into mobility promises enhanced accessibility but also risks algorithmic bias and data-driven exclusion

for people with reduced mobility. Nowotny (2021) describes a paradox of trust in which predictive algorithms, though designed to manage uncertainty, may inadvertently reduce human agency and perpetuate designers' biases (Nowotny 2021). This paradox highlights pressing ethical issues surrounding the delegation of moral decision-making to automated systems (Nyholm and Smids 2016; Dubljevic et al. 2021), particularly in the AV context where algorithmic choices directly shape access, prioritization, and safety outcomes for people. Ethical analysis emphasizes the importance of embedding transparency, accountability, and human values into algorithmic systems (Jobin et al. 2019).

Previous research confirms the essential role of engaging people with disabilities in the early stages of AV design and highlights the necessity of stringent accessibility standards (Allu et al. 2017). Exclusion from these processes risks reinforcing future challenges in adapting AVs to meet the needs of users with disabilities. Retrofitting existing AV models for accessibility is often costly and inefficient, with modifications increasing vehicle prices by 30% to over 60% (Allu et al. 2017). Consequently, integrating disability-centered design principles from the outset is both economically and socially beneficial, ensuring that AVs are built to accommodate diverse user needs rather than perpetuate systemic exclusions. Such inclusive design principles directly respond to ethical imperatives of fairness, justice, and respect for human dignity in technology development (Lin 2015; Dubljević et al. 2022). While this body of work primarily addresses in-vehicle accessibility and the experience of PRM as passengers, a complementary strand of ethical concern centers on how autonomous decision-making treats PRM as vulnerable road users in traffic environments. Even when PRM are represented as passengers in AV, the core normative question often remains how risk is allocated between them and other external road users. Our analysis is situated within this latter strand, focusing on how PRM is perceived and weighed when automated decision-making systems determine which road users are protected in the AV context. This perspective highlights not only safety considerations but also how technology mediates social diversity perceptions—mechanisms that may become embedded in the design and governance of AI-based mobility systems.

Kesselring and Schönewolf (2021) argue that AI-based mobility systems are embedded within broader political, economic, and cultural discourses, where promises of efficiency and fairness often mask underlying biases (Kesselring and Schönewolf 2021). They highlight how AV technologies are shaped by decision-making processes that prioritize technical optimization over equitable mobility access, reinforcing pre-existing power structures. These risks extend to data gaps in AI models, where the absence of disability-relevant data leads to biased algorithmic behaviors that fail to recognize PRM within transport systems (Criado-Perez 2020). AI models trained on incomplete datasets are prone to errors in pedestrian detection, with potentially fatal consequences when AVs misidentify or fail to recognize wheelchair users as road users in the traffic environment (Whittaker et al. 2019). Such ethical concerns show the critical responsibility of designers and policymakers to proactively address potential harms arising from algorithmic bias (Borenstein et al. 2019), especially those that compromise the safety and visibility of PRM as road users.

The consequences of these biases are significant. If AI training data do not include individuals using mobility aids, such as wheelchairs or scooters, these individuals may not be classified as pedestrians, increasing the risk of accidents and exclusion from safety considerations (Whittaker et al. 2019). Similar concerns extend to human biases in data labeling processes, where annotators may misclassify disability-related mobility aids, leading to misrepresentations in AI training sets. The risks of these omissions are compounded by the lack of evaluation metrics explicitly designed to assess AV performance in detecting diverse human mobility patterns, further embedding systemic bias into AI-based transport infrastructures (Whittaker et al. 2019).

Empirical research further highlights the disparity in PRM's perceptions of AV technologies. While some studies indicate that people with disabilities anticipate increased mobility autonomy through AVs, others reveal strong concerns regarding safety, reliability, and accessibility (Hwang et al. 2020). Focus group research suggests that while transport industry experts are optimistic about AV integration, people with disabilities remain skeptical, fearing that infrastructure limitations and non-inclusive environments will hinder widespread AV adoption (Hwang et al. 2020). Similar patterns emerge in studies examining special needs groups' acceptance of AVs, with many individuals with disabilities expressing concerns over a lack of human assistance, safety risks, and technological uncertainties (Kassens-Noor et al. 2021). Notably, PRM are often less inclined to adopt AV technologies than those with visual impairments, suggesting that the extent to which a disability impacts independent mobility influences trust and acceptance of automated transport solutions (Kassens-Noor et al. 2021).

Ensuring the equitable integration of AI in mobility systems requires a proactive approach that prioritizes inclusive design, robust disability representation in training datasets, and critical scrutiny of algorithmic decision-making processes. As AV adoption accelerates, there is a pressing need to establish ethical and regulatory frameworks that address ableist biases in AI development and deployment, ensuring that autonomous transport systems do not perpetuate the exclusions inherent in traditional mobility infrastructures.

3 1Method and data

3.1 Sample strategy and data collection

This study[2] employs a semi-experimental method, combining large-scale online eye-tracking with a survey, to assess the perception of data subjects toward diversity used in AI systems. The case of autonomous vehicles serves as a proxy for AI systems that rely heavily on data to make automated decisions. We refer to "data subjects"—those targets or main users of automated technologies whose data feed the AI systems. Eye-tracking technology allowed us to explore individuals' perspectives that are not always conscious, explicit, or verbalizable (Kuhn and Kingstone 2009). Responses often reflect social norms and implicit biases that operate unconsciously, especially on topics where the underlying processes of algorithms are still not fully understood.

In this study, we recruited participants via the crowdsourced platform CINT, which includes online panel members from 130 countries. To design the sample, we applied a mix of strategic (Suri 2011) and representative sampling principles (Treiman 2009). We also considered the pragmatic constraints common to online panel studies, such as limited access to panels in different cities and the lack of direct experiment monitoring by researchers (Masso et al. 2020). Our large-scale eye-tracking study final sample included 1,272 participants from 26 cities worldwide.[3] Specifically, cities were chosen based on the Bloomberg Aspen Initiative on Cities and Autonomous Vehicles 2017 (Bloomberg Philanthropies and Aspen Institute 2017) and the CIMI Index 2020 (Berrone and Ricart 2020), covering a range of CIMI index values from high to low (where higher values indicate more advanced digital infrastructure and smart-city development, and lower values reflect less digitally developed urban contexts), under the assumption that exposure to smart-city technologies influences perceptions of autonomous vehicles. To further enhance sample representativeness, we used CINT's functionality to draw participants proportionally to national census data, ensuring balanced representation across key demographic variables, such as age, gender, and education. The final sample structure of the study is presented in Table 1.

Table 1 Sample structure of the study

Category	Sub-category	No. of participants	%
Gender	Female	522	41.03
	Male	750	48,97
Age	18–25	234	18.4
	26–55	880	69,18
	55	153	12.02
	Not known	5	0.45
Education	Basic	54	4.25
	Secondary	229	18
	Higher	973	76.5
	Other*	16	1.25
Total	1272		

*Participants who did not fit into any of the specified education categories

Furthermore, we conducted an in-lab study (April–May 2022) prior to the online experiment (September–October 2022) to refine our methodology and validate the online experiment. Using the same eye-tracking protocol supplemented by semi-structured interviews, we purposefully sampled (Suri 2011) 16 university participants. To ensure the variability of opinions, we included to the study the students and faculty members from engineering, computer science ($N=7$), and social science disciplines ($N=9$) to assess data science experts' perceptions toward disability in AV. We assumed that the participants with diverse disciplinary backgrounds might express varying awareness of potential biases in the AV development.

All individual participants provided informed consent, with in-lab participants signing paper forms and online participants giving their consent digitally. Both the online and in-lab studies were approved by [*details omitted for double-anonymized peer review*].

3.2 Eye-tracking & scenario method

Our online study was conducted via RealEye, which uses the computing power of a regular PC/laptop to run AI that analyzes eye movements via webcam. The AI detects a participant's pupils and predicts a gaze point with an accuracy of ~ 110 px (~ 1.5 cm) and an average viewing angle error of ~ 4.17 degrees. This allows analyzing users' interaction on a website with precision reaching the size of a single button. The platform did not record any image or sound to the participant, only storing the gaze point predictions in the form of basic text data similar to "Timestamp: 10, GazePointX: 200, GazePointY: 330". RealEye and CINT are fully compliant with GDPR and guarantee data protection for each participant. The camera was switched off immediately after each test. Whereas our in-lab study was conducted in the

[2] This paper is part of a larger study (Ibrahimi et al. 2025); however, the present analysis focuses specifically on visual engagement with PRM examined in comparison to other social categories, while additional analysis on security, safety, and algorithmic values are presented in separate publications.

