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Leveraging explainable artificial intelligence and big trip data to understand factors influencing willingness to ridesharing

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A R T I C L E I N F O

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A B S T R A C T

Carpool-style ridesharing, compared to traditional solo ride-hailing, can reduce traffic congestion, cut per-passenger carbon emissions, reduce parking infrastructure, and provide a more cost-effective way to travel. Despite these benefits, ridesharing only occupies a small percentage of the total ride-hailing trips in cities. This study integrates big trip data with machine learning and eXplainable AI (XAI) to understand the factors that influence willingness to take shared rides. We use the City of Chicago as a case study, and results show that users tend to adopt ridesharing for longer distance trips, and the cost of a trip remains the most important factor. We identify a strong diurnal pattern that people prefer to request shared trips during the morning and afternoon peak hours. We also find socio-economic disparities: users who requested trips from neighbourhoods with a high percentage of non-white, a low median household income, a low percentage of bachelor's degrees, and high vehicle ownership are more likely to share a ride. The findings and the XAI-based analytical framework presented in this study can help transportation network companies and local governments understand ridesharing behaviour and suggest new strategies and policies to promote the proportion of ridesharing for more sustainable and efficient city transportation.

1. Introduction

Transportation network companies (TNCs), such as Uber and Lyft, provide ride-hailing services that have been a common mode of transportation for residents in cities. According to a recent Juniper Research report published in December 2021, consumer spending on ride-hailing will approach US $937 billion by 2026, which is 50 times the total annual revenue of Transport for London, New York City's MTA, and Beijing Metro in 2021 (Juniper Research, 2021). While there is a large market for ride-hailing and it provides a convenient way to get around, it is also reported that TNCs have negative effects on cities. Research shows that ride-hailing competes with urban public transport, increases vehicle miles travelled, intensifies pollution and traffic congestion (Erhardt et al., 2019; Diao et al., 2021; Li et al., 2021). However, one type of service nested within ride-hailing that has been overlooked is the carpool style ridesharing (also known as ride-splitting or ride-pooling) such as Lyft Line and Uber Pool. Ridesharing matches multiple users in the same vehicle going in a similar direction, with drivers picking up and dropping off passengers along the route. It is reported that when compared to solo ride-hailing, shared rides can reduce traffic congestion, cut per-passenger carbon emissions, decrease parking infrastructure demand, and provide a more cost-effective way to travel (Shaheen and Cohen, 2019). Despite these advantages, ridesharing is only available in a few cities, and it accounts for a small percentage of total ride-hailing trips (6 %–20 % in cities such as Chengdu, Toronto, and Chicago) (Li et al., 2019; Young et al., 2020; Dean and Kockelman, 2021). There is a substantial opportunity to further adopt ride-sharing services to alleviate environmental and transportation issues. To that end, understanding why people choose to or not to take a shared ride is essential to potentially promoting ridesharing in current and new cities.

Preference to share rides has been recently studied in the literature using both survey data and TNC trip data in different cities. For example, Werth et al. (2021) conducted an online survey to determine public acceptance of ride-pooling. Based on the responses of 224 users in Germany, the findings show that attitudes toward use, perceived usefulness, and performance expectancy all affect behavioral intentions to use ride-pooling services. Environmental awareness, pricing value, and effort expectation, on the other hand, had no strong effect. Alonso-González et al. (2021) performed a choice modelling analysis based on the collected 1077 questionnaires. Results show that the percentage of

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people who prefer to share rides is mostly determined by the time–cost trade-off. Individuals who are accustomed to driving are also less likely to switch to more communal modes of transportation. They also discovered that the choice is dependent on the number of additional passengers. Kang et al. (2021) gathered data from 953 people in Austin, Texas about their preference for pooled versus private ride-hailing. They discovered that women, elderly people, and non-Hispanic/non-Latino whites have a low inclination to choose the pooled ride-hailing mode, but employed individuals, highly educated individuals, and those living in densely populated urban regions have a high propensity.

However, the major limitation of survey-based studies is that the small sample size may not reflect the distribution of the population (Kang et al., 2021; Werth et al. 2021). To that end, as big trip data from TNCs are becoming publicly available, more research is using statistical and machine learning models to explore factors that are associated with willingness to share. Brown (2020), for example, analysed Lyft trip data in Los Angeles County in 2016 with logistic and zero-inflated Poisson regression models and showed that people living in low-income neighbourhoods take shorter, cheaper, and more shared rides than those living in higher-income neighbourhoods. They also discovered that, with everything else being equal, journeys beginning in majority-white communities are less likely to be shared than trips originating in other racial-ethnic majority neighbourhoods. The models used in Brown (2020)'s study assume linear relationships between independent and dependent variables; however, there are possible complex non-linear relationships and interaction effects associated with willingness to share trips that are more appropriately modelled using machine learning methods (Hou et al. 2020; Xu et al., 2021; Wang and Noland 2021; Tu et al. 2021). For example, Hou et al. (2020) built a linear regression model and an eXtreme Gradient Boosting (XGBoost) machine learning model to predict the proportion of the trips that are pooled between the origin and destination census tracts based on 15-minute bins in the city of Chicago. They found that XGBoost model outperformed linear regression model and identified that income level and airport trips are the most important factors that are associated with the willingness to pool. Xu et al. (2021) applied Random Forest (RF) machine learning model to predict the ride splitting adoption rate for each O-D census tract pair and identified ethnic composition, income, and education level as the most important variables. They explored their nonlinear associations with ride splitting preference using partial dependence and accumulated local effects (ALE) plots. Also using RF model, Wang and Noland (2021) examined the importance and marginal effects of total price and trip duration in affecting people's willingness and found that the probability of authorizing a ride-sharing trip is highly elastic to the price per mile. In an Asian city context, with DiDi trip data in Chengdu, China, Tu et al. (2021) examined the non-linear effects of the built environment on the ridesplitting ratio using Gradient Boosting Decision Trees (GBDT) and found that distance to the city center is the most important among built environment factors.

Despite the high accuracy and flexibility of machine learning, a big challenge for machine learning models is their interpretability and explainability. Machine learning models are often criticized as black boxes, where the predictions of the models are not well understood. Even though there are existing explanatory tools, such as variable importance scores and partial dependency plots, they are, in a sense, limited, providing only an 'average' explanation without acknowledging that such importance or relationship may vary in space and time (Li, 2022). Recent developments in locally interpretable artificial intelligence (XAI) offer the opportunity to extract useful insights from each individual data point. Two of the most applied local XAI tools are LIME (Local Interpretable Model-agnostic Explanation) and SHAP (SHapley Additive exPlanations). LIME uses local surrogate models with perturbed samples to locally explain machine learning predictions (Ribeiro et al., 2016). SHAP pushes LIME forward and combines it with game theory in Shapely values to provide additive explanations from features to model predictions while addressing some of the technical issues in LIME (Lundberg and Lee, 2017). Recent work has demonstrated the utility of SHAP when applied to spatial temporal data (Just et al. 2020; Chakraborty et al. 2021; Viana et al. 2021), but SHAP has limited applications in transport research and, to our knowledge, has not been applied to explain user willingness in ridesharing services.

