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A Multifaceted Equity Metric System for Transportation Electrification

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A Multifaceted Equity Metric System for Transportation Electrification

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by

Takahiro Tsukiji

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ABSTRACT OF THE THESIS

A Multifaceted Equity Metric System for Transportation Electrification

by

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Master of Science in Civil Engineering

University of California, Los Angeles, 2023

Professor Jiaqi Ma, Chair

Transportation electrification will bring significant benefits to society such as the elimination of tailpipe emissions and less dependence on fossil fuel in the transportation sector. The equitable distribution of electric vehicles (EVs) and electric vehicle supply equipment (EVSE) is a critical challenge for a successful electrification transition. While existing research significantly contributes to understanding equity issues in transportation, additional challenges are brought by the emerging trend of transportation electrification. This thesis proposes a multi-dimensional equity metric system to fill this gap, which evaluates the equity implications of the projected EV and EVSE deployment across different socio-demographic groups. Specifically, four types of equity are considered: a fair share of resources and external costs that are grouped into horizontal equity, as well as inclusivity and affordability that refer to vertical equity. This thesis also performs a case study addressing equity issues of the projected EV and EVSE adoption in Los Angeles County (LA County) in 2035 by leveraging the proposed equity metric system. The results of the case study reveal disparities in EV and public charger adoption, EV trip distance, trip purpose, and economic status. These disparities result in uneven impacts on different socio-demographic groups, highlighting the need to address equity issues in transportation electrification. Based on the case study results, this thesis proposed recommendations to address these equity issues, which provides valuable insights for local governments and transportation agencies.

The thesis of Takahiro Tsukiji is approved.

Mathieu Bauchy

Regan F. Patterson

Jiaqi Ma, Committee Chair

University of California, Los Angeles

2023

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The contribution to this paper is confirmed by the author as follows: study conception, design, and review: Jiaqi Ma, Ning Zhang, Brian Yueshuai He; data collection: Takahiro Tsukiji, Qinhua Jiang, Ning Zhang, Brian Yueshuai He; analysis and interpretation of results: Takahiro Tsukiji, Ning Zhang; draft manuscript preparation: Takahiro Tsukiji, Ning Zhang.

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1. INTRODUCTION

Transportation systems are undergoing fundamental changes such as transition towards electrification, implementation of new technologies represented by connected and automated vehicle, and adoption of renewable energy. This paradigm shift can bring considerable benefits to society, such as climate change adaptation, air pollution reduction, safety improvement, road capacity enhancement, and human well-being improvement (Wagner et al., 2014; Chen et al., 2018; Guo et al., 2020; Ma et al., 2020; Raboy et al., 2020; Blondeau et al., 2022; Guo et al., 2022). Regarding the transportation electrification, the infrastructure related to electrification, particularly the electric vehicle supply equipment (EVSE, refers to public chargers in this study) for enabling the electric vehicle (EV) mobility, is insufficient at this stage, which not only makes the EV charging inconvenient and unreliable but also makes the coast-to-coast EVSE network difficult to implement. For instance, California has 38,082 charging ports in operation by March 2023 as published by the Department of Energy (2023), while to accommodate a future surge in EV fleets, the state is striving to deploy 1.3 million public and shared-private chargers by 2030 (State of California, 2022). The significant gap in EVSE over the next decade has inspired plenty of research focusing on statewide and nationwide charger need predictions and distributions, either through approaches based on the real-life data from test EV fleets and charger stations or based on people's travel information derived from travel survey or transportation simulations (Hilshey et al., 2013; Wagner et al., 2014; Brooker et al., 2015; Wang et al., 2018). However, the existing literature generally follows a customer-centric principle that seeks to maximize the efficient and reachable charging service for existing and candidate EV drivers, and it is utilitarian to pay ultra-attention to locations with a high-charging demand. This neglects underserved and disadvantaged areas in building a fully accessible EVSE network based on the presumption that they have a low charging need due to their low EV adoption rate. Such an issue can ultimately induce an unfair distribution of EVSE in transportation systems, which in turn reduces people's EV adoption willingness in disadvantaged communities and undermines the benefits of electrification to the entire society.

Equity evaluation measuring the distributional impact of resources and investments is a necessary component for gaining deeper insight into the implementation of EVSE deployment decisions to satisfy residents' EV charging demand, which helps reduce the risk of further neglecting disadvantaged areas (Haughton et al., 2009; Litman, 2023). In this study, we propose a multifaceted equity metric system for the electrified transportation system to quantify geographical equity among socio-demographic groups, while also incorporating utilitarianism to meet the need for public chargers for future EV fleets. First, we introduce our previous research, a holistic prediction model, to generate the public charger deployment plan for large-scale transportation networks according to people's travel trajectory and charging demand in time and space (Jiang et al., 2023). The developed prediction model guarantees the high resolution of deployment results, especially at the community level, which is important for an equity analysis. Second, based on the EV travels and EVSE deployment plans, we evaluate equity in the system via EV- or EVSE-related performance indicators and the widely applied equity index, the Gini index, in the four equity types introduced by Litman (2023): a fair share of resources and external costs that are grouped into horizontal equity, as well as inclusivity and affordability that are referred to as vertical equity. To compare disparity among communities in each equity type, communities are further grouped in terms of income, community disadvantage, multi-family-housing-unit (MFHU) rate, and race-ethnicity. Finally, inequitable properties across socio-demographic groups within the four equity types are investigated, with the aim to help decision-makers understand the implication of unfairness and potential negative impacts of candidate EVSE deployment decisions as well as provide suggestions for improving equity. Additionally, the combination of the existing EVSE prediction model and this equity evaluation model has been driving our research group to build a comprehensive research platform with series of studies called CREATE (charging resilience, equity, and accessibility in transportation electrification).

Contributions of this study are outlined below. First, in this study, an EV-user-centric framework is leveraged with the EV mobility and EV charging need analyses to evolve the EVSE deployment decision-making to consider the trade-off between equity and utilitarianism, which benefits the sustainable transition of transportation electrification (Jiang et al., 2023). Second, the multidimensional equity indicators and their comparison across diverse community groups provide a comprehensive quantitative equity metric system about how EVSE deployment affects residents' social well-being. Last, in this study, the proposed equity metric system is demonstrated through a large-scale transportation system in Los Angeles (LA) County of California. Overall, this study can guide planners to pursue equitable EVSE deployment at the upper planning stage rather than at the later allocation stage in small regions, thereby maximizing the equity benefits of the recommendations.

The rest of the thesis is organized as follows: **section 2** presents a literature review on equity measurement indices and EV- and EVSE-related performance indicators; **section 3** introduces the components and methodology of the equity metric system; **section 4** describes the specification and the assumption of the case study with the transportation system of LA County; **section 5** discusses the results of the case study; **section 6** proposes how to address the inequities revealed by the case study; and **section 7** draws conclusions and the extension of research interests.

2. LITERATURE REVIEW

Over the past decade, there has been a growing trend to incorporate equity into research in the transportation field, especially with regard to the transition to electrification. For a quantitative equity evaluation, indices to present how the public resources are distributed among people are required. In the field of transportation, it is common and beneficial to define and classify equity to discuss equity issues in multi-dimensional aspects. Moreover, indicators that can quantify the performance of EV and EVSE are necessary for calculating equity impacts. Therefore, this section reviews the literature related to equity evaluation indices, equity type in transportation, and EV- and EVSE-related performance indicators for equity evaluation in transportation electrification.

2.1 Literature Review on Equity Evaluation Indices

Equity evaluation on the distribution of benefits and impacts of transportation across different socio-demographic groups is necessary for determining the target of investment and estimating the effects of projects and policies (Haughton et al., 2009; Litman, 2023). To measure and quantify the equity benefits among different socio-demographic groups, several indices were investigated in the previous studies. Wee et al. (2021) found that the Gini index was the most frequently used index for equity evaluation due to its ease of interpretability and communication. Meanwhile, Camporeale et al. (2019) revealed that the Theil index was popular for equity evaluation because of its ability to describe the equity both within and across socio-demographic groups. These two indices were also referred to in other related studies. For example, Su et al. (2018) presented a method of investigating the spatial equality in taxi-hailing service in China by calculating different service rates via the Gini index and the Theil index, and revealed that inequality substantially existed within cities rather than between cities. Jin et al. (2019)

investigated the contribution of a shared mobility to improve equity in urban transport of New York City by using the Gini index and disclosed the insufficient role of the shared mobility in acquiring equity. Fan et al. (2022) estimated the change of income, disparity, and inequality caused by the development of high-speed railway in China by using the Theil index and found that the urban-rural income gap decreased due to the increase in rural income but the disparity of income among rural areas increased with the improvement of accessibility. In addition to these two indices, Feng et al. (2014) presented mean log deviation, relative mean deviation, coefficient of variation, and Atkinson index. They investigated the improvement of spatial equity of accessibility by road capacity enhancement via the indicators and revealed that equity measurements were sensitive to the selection of links to enhance capacity as well as the scale of the enhancement. Cai et al. (2013) also measured the equity of transportation investment in China as a case study by using the multiple aforementioned indices and revealed that equity performances under the same investment were different among the four indices and the investment for transportation was unequally distributed. Generally, Behbahani et al. (2019) reviewed historical social equity theories including above six indices and research on their application to transportation network design problems. They recommend that decision-makers could choose either one or multiple indices for equity evaluation depending on specific conditions and requirements.

2.2 Literature Review on Equity Type in Transportation

In the transportation field, there are multiple types of equity and a multi-dimensional understanding of equity based on the equity-type classification can provide comprehensive insights for decision-making on transportation policies and projects. Litman (2023) defined social equity in terms of the allocation of benefits and costs and classified equity in transportation into two major categories: horizontal and vertical equity. Horizontal equity means that people across socio-demographic backgrounds should equally share resources and is represented by two types of equity: a fair share of resources and external costs. A fair share of resources addresses whether public resources such as transportation budget are equally distributed to people and external costs concern the benefits or risks that people provide other individuals. Vertical equity means that people with disabilities should be treated well and is comprised of two types of equity: inclusivity and affordability. Inclusivity discusses how people with disabilities and special mobility needs are served in transportation and affordability addresses how low-income people can afford to receive transportation services. **Table 1** gives a summary of the classification of equity types and definition of each equity type introduced by Litman. The equity metric system proposed in this thesis exactly follows the abovementioned classification of equity type in **Table 1**.

Table 1. Classification and definition of equity type

Equity type		Definition
Horizontal equity	A fair share of resources	Assumption that public resources should be equally distributed to people.
	External costs	Supposition that benefits or risks of travel activities should be equally distributed to individuals.
Vertical equity	Inclusivity	Presumption that people with disabilities or other travel restrictions should be favorably treated in transportation.
	Affordability	Belief that low-income people should be able to participate in travel activities.

2.3 Literature Review on EV- and EVSE-related Performance Indicators

As stated above, for the equity evaluation in transportation electrification, the indicators to quantitatively show the performance of EV and EVSE are required for understanding the degree of the existing inequities and to what extent those inequities should be addressed. This subsection provides the literature review on EV- and EVSE-related performance indicators by referring to the four equity types described in section 2.2.

In the aspect of the fair share of resources, accessibility is a commonly evaluated variable in transportation equity evaluation (Feng et al., 2009; Wee et al., 2021). Accessibility is defined as people's ability to reach the destinations where they can enjoy services and engage in activities, as well as the potential opportunity for human activities generated by transportation (Kim et al., 2015; Behbahani et al., 2019). As an indicator for EV and EVSE performance, public charging accessibility defined as the number of electric charging stations available within a certain distance from an EV-user's residence is an important factor to evaluate the service level of the existing charging facilities and evaluate people's willingness to adopt EVs (Blondeau et al., 2022). Nazari et al. (2018) also analyzed the accessibility of charging stations by calculating the number of charging facilities in a census block and proposed a dynamic model to predict consumers' decision-making on adopting EVs. The results revealed that accessibility to charging stations critically affected the individuals' intention to purchase EVs.

Regarding external costs, Litman (2023) evaluated the external costs of noise and air pollution, crash damages, and traffic congestion per user by travel mode and revealed that automobile has larger external impacts than other modes. Litman (2016) also discussed the way to estimate transportation costs and benefits in monetary value and showed that the air pollution and greenhouse gas (GHG) emission cost of EVs is lower than that of non-EVs. In other studies, emissions of air pollutants such as carbon monoxide (CO), nitrogen oxides (NO_X), particulate matter (PM), sulfur oxides (SO_X), and volatile organic compounds (VOCs) as well as emissions of GHGs such as carbon dioxide (CO_2), methane, and nitrous oxide during the electricity generation or EV trip have been often assessed as external impacts. For example, Brady et al. (2011) estimated the total amount of CO_2 emissions from electricity generation and reduced tailpipe emissions under the deployment of 230,000 EVs in Ireland that was planned for 2020.

Holland et al. (2016) measured the emissions of air pollutants and GHGs per mile of 11 EV models in 2014 in the U.S. Environmental Protection Agency (EPA) fuel efficiency database as well as the daily emissions of air pollutants and GHGs at 1,486 power plants in the U.S.

For inclusivity, Brumbaugh (2018) and Litman (2023) presented travel mode share by people's disability status and showed that people with disabilities tend to drive less and travel more by walking, taxi, and public transit than those without travel restrictions. Brumbaugh (2018) also analyzed inclusivity with individuals' average travel distance and travel time by disability condition by using 2017 National Household Travel Survey data of U.S. Department of Transportation, Federal Highway Administration and revealed that people with disabilities tend to travel for shorter time as well as smaller distance than able-bodied people. The proposed indicators can be effective for equity evaluation in an electrified transportation system.

In terms of affordability, Litman (2023) investigated the share of household spending on housing and transport by income level in the U.S. and found that the ratio is considerably high in lower income groups. Litman (2023) also analyzed affordability via typical annual user costs that are user-paid parking fee and vehicle expenses by travel mode and revealed that the costs of automobile were more than five times higher than that of other modes. For the evaluation of affordability in transportation electrification, the energy consumption cost of EVs is an important factor to evaluate the performance of EVs and determine the location or the number of EVSE required for the deployment of EVs. Chen et al. (2022) calculated the daily power consumption cost of EV users through the charging time, the charging capacity per unit time of EVs, electricity fee, and other related service fee to propose a strategy of orderly charging EVs to shave the peak and fill the valley of a power grid operation in a day as well as minimize the power consumption cost of EV users.

While previous studies have introduced a series of indicators for equity evaluation in the context of transportation electrification, none of them have addressed equity issues specifically related to EV and EVSE performance across all four equity classes. This study aims to fill this gap by presenting a multifaceted equity metric system that incorporates specific performance indicators for each equity type, allowing for a comprehensive evaluation of equity in transportation electrification.

3. METHODOLOGY

This section presents the framework and critical components of the multifaceted equity metric system for future transportation electrification. **Section 3.1** describes the overall framework of the equity metric system of this study. **Section 3.2** briefly introduces the inputs and outputs of the existing public charger prediction model developed by our group, which provides the data foundation for this study. **Section 3.3** details the method of socio-demographic group classification, EV- and EVSE-related performance indicators, the equity measurement index, and the control variable for the equity evaluation.

3.1 Framework of the Equity Metric System

As defined in **Table 1** in **section 2.2**, Litman (2023) grouped equity in transportation into two major categories that are horizontal and vertical equity as well as into four types in more detail: a fair share of resources, external costs, inclusivity, and affordability. The equity metric system proposed in this study follows this equity type classification to enable a multifaceted equity evaluation and the equity evaluation from both horizontal and vertical aspects in transportation electrification. **Table 2** summarizes the scope of the equity metric system describing the four equity types, the potential equity performance indicators for each type that were addressed in the existing studies in the literature review (**section 2.3**), and EV- and EVSE-related performance indicators for each equity type. Note that considering the data limitation and the ability of each indicator for quantification and statistical analysis, indicators shown in the third column of **Table 2** are the ones adopted by the equity metric system of this study, which are explained in depth with the following paragraphs.

In terms of horizontal equity and the fair allocation of resources, Nazari et al. (2018) and Blondeau et al. (2022) found that the distribution of public chargers significantly influences people's willingness to adopt EVs. A higher density of public chargers reduces individuals' concerns about running out of energy during their trips. Therefore, the number of public chargers in a specific area, known as public charger density, serves as a crucial indicator in this study for evaluating the fairness of resource allocation for EV operation.

External costs, which involves measuring the impact of travel activities on others, has been extensively discussed in previous studies, particularly in relation to environmental concerns, as outlined in the literature review (**section 2.3**). Litman (2016) also highlighted the importance of considering safety as a critical factor in transportation cost and benefit analysis. Therefore, external crash cost per person and the cost reduction associated with air pollution and GHG emissions were chosen as indicators for evaluating horizontal equity in this study.

As a type of vertical equity, inclusivity focuses on ensuring the participation of individuals with disabilities or travel restrictions in transportation activities. As mentioned in the literature review (**section 2.3**), Brumbaugh (2018) examined the average travel distance and time for people with disabilities and found those variables to be significant for quantifying inclusivity. Since the average travel distance will be thoroughly discussed in the aforementioned section on external costs, this study adopts the average EV travel time as an indicator for evaluating inclusivity.