[3] Cities selected for the experiment: London, New York, Paris, Tokyo, Reykjavík, Los Angeles, Helsinki, Stuttgart, São Paulo, Guayaqui, Bueno Aires, Manila, Johannesburg, Ankara, Jakarta, Mexico City, Hồ Chí Minh, New Delhi, Salvador, Mumbai Curitiba, Berlin, Amsterdam, Singapore, Hong Kong, and Zurich. The experiment was conducted in English.

eye-tracking lab at [*details omitted for double-anonymized peer review*], using the Eyelink Portable Duo (SR Research Ltd., Ottawa, ON, Canada)—a high-precision eye tracker with a sampling rate of up to 2000 Hz.

To build the experiment, we used the scenario method (Ramirez et al. 2015), in the form of visual narratives, as eye-tracking stimuli to assess how data subjects and data science experts perceive people with reduced mobility (PRM) in high-stakes scenarios. PRM were operationalized as wheelchair users—visually identifiable in traffic scenes—to focus on mobility restrictions relevant to AV decision-making. We acknowledge this represents only a subset of disabilities. Future work should incorporate non-visible impairments (e.g., cognitive decline, affecting walking speed, seizures, and tics affecting gait).

Participants viewed two sets of visual narratives: one in which an autonomous vehicle (AV) algorithm must decide, and one in which a human driver (non-AV) does in sudden brake-failure scenarios (see an illustrative example—Fig. 1A for the AV setting, and Fig. 1B for the non-AV setting). Each set covers the same seven scenario categories, depicted with two side-by-side images—a choice between two pedestrians or two passengers. In the non-AV setting, a human driver is shown to signal human agency in the decision; however, participants were explicitly informed in the instructions, before the experiment started, that the driver would not be sacrificed in any case.[4] Only passengers inside the vehicle and pedestrians outside the vehicle were at risk. In each scenario, they had to select one image by mouse clicking on their choice. The starting point of this experiment was the trolley problem used in the Moral Machine (Awad et al. 2018). However, we were not interested in the moral dilemma '*what should*' happen ethically, but rather '*what will*' the action be based on participants' own experience and knowledge. We therefore tried to avoid utilitarianism cues such as "save more lives" or traffic-law violations, which might introduce other variables related to moral reasoning or legal adherence that lie outside the scope of this study. Representing PRM as passengers in the illustrated scenarios prevented unintended perceptual biases (e.g., differences in speed or visibility) that arise when depicting wheelchaired pedestrians in motion.

While the Moral Machine is criticized for lacking agents' character information and for its focus on high-stakes rather than mundane, everyday scenarios (Cecchini et al. 2025), we did not assess moral judgments. Instead, our high-stakes sacrificial dilemmas, though structurally similar to trolley problems, focus on perceptions of diversity cues under high-stakes pressure. Using high-stakes emergencies, we concentrate decision urgency and isolate visual attention on critical risk trade-offs (Sütfeld et al. 2017), enabling us to reveal implicit biases in how participants think AVs make critical decisions and who is neglected or prioritized.

Our scenarios center on how people with reduced mobility are perceived in AV contexts. For comparison, we also included six other social categories—age, nationality, income, micromobility role, COVID-19[5] vaccination status, and urban/rural residency—each crossed with sex and race following (Crenshaw 1989) and Vertovec's (2007) intersectional frameworks. We generated 14 unique combinations with sex–race via a Python script to create intersectional profiles of pedestrians and passengers. In the online study, each participant evaluated seven scenarios (one per category) in both AV and non-AV settings for a total of 14 trials across the AV and non-AV settings. Participants were randomly assigned to begin with either the AV or non-AV setting, which differed only by decision-maker (algorithm vs human driver). After instructions, a 40-point eye-tracker calibration began (gray, black, white backgrounds), followed by 9-point validation, and then, the trials began.

Scenarios and eye-tracking have long been used methods to investigate attention and decision processes (Ramirez et al. 2015; Duchowski 2017), but have been less used in comparative settings and studying AI biases. In our study, AV scenarios serve as a controlled proxy for real-world, high-stakes choices—often not feasible or unethical to test directly. By systematically varying attributes, such as age, race, gender, disability status, and socioeconomic background, we trace how diversity cues drive both data subjects' and data experts' visual attention and decision reasoning across algorithmic versus human-driver conditions. These findings have broader implications for understanding how data subjects perceive and prioritize diversity cues in AI-based transport, offering insights into public expectations of fairness. Our experiment also shows how professional worldviews and cognitive framings influence the development of inclusive and equitable automated mobility systems.

[4] Because the driver is visually positioned closer to the barrier, the crash scenario could potentially be interpreted as asymmetric. Although the experiment relied on explicit instructions specifying that the driver would remain unharmed, future work could further validate the stimuli by examining how participants interpret the likely outcomes for the bus driver and passengers.

[5] Most of the categories in the experiment were visually distinguishable, while others such as *COVID-19* status were represented using symbols and *nationality* using country flag symbols. We note that *COVID-19* vaccination status differs from the other categories in that it is more politically contingent and less immutable. However, it was included as a contextually salient health-related attribute that shaped public discussions of vulnerability and responsibility during the data-collection period. Also, it served as a proxy for non-visible forms of diversity, which are equally important for mobility-infrastructure design yet often even more neglected. Although the variable was incorporated and analyzed using the same procedures as the other categories, we acknowledge this qualitative difference in its social meaning and address it in the interpretation of the results.

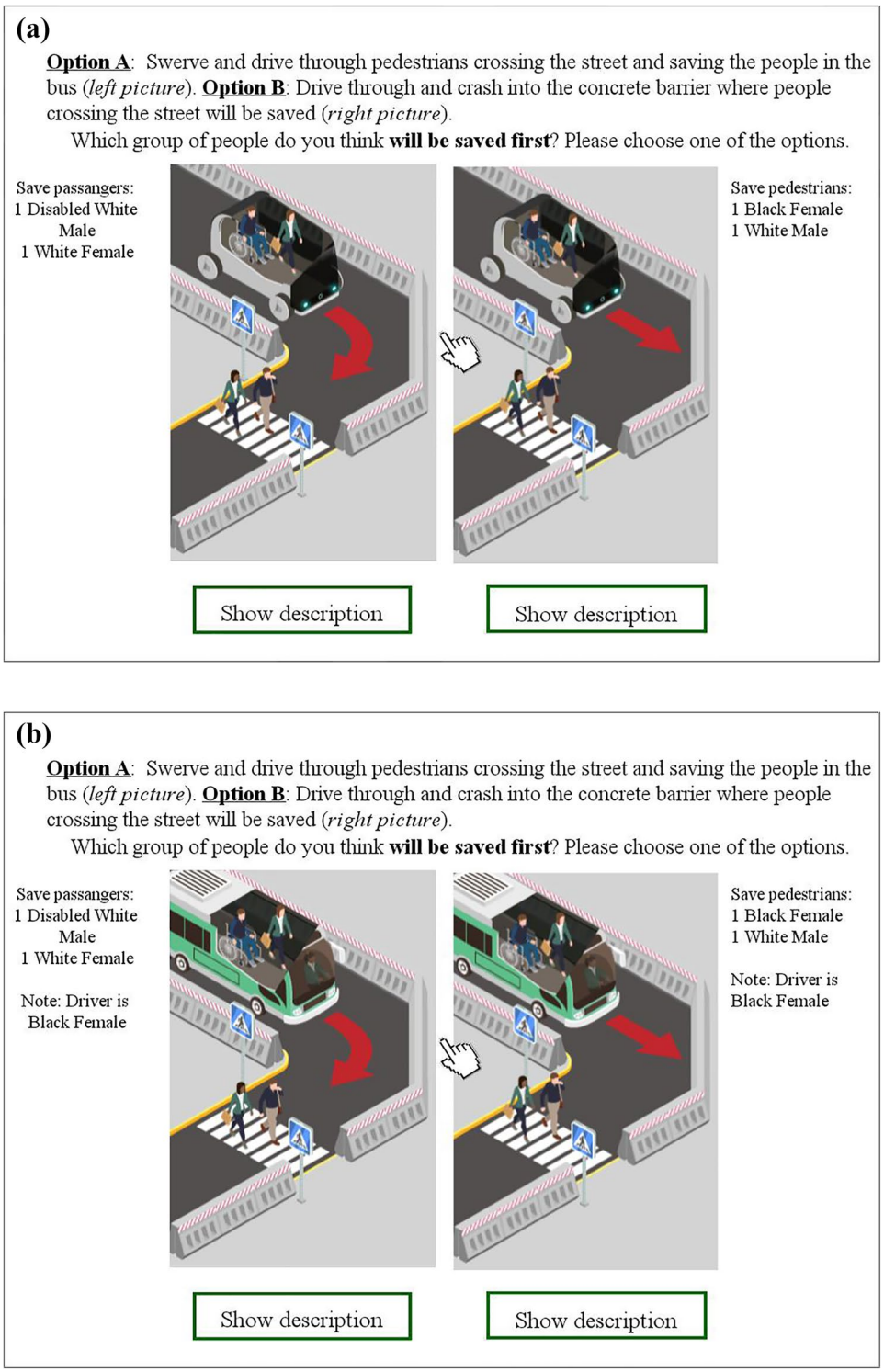

Fig. 1 **A** An illustrative example of one of the scenarios used in the study for the *AV* setting. This scenario includes people with reduced mobility as passengers of the autonomous shuttle. The shuttle is depicted without a human driver to emphasize algorithmic decision-making. **B** An illustrative example of one of the scenarios used in the study for the *non-AV* setting. This scenario includes people with reduced mobility as passengers of the manually driven shuttle. The driver is shown to signal human decision-making. In the experiment instructions, participants were explicitly informed that the driver would not be sacrificed in any case; only the passengers and pedestrians were at risk