Consequently, the aim of this study is to develop an analytical framework that combines big trip data, a scalable machine learning model, and explainable artificial intelligence (XAI) to better understand the factors that are associated with people's decisions to take shared rides. We are particularly interested in complex non-linearities and interaction effects that may have been overlooked in earlier investigations of the problem that used simple statistical methods. Although earlier machine learning-based research may have implicitly captured these complicated effects, it only provided limited explanations and did not provide many insights into the relationships that underlie ridesharing willingness. This work leverages the use of XAI to address challenges in both statistical and machine learning, brings attention to transportation researchers/practitioners of this new analytical framework, and provides an empirical application of understanding ridesharing willingness. Here, we use the city of Chicago as an example, and the workflow can be replicated to other cities of interest where trip data are available. The paper proceeds as follows. In Section 2, the study area and data used in this study are introduced. Section 3 describes the machine learning model and explanation method. The model performance and interpretations of the results are presented in Section 4. The paper concludes in Section 5 with discussions of policy implications, limitations, and future work.

2. Study area and data used

The City of Chicago publishes Uber, Lyft, and Via ride-hailing trip records from November 2018 to the most recent totalling 246 million records as of April 2022. Due to the COVID-19 pandemic, TNC suspended their carpool-style ridesharing services since March 2020. Therefore, we selected data from the entire year of 2019, which reflects a normal travel pattern unaffected by COVID-19. Each trip record is timestamped to the nearest 15 min and geocoded with location information. To protect privacy, most pick-up and drop-off locations are aggregated at the census tract level, but if there are two or fewer trips within a 15-minute time window in the same census tract, then the resulting location information is given at the community area leve1.[1] Given the size of the community area and the rarity of these trips, we only used records for which census tract level information is available. We also removed outlier trips with distances of less than 1 mile and greater than 50 miles, and duration of less than 5 min and greater than 2 h. The most important variable in this dataset is a binary label that indicates whether the user agreed to share a trip with others, regardless of whether the user was eventually matched. This variable is an explicit indicator of a user's willingness to ridesharing, and it is the dependent variable we used in our machine learning model.

From the literature, people's willingness to share a trip is expected to be influenced by the spatial–temporal dimension of the trip and the socioeconomics and built environment of the census tract where the passenger was picked up and dropped off (Hou et al., 2020; Dean and Kockelman, 2021; Xu et al., 2021). For trip attributes, we avoided including post-trip information that was not available when the user made the sharing decision. An example of this information is the actual trip distance, which is expected to be longer for shared trips than for private trips due to the detours to pick up or drop off other passengers. We argue that post-trip information does not have a direct causal association with the willingness to share the trip, though these factors are usually included in similar studies such as Hou et al., 2020 and Wang

[1] http://dev.cityofchicago.org/open%20data/data%20portal/2019/04/12/tnp-taxi-privacy.html.

and Noland (2021). Instead, we used the Euclidean distance between the two census tracts as an estimate for the user-perceived trip distance. This also reflects the fact that users usually have a rather rough perception of how far they are going (e.g. an airport trip is ~ 10 km, a trip to downtown is ~ 3 km). Similarly, for the cost of the trip, we included trip fare, additional charges (e.g. taxes, fees, discounts), and excluded the tip amount, which is an estimated upfront price when the user requests a trip. Based on the time of the pick-up, we calculated several temporal features, including working and non-working days (weekends and public holidays) and the hour of the day of the trip. To account for the weather, we linked the pick-up time with the Local Climatological Data (LCD) from the National Oceanic and Atmospheric Administration (NOAA), and included hourly wind, rain, and temperature conditions at the time the user started the trip.

For socioeconomics, we obtained median household income, education, race, gender ratio, and vehicle ownership statistics from the United States American Community Survey (ACS) 2014–2018 5-year estimate dataset at the census tract level. We removed census tracts with fewer than 500 people to avoid sampling uncertainties in the ACS data. For the built environment, we downloaded the US Environmental Protection Agency's Smart Location Database (SLD) version 3.0 and selected residential density, employment density, road network density, transit accessibility, and national walkability index. SLD data are originally at the census group block level but were aggregated (area weighted for density variables) to the census tract level.

Because shared trips only account for around 20 % of the total number of trips, the ride-share data were evenly balanced using a random under-sampling so that the final dataset has the same number of shared and non-shared trips. This is to avoid model bias towards the dominant class when input labels (shared vs not shared) are imbalanced (Sun et al., 2009). Under-sampling was preferred over over-sampling in this case because under-sampling keeps all the original sharing records, but an over-sampling approach will add non-authentic data, which introduces unnecessary assumptions and noise. The resulting dataset has 19.6 million trip records, which pertains to a high level of representativeness and was used as the input to the machine learning model. A complete list of features, their descriptions, and the summary statistics at the individual trip level can be found in Table 1.

Table 1
Variables, descriptions, and summary statistics of features used in the model.

Variable	Description	Min	Mean	Max	SD
Trip attributes					
Fare	Fare of the trip ($)	2.5	8.6	50.0	4.5
Additional Charges	Taxes, fees, and other additional charges ($)	0.0	2.0	17.7	1.2
Distance	Euclidean distance of the origin and destination census tracts (km)	0.0	4.9	41.3	3.6
Distance to downtown	Euclidean distance from the pick-up/drop-off location to downtown[2] Chicago (km)	0.3	5.6	27.1	4.1
Direction	Trip heading direction (°)	−180.0	8.1	180.0	102.0
Temporal attributes					
Month	Month of the trip	1.0	6.0	12.0	3.4
Working day	Whether the trip is on a working day (non-public holidays, non-weekends)	0.0	0.8	1.0	0.4
Hour	Hour of the trip starting time	0.0	14.3	23.0	6.0
Wind	Hourly wind speed (miles/hr)	0.0	10.4	38.0	5.2
Rain	Hourly rain condition (0: No; 1: Light; 2: Moderate; 3: Heavy)	0.0	0.1	3.0	0.3
Temperature	Hourly temperature (°F)	−32.0	38.8	79.0	20.2
Socioeconomics					
Median income	Median household income ($1000)	9.8	89.6	178.8	35.4
Pct non-white	Percentage of non-white population	3.3	34.6	100.0	22.8
Pct no car	Percentage of households with no vehicle	0.7	33.1	77.8	14.1
Sex ratio	Sex ratio (male/female)	37.9	100.4	866.0	25.6
Pct age 18–29	Percentage of people aged 18 to 29	5.7	29.2	84.0	12.6
Pct bach	Percentage of people with bachelor's degrees	0.0	30.8	77.0	13.8
Built environment					
Residential density	Log of gross residential density	−4.3	0.3	4.4	2.1
Employment density	Log of gross Employment density	−5.3	0.8	7.1	2.9
Network density	Log of total road network density	−0.2	2.3	4.2	1.1
Transit accessibility	Distance to the nearest transit stop (m)	23.5	298.1	861.0	111.6
Metro station	Whether the census tract has a metro station	0.0	0.4	1.0	0.5
Walkability	National walkability index	4.6	12.2	18.8	3.2

[2]The coordinates of downtown (41.8757° N, 87.6243° W) are obtained from Google.