For affordability, as outlined in the literature review (**section 2.3**), Litman (2023) emphasized the importance of considering annual user costs for different travel modes as they directly impact travelers' mode choices. In the context of EVs, the cost of public charging constitutes a significant portion of the operational expenses. Therefore, this study considers the burden of public charging cost relative to each individual's income as a crucial indicator for evaluating affordability.

Table 2. Scope of the equity metric system

Equity type	Potential equity performance indicators in the existing studies	EV- & EVSE-related performance indicators
Horizontal - A fair share of resources	- The number of public chargers within a certain distance or area (Nazari et al., 2018; Blondeau et al., 2022)	- Public charger density
Horizontal - External costs	- Air pollution and GHG emissions (Brady et al., 2011; Holland et al., 2016) - Noise, air pollution, GHG emission, crash damage, and traffic congestion cost (Litman, 2016, 2023)	- External crash cost per person - Reduction in air pollution and GHG emission cost per person
Vertical - Inclusivity	- Travel distance and travel time by disability condition (Brumbaugh, 2018) - Travel mode share by disability status (Brumbaugh, 2018; Litman, 2023)	- Average EV travel time
Vertical - Affordability	- Power consumption cost of EV (Chen et al., 2022) - Share of household spending on transportation by income level (Litman, 2023) - User costs by travel mode (Litman, 2023)	- Public charging cost burden per EV user

Fig 1 shows the research flow of the equity evaluation by the developed equity metric system, indicating in which steps the outputs, indicators, and variables introduced in this section are processed. First, multiple trip chain tables, multiple public charging demand profile tables, and public charger deployment plans extracted from the EVSE deployment decision-making model in our previous study are input in the equity metric system (see the introduction in **section 3.2**). Second, each EV- and EVSE-related performance indicator associated with the four equity classes is calculated based on the outputs in the first step, which are carefully delineated in **section 3.3**. Next, the products are analyzed via socio-demographic information to statistically show the distribution of EV- and EVSE-related impacts among individuals and its disparity across different socio-demographic statuses, as described in **section 3.3**. Finally, proposals for the reductions of inequities are drawn based on the results of the equity evaluation.

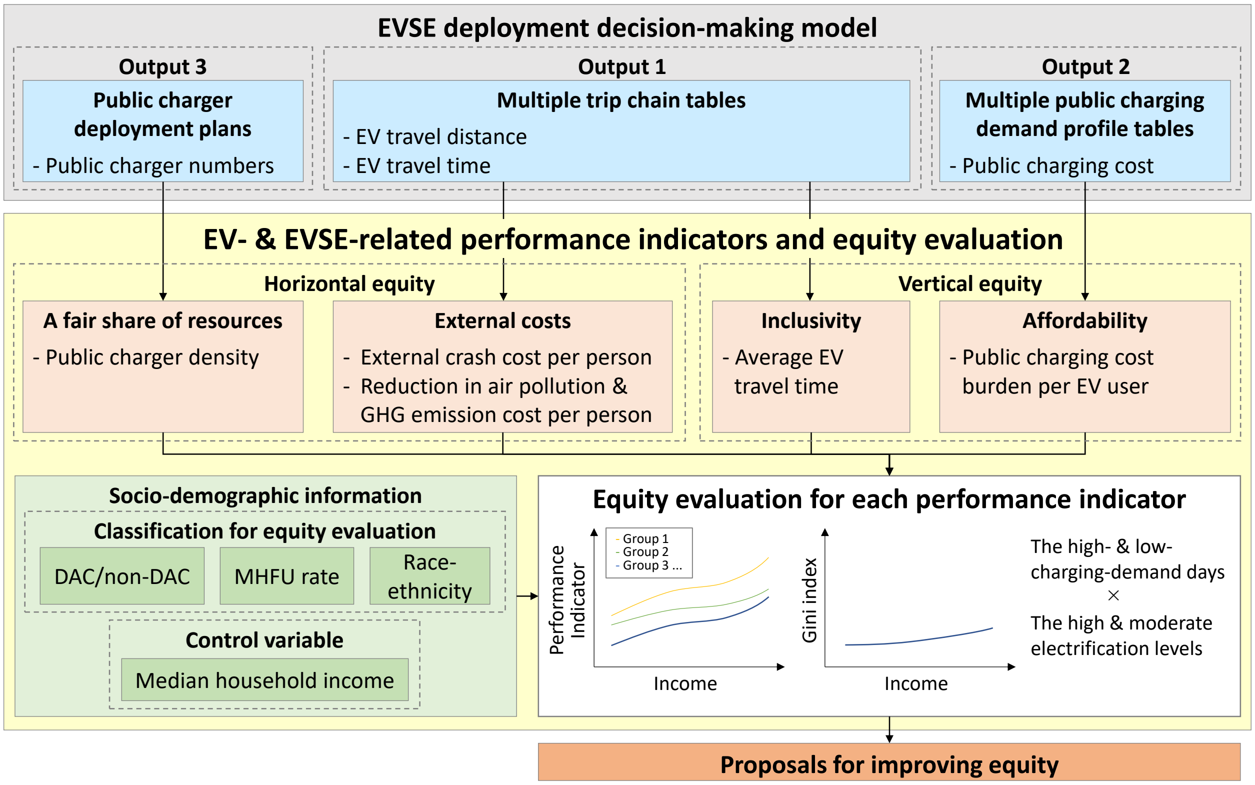


Fig 1. Research flow of the equity metric system

3.2 EV-user-centric EVSE Deployment Decision-making Model

The EVSE deployment decision-making model developed by our previous study derives the distribution plan of public chargers for future EV fleets at the community level. This decision-making model is closely dependent on the understanding of people's daily travel trajectories and the spatially varying EV adoption in the system, the learning of EV attributes and public charging behaviors, and the exploration of possible future electrification levels (Jiang et al., 2023). **Fig 2** shows the EVSE deployment decision-making model with three critical modules, including travel profile simulation module, charging demand profile generation module, and charger deployment planning module. **Fig 2** provides the process of what kind of input data is used, how the outputs are produced, and how the critical modules are connected in the model. Finally, the ultimate outcome of the distribution plan of public chargers is provided as Output 3. The core components of the model are introduced as follows.

The travel profile simulation module aims at simulating the daily travel trajectory baseline for people via multiple vehicle modes without application of charging events. This module employs the activity-based travel demand and agent-based traffic assignment models to capture the stochasticity of every individual's daily travel. Meanwhile, transportation variations are incorporated to present the diversity of the system's operation such as seasons, weekday and weekend, day-to-day, and special event day from the demand side as well as road network capacity reductions due to weather, incidents, and work zones from the supply side. First, the user activity-based traffic demand model is a regional transportation plan model to forecast travel needs associated with the survey of everyone's daily activities (Jiang et al., 2022). It gives people's travel plans based on their activity schedules. Next, the agent-based transportation simulation model assigns people's travel plans by simulating the movement of people and vehicles in the network (He et al., 2021). Finally, Output 1 shows individuals' daily trip chains that differs scenario by scenario when the inputted demand- and supply-side variances are different in tabular format.

The charging demand profile generation module learns the charging activities by i) understanding the possible future electrification levels such as the planned fleet size of EVs including battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) as well as the future installation scale of private residential and workplace chargers, ii) defining comprehensive and explicit charging strategies to allow the diverse real-life charging habits of EV users, and iii) considering the significant impacts of traffic conditions (e.g. traffic speeds and stops) on vehicles' energy consumption and the time-sensitive charging price on charger location selection (Cochran et al., 2021; Wang et al., 2021; Tal et al., 2020; Fetene et al., 2017). Then, this module applies the abovementioned future electrification configurations, EV user habits, and driving and charging characteristics to each travel trajectory table in Output 1. Output 2 is the prediction result to list the relevant individual, vehicle, location, and time of each charging event, which is scenario-based and has the same tabular format as Output 1.

The charger deployment planning module aggregates the daily public charging activities based on the charging event prediction table in Output 2 to obtain the peak charging demand at the system and community levels and the relative temporal attributes. Next, this module considers the shareability of public chargers to transform the spatiotemporal public charging need into the public charger deployment of the system by sharing every charger among multiple charging events at different times in the same community. The community defined in this study is census tract (CT), commonly used to describe the socio-demographic area. Finally, Output 3 is the EVSE deployment plan to provide the community-level public charger numbers for the electrified transportation system.

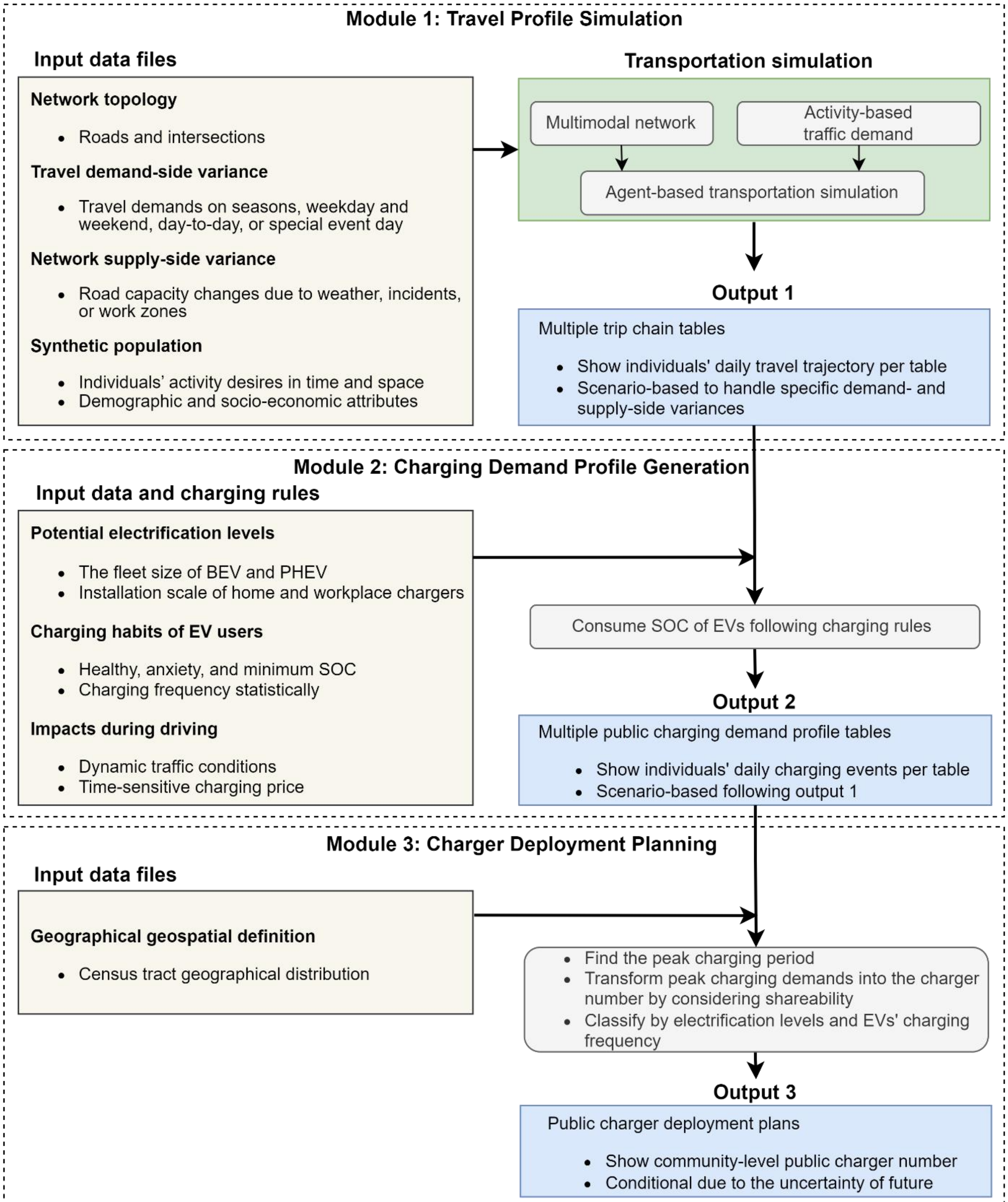


Fig 2. Flow of the EVSE deployment decision-making model

3.3 Classification Method, Indicators, and Variables for Equity Evaluation

3.3.1 Socio-demographic group classification

For statistical analyses in the equity evaluation, the census tracts (CTs) are grouped into three sets of bins based on socio-demographic variables.

- **Disadvantaged/non-disadvantaged communities** (DACs/non-DACs). CTs are DACs in this study (particularly in the case study) if they meet the criteria of Senate Bill (SB) 535 Disadvantaged Communities by the California Environmental Protection Agency (2022), which designates DACs as communities most vulnerable to environmental pollution and also facing economic challenges.
- **Multi-Family-Housing-Unit rate** (MFHU rate). The MFHU rate is calculated as the total MFHU units divided by the total housing units per CT (Hsu et al., 2021; Jiang et al., 2023). In CTs with high MFHU rate many people need to share public resources and spaces. For classification of CTs, the MFHU rate is divided into four groups with identical intervals: [0, 0.25], (0.25, 0.5], (0.5, 0.75], and (0.75, 1].

$$MFHU\ Rate_i = \frac{N_{mfhu,i}}{N_i} \tag{1}$$

  where $N_{mfhu,i}$ refers to the number of MHFU units in the *i*th CT and N_i refers to the total number of units in the *i*th CT.

- **Zonal major race-ethnicity**. Five racial-ethnic groups are considered: non-Hispanic Asian, non-Hispanic Black, non-Hispanic White, Hispanic, and no majority. CTs are grouped into these five groups based on the major race-ethnicity, which is defined as the race-ethnicity that accounts for more than 50% of the CT's population.

3.3.2 EV- and EVSE-related performance indicators

Five performance indicators are used for the evaluation of the four types of equity in this study, as shown in **Table 2**. Litman (2023) stated that there are several reference units for the measurement of transportation impacts such as per-capita, per-trip, per-passenger-mile, or per-dollar, but equity should generally be measured with per-capita because equity evaluation aims at the fair distribution of benefits or costs among people and the measurement with per-mile is not sensitive to the costs caused by high-mileage travelers. Therefore, most of the following indicators in this study use per-capita unit to represent the performance of EV and EVSE. Since this study focuses on how the transportation electrification will serve people and communities in the future, all the following indicators are only associated with EVs.

- **A fair share of resources indicator – Public charger density** (*PCD*). Regarding the fair share of resources, the public charger density that indicates how people can access and utilize the public chargers is an important factor that impacts people's intention to adopt EVs. The public charger density is defined as the number of public chargers per person for a given CT. The public charger density of a selected socio-demographic group is provided by the average value of all CTs within the group.

$$PCD_i = \frac{1}{N_i}\sum_{j=1}^{N_i}\frac{PC_j}{P_j} \tag{2}$$

  where i refers to the ith socio-demographic group, N_i refers to the number of CTs in group i, PC_j represents the number of public chargers in the jth CT of group i, and P_j represents the population of the jth CT of group i.

- **External costs indicator – External crash cost per person** (*ECC*). One of the indicators for equity evaluation in the external costs is the external crash cost that is the crash cost including medical care, lost wages and future earnings, and property damage or loss imposed on another person (Litman, 2016). The external crash cost per person is defined as the external crash costs caused by all trips in a given day of EVs whose owners live in a given CT divided by the population of the CT. The external crash cost of a selected socio-demographic group is represented by the average value of all CTs within the group.

$$ECC_i = \frac{1}{N_i}\sum_{j=1}^{N_i}\frac{ECC_{ev} \times VMT_j}{P_j} \quad (3)$$

where i refers to the ith socio-demographic group, N_i refers to the number of CTs in group i, ECC_{ev} is the external crash cost of EV introduced by Litman (2016) that is \$0.081 per vehicle miles traveled (VMT), VMT_j represents the total daily vehicle miles traveled of EVs owned in the jth CT of group i, and P_j represents the population of the jth CT of group i. The external crash cost of EV by Litman (2016) is converted from 2007 U.S. dollar to 2023 U.S. dollar by using the consumer price index inflation rate 1.48 as of February 2023 (U.S. Bureau of Labor Statistics, 2023).