Furthermore, in the survey, in addition to socio-demographic variables (such as age, gender, education, and income status), we asked participants to rate the importance of some of the key values and principles toward algorithmic solutions using measures drawn from previously validated studies (Masso et al. 2023)—such as Diversity (e.g. consideration of ethnic, gender, lifestyle, etc.), Equality (equal treatment of all data subjects, being target of data solutions, and Justice (socially justified activities and decisions in relation to the data). Additionally, we asked participants whether they agree or disagree with some statements in regard to "Society is just (fair) if…" by providing

different options such as "…there is equal access for different groups," "…benefits all groups of people," and "…identifies and prevents biases in data collected." These questions helped us to better understand how their attitudes relate to cluster membership (see Sect. 4.3).

3.3 Data analysis

To analyze the eye-tracking data across different AV and non-AV settings, we employed a multi-step analytical approach. We applied Factor Analysis (FA) and Cluster Analysis to identify non-linear associations in visual attention patterns, moving beyond individual fixation time variables to uncover broader patterns of viewing behavior.

Before applying FA, we conducted descriptive statistical analyses, including means and standard deviations, to examine overall fixation patterns. Additionally, we performed ANOVA to assess the significance of differences in fixation time distributions across two settings. To explore potential relationships between fixation time variables, we conducted Pearson correlation analysis. Given the significant correlations between several scenario categories indicating interdependencies in viewing behavior, we used FA to extract shared variance structures across scenario categories.

FA was then conducted to transform raw fixation time variables into standardized factor scores.[6] Given that fixation times did not show substantial variations, since we measured similar things across scenarios, FA captured shared dimensions of attention while retaining meaningful participant-level variation. This approach allowed us to move beyond the initial fixation data and capture underlying patterns in eye-tracking behavior, ensuring that subsequent clustering analysis was based on latent structures rather than raw fixation values. FA was conducted using the statistical programming language R, specifically the psych and GPArotation packages. Factors were extracted using the minimum residual (minres) method, with Varimax rotation applied to clarify the structure of loadings and interpretability of factors. We first examined two pre-specified factors based on content-related considerations in the experimental design, which explicitly distinguished between AV (algorithmic decision) and non-AV (human decision) settings. This two-factor solution is also statistically supported by FA diagnostics, including the application of Kaiser's eigenvalue criterion (eigenvalues > 1, *SS*-loadings $= 3.06$ and 2.82, cumulative variance $\approx 42\%$, and consistent item loadings $\approx$ 0.56–0.71). Then, for clustering, standardized factor scores were calculated using the regression method, resulting in one score per participant for each scenario category.

Following FA, k-means clustering was performed on the extracted factor scores to identify distinct participant subgroups based on their viewing behaviors. By clustering, we identified groups of participants with similar viewing behavior patterns, regardless of their individual characteristics. Prior to clustering, we z-standardized the FA scores within AV and non-AV settings (so each factor had *mean* ≈ 0 and SD ≈ 1), ensuring that all scenario categories contributed comparably to the distance metric used by k-means. Clustering was performed separately for AV and non-AV scenarios using kmeans (…, *centers* = 3, *algorithm* = "Hartigan-Wong", *nstart* = 25, *iter.max* = 1000) with *set.seed* = 123 for reproducibility. To evaluate sensitivity to initialization and resampling, we repeated clustering across 50 seeds (each replication with *nstart* = 100) and computed Adjusted Rand Index (ARI) and performed 100 bootstrap resamples to obtain per-cluster Jaccard stability means (stability diagnostics reported in Sect. 4.2).

Then, from the survey data, we examined associations between clusters and background variables, such as age, gender, trust toward AV, and values toward AI using Chi-square tests.[7] To determine the statistical significance of our results, we used p values with a conventional threshold of $p < 0.05$ for statistical significance, $p < 0.01$ for strong significance, and $p < 0.001$ for highly significant associations.

Moreover, the in-lab interviews were audio-recorded and then transcribed. We then imported all transcripts into MAXQDA for computer-aided qualitative analysis (Woolf & Silver, 2017), where we organized the interviews, applied thematic codes, and retrieved coded segments.

4 Results

4.1 Overall viewing patterns: general tendencies toward disability and AV perception

We examined fixation duration (Table 2)—the length of time participants' gaze remained on each scenario—across scenario categories within AV and non-AV setting. Overall, participants showed greater fixation on AV scenarios ($p = 0.007$), suggesting that the AV technology may draw more attention than non-AV. This heightened focus may stem from curiosity or concern about emerging technologies or from the greater media exposure and discussion surrounding AV (Fraedrich and Lenz 2016).

[6] While simple standardization (e.g., z-scoring each variable) places variables on a common scale, it does not account for shared variation across categories. FA, by contrast, extracts latent factors—shared dimensions of variation—that help us interpret how participants' attention across different categories (e.g., disability and nationality) may align, especially in AV versus non-AV contexts.

[7] We conducted also Cramér's V for categorical variables, but they show low associations.

Table 2 Fixation duration in seconds across scenario categories in AV and non-AV setting (mean and standard deviation)

Scenario category	AV		Non-AV		Wilcoxon-Statistic	*Z*-score	AV vs non-AV
	Mean	SD	Mean	SD			*p*-value
Disability	6.47	8.87	6.24	8.46	418,441.5	1.040	0.100
Age	6.68	8.72	6.28	8.81	422,215	1.328	0.037*
Country of origin	7.02	9.31	6.75	9.35	419,930.5	1.154	0.050*
COVID-19	7.05	9.3.0	6.62	9.22	417,748.5	0.987	0.137
Income	7.70	10.27	6.94	8.96	413,289.5	0.647	0.195
Micromobility	7.02	9.38	6.75	9.48	416,423	0.886	0.124
Residence	7.28	9.34	6.74	8.80	422,430.5	1.344	0.040*
Total	7.03	6.49	6.62	6.47	418,639	1.055	0.0074

AV Autonomous Vehicle, *non-AV* nonautonomous vehicle (human−driven vehicle)

*$p < 0.05$

We compared the Disability category[8] with other diversity categories, including Income, Micromobility, and COVID-19. We assume, based on prior studies (Vertovec 2007), that certain social categories (such as age, race/ethnicity, or nationality) have well-established social norms, stereotypes, or biases, so participants often exhibit stronger or more consistent reactions—reflected, for instance, in longer fixation times. Thus, although Disability is a critical social dimension, it may not be regarded by participants as a "universal" or "traditional" factor in the same way as age or nationality. Micromobility, similarly as Disability, is a relatively new concept in transportation studies (Cubells et al. 2023), so participants might not yet have strong preconceptions about it. This can lead to lower cognitive salience (and thus fewer notable differences in fixation or statistical measures). COVID-19 status, while relevant in recent years and visually not recognizable, might be perceived as a temporary or situational sociopolitical factor, rather than a stable demographic characteristic like age or country of origin. By contrast, Micromobility or Income, which have connotations of subjective feelings (Järv et al. 2021), may not trigger the same depth of immediate social response or cognitive load (i.e., the mental effort required to process information) unless participants have personal experience or strong beliefs about them. By contrast, Residence, Country of Origin, and Age all showed statistically significant differences in fixation times ($p < 0.05$) These categories are frequently discussed in diversity and inclusion contexts (Warnes et al. 2004; Millán-Franco et al. 2019)—Country of Origin and Age are perceived as fundamental social dimensions, while Residence (e.g., urban vs. rural) can be seen as another 'classical demographic' factor that has traditionally shaped daily life experiences (Vertovec 2007), such as commuting patterns and social environments. Because these categories are more frequently highlighted in public discourse, participants may be more attuned to them, resulting in measurable differences (e.g., in fixation times).