3. Machine learning model and explanation

In this study, we used Extreme Gradient Boosting (XGBoost) as our machine learning model. XGBoost is a gradient boosting method that uses a gradient descent optimization algorithm to sequentially ensemble decision trees to minimize model error (Chen and Guestrin, 2016). XGBoost is one of the most commonly used machine learning methods for supervised classification and regression tasks, and it has been reported that XGBoost typically outperforms other approaches, such as random forest or deep neural networks, on tabular data (Zamani Joharestani et al., 2019; Shwartz-Ziv and Armon, 2022). Additionally, XGBoost is highly scalable, which is appropriate for the data size in this study. The ride-sharing dataset was divided into 80/20 segments for training and testing, respectively. The hyperparameters of the XGBoost model were tuned using a Bayesian optimization algorithm with a 5-fold cross validation on the training set using the hyper-opt python package (Bergstra et al., 2015). We also fitted a logistic regression model as the baseline for performance comparison.

Then we used a local interpretable machine learning method SHAP (SHapley Additive exPlanations) to explain and attribute the XGBoost predictions (Lundberg and Lee, 2017) to each feature. SHAP has its theoretical roots in game theory as Shapley values, which were initially used to properly distribute player contributions when they jointly achieve a goal (Shapley, 1953). The approach was further applied to machine learning to quantify the contribution of each feature to the model prediction (Štrumbelj and Kononenko, 2014). The Shapley value for feature X_j in a model is given by:

$$Shapley(X_j) = \sum_{S \subseteq N\backslash\{X_j\}} \frac{k!(p-k-1)!}{p!}\left(f(S\cup\{j\}) - f(S)\right) \tag{1}$$

where p is the total number of features, $N\backslash\{X_j\}$ is a set of all possible combinations of features excluding X_j, S is a feature set in $N\backslash\{X_j\}$, $f(S)$ is the model prediction with features in S, and $f(S\cup\{j\})$ is the model prediction with features in S plus feature X_j. As indicated in Eq. (2), SHAP values break down each individual prediction into additive components, with each additive term $shap(.)$ denoting the impact of the relevant feature on the model prediction:

$$\hat{y}_i = shap_0 + shap(X_{1i}) + shap(X_{2i}) + \cdots + shap(X_{pi}) \quad (2)$$

where $\hat{y}_i$ is the model prediction value for the sample *i*, $shap_0 = E(\hat{y})$ is the mean prediction over all data, and $shap(X_{ji})$ refers to the SHAP value of the j^{th} feature for sample *i*, which represents the marginal contribution of the feature to the prediction when keeping other features constant. In this way, the sum of all the SHAP values is equal to the difference between the actual prediction and the average prediction across all the data. In our study, because there are same number of shared and solo trips after under sampling, $shap_0 = E(\hat{y}) = 0$. In addition, the absolute SHAP value can measure the importance of a given feature to the local prediction (Molnar, 2019). SHAP is a model-agnostic explanation framework that can be applied to any machine learning models; however, the generic SHAP algorithm is quite computationally intensive. To address this problem, Lundberg et al. (2020) proposed the Tree SHAP algorithm, which works in polynomial time for tree ensemble models such as random forests and gradient boosting trees. To that end, we employed Tree SHAP to efficiently estimate SHAP values for XGBoost predictions in this study. For classification problems, the SHAP values are reported as log-odds, and we converted them to probabilities that canters at zero for easy interpretation which is as shown in Eq. (3):

$$Shap_{prob} = \frac{exp\left(Shap_{log-odds}\right)}{1 + exp\left(shap_{log-odds}\right)} - 0.5 \quad (3)$$

The calculated SHAP value measures contributions of features to the probability of each trip being classified as a shared trip or a private trip. A positive SHAP value indicates that the feature contributes positively towards predicting a shared trip, whereas a negative SHAP value suggests that the feature contribute towards predicting a private trip. Both the sign and the magnitude of the SHAP value can be used to quantitively measure the willingness to share.

To summarize the section, we developed an analytical workflow that integrates the big trip data, scalable machine learning models, and XAI approaches to understand people's willingness to ridesharing, which is depicted in Fig. 1. The reproducible code that analysed, modelled, and interpreted the data can be found at this public repository: https://github.com/Ziqi-Li/Chicago_rideshare_XAI.

4. Results and discussion

4.1. Model accuracy assessment

Accuracy assessment measures of the XGBoost model and the baseline logistic regression (LR) models are shown in Table 2. For XGBoost, the out of sample model accuracy achieves 90.5 % for the independently held testing data with a true positive rate (shared rides correctly classified as shared rides) of 86.0 % and a true negative rate (solo rides correctly classified as solo rides) of 95.0 %. The F-1 score which balances the precision and recall of the model is 0.90. The model's testing accuracy is closely consistent with its training accuracy, which indicates a robust hyperparameter tuning and model fitting and process. XGBoost also shows excellent predictive accuracy compared to the baseline logistic regression model (an overall accuracy of 72.4 %). This is due to the fact that logistic regression only considers linear additive relationships, however potential non-linearities and interactions of features do exist, as will be seen in later sections.

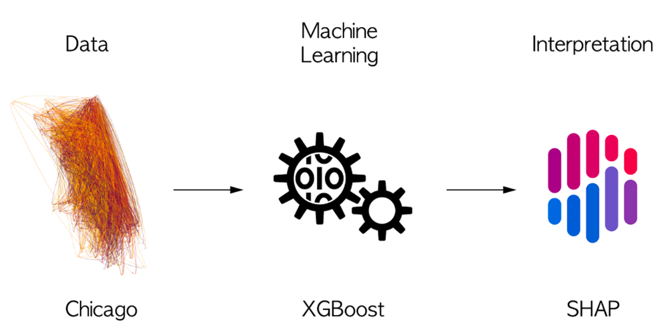

Fig. 1. A framework that integrates big trip data, machine learning model and explainable artificial intelligence.

Table 2
Training and testing accuracy of the XGBoost and a baseline logistic regression model.

	XGBoost		Logistic Regression	
	Training	Testing	Training	Testing
True Positive	86.8 %	86.0 %	69.5 %	69.4 %
True Negative	95.8 %	95.0 %	75.4 %	75.4 %
False Positive	13.2 %	14.0 %	30.5 %	30.6 %
False Negative	4.2 %	5.1 %	24.6 %	24.6 %
F1	0.91	0.90	0.72	0.72
Overall Accuracy	91.3 %	90.5 %	72.4 %	72.4 %

Fig. 2 shows the ROC (Receiver Operating Characteristic) curves measuring the performance of the classifier at all classification cut-offs in. The scale invariant Area Under the Curve (AUC) can be used to quantify the ability of the model to separate shared and solo rides. An AUC of 0.5 means that the model has no separability, and an AUC of 1 means that it perfectly distinguishes the binary outcomes. Our XGBoost model has an AUC of 0.90, which indicates a satisfactory performance. As comparison, the logistic regression model has an AUC of 0.72.