- **External costs indicator – Reduction in air pollution and GHG emission cost** (*CR*). Another indicator for the external costs is the reduction in air pollution and GHG emission cost based on the transportation cost and benefit analysis by Litman (2016). Air pollutants are CO, NO_X, PM, SO_X, and VOCs from tailpipe emissions and GHGs are CO_2, methane, and nitrous oxide described as lifecycle emissions which include emissions from fuel production, car manufacture and maintenance, as well as road infrastructure construction and maintenance (Litman, 2016). The cost represents the control cost that is required for the reduction of emissions, defense against risks, carbon retention, and compensating individuals affected by the impacts (Litman, 2012). Since the dataset used in this study focuses on EV trips, the cost reduction is calculated by comparing the air pollution and GHG emission cost of the EV fleet and that of comparable non-EVs. The reduction in air pollution and GHG emission cost of a given CT is provided by the average value of all CTs within the group.

$$CR_i = \frac{1}{N_i}\sum_{j=1}^{N_i}\frac{\left(C_{gas}^{pollution} - C_{ev}^{pollution}\right)\times VMT_j + \left(C_{gas}^{ghg} - C_{ev}^{ghg}\right)\times VMT_j}{P_j} \qquad (4)$$

where i refers to the ith socio-demographic group and N_i refers to the number of CTs in group i. $C_{gas}^{pollution}$ is air pollution cost of gasoline car that is \$0.059 per VMT, $C_{ev}^{pollution}$ is air pollution cost of EV that is \$0.015 per VMT, C_{gas}^{ghg} is GHG emission cost of gasoline car that is \$0.025 per VMT, and C_{ev}^{ghg} is GHG emission cost of EV that is \$0.006 per VMT introduced by Litman (2016). VMT_j represents the total daily vehicle miles traveled of EVs owned in the jth CT of group i and P_j represents the population of the jth CT of group i. The air pollution cost and GHG emission cost by Litman (2016) are converted from 2007 U.S. dollar to 2023 U.S. dollar by using the consumer price index inflation rate 1.48 as of February 2023 (U.S. Bureau of Labor Statistics, 2023).

- **Inclusivity indicator – Average EV travel time** (*ATT*). For the equity evaluation in inclusivity, average travel time is an important indicator to reveal people's travel activities (Brumbaugh, 2018; Litman, 2023). The average EV travel time is defined as the total daily travel time of EVs whose owners live in a given CT divided by the number of trips of EVs whose owners live in the CT. The average EV travel time of a selected socio-demographic group is provided by the average value of all CTs within the group.

$$ATT_i = \frac{1}{N_i}\sum_{j=1}^{N_i}\frac{TT_j}{n_j} \qquad (5)$$

where i refers to the ith socio-demographic group, N_i refers to the number of CTs in group i, TT_j is the total daily travel time of EVs owned in the jth CT of group i, and n_j refers to the total trip number of EVs owned in the jth CT of group i.

- **Affordability indicator – Charging cost burden** (*CCB*). Regarding the equity evaluation in affordability, the public charging cost burden for EV-users is a crucial factor to measure people's affordability in transportation electrification. The charging cost burden is defined by the average daily public charging cost per EV user living in a given CT divided by the median daily household income of the CT which is the median annual household income of the CT divided by 365. The charging cost burden of a selected socio-demographic group is represented by the average value of all CTs within the group.

$$CCB_i(\%) = \frac{1}{N_i}\sum_{j=1}^{N_i}\left(\frac{ADCC_j}{MDHI_j} \times 100\right) \tag{6}$$

where i refers to the ith socio-demographic group, N_i refers to the number of CTs in group i, $ADCC_j$ is the average daily public charging cost per EV user living in the jth CT of group i, and $MDHI_j$ is the median daily household income of the jth CT of group i.

3.3.3 Equity evaluation index

Among several indices for measuring equity described in **section 2.2**, the Gini index is used in this study to identify the disparity in the above performance indicators across different socio-demographic groups since it has been the most frequently applied in the previous studies on equity evaluation and distributions of accessibility (Wee et al., 2021; Jiang et al., 2023). The Gini index ranges between 0, which means a completely equal distribution, and 1, which means the most unequal distribution. The larger the Gini index, the more unequal distribution.

$$Gini\ index = \frac{1}{2n^2\bar{X}}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|X_i - X_j\right| \tag{7}$$

where n refers to the number of socio-demographic groups, X_i refers to the value of the selected equity performance indicator for group i and $\bar{X}$ is the mean of all X_i.

3.3.4 Control variable

To statistically show the distribution of abovementioned EV and EVSE performance indicators, the CTs are divided into four income groups by using the income ratio (*IR*) based on their average annual household income as introduced by Ong et al. (2022): [0%, 60%] for the lowest-income group, (60%, 80%] for the low-income group, (80%, 140%] for the middle-income group, and greater than 140% for the high-income group.

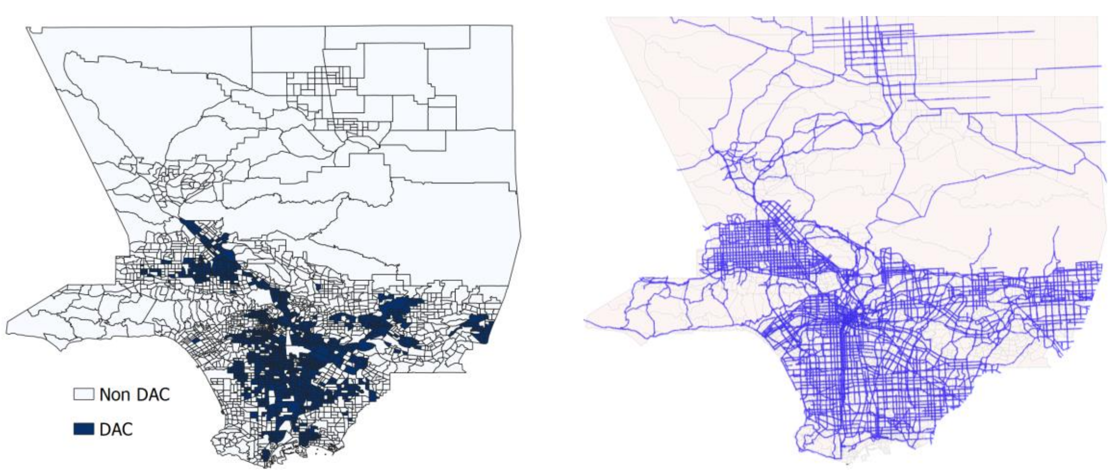
$$IR_i(\%) = \frac{MAHI_i}{AMI} \times 100 \tag{8}$$

where $MAHI_i$ refers to the median annual household income of the ith CT and *AMI* is the area median income of the region which the CT belongs to. For example, in the case study of this thesis, the area median income of LA County in 2022 ($91,100) is used (U.S. Department of Housing and Urban Development, 2023).

4. CASE STUDY AND DATA SPECIFICATION

4.1 Socio-demographic Data Specification and Assumption

As described in **section 1**, the state of California is attempting to adopt 1.3 million public and shared-private chargers by 2030 as part of efforts to achieve the goal of the executive order by the governor in September 2020 that requires all new passenger cars sold in California to be zero-emission vehicles by 2035 (State of California, 2020, 2022). Given this target, our previous study proposed a public charging demand profile prediction model and performed a prediction from 2022 to 2035 via the case study of LA County (Jiang et al., 2023). Based on this projection, this paper carries out an equity evaluation in a large-scale electrified transportation system in LA County in 2035. This transportation system includes 2,342 CTs, 38% of which are DACs, all primary and secondary roads, more than 10 million residents, and over six million vehicles with 1.23% market share of EVs in 2022 (Jiang et al., 2023). Due to the data limitation, this study simply assumes that people's travel behavior, median household income, MFHU rate, and racial-ethnic proportion of each CT will stay the same from 2022 to 2035, but the population will increase based on the estimation by Southern California Association of Governments (SCAG). **Fig 3** shows CTs with classification of DAC and non-DAC and road transportation network of LA County.



(a) (b)

Fig 3. CTs of LA County (a) and road transportation network of LA County (b)

4.2 Traffic Demand, Electrification Level, and Charging Condition Specification

In this case study, a typical traffic-demand day is selected for the equity evaluation of EV and EVSE performance. To incorporate the influence of varying electrification statuses in the future, two electrification levels in 2035 shown in **Table 3** are adopted based on the possible futures discussed in the Los Angeles 100% Renewable Energy Study: the high electrification level and the moderate electrification level (Cochran et al., 2021; Jiang et al., 2023). The total EV numbers described in **Table 3** are estimated based on the assumption that they will linearly increase with the EV market share of 2022 across all CTs. Other assumptions on public chargers and battery charging conditions are outlined in the following bullets and refer to our previous study which has been well developed and discussed (Jiang et al., 2023).

Table 3. Definitions and assumptions for the electrification levels in 2035

Electrification levels	Definitions and assumptions	Total EV numbers	Percentage of EV residents who have home and workplace chargers
High electrification level	The power of almost all devices and equipment will switch from natural resources to electricity and thus electricity demand will be high.	3.09 million	- 70% for home chargers - 28% for workplace chargers
Moderate electrification level	Power shift will be temperate and thus electricity demand will be moderate.	1.16 million	- 80% for home chargers - 14% for workplace chargers

- The public charger type assumed in this study is Level 2 (L2) charger since it is common for home, workplace, and public charging and has a large share that is approximately 90% or more in the public charger number in the U.S. (Tal et al., 2020; U.S. Department of Transportation, 2022; Jiang et al., 2023; U.S. Department of Energy, 2023).
- Our previous study simulated a large variance in charging needs in a day by choosing different initial SOC distributions across EV users since the initial SOC of an EV differs

depending on the charging frequency of the EV user (Tal et al., 2020; Jiang et al., 2023). Tal et al. (2020) showed that the average charging frequency of BEV and PHEV are 1.5 and 1.2 days, respectively, which indicates that an EV is recharged a day and a half after the last charge. Therefore, this study defines two initial SOC states for EVs: the low-charging-demand day where a given EV starts its trip with fully charged status (high initial SOC) and the high-charging-demand day where a given EV begins its travel with partially charged status (low initial SOC). Additionally, EV (BEV and PHEV) residents who have access to home chargers are assumed to begin their trip from home with 80% of the full SOC since 80% of the full SOC is the maximum state for battery if it is used without degradation (Kostopoulos et al., 2020; Jiang et al., 2023). For EV residents who do not have access to home chargers, two types of SOC are set for their first trip of a day: 80% and 40%. 80% is assigned for the low-charging-demand day, and 40% is assigned for the high-charging-demand day.

5. RESULTS AND DISCUSSIONS

This section provides the results and discussions of the equity evaluation with the proposed equity metric system in **section 3** via the case study described in **section 4**. All equity evaluations were performed for the four scenarios that are the high-charging-demand (low-SOC) day and low-charging-demand (high-SOC) day in the high and moderate electrification levels in 2035. However, since the electrification level determines the future transportation electrification status and agencies are striving to meet the charging demands at best, this study principally compares the results of the high and moderate electrification levels. Besides, the general trends were similar between the high- and low-charging-demand days in the results of the fair share of resources and affordability. Also, the results of the high- and low-charging-demand days were the same for external costs and inclusivity since whether there are charging events or not in people's daily travel does not impact their travel activities, which induces no difference in EV travel distance and time. Therefore, most of the discussions in this section are focused on the results of the high-charging-demand day, which are similar with or the same as the results of the low-charging-demand day.

5.1 Fundamental Statistical Data for Each Socio-demographic Group

This subsection describes all the fundamental statistical data for each socio-demographic group to support the discussion of the results of each equity type. **Fig 4** describes the percentage of CTs, and **Fig 5** shows the home and workplace charger adoption scale for each socio-demographic group against income level in the high and moderate electrification levels. **Table 4** provides the number of public chargers in each income group for the high-charging-demand day in the high and moderate electrification levels, and **Table 5** describes EV number per capita in each socio-demographic group in the high and moderate electrification levels. **Table 6** shows the average total daily EV travel distance per CT in the high and moderate electrification levels. **Table 7** describes the average population per CT in each socio-demographic group, and **Table 8** provides the median annual household income of each socio-demographic group. Since DACs are CTs not in the high-income group and there are no CTs for non-Hispanic Black population in the high-income group as shown in Fig 4 (a) and (c), DACs and non-Hispanic Black population do not have values in the high-income group for all equity performance indicators.

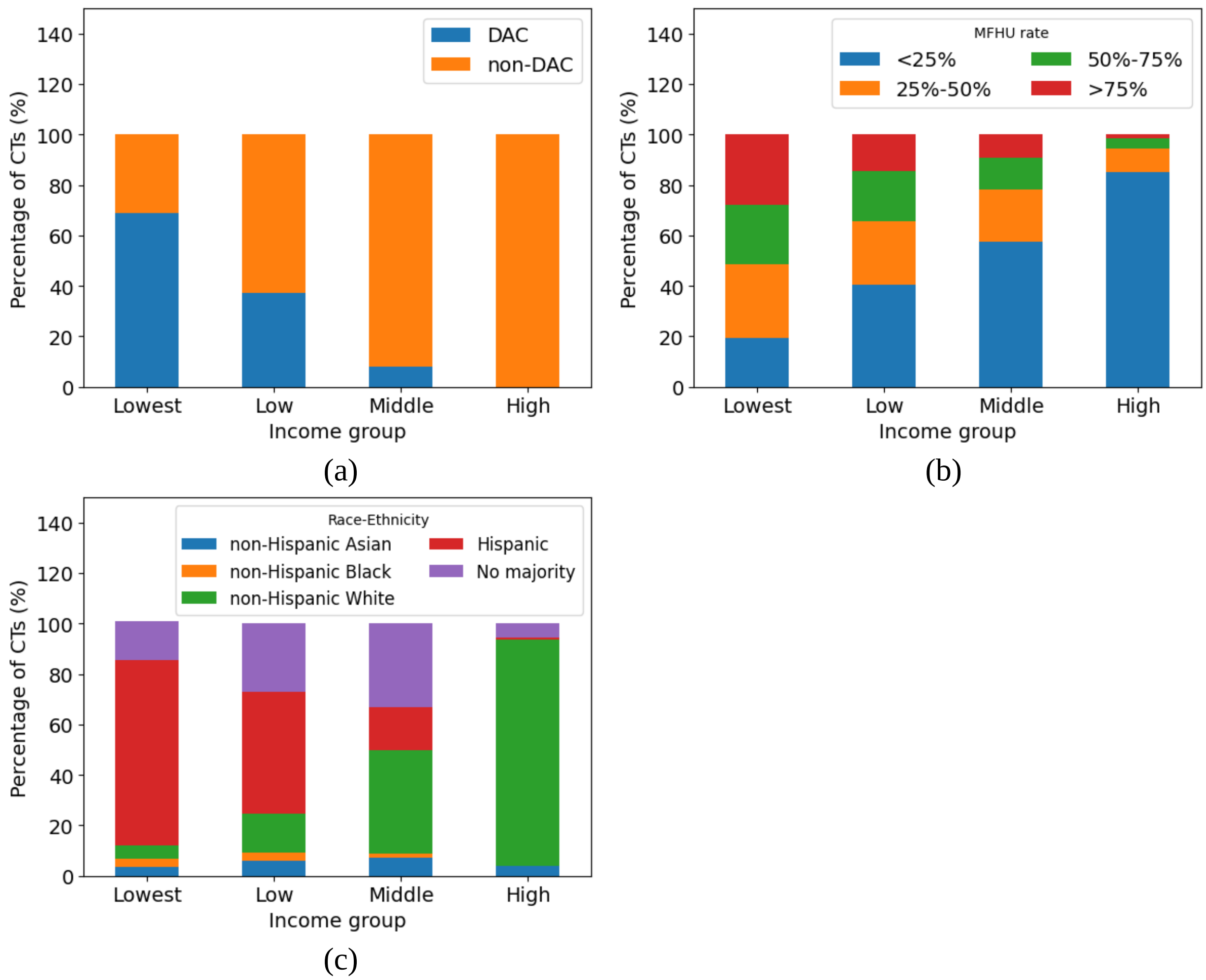


Fig 4. (a) CTs by community disadvantage, (b) CTs by MFHU rate, and (c) CTs by race-ethnicity

