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Spatiotemporal Analysis of Chicago Ridesharing Demand using Modified Spatial Error Model

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***Abstract* -** Ridesharing has transformed urban transportation by altering the mobility patterns in major cities. To understand the complex interplay of demographic, socioeconomic, and infrastructural factors, it is necessary to employ a spatial and temporal analytical approach. This study utilized a modified version of the Spatial Error Model (SEM) to evaluate the dynamics of rideshare demand in Chicago by analyzing data from 77 community areas over a 60-day period in 2022. Our modified SEM accounts for both spatial dependencies and temporal correlations. This study provides a nuanced understanding of how demographic, socioeconomic, and infrastructural factors impact rideshare usage. Our results indicate that population size, crime rates, and educational attainment are positively correlated with rideshare demand, whereas median age has a negative impact. Additionally, high transit accessibility enhances rideshare usage, suggesting a synergistic relationship with public-transportation systems. However, regions with high walkability showed reduced demand, indicating a preference for walking, or cycling over ridesharing in easily navigable areas. These insights are essential for urban planners and policymakers aiming to improve urban mobility and effectively integrate ridesharing into transportation ecosystems.

***Keywords*:** Mobility, Ridesharing, Spatial modeling, spatio-temporal modeling.

1. Introduction

Ridesharing has significantly impacted urban mobility, offering benefits such as reduced congestion, emissions, and the need for new infrastructure while supporting last-mile connectivity [1–3]. However, challenges persist, including concerns about personal security and loss of convenience offered by private vehicles [4]. The integration of ride-sharing systems within urban transport frameworks requires advanced modeling techniques to optimize their efficacy and address these challenges. Ridesharing has rapidly grown in popularity as an urban transportation mode, prompting significant research into its impact and the factors driving its use. The examination of spatial variability in ride-sharing, particularly in diverse urban environments, such as Chicago, has become a focal point for research because of the varied dynamics across different regions[5]. Furthermore, ride-sharing influences various urban outcomes, including auto accidents and environmental benefits [6,7], underscoring the need for comprehensive modeling approaches.

Factors influencing ride-sharing demand range from socioeconomic conditions to the ease of use of the services [8,9]. For example, vehicle availability and population density significantly affect the likelihood of choosing ride-sharing services[10,11]. Social networks also play a crucial role as people often prefer sharing rides with acquaintances [12].

Extensive research in Chicago has provided deep insights into ride-sharing user demographics, trip structures, and their broader effects on a city's transportation network. Studies have highlighted how demographic factors influence ride-sharing choices, revealing patterns that are essential for effective transport policymaking [13–15]. Additionally, investigations into the economic aspects of ride-sharing, such as the study by [16] , and the operational efficiencies [17], further enrich our understanding of ride-sharing's impact on urban mobility.

Moreover, the integration of ride-sharing with public transit systems has shown potential for synergistic effects that enhance overall transportation efficiency, as seen in studies from other regions, such as Xiamen [18]. Collaboration between ride-sharing companies and municipal authorities is crucial for leveraging ride-sharing data to improve urban transportation planning[19].

Research has revealed multiple determinants of ridesharing adoption, such as environmental consciousness, economic incentives, and social influence [20]. However, the spatiotemporal dynamics of these factors remain to be elucidated. Traditional studies have not fully captured the spatial or temporal variance within urban settings, often overlooking the complex interactions between socio-demographic elements and transportation infrastructure.

This study employs an adapted version of the spatial error model (SEM) [21]to analyze ride-sharing in Chicago, focusing on the correlation between ride-sharing demand and various urban factors, such as crime rates, employment density, and public transit availability [22]. Utilizing data from Chicago's 77 community areas, we explore the relationships between ride-sharing usage and a comprehensive set of variables, including demographic trends, economic status, and urban infrastructure metrics (https://www.cmap.illinois.gov/data/community-snapshots#Chicago_neighborhood_data_2017).

Key insights from our SEM analysis highlight the nuanced effects of urban dynamics on ride-sharing patterns, demonstrating the critical role of spatial modeling in understanding and planning urban mobility solutions [23]. This approach not only enhances our understanding of determinant factors, but also supports the development of more targeted, effective ride-sharing strategies that can be adapted to the specific needs and conditions of urban environments.

In this context, spatial error modeling (SEM) and other spatial-temporal analysis techniques are essential for simulating and understanding the complex dynamics of ride-sharing. Such models help to capture the intricate patterns of demand and supply in ride-sharing, facilitating more effective planning and implementation of these services in urban areas.

2. Methodology

In this section, the research methodology is described.