4.2. SHAP explanations to the model

Based on the predictions of the XGBoost model, SHAP values were calculated and converted into a marginal contribution to the probability of requesting a shared trip according to Eq. (3). The absolute SHAP values can be used to quantify the importance of the variables in the model. Due to the additivity property of the SHAP values, we can look at the impact of each group of features on the model prediction collectively. Fig. 3 shows the SHAP-based global variable importance rankings for five groups of features. The cost of the trip, including the base fare of the trip and additional costs (e.g. fees, discounts, taxes), is shown as the most important factor influencing whether a user requests a shared ride

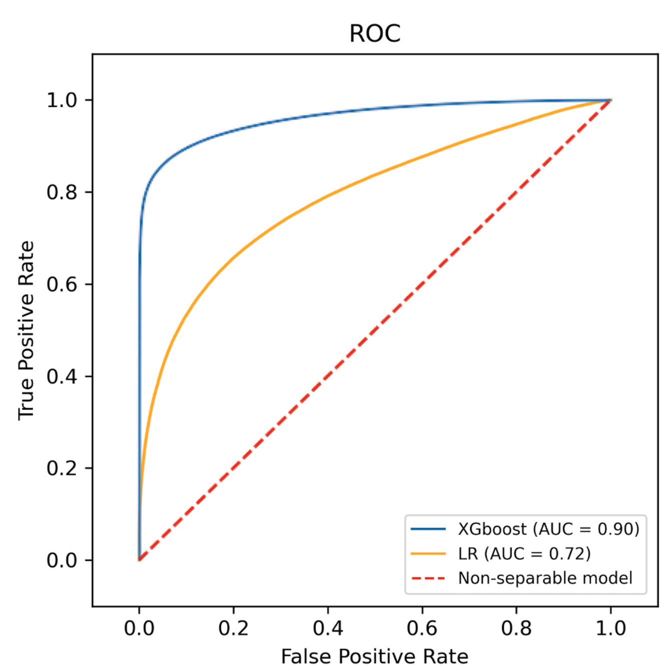

Fig. 2. ROC curve of the XGBoost model and the logistic regression (LR) model.

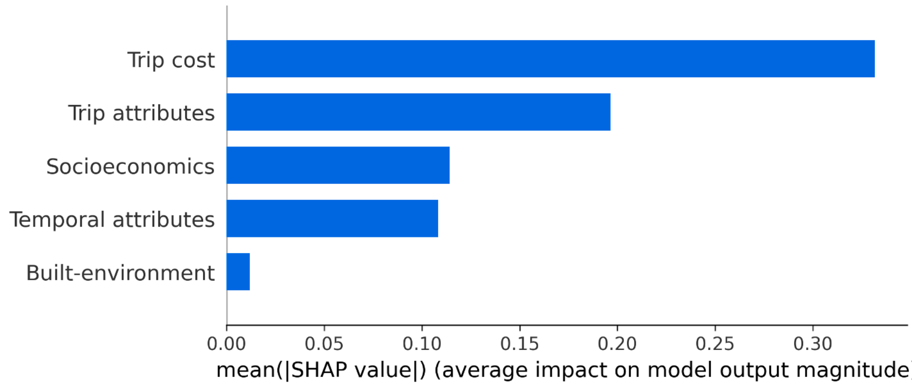

Fig. 3. SHAP-based global feature importance ranking for five groups of features.

with an average impact approaching 35 %. Other trip attributes, including trip distance, direction, and others, are ranked second, with an average impact of over 20 % on the probability to request shared rides. Temporal attributes and socioeconomics ranked third and fourth in influencing people's willingness to share, with an average probability of more than 10 %. When other factors are controlled for, the built environment variables have very little importance in the model. It is worth noting that the importance of the global variables only quantifies the average importance, but variation between trips is not observable from such a plot.

Next, we explore the marginal relationships between features and the prediction while holding everything else constant using SHAP based partial dependence plots. Compared to the traditional global partial dependence plots which depict average relationships, SHAP based local partial dependence plots can show the variability of relationships across all trips in regard to the same feature value. The marginal relationships between trip attributes and the willingness to share are depicted in Fig. 4. Point that is above (below) the zero dashed line indicates that the

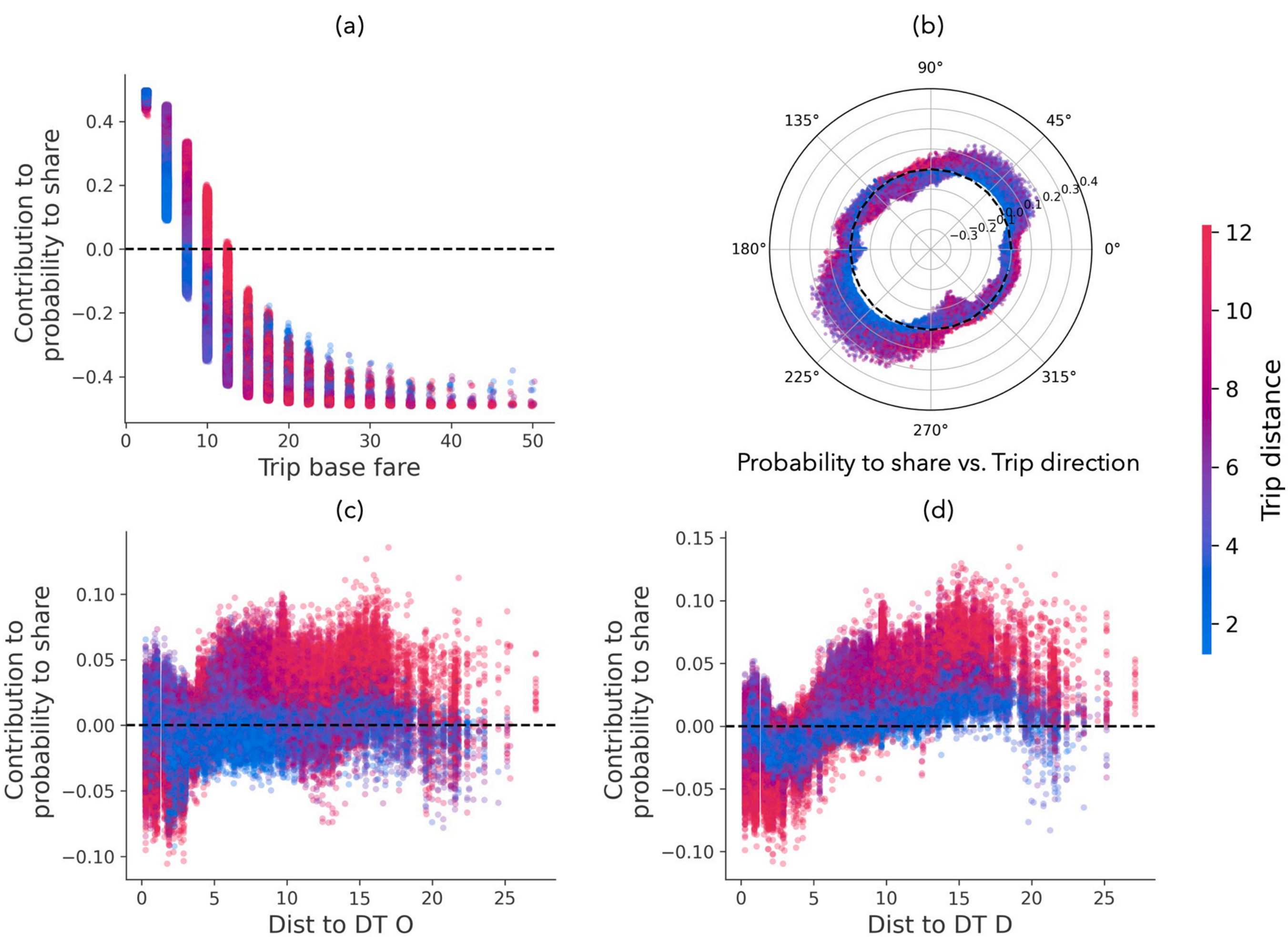

Fig. 4. SHAP-based partial dependence plots for trip attributes including: (a) trip base fare, (b) trip heading direction, (c) distance to downtown (origin), and (d) distance to downtown (destination). The points on each scatter plot are colour coded by the trip distance, showing the interaction effect between travel distance and that feature.