Beyond overall fixation duration, we calculated the proportion of fixation time directed at the target social diversity category (area of interest = AOI) relative to each participant's total fixation time within a scenario. This proportional measure provides a more direct indicator of visual attention, distinguishing between total scenario viewing time and focused attention on the salient social category. The results[9] (see Table 6 in the Annex) show that Disability and Age receive a comparatively small fraction of fixation time in both AV and non-AV settings, even when normalized by total fixation duration. This indicates consistently lower visual attention with disability and age-related cues. For Age, lower fixation may reflect well-established social intuitions about protecting younger individuals over older ones, a pattern documented in prior large-scale studies of moral decision-making, such as the Moral Machine experiment (Awad et al. 2018). Shorter visual attention should not be interpreted as reduced moral concern per se, because people often rely on fast, intuitive moral judgments (Suter and Hertwig 2011; Fiedler and Glöckner 2015). For Disability, however, the short visual attention may align with broader sociotechnical patterns in which people with reduced mobility are historically underrepresented, misrecognized, or made invisible in AI systems and training datasets (Whittaker et al. 2019; Newman-Griffis et al. 2023). Thus, proportional fixation may reflect not only rapid cognitive appraisal but also deeper structural mechanisms that render people with reduced mobility less salient within technologically mediated decision-making.

[8] We labeled "Disability" category for ease of reference and to align with the umbrella term used in international and academic discourse, operationalized in our study as scenarios depicting wheelchair users.

[9] Micromobility is the only category showing a significant AV–non-AV difference in proportional fixation. This may reflect the mixed representation of human-operated (cyclist) and non-human (delivery robot) actors, which can heighten perceived traffic vulnerability or unpredictability.

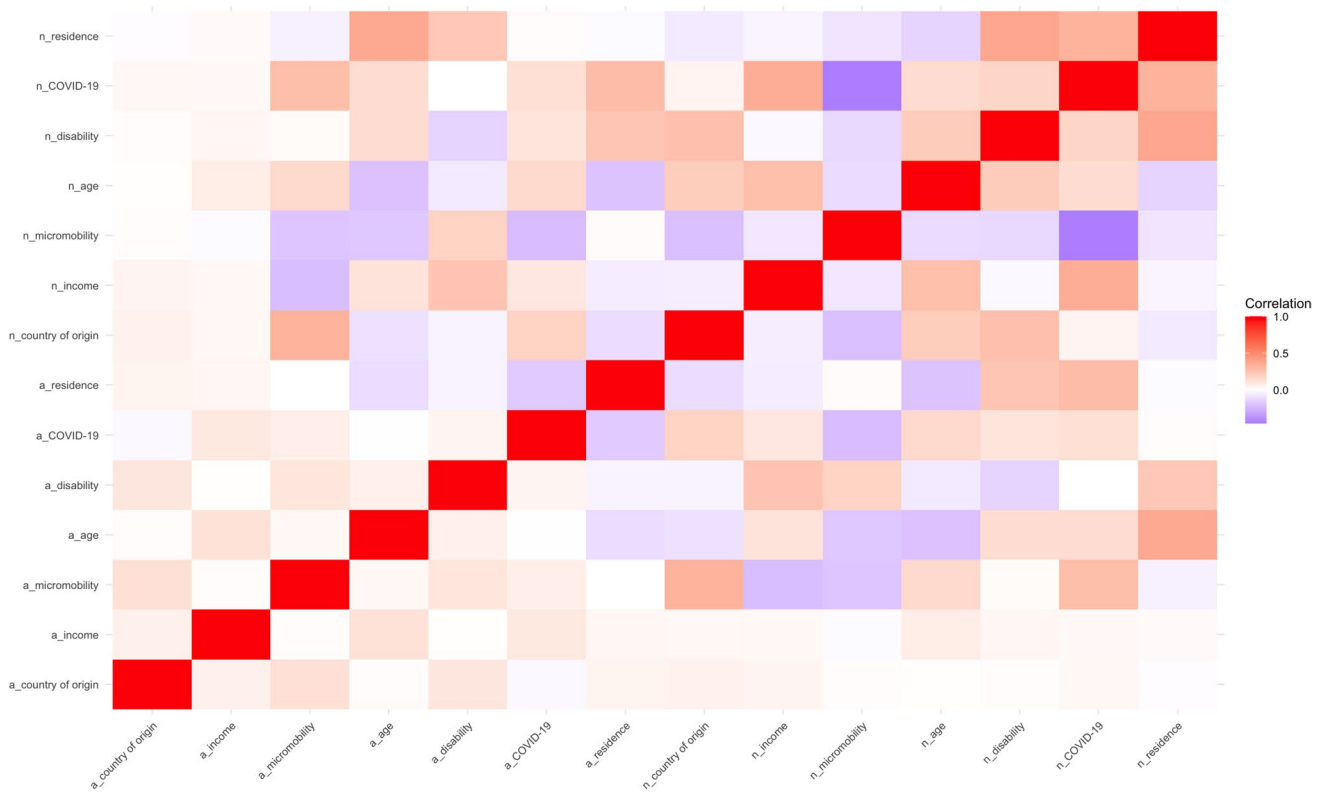

Fig. 2 Analysis of associations between scenario categories in AV ('a_'), and non-AV ('n_') setting using Pearson's correlation

Furthermore, the correlation matrix (Fig. 2) reveals that participants' attention to scenario categories shifts significantly between AV and non-AV conditions, highlighting that it is not only the differences among categories but the contrast between vehicle types that reshapes perceptions of the social world—reflecting our fears, neglect, and overall risk awareness. In both settings, several strong intra-condition correlations emerge, particularly within the AV condition. For example, a_income correlates highly with a_age and a_COVID-19, suggesting that participants may associate economic vulnerability with age or health risk in automated mobility settings. Given that COVID-19 vaccination status carried strong sociopolitical connotations during the period of data collection (Allcott et al. 2020), these associations may partly reflect broader political or cultural attitudes linked to health-related risk perception, rather than stable demographic characteristics.

Additionally, a_country of origin shows strong correlations with a_micromobility and a_disability. This may be due to the design of the stimulus, where the country-of-origin, micromobility, and disability all depict actors who may appear more exposed or at higher situational vulnerability in traffic (e.g., cyclists, delivery robots, or wheelchair users, as well as road users from different countries who may be perceived as behaving differently) and less predictable (Schadenberg et al. 2021). At the same time, the weak negative correlation between n_micromobility and n_COVID-19 suggests that participants did not perceive a strong connection between these categories in the non-AV setting. The presence of non-human actor (the delivery robot) may have reduced associations with human health vulnerability cues such as COVID-19.

By contrast, cross-condition correlations, for instance, between a_disability and n_disability, are notably weaker, implying that participants perceive and respond to the same social category differently across AV and non-AV settings. This asymmetry points to shifting contextual meanings in how categories are interpreted, depending on the technological framing. Furthermore, a_age was strongly correlated with n_residence, and a_disability with n_income, indicating that consistent social interpretations across both vehicle types may have shaped some participant attention patterns.

These patterns provided the rationale for conducting Factor Analysis (FA) to extract latent dimensions of visual attention based on correlated categories (see Sect. 4.2). Therefore, FA allowed to extract factors that capture the shared variance across our initial variables.

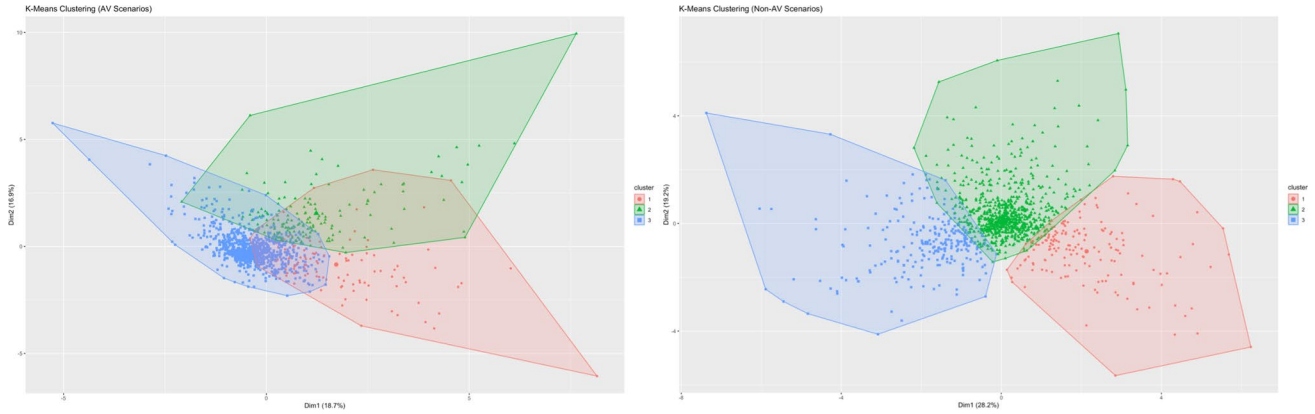

Fig. 3 k-means clustering, AV (left figure) and non-AV (right figure)

4.2 Cluster analysis: perceptions of disability and social diversity

Cluster analysis was conducted to group participants according to their views on Disability and other scenario categories across AV and non-AV settings (Fig. 3). K-means clustering was performed separately for AV and non-AV variables, resulting in a total of six clusters. However, because both conditions capture the same underlying social diversity dimensions—with the only difference being vehicle type—the analysis converged on a similar three-cluster structure in each condition. Thus, the clusters form three comparable pairs that reflect the same conceptual distinctions, allowing us to treat them as three key groupings across both AV and non-AV contexts. We selected a three-cluster-solution, based on both statistical and content-related considerations. First, based on the statistical criteria, our analyses revealed that a three-cluster solution maximized between-cluster variance and produced robust group separation. Then, from a content perspective, three clusters provided the clearest conceptual distinctions among participants' views on Disability and other categories, avoiding less interpretable and overly fragmented groupings (see also Sect. 4.4. for cluster analysis validation).