2.1 Explanatory Data Analysis

To study rideshare determinants in Chicago, we consider some of the demographic and transportation predictors employed in authors' previous work in a Bayesian spatiotemporal analysis [24]. Specifically, we considered the 2020 total population size, daily crimes, and the ratio of the population with a bachelor's degree or higher. In addition, we considered the economically active ratio, median income, and median age for each of the 77 regions. Moreover, we considered transit and walkability indices (categorized as Low, Medium and High). Finally, we add two temporal predicators: one for the possible trend and a dummy variable for weekend days. A spatiotemporal presentation of some indicators is shown in Fig.1.

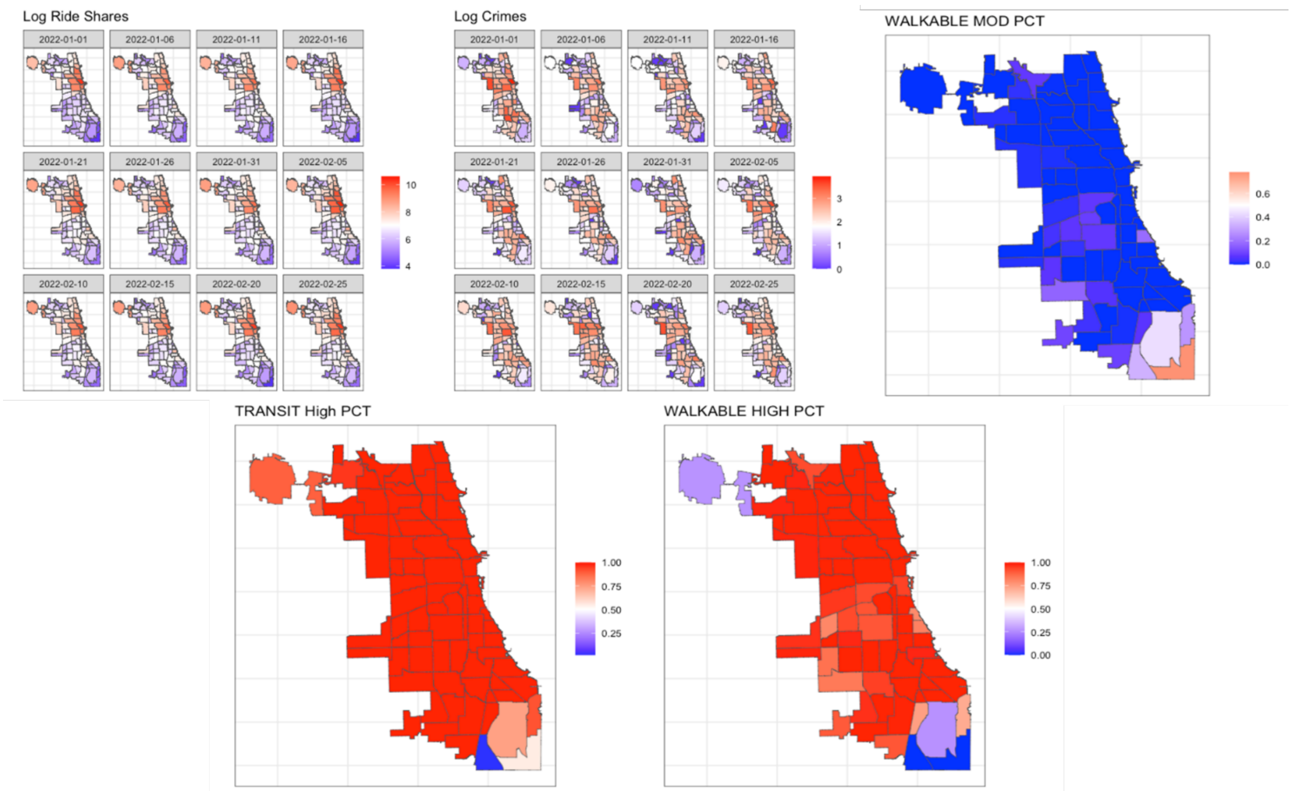

Fig. 1: EDA

We employed an updated version of the Spatial Error Model (SEM) to model the daily rideshares for each of the 77 geographical regions in Chicago. The SEM [25] is a linear regression model with autocorrelated errors, which can be written as

$$y = X\beta + u \text{ and } u = \lambda W u + \varepsilon \quad (1)$$

where λ is the autocorrelation coefficient and ε are independent errors. While W is the neighborhood matrix where the $(i,j)^{th}$ element takes one if the two regions i and j adjacent and zero if not. The model in Eq (1) can model spatial data of (S) regions where y and ε are vectors of the same length (S) and the matrix W is of dimensions ($S \times S$).