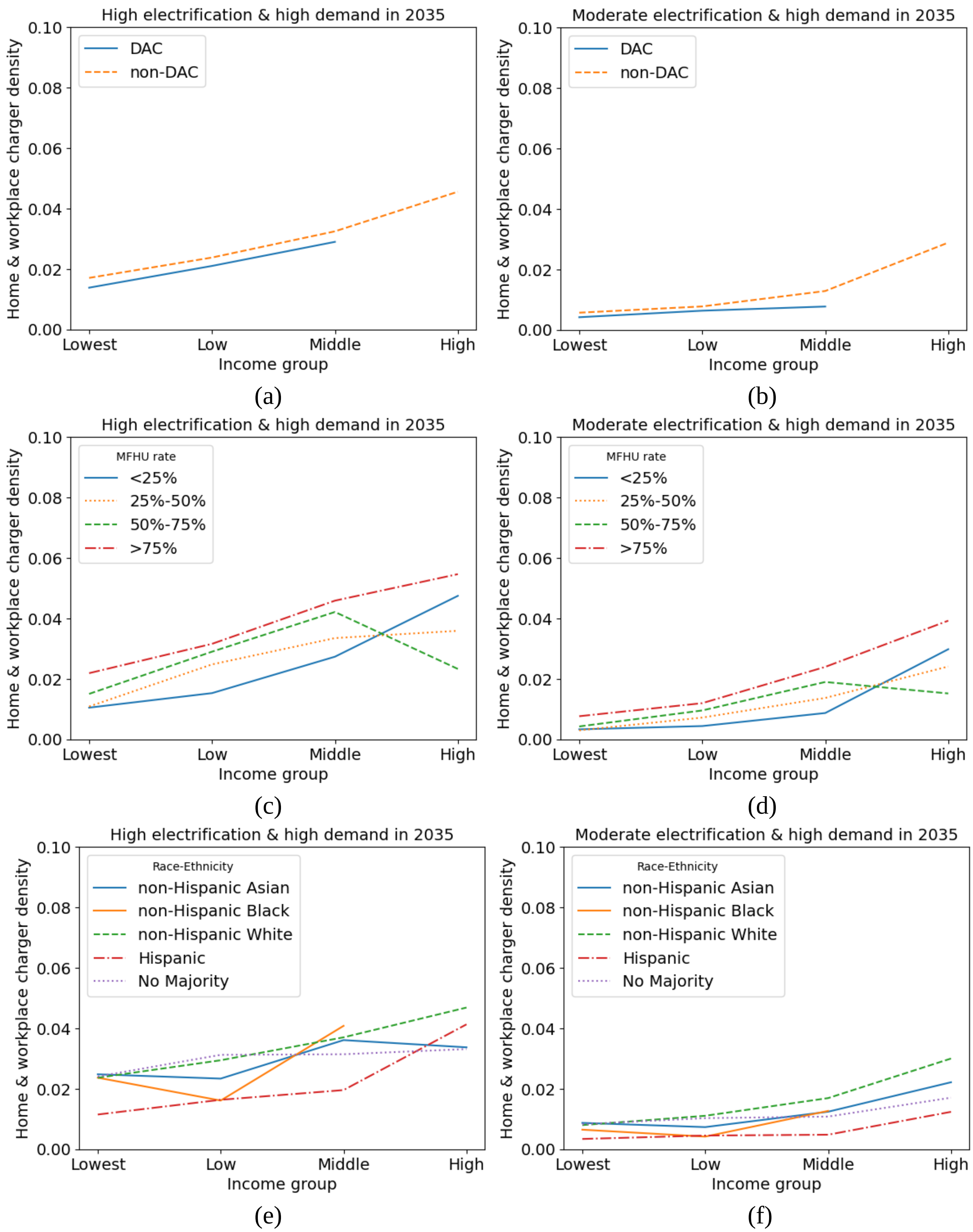


Fig 5. Home and workplace charger density by socio-demographic groups for the high-charging-demand day in the high electrification level (a, c, e) and the moderate electrification level (b, d, f) in 2035

Table 4. Public charger number in each socio-demographic group for the high-charging-demand day in the high and moderate electrification levels in 2035

Socio-demographic group	High electrification level				Moderate electrification level			
	Lowest income	Low income	Middle income	High income	Lowest income	Low income	Middle income	High income
DAC	48,370	20,000	7,620	-	17,920	7,300	2,290	-
Non-DAC	27,750	36,500	90,630	22,470	10,300	13,520	34,860	10,910
MFHU rate: <25%	15,720	22,500	48,900	18,210	5,900	8,080	16,650	8,700
MFHU rate: 25% - 50%	19,590	13,380	20,670	2,780	6,770	4,500	8,340	1,430
MFHU rate: 50% - 75%	19,670	12,020	17,610	1,250	7,470	4,610	7,610	640
MFHU rate: >75%	21,140	8,600	11,070	230	8,080	3,630	4,550	140
non-Hispanic Asian	4,520	4,030	5,300	1,530	1,640	1,650	1,810	710
non-Hispanic Black	4,040	2,530	2,480	-	1,610	940	1,250	-
non-Hispanic White	4,550	9,690	48,710	20,110	1,680	3,730	19,780	9,860
Hispanic	47,720	23,560	11,640	280	17,310	8,270	3,640	70
No majority	15,290	16,690	30,120	550	5,980	6,230	10,670	270
Total (high-demand day)	76,120	56,500	98,250	22,470	28,220	20,820	37,150	10,910
Total (low-demand day)	37,150	28,160	48,670	11,300	15,080	10,690	20,430	5,760

Table 5. EV number per capita in each socio-demographic group in the high and moderate electrification levels in 2035

Socio-demographic group	High electrification level				Moderate electrification level			
	Lowest income	Low income	Middle income	High income	Lowest income	Low income	Middle income	High income
DAC	0.17	0.29	0.33	-	0.05	0.09	0.10	-
Non-DAC	0.24	0.35	0.47	0.65	0.08	0.11	0.18	0.41
MFHU rate: <25%	0.15	0.18	0.38	0.65	0.05	0.05	0.12	0.41
MFHU rate: 25% - 50%	0.12	0.38	0.49	0.61	0.04	0.11	0.20	0.40
MFHU rate: 50% - 75%	0.21	0.43	0.66	0.45	0.06	0.14	0.29	0.29
MFHU rate: >75%	0.28	0.51	0.67	0.94	0.10	0.19	0.32	0.60
non-Hispanic Asian	0.34	0.35	0.55	0.53	0.11	0.11	0.19	0.32
non-Hispanic Black	0.24	0.23	0.45	-	0.07	0.06	0.15	-
non-Hispanic White	0.37	0.46	0.55	0.66	0.12	0.17	0.24	0.43
Hispanic	0.14	0.20	0.21	0.52	0.04	0.06	0.06	0.15
No majority	0.34	0.49	0.46	0.47	0.11	0.15	0.16	0.23

Table 6. Average total daily EV travel distance per CT in each socio-demographic group in the high and moderate electrification levels in 2035 (mile)

Socio-demographic group	High electrification level				Moderate electrification level			
	Lowest income	Low income	Middle income	High income	Lowest income	Low income	Middle income	High income
DAC	2,539	3,950	6,773	-	745	1,181	2,064	-
Non-DAC	4,455	7,505	11,260	15,759	1,539	2,436	4,316	9,784
MFHU rate: <25%	3,125	3,970	8,862	15,297	1,078	1,122	2,881	9,374
MFHU rate: 25% - 50%	2,277	4,934	12,548	18,198	656	1,409	5,022	12,542
MFHU rate: 50% - 75%	3,248	8,437	14,885	17,457	922	2,669	6,758	10,574
MFHU rate: >75%	3,976	11,367	14,421	22,038	1,351	4,332	6,248	13,640
non-Hispanic Asian	7,700	8,813	12,966	24,823	2,213	2,658	4,590	15,561
non-Hispanic Black	3,085	3,935	10,637	-	820	1,042	3,622	-
non-Hispanic White	5,983	12,028	14,175	15,396	1,829	4,407	5,975	9,801
Hispanic	2,121	3,037	4,167	29,671	618	843	1,194	8,464
No majority	5,994	8,249	9,860	13,265	2,197	2,584	3,250	5,574

Table 7. Average population per CT in each socio-demographic group in 2035

Socio-demographic group	Lowest income	Low income	Middle income	High income
DAC	4,608	4,955	5,343	-
Non-DAC	5,022	5,177	5,356	5,302
MFHU rate: <25%	5,442	5,206	5,305	4,985
MFHU rate: 25% - 50%	4,792	5,112	5,267	6,635
MFHU rate: 50% - 75%	4,728	5,000	5,733	8,789
MFHU rate: >75%	4,194	4,888	5,359	6,010
non-Hispanic Asian	5,155	5,804	4,826	7,854
non-Hispanic Black	4,288	5,297	6,425	-
non-Hispanic White	5,673	5,350	5,485	5,254
Hispanic	4,636	4,858	5,201	10,196
No majority	4,925	5,195	5,339	3,570

Table 8. Median annual household income of each socio-demographic group (dollar)

Socio-demographic group	Lowest income	Low income	Middle income	High income
DAC	40,708	62,479	81,698	-
Non-DAC	42,964	63,902	93,060	158,049
MFHU rate: <25%	45,067	63,756	93,992	160,186
MFHU rate: 25% - 50%	42,323	63,524	90,654	151,933
MFHU rate: 50% - 75%	42,400	63,073	89,030	137,145
MFHU rate: >75%	37,127	62,474	88,235	129,475
non-Hispanic Asian	42,182	62,205	92,321	143,792
non-Hispanic Black	40,584	63,381	89,051	-
non-Hispanic White	44,812	64,717	98,218	159,381
Hispanic	41,056	62,613	82,977	135,811
No majority	41,842	64,236	89,409	149,336

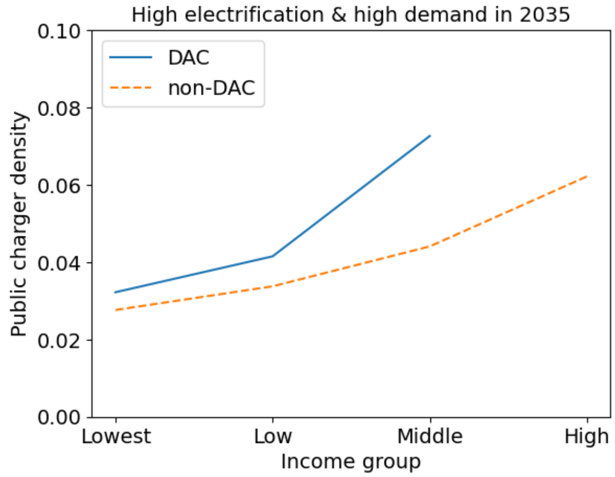
5.2 Results of Equity Evaluation in the Fair Share of Resources

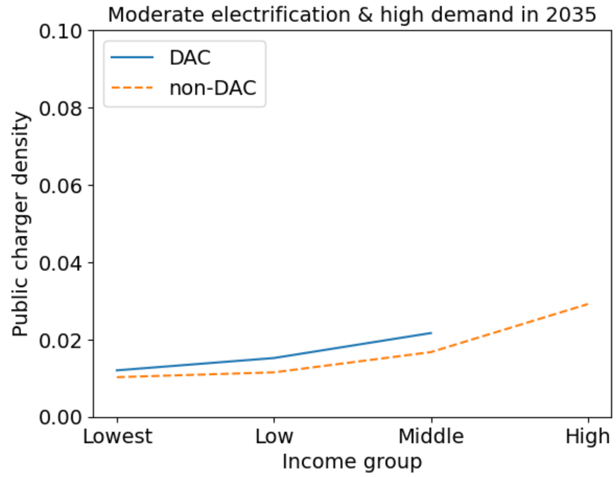
5.2.1 Performance of the public charger density by socio-demographic groups

Fig 6 and **7** show the public charger density in the studied electrified transportation system that is the equity performance indicator of the fair share of resources. As key findings, DACs, MFHU rate lower than 25%, and non-Hispanic White and Hispanic population have higher public charger density than other socio-demographic groups in general. The reasons and other major findings are listed as follows.

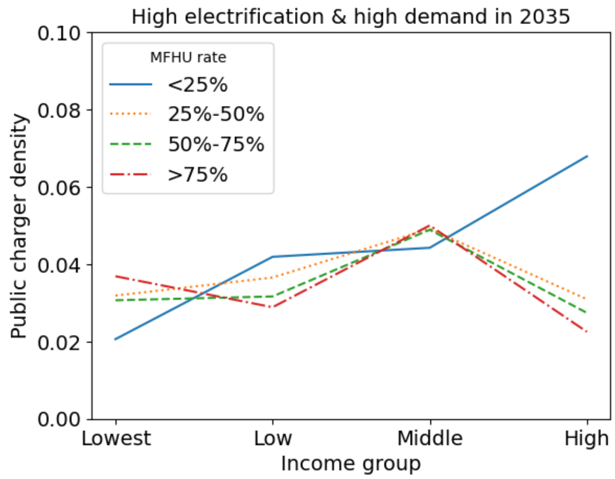
- The high electrification level has higher values than the moderate electrification level since it has more public chargers and EVs per capita as in **Table 4** and **5**. Also the values are larger in the high-charging-demand day than in the low-charging-demand day due to the difference in public charger number as shown in **Table 4**.
- DACs have higher public charger density than non-DACs for both electrification levels in **Fig 6 (a)** and **(b)**. That is probably because non-DACs have higher home and workplace charger density in **Fig 5 (a)** and **(b)**, which reduces the needs for public charging. CTs that are non-DACs decide the general trend particularly in the high-income group as in **Fig 4 (a)**.
- MFHU rate lower than 25% has relatively high public charger density in **Fig 6 (c)** and **(d)**. The possible reason is that this MFHU rate has low home and workplace charger density in **Fig 5 (c)** and **(d)**, which makes the public charging needs higher. The influence of CTs with MFHU rate below 25% becomes large with income, see **Fig 4 (b)**.
- As shown in **Fig 6 (e)** and **(f)**, non-Hispanic Black population has high values in the lowest- and middle-income groups. However, since the percentage of their CTs is small across all income groups in **Fig 4 (c)**, the results of the public charger density are subject to the extremely large values and might be unreliable. As another finding, non-Hispanic White and Hispanic

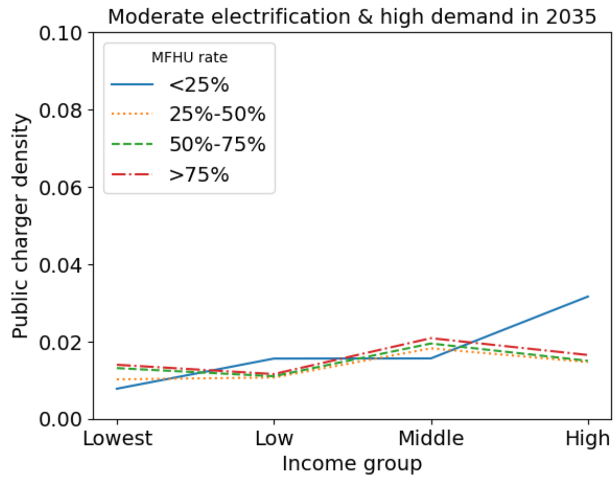
population generally have larger values than other racial-ethnic groups. These are because non-Hispanic White population have the greatest EV number per capita as shown in **Table 5** and Hispanic population have a low home and workplace charger density in **Fig 5 (e)** and **(f)**, which induces high-public-charging demand, while the EV number per capita is in a low level in **Table 5**. Also, non-Hispanic Asian population generally have lower values of the public charger density due to the relatively high home and workplace charger adoption scale.



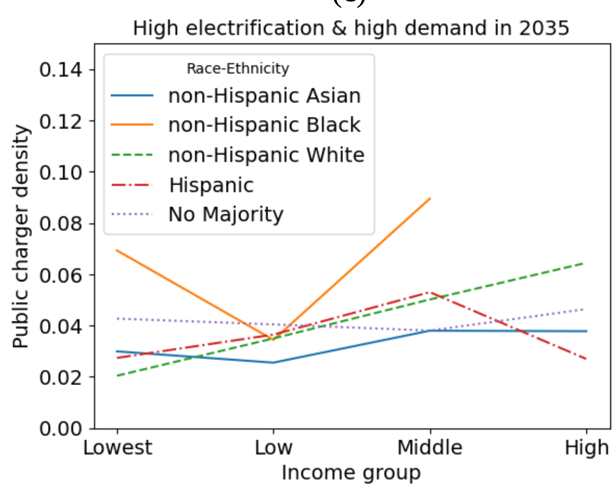


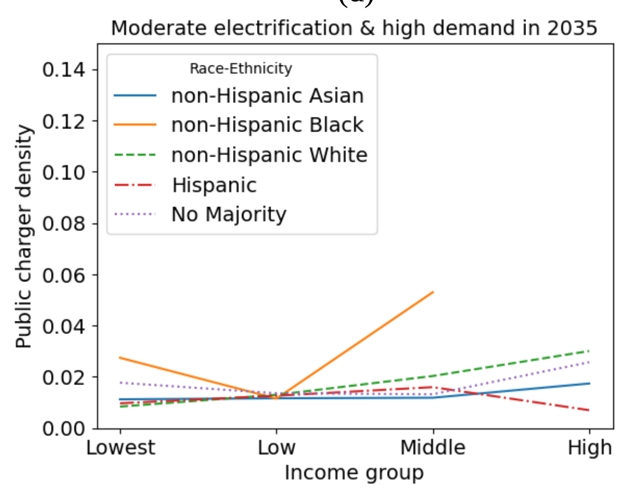
(a) (b)





(c) (d)





(e) (f)

Fig 6. Public charger density by socio-demographic groups for the high-charging-demand day in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