When we evaluated the reproducibility of the reported three-cluster solutions, the repeated-seed comparisons produced high Adjusted Rand Index (ARI) values, indicating strong agreement across random starts (*mean ARI* = 0.953 for AV; 1.000 for non-AV). Bootstrap resampling (100 resamples) yielded per-cluster Jaccard stability means of AV = [0.554, 0.389, 0.838] and non-AV = [0.677, 0.884, 0.855]. Taken together, these diagnostics support the reliability of the three-cluster solutions, particularly for the non-AV condition where all clusters show good-to-very high stability ($J \approx 0.68$–0.88) and $ARI = 1.0$. The AV condition is also reproducible across initializations (high ARI), but one AV cluster displays only moderate bootstrap stability[10] ($J \approx 0.39$).

Statistically, the ANOVA results in Table 3 demonstrate that all variables significantly contributed to the constitution of cluster membership, with η^2 values exceeding 0.14, a threshold often associated with large effect sizes. Notably, Income shows the highest effect ($\eta^2 = 0.29$), suggesting that cluster membership strongly influences how participants perceive income-related scenarios. The lowest value (Disability = 0.149) still falls in the medium–large effect size, meaning that it has a moderate impact, but less than the others.

Although the lowest effect size for Disability indicates a moderate impact compared to the other variables, these differences provided a foundation for deeper analysis to explain the reasons for neglect. To explore how participants perceive Disability alongside other social dimensions, we further analyzed the mean values of these variables separately for AV and non-AV settings within each cluster. This analysis revealed three distinct clusters, that we have named

Table 3 ANOVA test for differences in three-cluster membership across variables

Variable	*F*_Value	*P*_Value	H^2
Disability	111.407	***	0.149
Age	244.074	***	0.278
Covid19	132.072	***	0.172
Income	259.690	***	0.29
Micromobility	116.729	***	0.155
Nationality	242.152	***	0.276
Residence	115.232	***	0.154

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

[10] We therefore interpret the AV cluster's descriptive features with caution while retaining the three-cluster solution for consistency and cross-condition comparability.

Table 4 Cluster centroids based on the mean values of single social categories

Scenario categories	AV			Non-AV		
	High disability awareness	Adaptive disability evaluators	Low disability awareness	High disability awareness	Adaptive disability evaluators	Low disability awareness
Disability	0.343	0.019	– 0.056	0.241	– 0.043	– 0.129
Age	– 0.024	0.872	– 0.097	0.083	0.045	– 0.359
Country of origin	1.537	– 0.096	– 0.229	0.210	– 0.030	– 0.155
Covid-19	0.052	0.351	– 0.049	0.050	– 0.002	– 0.062
Income	– 0.161	1.593	– 0.160	0.033	0.068	– 0.403
Micromobility	0.623	0.030	– 0.101	– 0.279	0.013	0.341
Residence	0.042	– 0.190	0.016	0.000	0.000	0.000
Mean	0.368	0.345	– 0.097	– 0.110	0.007	0.048
Standard deviation	0.648	0.587	0.080	0.248	0.039	0.170
No of participants:	116 (9.12%)	156 (12.26%)	1000 (78.62%)	165 (12.97%)	856 (67.3%)	243 (19.1%)

as 1. *Individuals with High Disability Awareness*, 2. *Adaptive Disability Evaluators*, and 3. *Individuals with Low Disability and Diversity Awareness* (Table 4).

Individuals with high disability awareness (prioritizing disability in both AV and non-AV settings): In the AV setting, Disability showed a strong positive mean (+ 0.343), while other categories such as COVID-19 and Country of Origin also remain robustly positive, indicating a broadly inclusive perspective of different social diversity dimensions. It is important to note that COVID-19 vaccination status carried strong political and cultural meanings during the data-collection period, and its positive score in this cluster may therefore reflect broader and controversial sociopolitical orientations toward collective health responsibility. Furthermore, the mean scores for Age and Income are negative. We assume that these categories are somewhat more embedded in societal norms and decision-making heuristics that they trigger almost automatic responses. In high-stake contexts, there may be an implicit tendency to favor the young over the senior or to assume that individuals with lower income may be more vulnerable (Awad et al. 2018)—leading to a faster prioritization. In the non-AV setting, while Disability remains positive (+ 0.241), other categories such as Micromobility turn negative. This may be because participants relate more personally to human drivers—often putting themselves in the driver's seat—and, when faced with life-or-death decisions involving humans versus alternative mobility options like a delivery robot, they make faster, more intuitive judgments. Overall, this cluster retains a consistently higher disability awareness across both settings and demonstrates a broadly inclusive stance toward multiple social dimensions.

Adaptive disability evaluators (shifting sensitivity between AV and non-AV): In this cluster, participants demonstrate a balanced and context-dependent approach to evaluating social categories. In AV setting, the participants' fixation score for Disability and Micromobility scenarios is close to zero, reflecting a neutral or balanced attention in the automated context. In addition to acknowledging Disability, participants in this cluster place significant emphasis on other categories as critical factors: Income reflecting access to technology and resources; Age highlighting generational differences in technology adoption and risk perception; and COVID-19 representing a contemporary, and often politically charged, health-related concern that influences attitudes toward safety and collective responsibility in a technologically mediated environment. In AV scenarios, where algorithmic fairness and the integration of diverse social factors are under intense scrutiny, these dimensions naturally assume greater importance. In non-AV contexts, however, Disability shifts slightly negative (− 0.043) and other categories adjust accordingly, suggesting that the evaluative criteria become less uniform in human-driven settings, likely due to inherent biases and personal prejudices. This shifting sensitivity between AV and non-AV indicates that participants in this cluster perceived diversity priorities based on whether decisions are made by an algorithm or a human, highlighting the dynamic nature of their social evaluations. It is important to highlight that the AV-specific centroid for this subgroup demonstrated only moderate bootstrap reproducibility ($J \approx 0.39$), which likely reflects greater internal heterogeneity within that subgroup.

Individuals with low disability and diversity awareness (persisting biases across AV transition): Participants in this cluster consistently exhibit negative scores for Disability in both AV (− 0.056) and non-AV (− 0.129) settings, indicating that they allocate lower attention to Disability. In AV scenarios, negative scores for other categories, such as Income, Country of Origin, and Micromobility, suggest that these participants may assume algorithms make pre-defined

decisions based on available data or they did not see any relation of such categories in decision-making, thereby diminishing the need for additional cognitive focus on these dimensions. In non-AV contexts, while some categories like Age and Residence shift slightly positive, Disability remains consistently low, implying that participants may not perceive Disability as a key factor influencing outcomes. This pattern reflects a persistent low attention to Disability across AV transition.

Overall, the majority of participants in AV scenarios fall into the *Low Disability and Diversity Awareness* cluster, while most in non-AV contexts are classified as Adaptive Disability Evaluators. Although we label these clusters in reference to "disability awareness," it is important to note that Disability remains comparatively overlooked in relation to other social dimensions, with relative variations in how it is perceived between AV and non-AV settings and within each context. This analysis highlights that longer fixation times (indicated by positive mean scores) reflect more deliberate evaluation, whereas negative mean scores suggest lower attention and thus neglect certain scenarios. Additionally, shorter fixation durations may also reflect rapid, automatic normative judgment without extended visual inspection (Suter and Hertwig 2011; Fiedler and Glöckner 2015). In this context, shorter visual attention may indicate an immediate sense of moral priority assigned to, i.e., people with reduced mobility, occurring before sustained visual processing becomes necessary. While rapid normative judgment is possible for some participants, the overall attentional pattern across clusters, including consistently lower mean scores and weaker contribution to cluster differentiation, indicates that Disability remains comparatively overlooked relative to other social categories.

Importantly, the three clusters should not be interpreted as fixed personal traits but as context-dependent patterns of attention. The shifts in cluster membership between AV and non-AV conditions indicate that participants' attention to PRM varies systematically depending on whether a decision is made by an algorithm or a human driver. This suggests that disability-related cognitive engagement is sensitive to the perceived nature of the decision-maker, rather than representing a stable, individual-level orientation. Such context-specific variation aligns with research on trust in automation and algorithmic aversion, where individuals adjust their evaluative strategies depending on whether decision authority is delegated to humans or machines (Dietvorst et al. 2015; Araujo et al. 2020).