Here, we consider an adapted version of the SEM in Equation (1) to account for the spatiotemporal dependence in our data [26]. The daily rideshare data if for ($T = 60$) days and therefore the response variable y of length (ST) is stalked data over space then time. We update the spatiotemporal neighborhood W matrix to be of dimensions ($ST \times ST$). Now, $(i,j)^{th}$ node takes one if the two regions i and j adjacent at the same time point or if this node corresponds to consecutive time points for the same region and zero otherwise.

To investigate the factors that influence ridesharing in Chicago, we utilized demographic and transportation predictors that were previously employed by the authors. These predictors included the 2020 total population size, daily crimes, and the ratio of the population with a bachelor's degree or higher. Additionally, we considered the economically active ratio, median income, and median age for each of the 77 regions. We also examined transit and walkability indices, which were categorized as low, medium, or high. Furthermore, we added two temporal predictors: one for the possible trend and a dummy variable for weekend days. The data for crimes was obtained from the Chicago data portal, which is available at <https://data.cityofchicago.org/Public-Safety/Crimes-2022/9hwr-2zxp/about_data>. All other predictors were obtained from the Chicago community data snapshots, which are available at <https://www.cmap.illinois.gov/data/community-snapshots>.

To achieve the model's linearity and to increase its power, we have applied log transformations to each of the daily rideshares, total population, crimes, and median income. Additionally, we have employed logit transformations for each of the ratios of the economically active and the population with bachelor's degrees or higher.

Results and discussion

Table 1 shows the fitted estimates of the spatiotemporal model for the rideshare determinants in Chicago. To determine the statistically significant determinants for total rideshares over the 77 areas, we estimated the spatial regression model in Equation (1). Owing to multicollinearity, we employed a stepwise model selection procedure to identify the model with the best subset of significant predictors. We assessed the model's performance using Bayesian Information Criterion (BIC). The estimated adapted SEM has a BIC of 4971 (BIC = 6606 if we assume independent errors model).

Table 1: Model coefficient

Predictor	Estimate	Std.	z value	Pr(>|z|)
Intercept	2.079	0.162	12.837	2.2e-16
Population 2020	0.71	0.0143	49.786	2.2e-16
Daily Crimes	0.337	0.011	31.309	2.2e-16
Bachelor_Grad	0.467	0.008	62.323	2.2e-16
Median Age	-0.022	0.002	-11.357	2.2e-16
Transit High PCT	1.054	0.099	10.628	2.2e-16
Walkable Moderate PCT	-5.148	0.115	-44.635	2.2e-16
Walkable High PCT	-3.18	0.087	-36.568	2.2e-16

Fig.2 shows a strong positive correlation (r=0.95) between the actual rideshares and fits of the spatiotemporal model.