trip's feature has a positive (negative) contribution towards probability to share. Figures in Fig. 4 (and subsequent partial dependence plots) are coloured by the trip distances showing how trip distances interact with each feature and collectively contributes to the model prediction. Trip distance was chosen as the interaction effect of interest because it is a very objective factor related to the actual travel need, regardless of mode choice, and because it is one of the most important factors in the model. Due to the density of the points, a small amount of transparency was added to enhance the visualisation. In Fig. 4a, we can see that the trip fare has a non-linear relationship with the willingness to share a trip; that the willingness decreases drastically as the fare increases initially, then flattens out gradually. Also, for the same base fare, an interaction effect with perceived travel distance can be observed. For example, when the trip base fare is below $15 (which accounts for 89.0 % of total trips), longer trips have a higher probability of sharing. It is to be expected that there is a higher economic saving for shared travel if one considers the miles travelled per dollar. For more expensive trips which are dominated by long distance travels, this interaction is less visible. From Fig. 4b, we find a directional effect that those trips going towards a north-east or south-west heading direction a have a higher probability to share. We find a similar pattern in both Fig. 4c and Fig. 4d when concerning trip origin/destination distance to downtown. When either the

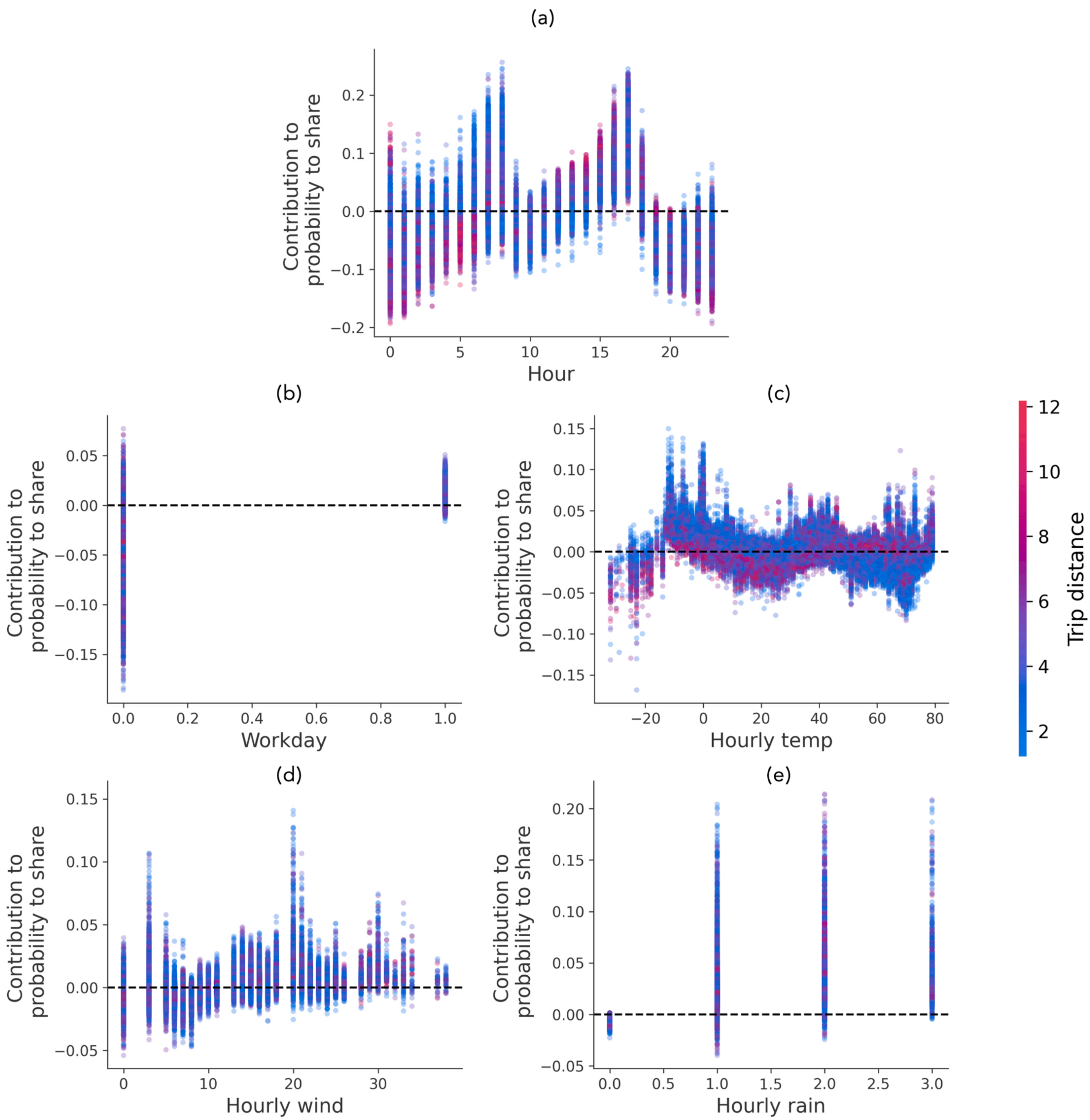

Fig. 5. SHAP-based partial dependence plots for temporal attributes including: (a) starting hour, (b) workday or not, (c) hourly temperature, (d) hourly wind speed, and (e) hourly rain condition. The points on each scatter plot are colour coded by the trip distance, showing the interaction effect between travel distance and that feature.

origin or destination is within 5 km near downtown, longer distance trips are more likely to be private. However, this relationship is reversed when the origin or destination is beyond 5 km from downtown, and longer trips are more likely to be shared.

Fig. 5 depicts how temporal features are linked to the willingness to share. When it comes to when the travel was requested during the day, we discover a clear diurnal pattern. During the morning and afternoon commute hours, people are more likely to request shared rides, with the highest possibility occurring at 8 am and 5 pm. One possible explanation is that a solo ride can be substantially more expensive than a shared ride during these peak hours due to dynamic surge pricing. Private trips are favoured over shared trips in the evening (7 pm–12am), which indicates a certain level of reluctance when sharing with unknown passengers for night-time travels. A similar temporal pattern was identified in Los Angeles, California, based on Lyft trip data (Brown, 2020). Moreover, people prefer to travel privately on non-workdays (holidays and weekends), because even while these travels are private (single party), they may include multiple passengers, such as friends or family members. In terms of weather, users prefer solo trips when the hourly temperature is below −20 °F (-29 °C). There is no particular pattern for wind condition,