4.3 Associations of clusters with background variables

To assess the variation within clusters and further explain the differences and similarities across clusters, we examined the associations with key socio-demographic factors, such as age, gender, education, minority status, income level, readiness to use a fully autonomous vehicle, and data and algorithm awareness (Table 5).

The pattern of results in Table 5 indicates that cluster membership—High Disability Awareness, Adaptive Disability Evaluators, and Low Disability Awareness—is systematically related to participants' socio-demographic and attitudinal characteristics. First, education emerged as a robust predictor: individuals with a higher degree were disproportionately represented in the *High* and *Adaptive* clusters in both AV and non-AV settings. In contrast, those reporting comfortable household incomes were most prevalent in the *Low*-Awareness cluster under AV conditions, suggesting that financial security alone does not guarantee heightened sensitivity to mobility diversity.

In the non-AV context, national-minority participants were significantly more likely to belong to the *Adaptive* cluster, underscoring that lived experience of marginalization does not uniformly translate into higher disability awareness but may foster context-sensitive assessments. Readiness to adopt fully AV also differentiated clusters: participants who affirmed their willingness to use AVs clustered most heavily in the *Low*-Awareness group, implying that enthusiasm for automation may coincide with an overreliance on algorithmic decision-making and reduced attention to the needs of wheelchair users. Conversely, participants who express skepticism toward AV systems are more attuned to the potential shortcomings of automation in addressing diverse needs, prompting them to scrutinize Disability as a critical social dimension more closely.

Finally, participants who have participated in similar studies at least once and are presumably more aware of data and algorithm processes are more likely to fall in *Low Awareness* cluster in AV setting. They may view algorithmic decisions as sufficiently standardized, thereby relying on established heuristics that reduce the need for detailed analysis of Disability. However, those who never participated in similar studies and are assumingly less aware of data and algorithm commonly fall into the *Adaptive* cluster. They may approach these decisions with greater caution and nuance, leading to more context-sensitive evaluations. It is important to note that our sample is drawn from a digitally aware and literate global panel on the CINT platform, where panel members are frequently engaged in international and similar studies.

In addition, when we asked participants to rate the importance of some key values and principles that public and private institutions may or may not consider when developing AV technologies, a large majority of the participants rated *Diversity*, *Equality*, and *Justice* as important values across clusters. In terms of cluster associations, the significant differences ($p = 0.002$) in *Justice* in non-AV scenarios indicate that cluster membership is linked to how strongly

Table 5 Associations of clusters with background variables

Variables	Categories	AV				Non-AV			
		% High disability awareness	% Adaptive disability evaluators	% Low disability awareness	*p* value*	% High disability awareness	% Adaptive disability evaluators	% Low disability awareness	*p* value*
Age	18-25y	19.87	21.55	17.80	0.351	19.75	18.52	15.76	0.585
	26-55y	63.46	66.38	70.40		68.72	69.56	67.88	
	55 + y	16.67	12.07	11.30		11.11	11.46	16.36	
Gender	Female	42.31	48.28	40.00	0.216	41.98	41.32	38.18	0.714
	Male	57.69	51.72	60.00		58.02	58.68	61.82	
Education	Basic	0.64	2.59	5.00	0.019	3.70	4.98	1.21	0.013
	Secondary	13.46	15.52	19.00		16.87	19.56	11.52	
	Higher	85.90	79.31	74.70		79.01	74.07	85.45	
National minority belonging	Yes	27.56	21.55	31.10	0.231	21.40	32.64	27.27	0.003
	No	66.03	68.97	61.40		67.49	61.00	64.24	
Current income level of their household	Live comfortably	28.21	30.17	37.50	0.027	36.63	36.46	30.30	0.023
	We can handle	45.51	44.83	37.40		41.56	36.34	49.70	
	It is difficult to cope	23.08	19.83	20.60		17.70	22.11	18.79	
Readiness to use a fully AV	Yes	61.54	59.48	66.4	0.0001	60.9	66.9	62.43	0.374
	No	29.48	30.17	26.4		29.63	25.47	32.13	
	Don't know, can't say	8.97	10.34	7.20		9.47	7.64	5.45	
Data and algorithm awareness	Data and algorithm aware	34.62	31.03	41.50	0.035	34.98	42.48	32.12	0.011
	Data and algorithm less aware	65.38	68.97	58.50		65.02	57.52	67.88	
Immportance of values In AV development									
Diversity	Insignificant	18.59	18.10	18.70	0.993	16.46	19.21	18.79	0.721
	Neither important nor insignificant	22.44	20.69	22.40		24.28	22.22	19.39	
	Important	58.97	61.21	58.90		59.26	58.56	61.82	
Justice	Insignificant	12.82	13.79	15.10	0.492	9.88	17.48	7.27	0.002
	Neither important nor insignificant	12.82	12.93	16.60		16.87	15.05	18.18	
	Important	74.36	73.28	68.30		73.25	67.48	74.55	
Equality	Insignificant	10.26	8.62	14.70	0.054	9.47	15.97	7.27	0.001
	Neither important nor insignificant	10.26	12.07	15.00		12.35	15.39	10.30	
	Important	79.49	79.31	70.30		78.19	68.63	82.42	
Society is just (fair) if:									
Equal access to the data collection	Agree	72.44	73.28	63.20	0.050	64.61	65.28	66.06	0.625
	Disagree	21.15	18.97	28.90		27.57	27.55	23.64	
Data collection benefits all groups	Agree	67.95	69.83	62.10	0.328	60.49	64.00	65.4	0.838
	Disagree	25.64	23.28	31.00		31.69	29.40	27.88	
It can identify and prevent bias in data	Agree	67.31	67.24	62.30	0.605	58.44	63.89	67.88	0.297
	Disagree	24.36	25.00	29.60		32.10	27.89	26.67	
Total no		156	116	1000		243	864	165	
Average %**		97.63	96.95	97.18		96.83	97.29	97.39	

*Significance of the chi−square test ($p < 0.05$)

**Categories as "no answer" and "don't know" have been handled as missing values (the size remaining <5%), to support the generalizability and explanation of the results

participants believe in the fairness of human-driven decisions. Similarly, the moderate significant differences in *Equality* ($p = 0.054$) within the AV condition (and significant differences in non-AV, $p = 001$) suggest that cluster membership also reflects distinct perspectives on equal treatment.

Additionally, we explored the perceptions of what makes a society fair in the context of data usage. Comparisons across clusters reveal a borderline significant difference ($p = 0.050$) for the statement "Society is just (fair) if equal access for different groups to the data collected about them" in the AV condition. Specifically, cluster *High Awareness* tend to endorse the fairness principle more strongly, whereas cluster *Low Awareness* shows less agreement. This suggests that in AV scenarios, where algorithmic fairness is critical, participants' views on what constitutes a just society vary, reflecting differing expectations for how technology should accommodate diverse social groups.

These findings collectively suggest that while background variables do contribute to the formation of clusters, the significant differences observed, particularly in education, income, and AV readiness, highlight that cluster membership reflects meaningful differences in how participants perceive and prioritize disability and other intersectional diversity dimensions in both AV and non-AV contexts. Taken together, these associations suggest that the sensitivity to whether decisions are made by an algorithm or a human is not random but patterned. Participants with higher education, lower AV readiness, and less prior exposure to algorithmic systems tend to show more adaptive, context-sensitive attentional shifts between AV and non-AV scenarios. In contrast, individuals who report high readiness to adopt AVs or greater familiarity with data and algorithmic processes more often maintain consistently lower attention to disability in AV contexts. These patterns indicate that attentional responses to the driver type (algorithm vs human) are shaped by socio-demographic and attitudinal factors, even if disability awareness itself is not a stable trait.

4.4 Validation and cross-study comparison: online vs. in-lab eye-tracking experiment

To validate our three-cluster solution and assess the robustness of our categorization, we compared the online results with those from our in-lab eye-tracking experiment. The design and procedure of the in-lab study are described in detail in Sects. 3.1 and 3.2, and here, we focus on the comparative patterns of visual attention and cluster structure.

Across both studies (Fig. 4), the pattern of attention toward disability remained consistent. In both AV and non-AV conditions, the *Low Disability and Diversity Awareness* cluster exhibited notably lower mean FA values for Disability compared to the *High Disability Awareness* and *Adaptive Disability Evaluators* clusters, while in the *Adaptive Disability Evaluators* cluster, Disability consistently remained near zero.