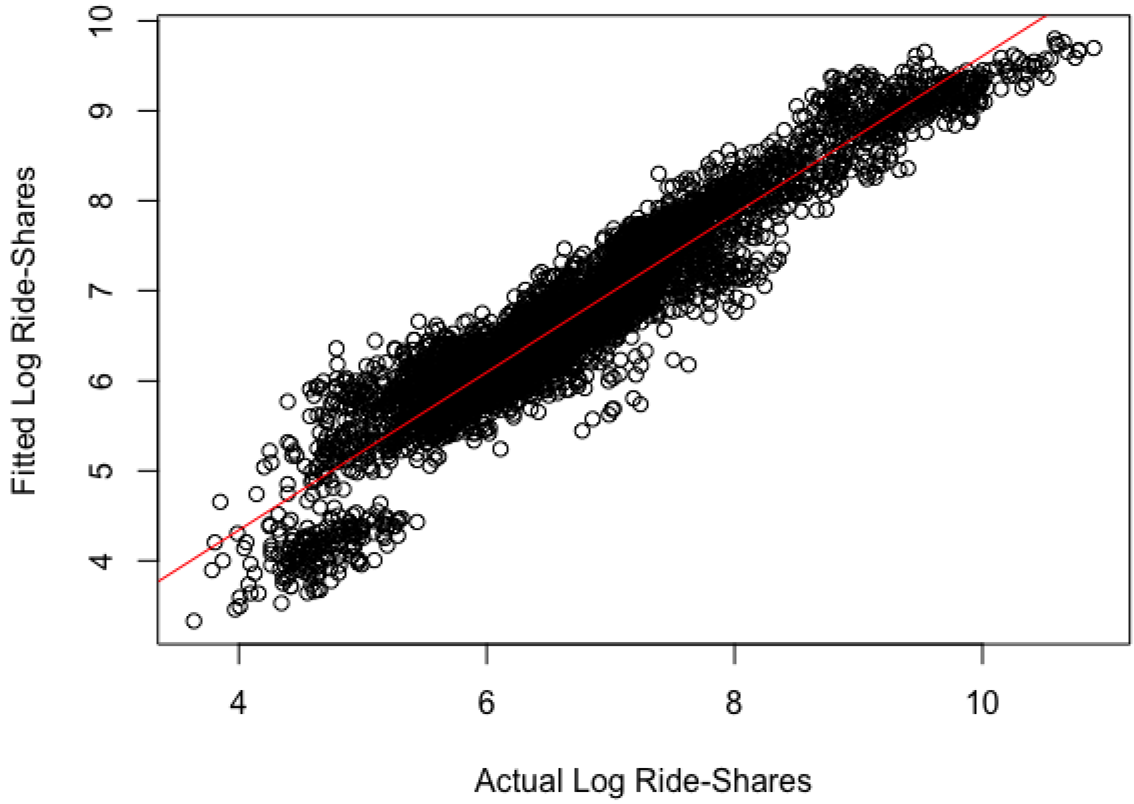

Fig. 2: Relationship between the actual data and the fitted data

Figure 2 shows the relationship between the actual dataset and the fitted dataset. Both axes indicate that the relationship between the log of the actual dataset and the log of the fitted dataset is strong, as evidenced by the coefficient of correlation of 0.95. The plot also reveals a noticeable dispersion, particularly at the lower and higher extremes of the scale. This suggests that the accuracy of the model decreases slightly with extremely low or high values, which might be attributed to outliers or inherent variability in the data. Nonetheless, the plot reflects a robust model with good predictive capabilities across most of the data range, and adjustments may enhance its performance at the extremes. The spatial along time frames for the predicted ridesharing is shown in Figure 3.