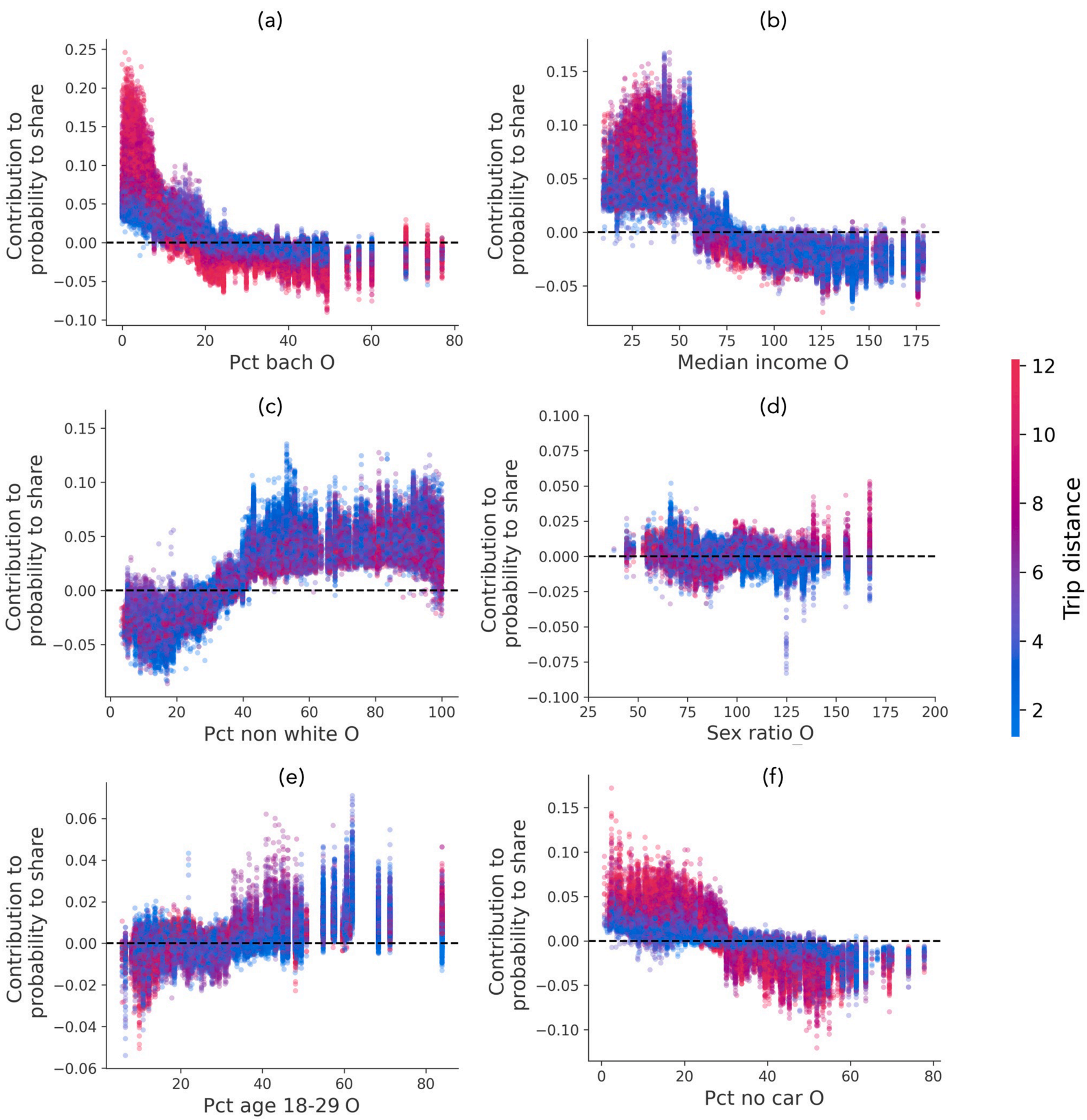

Fig. 6. SHAP-based partial dependence plots for socioeconomic variables (a) percentage of people with a bachelor's degree, (b) median household income in 1,000 dollars, (c) percentage of non-White population, (d) sex ratio, (e) percentage of population aged between 18 and 29, and (f) percentage of households with no cars in the origin (O) pick-up census tract. The points on each scatter plot are colour coded by the trip distance, showing the interaction effect between travel distance and that feature.

and people request more shared trips on rainy days (hourly rain condition >=1), probably to avoid taking public transportation. There are no strong interaction effects between trip distance and temporal parameters.

Fig. 6 shows the marginal associations between socioeconomic factors and willingness to share. When all other factors are held constant, education has a substantial association with willingness to share, and it appears to be a non-linear relationship in which neighborhoods with more people without degrees are more likely to share rides. There is also a noticeable interaction effect between trip distance and education that lower education attainment neighborhoods tend to use ridesharing for longer trips while higher education attainment neighborhoods prefer private rides for longer trips. Median household income is adversely related to the willingness to share that those travels originate from high-income (>$75,000) neighborhoods are more likely to be private. In Fig. 6c, we also show that non-white neighborhoods are more inclined to share. At the census tract level, the sex ratio has no discernible relationship with the willingness to share. Additionally, we discover that neighborhoods with a higher proportion of young age (18–29) group population are more willing to share, but the effect is minor as measured by the SHAP values. The link between socioeconomics and willingness to share is generally consistent with existing analyses in the literature at