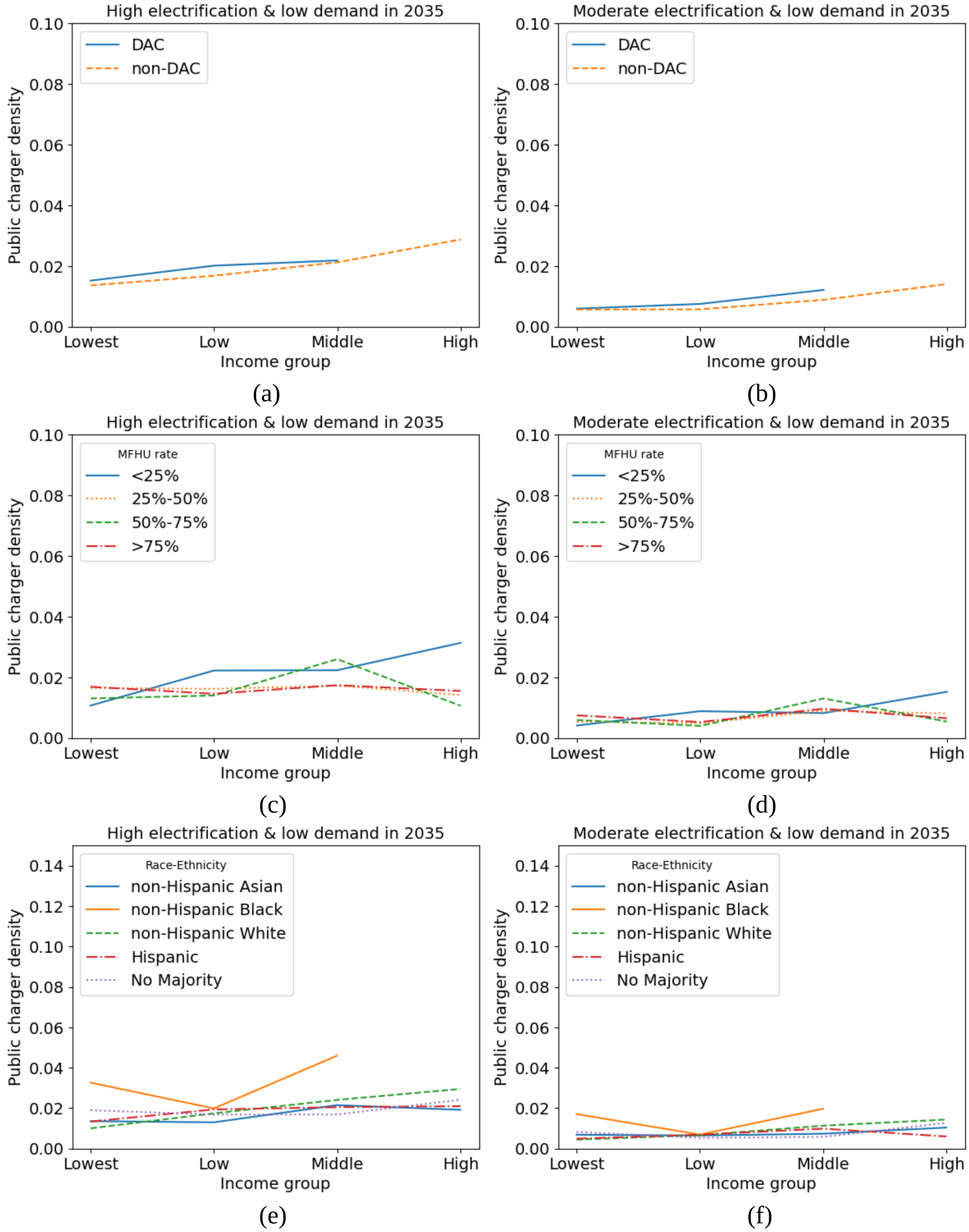


Fig 7. Public charger density by socio-demographic groups for the low-charging-demand day in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

5.2.2 Disparity in public charger density across different socio-demographic groups

This subsection with **Fig 8** provides the disparity in public charger density across different socio-demographic groups via the Gini index. Major findings are that the disparity is large between DACs and non-DACs in the middle-income group for the high electrification level, it is high across different MFHU rates in the high-income group, and it is high among different race-ethnicity especially in the lowest- and middle income groups. The reasons and other findings are outlined in the following bullets.

- The disparity in the public charger density between DACs and non-DACs is relatively high in the middle-income group for the high electrification level in **Fig 8 (a)** is driven by the big jump in the public charger number in non-DACs in the middle-income group as in **Table 4**. The Gini value is highest in the high-income group because DACs do not have the public charger density values in this income group.
- In **Fig 8 (c)**, the disparity in the public charger density across different MFHU rates is high in the high-income group for both electrification levels. This is because the Gini index is calculated based on the values of the public charger density in **Fig 6 (c)** and **(d)**, which indicate the gap among different MFHU rates is large in the high-income group.
- In **Fig 8 (e)**, the Gini value is high in the lowest-, middle-, and high-income groups because non-Hispanic Black population have large values of the public charger density in the lowest- and middle-income groups, and have no values in the high-income group. Although non-Hispanic Black population's small share of CTs might result in an unreliable outcome, the large Gini value indicates the disparity in the public charger density across different race-ethnicity. That possible reason is the large gap in public charger number among different race-ethnicity compared with other socio-demographic group classifications in **Table 4**.

- **Fig 8 (b)** shows a rise in the disparity in the middle-income group, and **Fig 8 (d)** indicates a rise in the low-income group for the moderate electrification level. The possible reasons of these disparities are that in the low-charging-demand day all EVs with home chargers start their daily trips with a high SOC value (80% of a full SOC), with which most of trips of a day can be finished without charging and thereby expects a low number of public chargers.

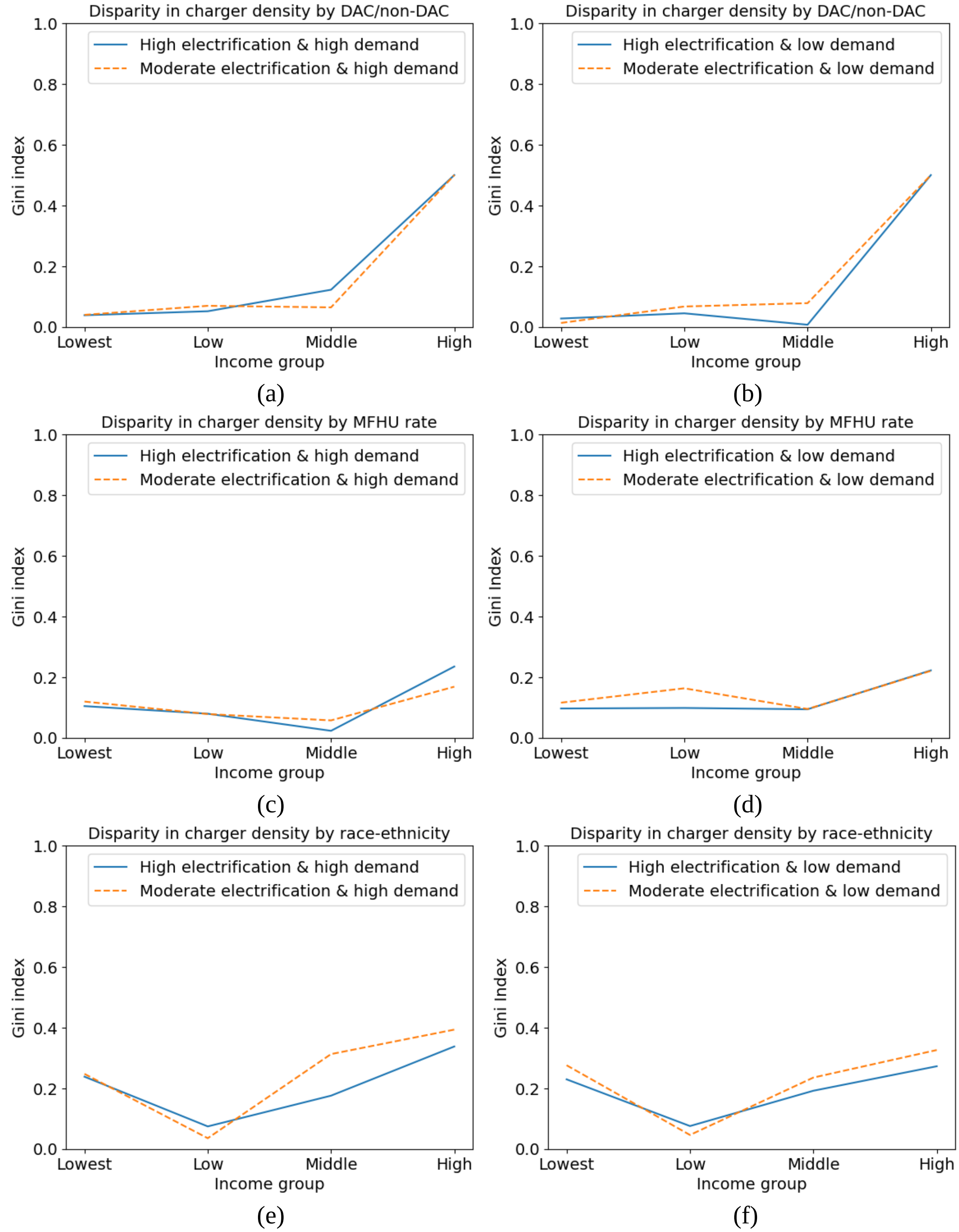


Fig 8. Disparity in public charger density across different socio-demographic groups for the high-charging-demand day (a, c, e) and the low-charging-demand day (b, d, f) in the high and moderate electrification levels in 2035

5.3 Results of Equity Evaluation in External Costs

This subsection involves the outputs of the equity evaluation in external crash cost and air pollution and GHG emission cost reduction, which are the performance indicators of external costs.

5.3.1 Performance of the external crash cost by socio-demographic groups

The results of daily external crash cost per person are presented with **Fig 9**. Major implications are that non-DACs have larger values of the external crash cost than DACs, while MFHU rate lower than 25% and non-Hispanic Black and Hispanic population have lower costs. The causes and other fundamental findings are discussed in the following bullets.

- It is obvious that the high electrification level has larger values than the moderate electrification level due to the larger EV number per capita as in **Table 5** and the external crash cost increases with income in almost all socio-demographic groups.
- In **Fig 9 (a)** and **(b)**, non-DACs have higher values of the external crash cost than DACs at the same income level for both electrification levels. This is because the travel distance is larger in non-DACs in **Table 6**, which induces more potential crashes.
- In **Fig 9 (c)** and **(d),** MHFU rate below 25% stays at lower values since the travel distance is shorter than other rates as in **Table 6**. Also, there is a drop in the high-income group for MFHU rate 50% to 75% because the travel distance is short in this MFHU rate in the high-income group in **Table 6** while the average population is relatively high in **Table 7**, which makes the external crash risk of EV per person small.
- **Fig 9 (e)** and **(f)** show that non-Hispanic Black and Hispanic population have the lowest crash costs in all income groups. The reason is that their travel distance is the lowest in almost all income groups in **Table 6**.

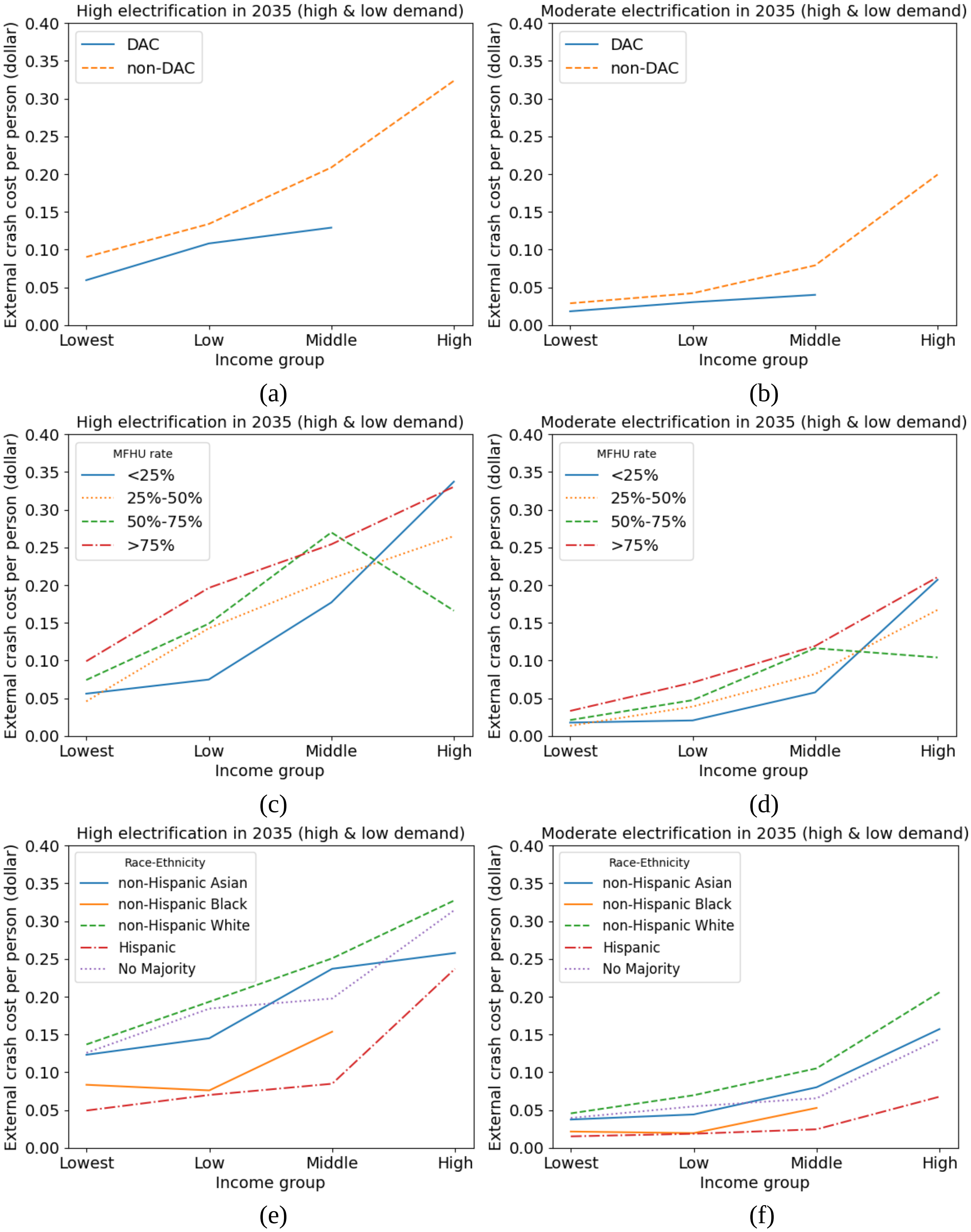


Fig 9. Daily external crash cost per person by socio-demographic groups for the high- and low-charging-demand days in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

5.3.2 Disparity in the external crash cost across different socio-demographic groups

This subsection provides the disparity in the external crash cost across different socio-demographic groups with **Fig 10**. The results indicate that the disparity is high between DACs and non-DACs in the middle-income group, it is large across different MFHU rates in the lowest- and low-income groups, and it keeps a high level across different race-ethnicity in all income groups. The considerations and other implications are outlined as follows.

- In **Fig 10 (a)**, the disparity is high in the middle-income group for both electrification levels. The reason might be that the travel distance is smaller in DACs than in non-DACs in **Table 6** while the average population per CT is almost the same in **Table 7**, which makes the gap in the external crash cost between DACs and non-DACs large. The Gini index becomes 0.5 in the high-income group due to the absence of the external crash cost values for DACs.
- **Fig 10 (b)** shows that the disparity across different MFHU rates is relatively high in the lowest- and low-income groups for both electrification levels. The possible reason is the relatively short travel distance against the relatively high average population in CTs with MFHU rate below 25% in **Table 6** and **7**, which makes the external crash cost of this MFHU rate keeps a low position in **Fig 9 (c)** and **(d)**.
- In **Fig 10 (c)**, the disparity across different racial-ethnic groups keeps a relatively high level around 0.2 to 0.3 for both electrification levels. This is because the gap in the travel distance at the same income level is large among racial-ethnic groups in **Table 6**, which induces a large difference in the external crash cost. The null external crash cost of non-Hispanic Black population also contributes to the high Gini value in the high-income group.