Furthermore, in the in-lab experiment, overall fixation times were significantly longer in non-AV settings ($M = 14.74$ s, $SD = 3.65$) than in AV setting ($M = 1.06$, $SD = 1.90$, $p < 0.001$), representing about 38.75% less fixation time in AV contexts. Interviews revealed that data experts had to weigh human drivers' personal biases and beliefs in the non-AV setting. In contrast, AV scenarios elicited faster, more uniform responses based on the assumption of pre-defined, rule-based algorithms. However, the online experiment showed the opposite—overall fixation times were longer in the AV setting. Additionally, within the AV setting in in-lab experiment, technical experts (the data and algorithm aware group) showed lower engagement with Disability scenarios ($M = -0.171$, $SD = 0.752$) than social science experts (assumingly less aware of technical algorithmic processes) ($M = 0.133$, $SD = 0.322$), suggesting that the technical experts may rely on heuristic processing when evaluating algorithmic decisions. Conversely, in non-AV scenarios, the data and algorithm less aware group spent less time on Disability ($M = -0.149$, $SD = 0.386$) than the data and algorithm aware group ($M = 0.191$, $SD = 0.473$), reflecting a shift in attention when human drivers are involved.

Online results mirror these trends: the data and algorithm less aware participants paid more attention, especially in AV scenarios, likely due to their relative unfamiliarity with algorithmic processes, prompting more careful scrutiny of the information presented. Together, these findings confirm the choice of a three-cluster solution in this study and reveal that both online and in-lab experiments yield consistent profiles regarding disability and other intersectional dimensions. The similarity in clustering patterns observed in both the online and in-lab experiments confirms that the visual attention behaviors are not simply products of the experiment environment. Instead, these patterns illustrate how participants, whether less or more familiar with algorithmic processes, engage differently with AV and non-AV scenarios.

5 Discussion

The integration of autonomous vehicles (AVs) into modern mobility systems raises critical ethical, behavioral, and societal issues (Rahwan et al. 2019; Dubljevic et al. 2021). While theoretical debates on *mobility data justice* (Behrendt and Sheller 2024) and the *mobile risk society* (Kesselring 2024) have illuminated potential risks and exclusions in AI-based mobility, empirical evidence on diversity, ethical implications, and what it means in practice remains scarce. Prior research has focused on diversity in AI systems in terms of race, gender, and other social dimensions (Jackson 2021; Chen 2023); however, disability has often been overlooked.

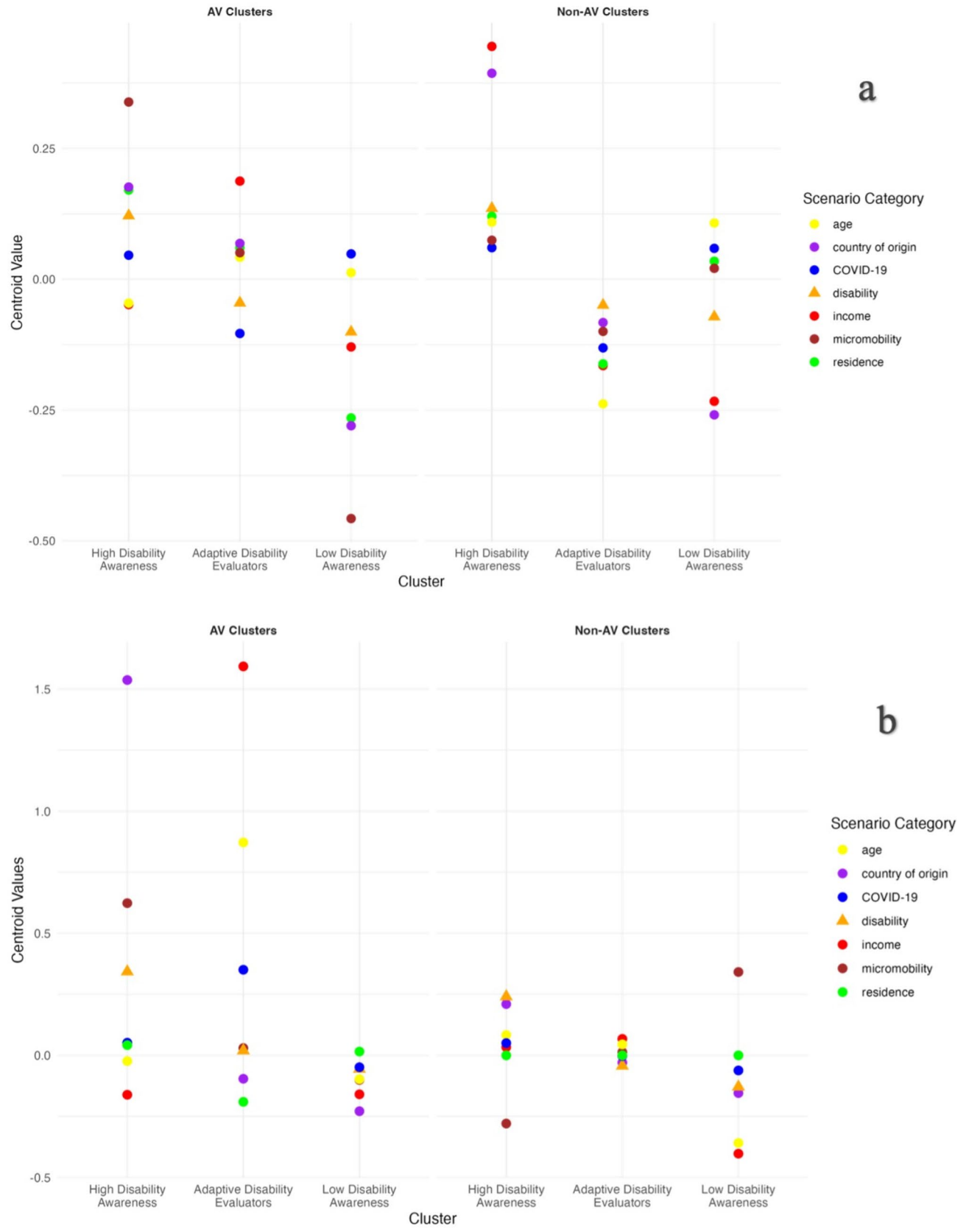

Fig. 4 Scatter plot of clusters for **a** in-lab experiment and **b** online experiment

This study responds by mapping how people with reduced mobility (PRM) are perceived compared to other diversity categories, comparing algorithmic versus human (non-AV) contexts, and analyzing data subjects' individual and contextual characteristics, such as technology adoption readiness and algorithmic awareness, that may drive the relative neglect of disability cues. These comparisons hold significant ethical implications, highlighting the potential for AV systems to unintentionally reinforce ableist biases if ethical principles are not adequately integrated into their design and governance. While safety and infrastructure design remain central to how AV systems protect vulnerable road users (Kapsalis et al. 2024), this study focuses on how technology mediates our social diversity perceptions—that is, how perceptions toward PRM become embedded into technology. In doing so, we highlight the underlying mechanisms through which some social categories are made visible, while others are overlooked in AV contexts. These insights can inform ethical debates and guide future design considerations in the development and governance of autonomous mobility systems.

Shifts to greater automation, particularly through the use of AI technologies, risk further embedding current ableist paradigms into both technological and policy infrastructure (Newman-Griffis et al. 2023). This increases the risks of social exclusion and produces additional and sometimes even new uncertainties and everyday insecurities to cope with. To better understand the potential biases of AI solutions, we studied how PRM in comparison with other intersectional social categories are perceived by data subjects ($N = 1272$) in the context of autonomous vehicles (AV). We have used AV as a proxy AI system example that relies heavily on data to make high-stake decisions. We employed a mixed-method approach, combining eye-tracking in visual scenarios that simulate ethical dilemmas with a short survey, drawing on the Moral Machine (Awad et al. 2018) as our experimental foundation.

First, our findings suggest that while traditional categories, such as nationality and age, tend to receive more attention, likely due to their long-established roles in public discourse, PRM is comparatively neglected in the AV context. This is particularly concerning given the potential of AV systems to transform transportation by improving accessibility for PRM. Yet, if AI designs neglect PRM, they risk perpetuating ableist biases that undermine equity and increase the level of uncertainty PRM have to cope with. Furthermore, when we clustered participants to identify distinct subgroups based on their viewing behaviors, our results reveal that Disability tends to receive less attention overall, particularly as most of the participants fall within the *Low Disability and Diversity Awareness* cluster, where mean fixation values for Disability are notably lower than in the *High Disability Awareness* and *Adaptive Disability Evaluators* clusters. Although fixation duration in our experiment should not be interpreted as a direct proxy for moral choice, prior work shows people often rely on fast, intuitive moral judgments under time constraints (Suter and Hertwig 2011; Fiedler and Glöckner 2015). This helps contextualize why certain social categories, such as PRM, may receive lower gaze yet still trigger immediate normative assumptions. Second, our findings showed that participants paid more attention overall in AV scenarios than in non-AV, likely reflecting deeper interest or concerns over algorithmic handling of diversity versus intuitive, bias-driven judgments for human drivers.