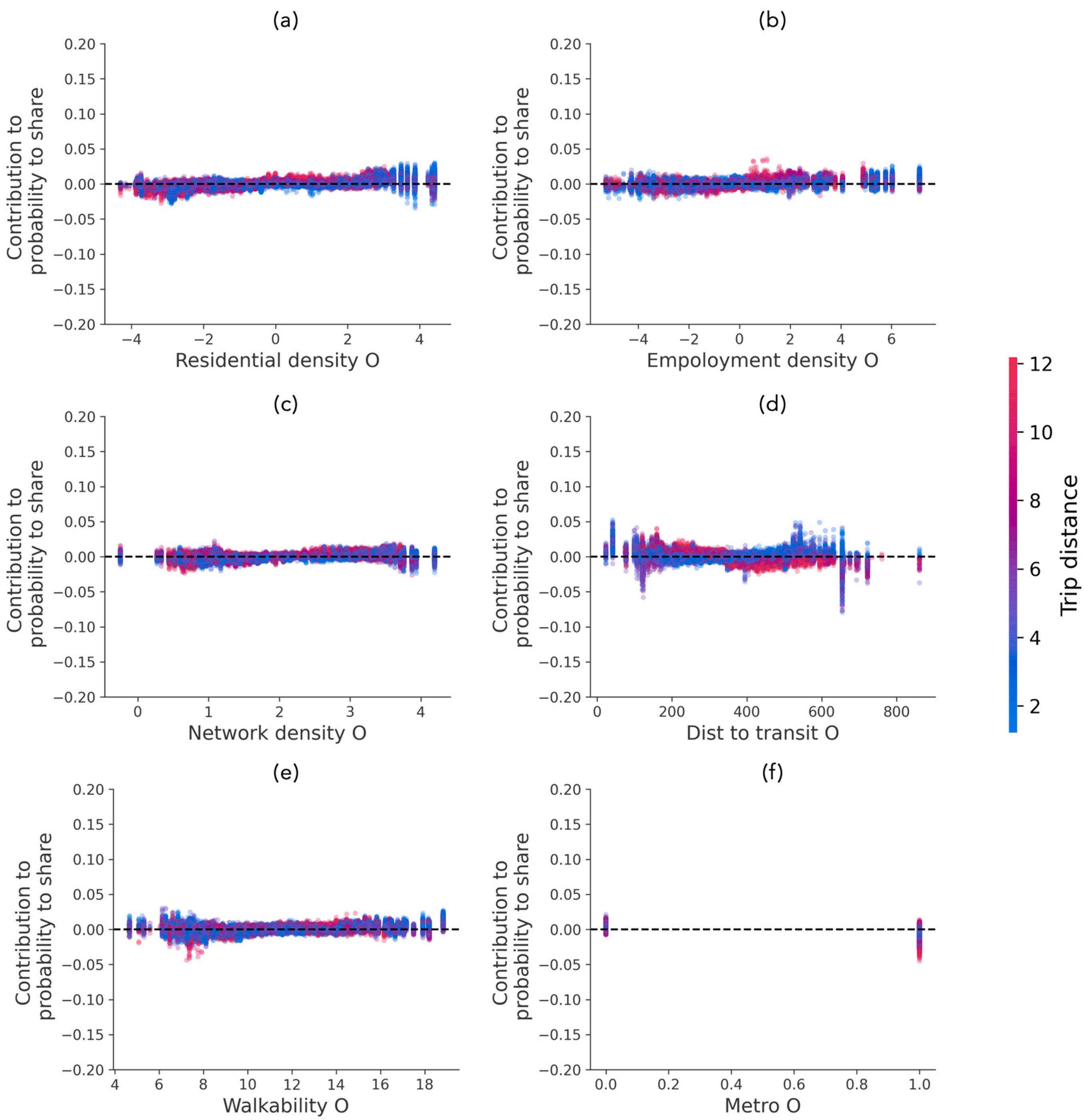

Fig. 7. SHAP based partial dependence plots for built environment features (a) residential density, (b) employment density, (c) network density, (d) transit accessibility, (e) walkability, and (f) having metro stations or not in the origin (O) census tract. The points on each scatter plot are colour coded by the trip distance, showing the interaction effect between travel distance and that feature.

the trip or census tract level (Brown, 2020; Dean and Kockelman, 2021); however, these studies do not show such detailed localized non-linear relationships nor how these relationships interact with trip distances as revealed by of the XAI methodology. One intriguing finding is that vehicle ownership is adversely associated with willingness to share, and that neighborhoods with a higher proportion of non-vehicle households prefer shared rides, implying that shared rides may compete with driving personal vehicles. This possibly due to the traffic and parking concern in Chicago. This also suggests that if ridesharing becomes more available and accessible, there is an opportunity to reduce the utilization of existing vehicles and further decrease the vehicle ownership.

After all other factors held constant, we do not find substantial linkages between the built-environment variables and the willingness to share at the trip level as shown in Fig. 7. The magnitude of impact the model is minimal (mostly less than 5 %). Though Dean and Kockelman (2021) found built environment variables are useful in predicting ratio of sharing in a census tract in Chicago, such analysis was based on aggregated trip data that the finding may not hold at the individual trip level.

SHAP provides explanations for each individual trip which allows us to examine the factors influencing willingness to share that may vary across trips. To further demonstrate the local nature of the SHAP explanations, we selected two neighborhoods: 1) Neighborhood A, located to the northwest of downtown Chicago, with a median household income of $168,353 and 36.3 % of people holding a bachelor's degree; 2) and Neighborhood B, located to the southwest of downtown Chicago, with a median household income of $32,308 and 2.0 % of people holding a bachelor's degree. For Neighborhood A, we chose two trips, a shared trip to downtown Chicago in the morning (8am) and a private trip back to the neighborhood in the evening (10 pm). For neighbourhood B, we also selected a shared trip to downtown Chicago in the morning (7am). Three example trips are shown in Fig. 8. SHAP values were computed for the three trips, and the results are shown in Table 3. We compared the time of the trip and the contribution of the two socio-economic variables in predicting the shared or private trips for these three trips. For trips between neighbourhood A and downtown, the probability of an 8am trip being a shared trip increased by 22.4 % because of the time of the request, while the probability of an evening trip being a shared trip decreased by 15.5 %. This suggests a strong temporal pattern that is shown in Fig. 5a. Median household income and educational attainment of neighborhood A did not contribute significantly to either trip. For the trip from B to the downtown, we can see that the probability of being shared is pushed up by 13.0 % attributed to median income of neighborhood B, by 17.4 % attributed to education and by 16.2 % due to it being a morning (7am) trip. These observations indicate that feature contributions to the prediction outcome are varying across trips.

5. Conclusion

This work presents a machine learning model based on more than 20 million trip records in the city of Chicago to understand users' willingness to share when requesting ride-hailing services. We demonstrated the use of the local explainable AI method, SHAP, to interpret the