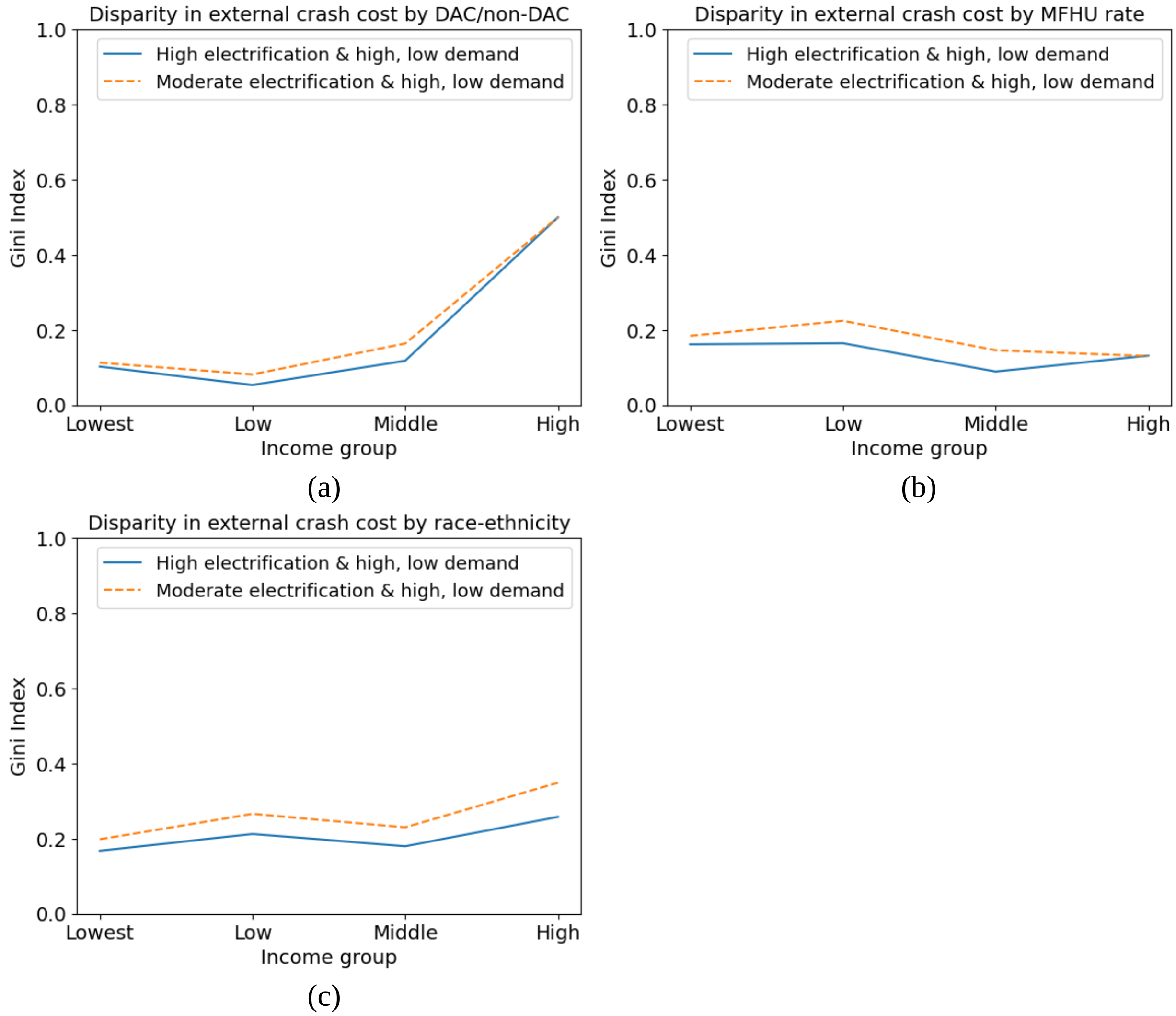


Fig 10. Disparity in the daily external crash cost per person by community disadvantage (a), MFHU rate (b), and race-ethnicity (c) for the high- and low-charging-demand days in the high and moderate electrification levels in 2035

5.3.3 Performance of the reduction in air pollution and GHG emission cost per person by socio-demographic groups

The results of air pollution and GHG emission cost reduction per person, which is an equity performance indicator of external costs, are given via **Fig 11**. The major findings are that the values are higher in non-DACs than in DACs, while MFHU rate lower than 25% and non-Hispanic Black and Hispanic population have the lowest air pollution and GHG emission cost reductions. The reasons and other fundamental findings are outlined in the following bullets.

- It is clear that the values are larger in the high electrification level than in the moderate electrification level due the difference in EV number per capita in **Table 5**, and the benefit of air pollution and GHG emission cost reduction increases with income in nearly all socio-demographic groups.
- **Fig 11 (a)** and **(b)** indicate that non-DACs have higher values than DACs at the same income level because the travel distance of non-DACs is larger than that of DACs in all income groups in **Table 6**, which means that more air pollutant and GHG emissions from conventional vehicles are reduced by the long-distance travel of EVs.
- **In Fig 11 (c)** and **(d)**, MFHU rate below 25% keeps a low level due to the short travel distance in **Table 6**. For MFHU rate 50% to 75%, a drop is observed in the high-income group, which is caused by the relatively short travel distance against relatively high population per CT in **Table 6** and **7**.
- **Fig 11 (e)** and **(f)** indicate that non-Hispanic Black and Hispanic population have the lowest cost reductions in all income groups because of their extremely low values of the travel distance in **Table 6**, which indicates that the reduction in air pollutant and GHG emissions from non-EVs is low for these population groups.

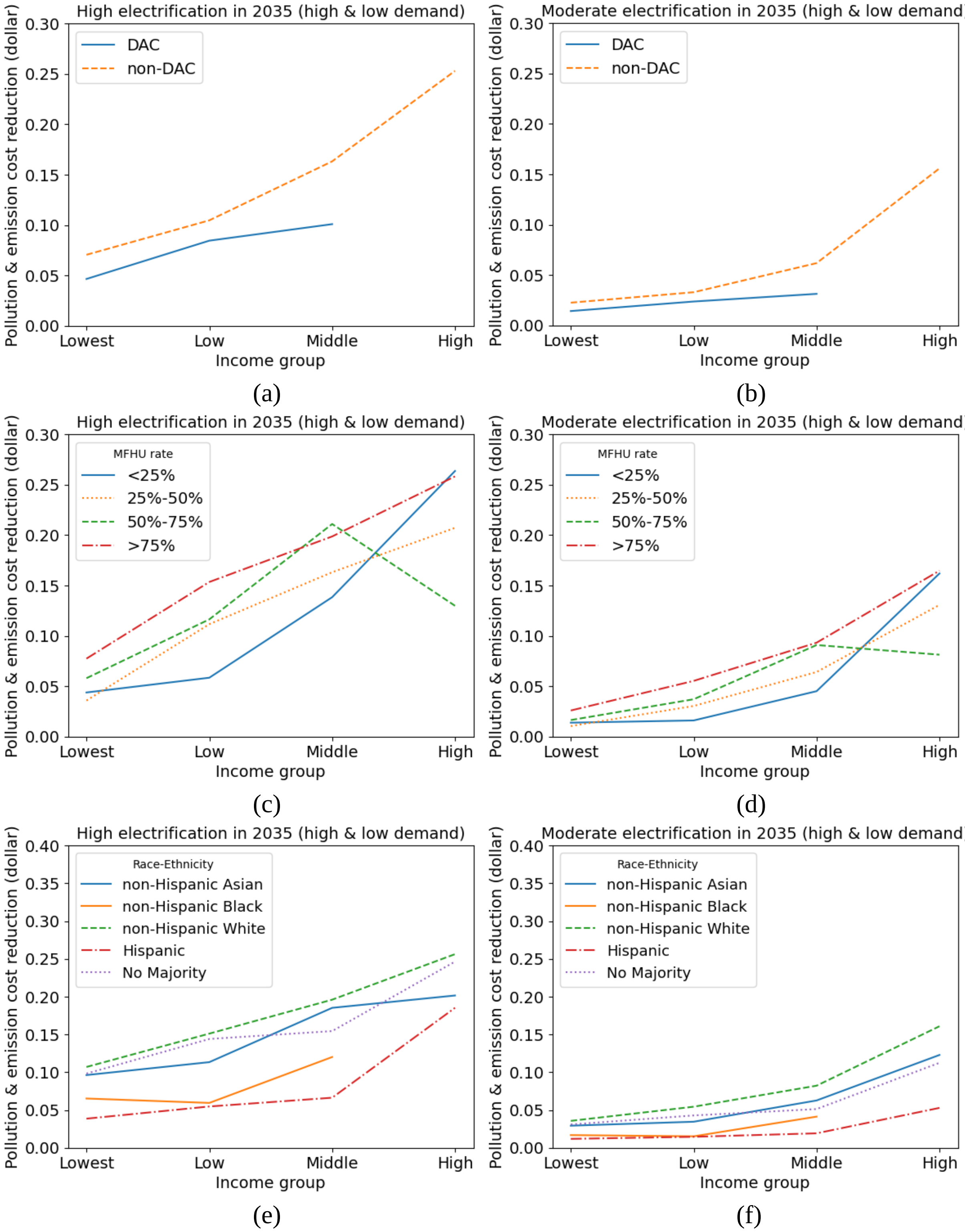


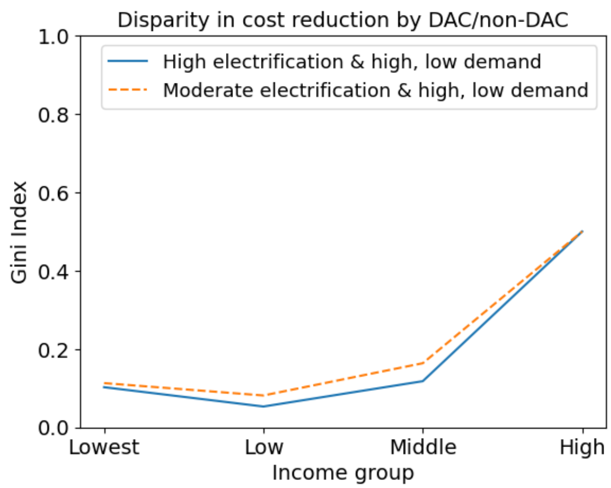
Fig 11. Reduction in air pollution and GHG emission cost per person by socio-demographic groups for the high- and low-charging-demand days in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

5.3.4 Disparity in the air pollution and GHG emission cost reduction across different socio-demographic groups

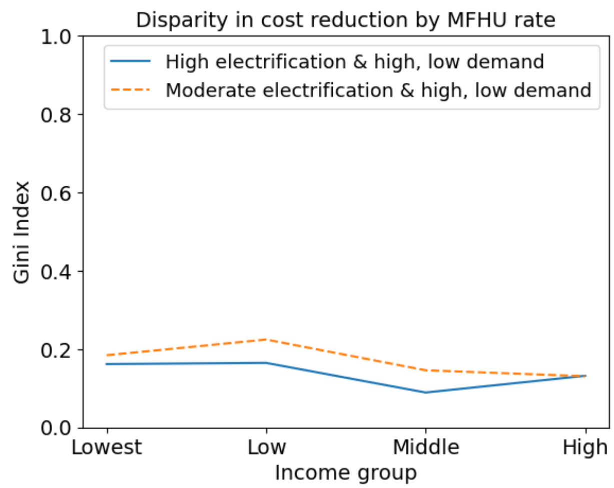
This subsection with **Fig 12** provides the disparity in the air pollution and GHG emission cost reduction across different socio-demographic groups via the Gini index. The fundamental results are that the disparity is large between DACs and non-DACs in the middle-income group, it is high in the lowest- and low-income groups across different MFHU rates, and it is relatively high at all income levels across different racial-ethnic groups. The discussions and other findings are summarized as follows.

- **Fig 12 (a)** shows that the disparity is relatively high in the middle-income group for both electrification levels. The possible reason is the difference in the travel distance between DACs and non-DACs against the same level of population in **Table 6** and **7**. The absence of the cost reduction values for DACs in the high-income group makes the Gini value highest in this income group.
- In **Fig 12 (b)**, the disparity across different MFHU rates is relatively high in the lowest- and low-income groups for both electrification levels. This is because the air pollution and GHG emission cost reduction in MFHU rate below 25% keeps a low position in these income groups in **Fig 11 (c)** and **(d)**, which is caused by the relatively low travel distance against the relatively high population in **Table 6** and **7**.
- From **Fig 12 (c)**, the disparity across race-ethnicity stays at a relatively high level around 0.2 to 0.3 for both electrification levels. This is because the difference in the travel distance at the same income level is large among population groups in **Table 6**, which makes the gap in the air pollution and GHG emission cost reduction among race-ethnicity large as well. The null

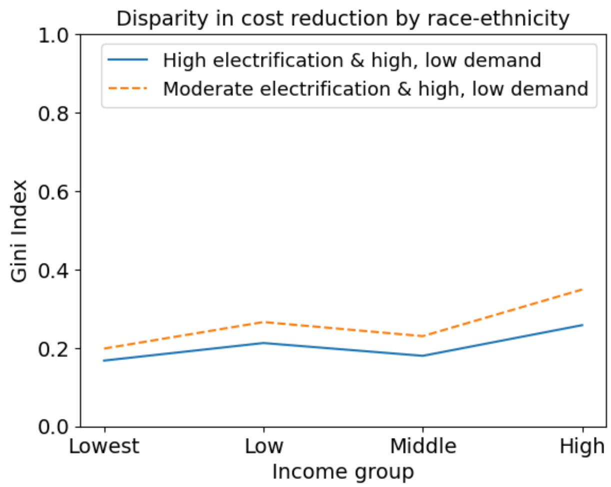
cost reduction of non-Hispanic Black population also contributes to the increasing of the Gini value in the high-income group.



(a)



(b)



(c)

Fig 12. Disparity in air pollution and GHG emission cost reduction per person by community disadvantage (a), MFHU rate (b), and race-ethnicity (c) for the high- and low-charging-demand days in the high and moderate electrification levels in 2035

5.4 Results of Equity Evaluation in Inclusivity

5.4.1 Performance of the average EV travel time by socio-demographic groups

Fig 13 shows the results of average EV travel time that is the performance indicator of inclusivity. As additional information, **Appendix A-Table A** provides the trip number share and average travel time by trip purpose and **Appendix A-Table B** to **E** describe the trip number share by purpose in each income and socio-demographic group. **Appendix A-Table A** indicates that among trip purposes, home, work, maintenance, shop, and escort have relatively large shares of trip number, and university, home, and work have the top three long travel time. Based on these results, the trips whose purpose is home or work, which account for nearly 50% of all EV trips, greatly impact the general trend of average EV travel time. The results reveal that non-DACs have larger values than DACs, while MFHU rate above 75% and non-Hispanic Black and White populations have high values. The reasons and other fundamental implications are listed as follows.

- There is a general increasing trend in the average EV travel time with income in almost all socio-demographic groups for both electrification levels since the share of trips whose destination is home or work generally increases with income for all EV trips in **Appendix A-Table B**, which means that more people tend to travel for a long time in higher income groups.
- **Fig 13 (a)** and **(b)** show that non-DACs have higher values than DACs, probably because the share of trips heading to home or work is higher in non-DACs in **Appendix A-Table C**, which means that large share of trips have longer travel time.
- **Fig 13 (c)** to **(f)** show that MFHU rate above 75% and non-Hispanic Black and White population remain relatively high. This might be because the share of trips heading to home or work is a little high in these groups in **Appendix A-Table D** and **E**, which indicates that more people of these population groups are likely to travel for a long time.

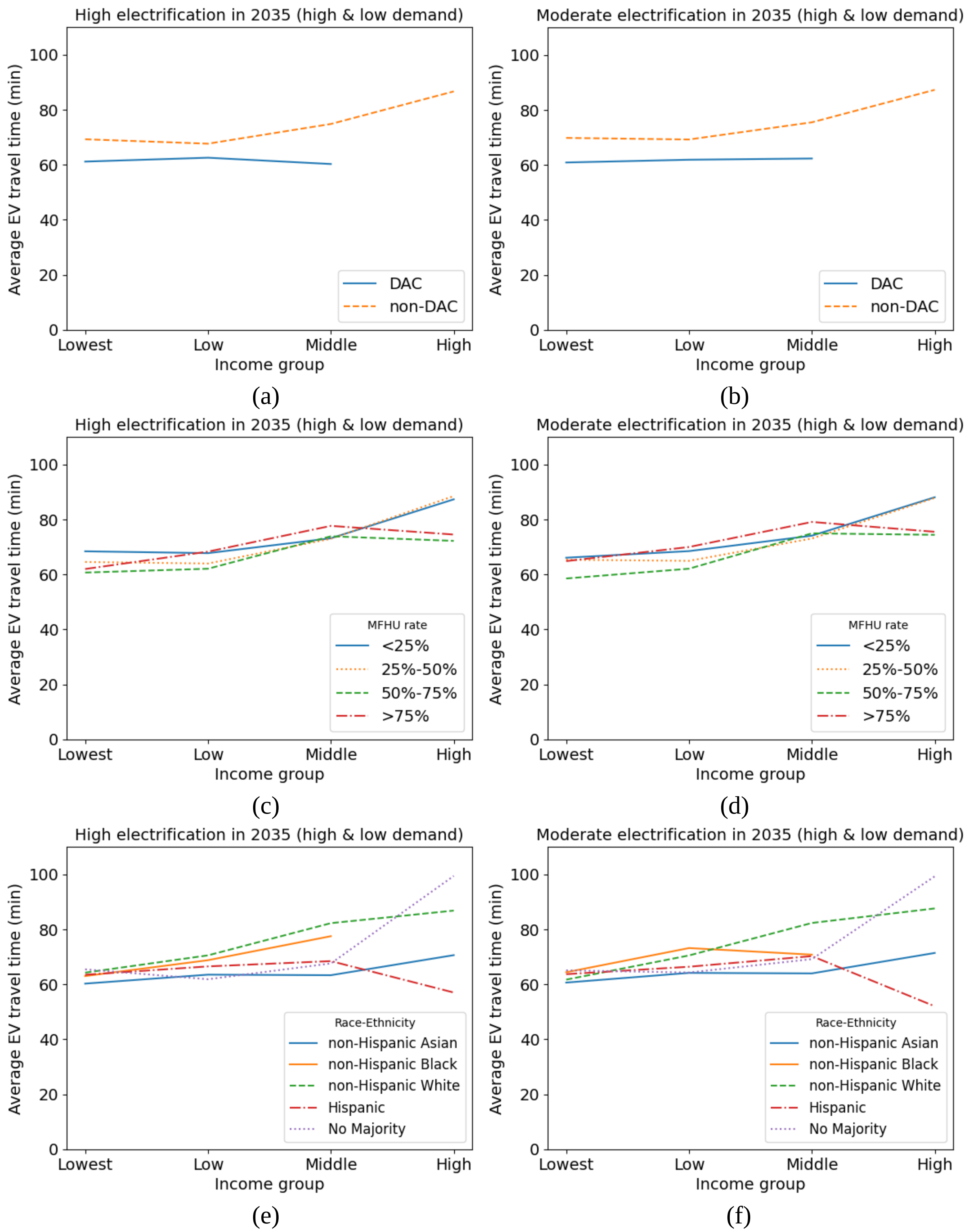


Fig 13. Average EV travel time by socio-demographic groups for the high and low-charging-demand days in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

5.4.2 Disparity in the average EV travel time across different socio-demographic groups

The disparity in the average EV travel time across different socio-demographic groups is discussed based on **Fig 14**. The major results are that there are almost no disparities between DACs and non-DACs and across different MFHU rates, while the disparity increases with income across race-ethnicity. The considerations and other findings are discussed as follows.