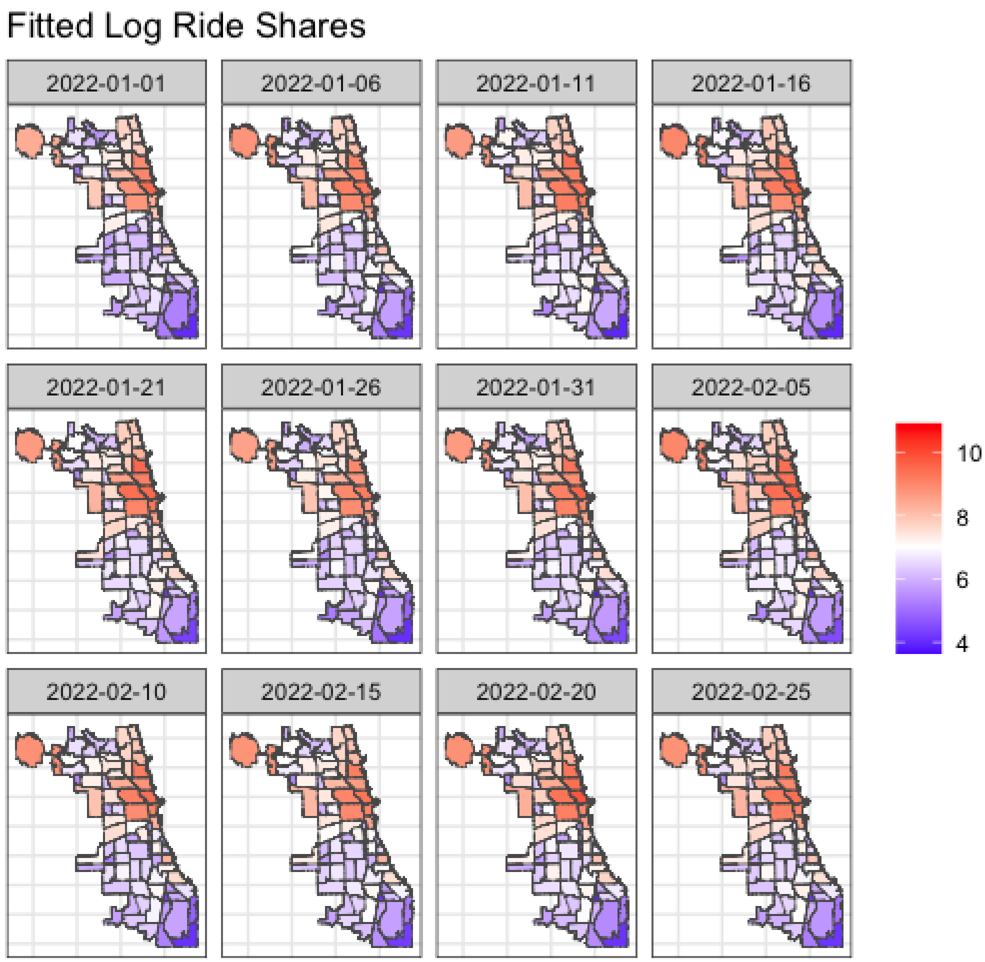

Fig. 3: Spatio-temporal fitted ridesharing data

The set of subplots shows the distribution of ridesharing activities throughout Chicago on various dates between January 1, 2022, and February 25, 2022. Each subplot utilizes a color gradient that progresses from blue (signifying lower ride shares) to red (indicating higher ride shares), providing a visual representation of the temporal and spatial variations in rideshare usage. It is worth noting that regions consistently displayed in red typically denote commercial or densely populated zones with substantial rideshare demand, while areas depicted in purple are likely to be residential or less crowded regions. This visualization is helpful in comprehending urban mobility patterns, enabling city planners and transport authorities to identify high-demand areas and potential requirements for infrastructure enhancements or service adjustments, particularly in response to fluctuations that may impact daily and seasonal transportation planning.

Discussion

Our investigation, employing an adjusted Spatial Error Model (SEM), supplied profound insights into the dynamics of rideshare utilization in Chicago, especially examining the interplay of demographic, socioeconomic, and infrastructural factors throughout a period of 60 days in early 2022. The findings emphasize substantial positive correlations between rideshare demand and factors including population size, crime rate, and educational attainment, while exposing a negative effect of median age on rideshare usage.

Our research supports existing literature emphasizing the impact of demographic and economic factors on transportation choices [20,27–29] . Importantly, the positive connection between educational attainment and rideshare usage aligns with studies suggesting that higher education levels are associated with greater adoption of technology-driven services [7]. This suggests that rideshare companies could strategically improve their services in areas with higher educational attainment to better serve these communities.

The strong relationship between rideshare usage and transit accessibility underscores the potential of integrated multimodal transportation systems that harness the synergy between public transit and ridesharing [30,31]. Urban planners might consider initiatives that facilitate such integration, potentially improving the efficiency and appeal of public transportation systems. Additionally, our study emphasizes the need for targeted policies addressing the needs of younger populations and regions with high crime rates, where ridesharing could provide a safer alternative to other modes of transportation.

Conclusion

This research project utilized a state-of-the-art spatial error model (SEM) to examine the determinants of rideshare utilization across the 77 geographical regions of Chicago during the first 60 days of 2022. By incorporating demographic, socioeconomic, and geographical predictors into our model, we were able to gain significant insights into the complex dynamics that influence rideshare demand in an urban environment.

The analysis revealed several key factors that contribute to rideshare usage. It was observed that areas with larger populations and higher crime rates exhibited increased rideshare activity, suggesting the critical role of ridesharing in providing safe and reliable transportation in densely populated urban areas. Additionally, regions with a higher percentage of residents holding at least a bachelor's degree also saw greater rideshare usage, highlighting the link between educational attainment and the adoption of technology-driven services.

Importantly, the model demonstrated the nuanced impact of urban infrastructure on ridesharing. High transit accessibility was found to be positively correlated with rideshare demand, indicating that ridesharing complements public transit systems effectively. Conversely, areas with high walkability experienced lower rideshare demand, suggesting that rideshare services are less utilized when alternative modes of transport are easily accessible and convenient.

The findings of this study present several practical recommendations for urban planners and policymakers. Policies could be formulated to bolster rideshare services in regions with high population density and elevated crime rates, thereby enhancing safety and accessibility. Marketing strategies and service modifications could be tailored to cater to younger demographics, particularly in neighborhoods with lower median ages. Integrating rideshare solutions with public transportation hubs may prove beneficial, as the positive correlation between rideshare use and high transit accessibility indicates. This integration could streamline transportation options, reduce wait times, and optimize service efficiency. In highly walkable areas, ridesharing services could emphasize value-added services, such as carpooling options or off-peak discounts, to attract riders who might otherwise opt for walking.

Future research could delve into the long-term consequences of ridesharing on urban sprawl, traffic congestion, and public transportation use. Furthermore, expanding this investigation to encompass additional cities with various urban configurations and transportation systems could lend credence to our results and potentially illuminate distinct regional disparities.

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