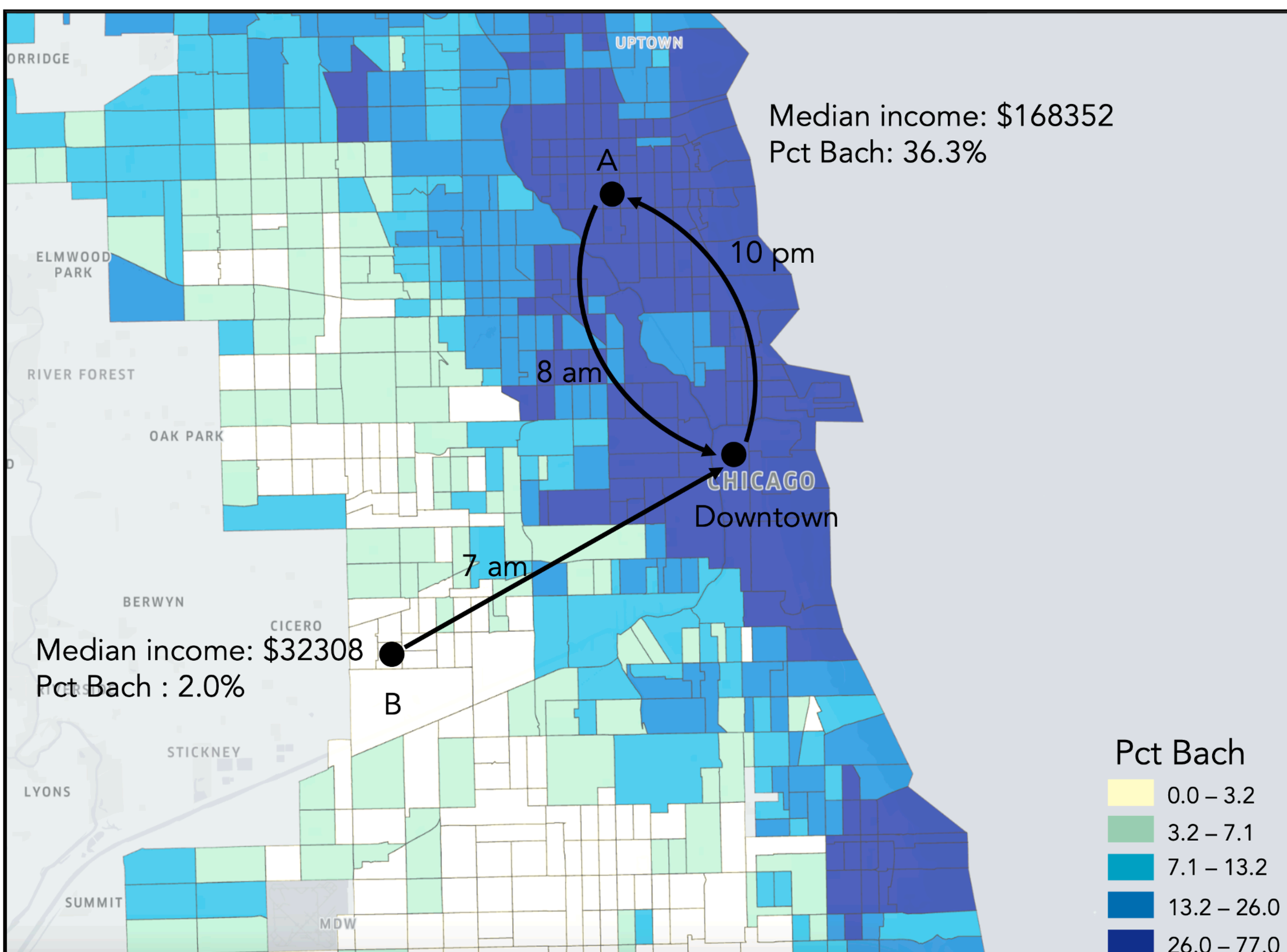

Fig. 8. A map of three example trips in the local SHAP analysis.

Table 3
Feature values and their SHAP contributes to three example trips in Fig. 8.

Neighborhood	Trip	Shared	Time	SHAP (Hour)	Median Income	SHAP (Median Income)	Pct Bach	SHAP (Pct Bach)
A	A to Downtown	Yes	8am	+22.4 %	168,352	− 0.2 %	36.3 %	+ 0.4 %
	Downtown to A	No	10 pm	−15.5 %		− 2.6 %		− 1.7 %
B	B to Downtown	Yes	7am	+16.2 %	32,308	+ 13.0 %	2.0 %	+17.4 %

XGBoost machine learning model and identified key factors and relationships that influence people's ridesharing mode choice. Specifically, the cost of the trip remains the dominant incentive for people to share a ride with others, and it shows a negative non-linear relationship with the probability of sharing. Trip attributes such as distance, direction, as well as temporal aspects are also identified to play a role in people's decisions. In particular, people tend to request shared trips for longer distance trips and during morning and afternoon commute peak hours. Shared trips have a larger discount for longer trips when compared to solo trips, and during peak hours, solo rides have a surging price, which makes them less desirable. Regarding socioeconomics, users who requested trips from neighborhoods with a high percentage of non-white, a low median household income, a low percentage of degrees, and high car ownership are more likely to share rides. Riders from these neighborhoods may be relatively sensitive to price, therefore preferring shared rides over solo rides. We did not find that built-environment factors have substantive associations with willingness to share after other factors are controlled. We also investigated the potential of using SHAP to explain individual trip behaviours. The local property of SHAP will be particularly useful to examine certain special situations, examples of which include studying local ridesharing pattern anomalies when the public transport is disrupted or when there is a large public event. We also identified challenges when applying SHAP. SHAP certainly presents a great opportunity to look at more granular relationships and interactions. But with the advent of big data, we are now faced with "big explanations", meaning that the amount of local explanations will also expand and become overwhelmed, less interpretable, and hard to visualise. One of the possible solutions is to develop interactive visualisation (e.g. web-based dashboard) so that the end users can select data points that are of interest and to look at individual and aggregated explanations more at ease.

These findings help local transportation agencies and TNCs to understand why people choose or not to choose a shared ride and lead to policy and strategy implications to better design geo-targeted and time-related pricing models to promote the use of shared rides over solo rides. From the socio-economic aspect, we find that private rides are preferred in more affluent neighbourhoods, possibly due to residents being less sensitive to price and/or the ride matching may be less effective, which leads to longer waits. It is suggested further advertisement in these areas can be beneficial to increase people's awareness of the environmental benefits of ridesharing. Additionally, enlarging the price gap between shared and non-shared rides may bring more incentives to choose shared rides. Also, local transport and planning agencies can create High Occupancy Vehicle lanes, which are currently not available in Chicago, and build pick up/drop off zones and reduce toll prices to support the use of shared services. These actions have been shown to be effective in promoting shared mobility (Shaheen and Cohen, 2019). Additionally, drivers that provide more shared services can be incentivised by the TNC company to increase the availability of shared services. One opportunity identified from this research is the relationship between willingness to share and vehicle ownership that shared rides are preferred in neighbourhoods with high vehicle ownership. This suggests that sharing rides is an alternative to driving alone, and that if the incentives and availability of shared rides can be improved, it may further reduce vehicle ownership. From the temporal aspect, the results show a strong diurnal pattern that people prefer shared rides during commute hours, increasing service availability around these periods may further encourage the usage. In the nighttime, a decreased willingness to use shared services is observed, additional safety measures can be regulated to enhance the security of the riders (Chaudhry et al., 2018).

The major limitations of this study are primarily due to the data availability. Firstly, the pick-up and drop-off locations and the socioeconomics are at the census tract level; therefore, the interpretation of the relationships cannot be made to each individual rider. Survey-based studies may be preferred for individual level analysis, but it is challenging to gather large and representative samples. On the other hand, policies cannot usually target specific sociodemographic groups due to ethical and equality considerations, so the findings at the census tract level still have useful implications for the stakeholders. One possible future work is to combine survey approach with big trip approach to offer a richer and complementary way to understand travel behaviour. Secondly, waiting time is expected to have a strong influence on the willingness to share but is not considered in the model because of data availability. It has been reported that shared rides usually have longer waiting times due to fewer drivers, especially for less serviced areas, and they are not preferred for time sensitive trips (Hou et al., 2020; Bahrami et al., 2022). This may partly explain why the model performs better when classifying solo rides, as riders would simply choose to ride alone because of the long waiting time for shared rides. Thirdly, the current trip data do not contain price comparison information when user making the decision. It is expected that user will prefer to choose carpool if there is a larger discount. Hou et al. (2020) made an effort to estimate the discount information by aggregating trips and calculating the difference between the average regular fare and the average pooled trip fare. However, this variable is not important in their model, possibly due to the inaccurate estimate of the discount factor because of the loss of temporal granularity when combining. However, it would be useful to develop new methods to investigate how the sensitivity to price may vary across space and time and demographics. Fourthly, the data in this study can only support the findings of the direct competition between shared and solo rides. How shared rides compete with public transportation remains a challenging and important problem, which has not been widely discussed in the literature. If more detailed pick-up and drop-off locations are available, researchers can match them up with public transit stops and schedules for mode choice comparison and analysis. Fifthly, the presented results and factors influencing willingness to share are conditional on the data used in the model. For example, transit accessibility factor used in this study is measured by the distance to the nearest stop, which is provided in the SLD. Alternative accessibility measures such as travel time and transit facility density may result in different model behaviours. Finally, due to service suspension, this research does not consider COVID-19 which is expected to have a substantial impact on transport systems, particularly on shared transport. For example, based on survey data from 2019 and 2020, Jabbari and MacKenzie (2020) found that people's willingness to share to save money declined after the pandemic. As TNC gradually resumes their shared ride services and new data become available, it would be insightful to replicate the study with new data to investigate the changes in factors associated with willingness to share due to COVID-19.

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CRediT authorship contribution statement

Ziqi Li: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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