- **Fig 14 (a)** shows that the Gini value keeps a low value in the lowest-, low-, and middle-income groups, which means that there is not substantial gap in the average EV travel time between DACs and non-DACs.
- **Fig 14 (b)** reveals that the disparity across different MFHU rates remains extremely low in all income groups for both electrification levels, which means that there is almost no considerable difference in the average EV travel time across different MFHU rates.
- **Fig 14 (c)** indicates that the disparity across different racial-ethnic groups increases with income for both electrification levels. This is because the Gini index is calculated based on the values in **Fig 13 (e)** and **(f)**, which shows increasing difference in the average EV travel time across different groups probably caused by the gap in the share of trips heading to work in **Appendix A-Table E**. Additionally, the travel time values are absent for non-Hispanic Black population in the high-income group, which induces a significant jump in the Gini index.

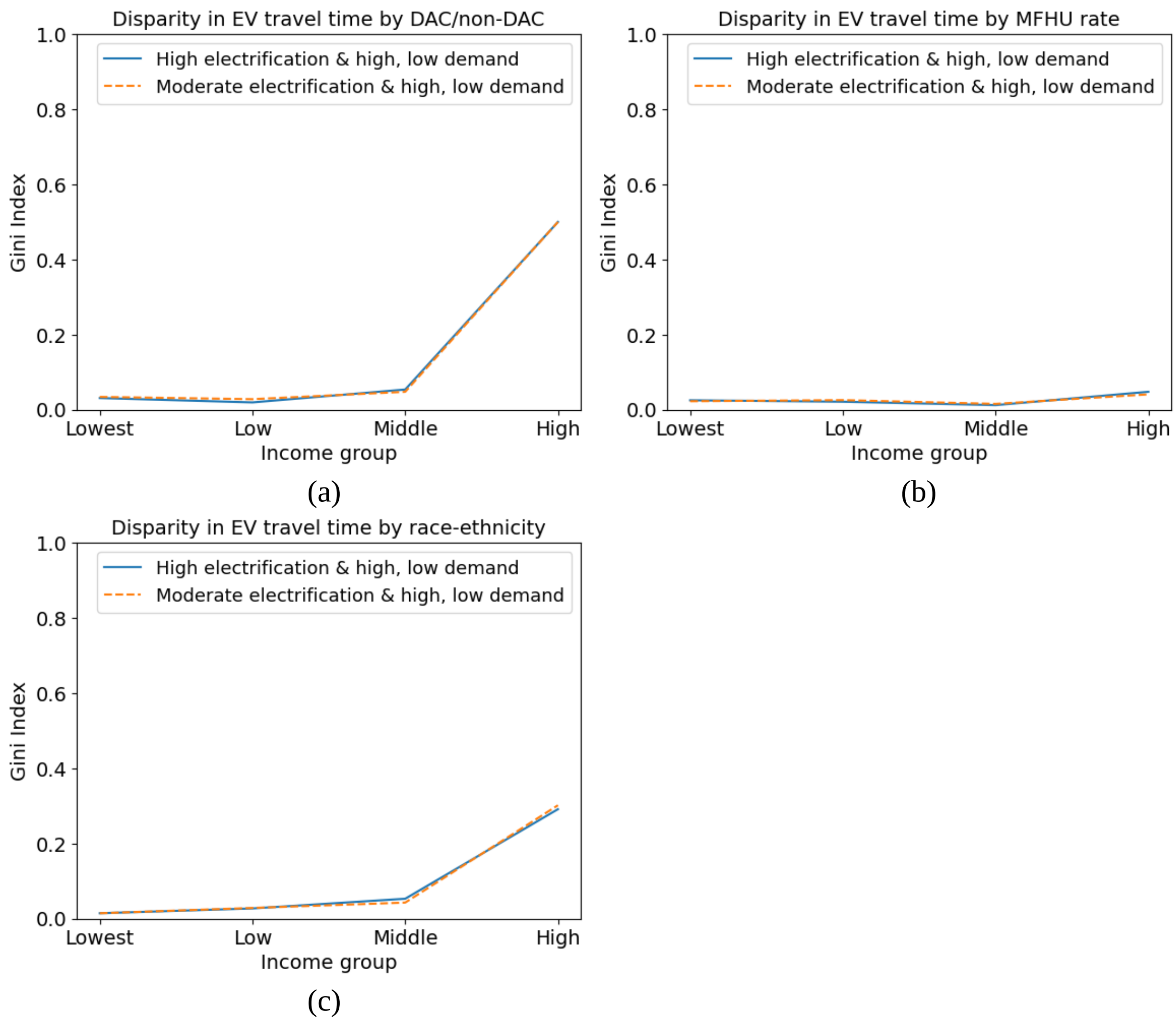


Fig 14. Disparity in the average EV travel time by community disadvantage (a), MFHU rate (b), and race-ethnicity (c) for the high- and low-charging-demand days in the high and moderate electrification levels in 2035

5.5 Results of Equity Evaluation in Affordability

5.5.1 Performance of the charging cost burden by socio-demographic groups

This subsection summarizes the results of charging cost burden per EV user, the performance indicator of affordability, via **Fig 15** and **16**. Fundamental implications are that non-DACs have higher values than DACs in the lowest- and low-income groups, and MFHU rate larger than 75% and non-Hispanic White population have a high charging cost burden. The causes and related discussions are provided in the following bullets.

- The charging cost burden decreases with income in all socio-demographic groups and the high electrification level has higher values than the moderate electrification level. Also the values are larger in the high-charging-demand day than in the low-charging-demand day.
- In **Fig 15 (a)** and **(b)**, non-DACs have higher values than DACs in the lowest- and low-income groups. The reason is that the travel distance is longer in non-DACs in **Table 6**, which induces more energy consumption and thus more charging cost, while the median annual household income is similar between DACs and non-DACs in **Table 8**.
- In **Fig 15 (c)** and **(d)**, MFHU rate larger than 75% keeps a higher level of the charging cost burden. The reason is the high energy consumption and charging demand caused by the high scale of the travel distance in **Table 6** against relatively low median annual household income compared with other MHFU rates in **Table 8**.
- **Fig 15 (e)** and **(f)** show that non-Hispanic Black population have the highest values in the lowest income group. However, because non-Hispanic Black population have the small share of CTs as shown in **Fig 4 (c)**, their results might be impacted from supreme values and thus not be reliable. In the low- and middle-income groups, non-Hispanic White population have relatively high values of charging cost burden. This is because they have the longest travel

distance in **Table 6**, which makes their energy consumption and thus charging demand highest as well while the median annual household income is the same level as other racial-ethnic groups in **Table 8**.

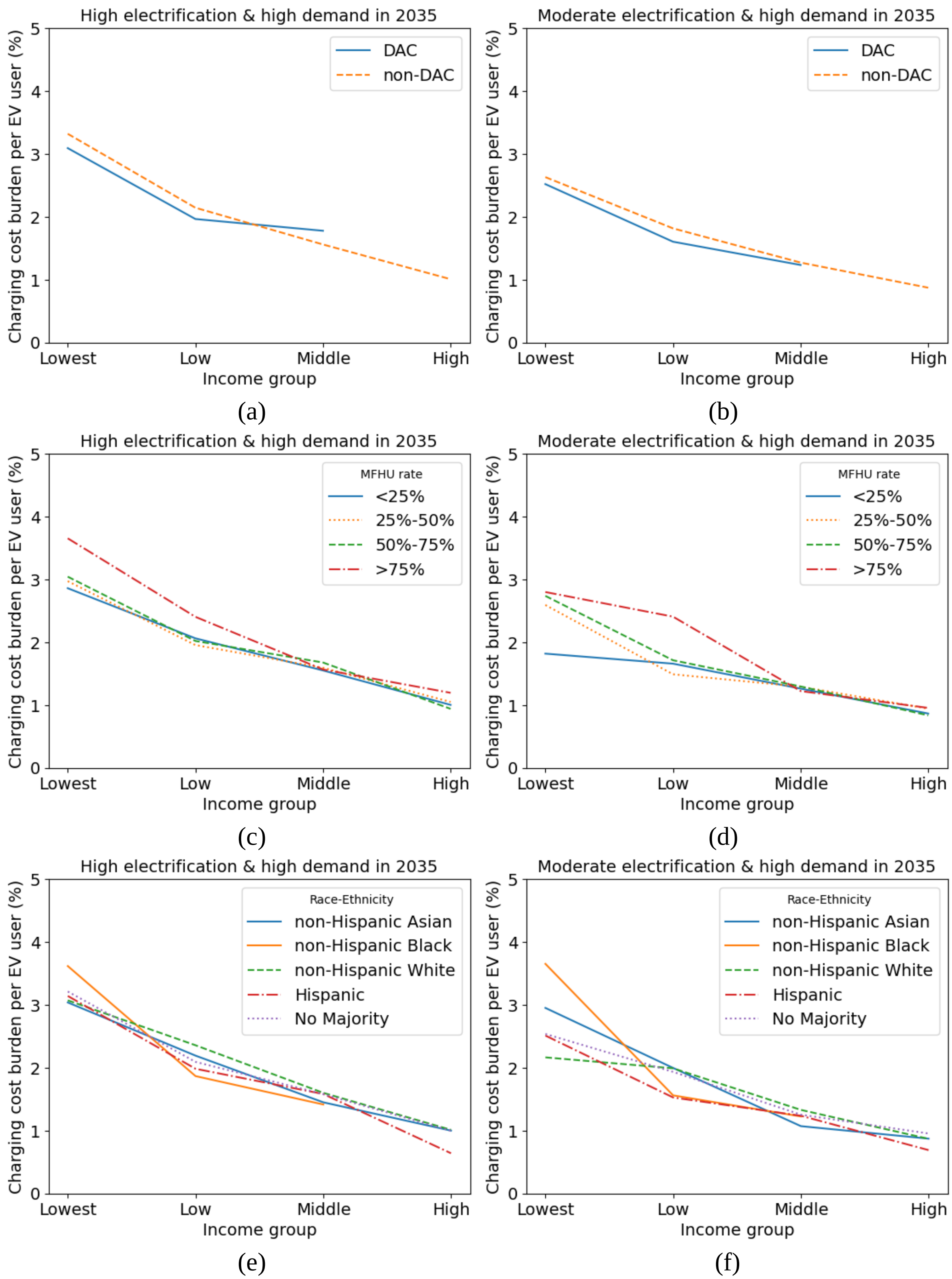


Fig 15. Charging cost burden by socio-demographic groups for the high-charging-demand day in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

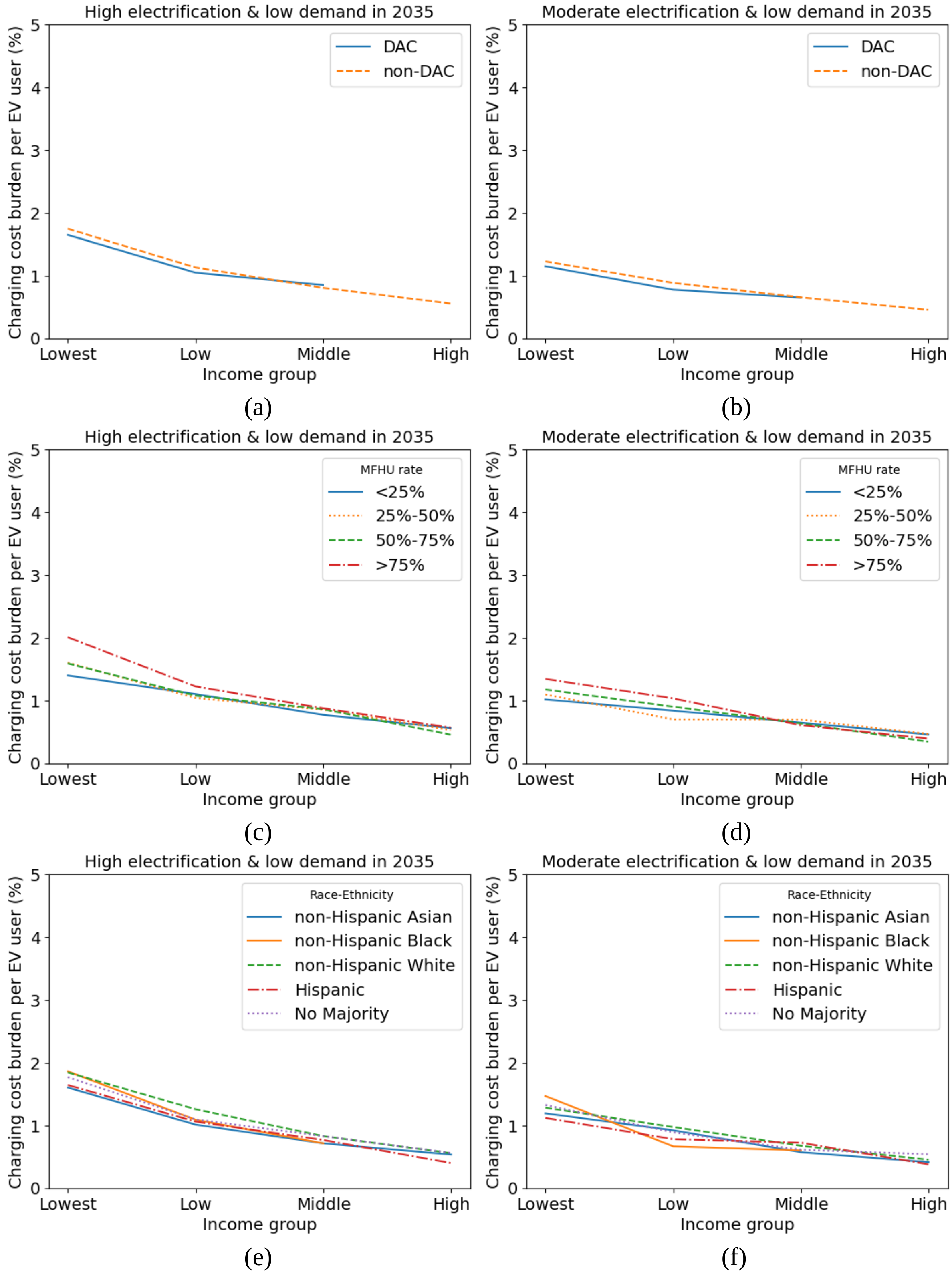


Fig 16. Charging cost burden by socio-demographic groups for the low-charging-demand day in the high electrification level (a, c, e) and in the moderate electrification level (b, d, f) in 2035

5.5.2 Disparity in the charging cost burden across different socio-demographic groups

The results of the disparity in the charging cost burden across different socio-demographic groups are shown in **Fig 17**. As key findings, there are almost no disparities between DACs and non-DACs, the disparity across different MFHU rate is relatively high in the low-income group for the moderate electrification level, and the disparity across different race-ethnicity is large in the lowest-income group for the moderate electrification level. The considerations and other findings are listed as follows.

- **Fig 17 (a)** shows that the disparity in charging cost burden between DACs and non-DACs is not significant since the Gini index keeps almost 0 except for the high-income group, where the Gini value becomes high due to no values of DACs.
- In **Fig 17 (c)**, the disparity across different MFHU rate is relatively high in the low-income group for the moderate electrification level. This is caused by extremely long travel distance of MFHU rate above 75%, which is approximately four times larger than the smallest value against almost the same annual household income among all MHFU rates in **Table 6** and **8**.
- In **Fig 17 (e)**, the disparity across different racial-ethnic groups is relatively high in the lowest-income group for the moderate electrification level. This is because the difference of charging cost burden across different race-ethnicity is large as shown in **Fig 15 (f)** due to the varying values of travel distance for every income level in **Table 6**. The Gini index is also high in the high-income group, which is because there are no values of non-Hispanic Black population.
- **Fig 17** indicates that the general trend and scale of the disparity in charging cost burden are similar between the high- and low-charging-demand days for both electrification levels.