Third, our study provides clear evidence that perceptions of PRM and social diversity vary by individual and contextual factors (e.g., algorithmic familiarity and technology adoption readiness). Importantly, the systematic shift in cluster membership between AV and non-AV settings indicates that disability awareness is not a fixed personal trait, but a context-sensitive response shaped by whether participants are evaluating an algorithmic or human driver. In AV scenarios, a larger share of participants were classified into lower-awareness profiles, whereas non-AV scenarios saw a greater proportion in more adaptive, context-responsive groups. Although the *Adaptive* cluster in the AV setting shows moderate stability, the overall shift in cluster membership across AV and non-AV settings remains evident. The attention patterns we observed indicate that technology optimism and algorithmic familiarity both predict lower disability awareness: participants eager to adopt AVs and those with prior exposure to similar studies tend to rely on algorithms and overlook wheelchair users. In contrast, skepticism toward automation and less algorithmic familiarity drive more adaptive, context-sensitive attention to mobility constraints.

This discussion is further validated by our in-lab experiment, where we run the same experiment with data experts ($N = 16$) to provide additional insights. Technical experts tended to engage less with disability-related scenarios in AV contexts, possibly due to a reliance on established heuristics regarding algorithmic fairness, whereas social science experts exhibited greater sensitivity to the social implications of disability representation. In non-AV contexts, the pattern reversed somewhat, with technical experts showing increased attention to PRM, and this may be due to their skepticism about human-driven bias—a sentiment further highlighted during interviews. This echoes Whittaker et al. (2019) that disability has been largely omitted from the AI-bias conversation, and that trainers and system designers themselves might misrecognize PRM (Nakamura 2019). Future research should incorporate varied expert perspectives (e.g., industrial designers and transport engineers) to capture broader perspectives on AV equity. Ethically, these results show the urgent need to ensure diverse user representation and proactive attention to diversity in the development and deployment of AV systems. Although the data science experts and the data subjects

in our study do not represent society as a whole or account for specific regional and jurisdictional differences, they nonetheless provide critical insights from an important segment of society whose perspectives policymakers and engineers should carefully consider. Increasing public confidence in AV policies requires explicitly incorporating diverse societal values by involving varied societal groups in defining norms and systematically addressing multiple dimensions of automated decision-making (Dubljevic et al. 2021).

Furthermore, new methodological approaches are needed to better understand inclusion and equity in mobility design (Cecchini et al. 2025), particularly for marginalized groups such as people with disabilities (Parent 2016). This study offers a significant methodological contribution to the interdisciplinary field of cognitive research and technology perception by employing eye-tracking as a crucial window into the cognitive processes underlying how the public assesses social diversity in AI systems. Moreover, our results add to a body of evidence that neglecting people with disabilities in AV/AI development perpetuates ableist "blind spots" (Bennett and Keyes 2020; Dicianno et al. 2021). Our study illustrates that examining public perceptions of people with disabilities is key for equitable automated mobility design, as it enables us to assess whether AV systems reflect users' lived experiences, thereby potentially building trust and acceptance. This aligns with recent discussions highlighting the importance of design decisions throughout the lifecycle of AI and other data technologies in terms of their impact on disability equity, accessibility, and inclusion when used in practice (Trewin et al. 2019; Newman-Griffis et al. 2023). Equally, investigating data experts' perception is essential, since they have the power to alter the development of automated systems and indirectly impact the lives of many people, including people with disabilities as a vulnerable group.

These findings highlight a strong need for a unified, inclusive approach to AI design—one that integrates insights from diverse stakeholders, including both data experts and general data subjects—to mitigate bias and promote equitable outcomes in AI systems. More specifically, institutions should adopt strategies that foster cross-disciplinary dialog and shared decision-making. For example, establishing cross-functional advisory boards that include both data experts as well as data subjects who are directly affected by algorithmic decisions can help integrate diverse perspectives throughout the design and evaluation stages of automated systems. Moreover, institutional communication strategies, such as regular stakeholder workshops, public consultations, and transparent reporting on design decisions, can break down silos and challenge existing boundaries. Furthermore, embedding equity-focused performance metrics and providing interdisciplinary training can further ensure that diversity is prioritized in day-to-day practices. By structurally integrating the multiple perspectives and diversity of users, designers, and producers into the development process at an early stage instead of ex-post, incremental risks can be limited and reduced. In addition, unwanted developments and failures can be identified and avoided, and unintended consequences of a linear modernization of mobility systems can be minimized (Beck et al. 2003; Kesselring 2008).

Although our study provides valuable insights into people with disabilities and social diversity perceptions in AV contexts, several limitations must be acknowledged. We focused specifically on wheelchair use as a representative, visually recognizable to traffic scenarios; however, this approach does not capture the full spectrum of disabilities, many of which are non-mobility related or not visually apparent and may inadvertently reinforce stereotypes. Additionally, our study did not include participants with reduced mobility, as the focus was on how digitally active crowd-workers, often involved in data practices that shape AI systems, perceive social diversity in automated decision-making. However, including participants with reduced mobility in future work would help deepen understanding of how lived experience shapes perceptual and cognitive engagement with automation. Moreover, our online sample—primarily comprising adults, highly educated, and digitally active individuals—may over-represent these viewpoints while underrepresenting older and more vulnerable groups who might have different experiences and perspectives on automated mobility. Additionally, previous work suggests that political orientation can shape attitudes toward technology, risk perception, and evaluations of social groups (Graham et al. 2009; Kahan et al. 2011). Although participants' political affiliation was not measured in this study, this factor, together with broader political discourses that shape how emerging technologies are framed and politicized, may influence how participants perceive AVs. This is particularly relevant for categories that have become politically charged in some contexts, such as COVID-19 vaccination status (Allcott et al. 2020). Future research should therefore consider not only individual political orientation but also the wider sociopolitical narratives surrounding AVs to better disentangle their potential influence on perceptions of disability, fairness, and automated risk allocation. Finally, future work should also examine safety perceptions in AV contexts, as these perceptions may influence both societal expectations and the design priorities embedded in AI-based mobility systems.

Appendix

See Table 6.

Table 6 Proportion of fixation time in milliseconds allocated to AOIs relative to total fixation duration across AV and non-AV settings

Scenario category	*N* (pairs)	Mean AOI fix (AV)	Mean total fix (AV)	AOI Prop. AV	95% CI AV	Mean AOI fix (NON-AV)	Mean total fix (Non-AV)	AOI Prop. Non-AV	95% CI Non-AV	DIFF (AV − NON-AV)	95% CI DIFF	*t*	*df*	*p*
Disability	1244	392.15	6577.21	0.056	[0.051, 0.061]	424.68	6368.93	0.061	[0.055, 0.066]	−0.005	[−0.012, 0.002]	−1.378	1243	0.168
Age	1245	390.50	6815.34	0.055	[0.050, 0.060]	382.38	6397.51	0.056	[0.051, 0.061]	−0.001	[−0.008, 0.005]	−0.399	1244	0.690
Country of origin	1245	535.50	7147.24	0.072	[0.066, 0.077]	507.84	6869.53	0.070	[0.065, 0.075]	0.001	[−0.006, 0.008]	0.387	1244	0.699
Covid-19	1248	404.86	7165.62	0.056	[0.051, 0.061]	453.87	6732.37	0.063	[0.058, 0.068]	−0.007	[−0.014, 0.000]	−1.884	1247	0.060
Income	1248	461.50	7830.29	0.057	[0.052, 0.062]	443.42	7048.34	0.063	[0.057, 0.069]	−0.006	[−0.013, 0.002]	−1.443	1247	0.149
Micromobility	1249	401.57	7122.47	0.053	[0.049, 0.058]	533.74	6869.17	0.070	[0.064, 0.075]	−0.016	[−0.023, −0.009]	−4.565	1248	***
Residence	1245	470.26	7427.1	0.059	[0.054, 0.064]	454.37	6877.58	0.063	[0.057, 0.068]	−0.004	[−0.010, 0.003]	−1.098	1244	0.273

This table reports (a) mean fixation time on the Area of Interest (AOI) directed to the social-category target (passengers and pedestrians) within each scenario, (b) mean total fixation time for the scenario (a proxy for decision duration), and (c) proportional fixation (AOI fixation/total fixation). Values include mean fixation times in milliseconds. Proportional fixation reflects the fraction of the visual decision-making process directed toward each social category. Confidence intervals (95%) and paired t tests assess differences between AV and non-AV settings

***$p < 0.001$

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Author contributions M.I. and A.M. wrote the main manuscript text. M.I. performed data analysis and prepared all figures and tables. S.K., K.L., and D.NG. contributed to the Theory and Discussion sections. A.M., S.K., and K.L. reviewed the manuscript.

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Data availability The data that support the findings of this study are available on reasonable request from the corresponding author. In such cases, a confidentiality agreement will be established between the researchers, in line with the data processing principles required by the research ethics committee. The data are not publicly available due to their containing information that could compromise the privacy of research participants. However, we have prepared thorough metadata descriptions to provide detailed explanations of the methodology used in the study. These metadata are openly available here: (https://doi.org/10.5281/zenodo.13919434).

Declarations

Conflict of interest The authors declare no competing interests.

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