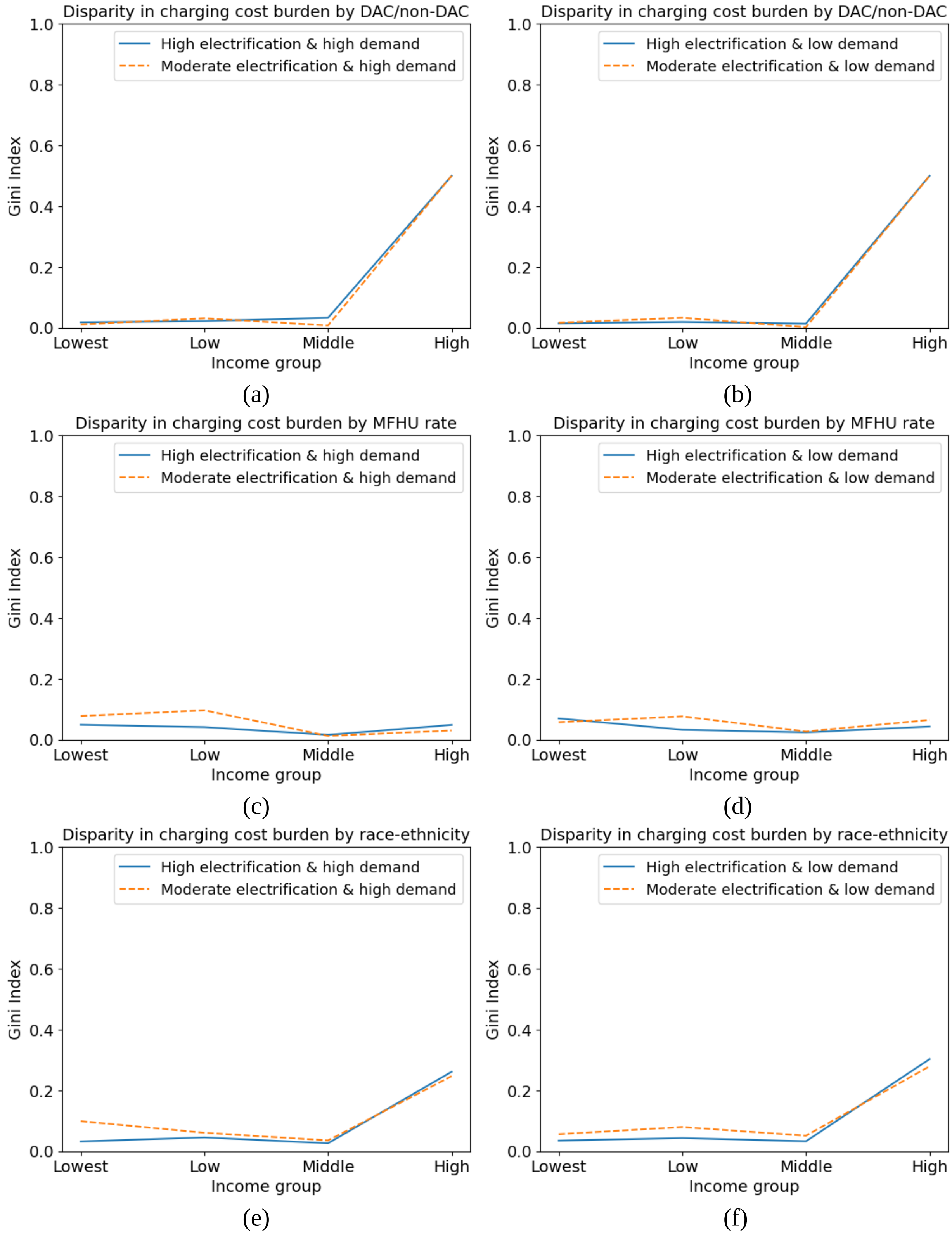


Fig 17. Disparity in the charging cost burden across different socio-demographic groups for the high-charging-demand day (a, c, e) and the low-charging-demand day (b, d, f) in the high and moderate electrification levels in 2035

6. PROPOSAL FOR EQUITY IMPROVEMENTS

From the results of the equity evaluation in the aspect of the fair share of resources, external costs, inclusivity, and affordability in **section 5**, it was found that disparities exist in the transition of transportation electrification across different socio-demographic groups. The disparities were quantitatively revealed by the Gini index ranging from 0.02 to 0.31 in the public charger density, 0.05 to 0.27 in the external crash cost and air pollution and GHG emissions cost reduction, 0.01 to 0.05 in the average EV travel time, and 0.002 to 0.10 in the public charging cost burden except for the high values in the high-income group due to the absence of performance indicator values in DACs and non-Hispanic Black population. As described in section 3.3.3, the larger the Gini value (closer to 1), the greater the disparity among equity performance indicators. The Gini values calculated in this study were low in general relative to the results of existing studies (Su et al., 2018; Jin et al., 2019), which may indicate less inequity in the projected EV and EVSE deployment. However, the results also revealed that the disparities were larger in the fair share of resources and external costs grouped into horizontal equity than in inclusivity and affordability classified as vertical equity. In other words, this study emphasized the inadequacy of horizontal equity in the future transportation electrification. Based on the results, the following improvements are proposed to achieve equity. The first two address the enhancement of horizontal equity, while the latter ones refer to the improvement of vertical equity.

6.1 Enhancement of Public, Home, and Workplace Charger Adoption

People’s willingness to adopt EVs is closely dependent on public charger distribution because high charger density provides a more reliable charging environment for people, particularly for those long-range travels. From the results of the equity evaluation in the fair share of resources in **section 5.2**, disparities in public charger density exist across different socio-demographic groups. To achieve this kind of equity, it is important to deploy more public chargers in the groups with currently a low public charger density, such as the lowest- and low-income groups, non-DACs, and non-Hispanic Asian groups, by prioritizing or increasing the budget to allocate considerable EVSE. However, since the groups with relatively high public charger density such as DACs, MHFU rate lower than 25%, and Hispanic communities have the low adoption scale of home and workplace chargers as shown in **Fig 5**, it is also necessary to enhance the home and workplace charger adoption level in a supportive way such as subsidies for EV purchase.

6.2 Improvement of EV Adoption

The results of equity evaluation in the fair share of resources in **section 5.2** also revealed the disparity in the adopted EV number per capita between the two electrification levels and across different socio-demographic groups as shown in **Table 5**. This implies the need to increase the EV fleet size in the communities with currently low-EV-adoption scale such as DACs, MFHU rate lower than 25%, and Hispanic communities. This will reduce the gap in EV adoption level and thus result in the acceleration of transportation electrification. The possible methods are development of more public chargers, which encourages people to adopt EVs by alleviating their anxiety about charging opportunity, subsidies for EV purchase, and discussion with or subsidies for manufacturers to promote EVs.

6.3 Increase of Travel by EV

According to the results of the equity evaluation in **section 5.3**, the benefit of reduction in air pollution and GHG emission cost increases with income because people with relatively high income have a higher adoption rate of EV and travel longer distances. The results also show that the environmental benefit is relatively low for MFHU rate below 25%, non-Hispanic Black population, and Hispanic population due to relatively short EV travel distance. To improve equity in the environmental benefit, subsidies for EV purchase are recommended and more public, home, and workplace chargers should be installed in communities with higher proportions of lower income groups, MFHU rate below 25%, non-Hispanic Black population, and Hispanic population since a reliable charger accessibility will reduce EV-users' anxiety about losing energy and thus encourage them to adopt EVs in the aforementioned ways (Holland et al., 2016; Tal et al., 2020; Blondeau et al., 2022).

Moreover, in **section 5.3**, although the external crash cost of gasoline vehicle and EV introduced by Litman (2016) are the same, Highway Loss Data Institute (2020) reported that EVs had considerably lower insurance claim frequency than conventional counterparts, which indicates that potential crash risk of EV was lower than that of non-EV. Therefore, the transition to EVs in the abovementioned groups may lead to the reduction of total external crash cost by reducing the potential crashes by non-electric cars.

6.4 Reduction of Public Charging Cost Burden

From the results of the equity evaluation in affordability in **section 5.5**, the public charging cost burden differs by income level and socio-demographic groups because of the difference in EV travel distance and household income of each group. To achieve the equity in affordability, the reduction of public charging cost burden is important, particularly for the lower income groups, non-DACs, MFHU rate above 75%, and non-Hispanic White communities, whose EV travel distance is significantly large as discussed in **section 5.5**. The possible approaches to reduce public charging fee can be providing subsidies for EV purchase; developing more energy-efficient EVs by manufacturers; and increasing the share of renewable energy such as bioenergy, geothermal energy, hydrogen, hydropower, marine energy, solar energy, and wind energy that is expected to reduce the electricity generation cost compared with traditional energy (U.S. Department of Energy, 2023). However, since most of the results of the equity evaluation in **section 5** indicate that the lower income groups; DACs; MFHU rate lower than 25%; and non-Hispanic Asian, non-Hispanic Black, and Hispanic population are underserved in the performance of EV and EVSE as discussed above, targeted efforts to reduce the public charging fee for these groups will also be effective and recommended for achieving equity.

7. CONCLUSIONS

This paper performed an equity evaluation with regard to the projected EV and EVSE deployment for the future transportation electrification across different socio-demographic groups with four equity aspects, which are the fair share of resources, external costs, inclusivity, and affordability. A case study of LA County in 2035 is implemented with the developed equity metric system. The case study described the disparity in the EV- and EVSE-related system performance across people with different socio-demographic backgrounds by using Gini index, which has been widely applied in many existing equity evaluation studies.

The case study results reveal some equity issues: (1) The public charger density that is a performance indicator for the fair share of resources shows a general increasing trend with income while it varies across socio-demographic groups depending on the public charger adoption scale; (2) The external costs that are represented by the external crash cost and the reduction in air pollution and GHG emission cost increase with economic status due to the growing EV travel distance though the values differ by socio-demographic group due to the gap in EV travel distance; (3) The average EV travel time that is a performance indicator for inclusivity also grows with income level because of the growing share of trips heading to home and work while the variance can be observed across different socio-demographic groups due to the difference in trip purpose; and (4) The public charging cost burden that is a performance indicator for affordability decreases with the growth of income and varies among people with different socio-demographic background depending on the EV travel distance. Based on these results, the following recommendations to enhance equity are proposed: i) enhancement of public, home, and workplace charger adoption; ii) improvement of EV adoption; iii) increase of travel by EV; and iv) reduction of public charging cost burden. These can be implemented by developing policies of subsidies for EV purchase, prioritization of budget, further promotion of EVs, and adoption of renewable energy in the currently underserved communities.

However, this study also has limitations. One of the limitations is the assumption of EV adoption rate. Our previous study projected the number of EVs based on the EV population in 2022, but Nazari et al. (2018) and Blondeau et al. (2022) pointed out that people's intention to purchase EVs is dependent on charger accessibility, which indicates that the more public, home, and workplace chargers, the more EVs adopted by people. A more enhanced method can be used to predict the number of EVs considering the increase in the public, home, and workplace charger density in further study. Another limitation of this study is the indicator of the environmental benefit of EVs. This study addresses the reduction in air pollution cost that derives from tailpipe emissions and lifecycle GHG emission cost based on the assumption that the air pollution cost from upstream emissions such as electricity generation and fuel production is significantly large and hard to quantify (Litman, 2016). However, U.S. Department of Energy (2023) shows that the air pollution and GHG emissions including upstream emissions of non-electric vehicles is larger than that of EVs. A more sophisticated equity metric system will be able to estimate the lifecycle environmental benefit of EVs in the future study.

APPENDIX A: TRIP NUMBER SHARE BY PURPOSE

Table A. Trip number share and average travel time by purpose of all EV trips in the high and moderate electrification levels in 2035

Purpose	High electrification level		Moderate electrification level	
	Trip number share	Average travel time (min)	Trip number share	Average travel time (min)
University	1%	96	1%	98
Home	35%	84	35%	87
Work	13%	82	13%	84
Visiting	3%	65	3%	66
Discretionary	6%	64	6%	66
Maintenance	13%	60	13%	61
Shop	10%	60	9%	61
Eatout	4%	59	4%	61
Escort	12%	47	12%	48
School	3%	33	3%	35

Table B. Trip number share by purpose of all EV trips in each income group in the high and moderate electrification levels in 2035

Purpose	High electrification level				Moderate electrification level			
	Lowest income	Low income	Middle income	High income	Lowest income	Low income	Middle income	High income
University	1.1%	1.0%	1.0%	1.1%	1.1%	1.0%	1.0%	1.1%
Home	35.3%	35.3%	35.4%	35.6%	35.2%	35.4%	35.5%	35.6%
Work	12.1%	12.5%	12.8%	14.1%	12.0%	12.9%	13.3%	14.7%
Visiting	2.8%	2.8%	2.8%	2.7%	2.8%	2.8%	2.7%	2.7%
Discretionary	5.8%	5.8%	5.8%	5.7%	5.7%	5.8%	5.7%	5.7%
Maintenance	13.4%	13.3%	13.0%	12.7%	13.6%	13.0%	12.9%	12.4%
Shop	10.0%	9.6%	9.5%	9.1%	10.1%	9.5%	9.4%	8.8%
Eatout	4.3%	4.2%	4.2%	4.3%	4.3%	4.2%	4.2%	4.2%
Escort	12.3%	12.4%	12.3%	11.6%	12.3%	12.2%	12.1%	11.6%
School	3.0%	3.1%	3.2%	3.1%	2.9%	3.1%	3.2%	3.2%

Table C. Trip number share by purpose in DAC and non-DAC in the high and moderate electrification levels in 2035

Purpose	High electrification level		Moderate electrification level	
	DAC	non-DAC	DAC	non-DAC
University	1.1%	1.0%	1.1%	1.0%
Home	35.2%	35.4%	35.1%	35.5%
Work	11.9%	13.0%	11.6%	13.6%
Visiting	2.8%	2.8%	2.8%	2.8%
Discretionary	5.7%	5.8%	5.7%	5.7%
Maintenance	13.6%	13.0%	13.9%	12.8%
Shop	10.1%	9.4%	10.2%	9.3%
Eatout	4.2%	4.2%	4.3%	4.2%
Escort	12.3%	12.2%	12.4%	12.0%
School	3.0%	3.1%	3.0%	3.1%

Table D. Trip number share by purpose in each MFHU rate in the high and moderate electrification levels in 2035

Purpose	High electrification level				Moderate electrification level			
	MFHU <25%	MFHU 25%-50%	MFHU 50%-75%	MFHU >75%	MFHU <25%	MFHU 25%-50%	MFHU 50%-75%	MFHU >75%
University	1.0%	1.0%	1.0%	1.1%	1.0%	1.0%	1.0%	1.1%
Home	35.2%	35.4%	35.6%	35.6%	35.3%	35.4%	35.8%	35.5%
Work	12.1%	12.5%	13.3%	13.8%	12.8%	13.1%	13.8%	13.9%
Visiting	2.8%	2.7%	2.8%	2.8%	2.8%	2.7%	2.8%	2.8%
Discretionary	5.8%	5.8%	5.8%	5.7%	5.8%	5.8%	5.7%	5.6%
Maintenance	13.3%	13.3%	12.8%	12.9%	13.1%	13.1%	12.5%	12.9%
Shop	9.8%	9.7%	9.2%	9.3%	9.6%	9.5%	9.1%	9.2%
Eatout	4.2%	4.3%	4.4%	4.2%	4.2%	4.3%	4.3%	4.2%
Escort	12.6%	12.2%	11.9%	11.7%	12.3%	12.1%	11.8%	11.7%
School	3.2%	3.1%	3.1%	3.0%	3.2%	3.1%	3.2%	3.1%

Table E. Trip number share by purpose in each race-ethnicity in the high and moderate electrification levels in 2035

Purpose	High electrification level					Moderate electrification level				
	Asian	Black	White	Hispanic	No majority	Asian	Black	White	Hispanic	No majority
University	1.0%	1.2%	1.1%	1.0%	1.0%	0.9%	1.2%	1.1%	0.9%	1.0%
Home	34.9%	35.4%	35.6%	35.1%	35.4%	34.9%	35.7%	35.7%	35.1%	35.3%
Work	10.7%	15.7%	14.0%	11.1%	12.5%	10.7%	15.5%	14.6%	11.0%	12.6%
Visiting	2.8%	2.8%	2.8%	2.8%	2.8%	2.7%	3.0%	2.7%	2.8%	2.8%
Discretionary	5.7%	5.6%	5.8%	5.8%	5.8%	5.6%	5.7%	5.8%	5.8%	5.7%
Maintenance	13.7%	12.2%	12.8%	13.8%	13.1%	13.5%	12.0%	12.5%	13.9%	13.3%
Shop	10.3%	8.7%	9.1%	10.2%	9.7%	10.4%	8.5%	8.9%	10.3%	9.7%
Eatout	4.1%	4.3%	4.3%	4.2%	4.2%	4.2%	4.6%	4.3%	4.3%	4.1%
Escort	13.6%	11.1%	11.5%	12.8%	12.5%	13.8%	10.7%	11.4%	12.9%	12.4%
School	3.3%	3.0%	3.1%	3.1%	3.1%	3.4%	3.1%	3.1%	3.0%	3.1%

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