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Land Use Impacts on Traffic Congestion Patterns: A Tale of a Northwestern Chinese City

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Abstract: Traffic congestion is a contemporary urban issue plaguing transportation planners, land developers, policy-makers, and citizens. While many studies have investigated the impact of built environments on traffic behavior in large metropolises on a regional scale, little attention has been paid to smaller urban areas, in China's context, especially on a neighborhood level. This study investigates the spatial–temporal pattern of traffic congestion in a small-scale city, Xining, in China. By applying multivariate least-square regression analysis to social-sensing hyperlocal travel data, the results indicate that Xining is experiencing morning and evening traffic peaks on the weekdays and pre-weekends and only the evening peak during the weekends or holidays. The pre-weekend congestion is significantly worse than on a normal weekday, implying that stronger measures to consolidate traffic management should be implemented during this time. Educational land use and residential areas were found to contribute significantly to traffic congestion in Xining, and their combined effects tend to exacerbate the situation. The study furthers the understanding of traffic congestion in small urban areas, providing urban planners and policy-makers with new insights to formulate evidence-based strategies for mitigating traffic congestion.

Keywords: smaller urban areas; built environment; land use; traffic congestion; spatial–temporal pattern

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1. Introduction

By 2050, it is projected that more than two-thirds of the world population will live in urban areas. Urban areas, as a compact economic center, provide public services such as better education, transit, employment and medical services to the influx of talents around the world [1]. However, these benefits of urbanization do not come without costs. One serious urbanization dilemma is the rising awareness of environmental health and increasing traffic congestion. According to statistics of the top 101 largest US urban centers, the total travel delay time caused by traffic congestion reached 4.8 billion hours in 2011 [2]. Environmental issues such as severe air pollution, increasing carbon emissions and intensified greenhouse effects are the byproducts of uncontrolled traffic congestion [2,3]. According to an air pollutant property analysis, vehicle exhaust in Beijing, Jinan, Hangzhou has surpassed coal as the main source of urban air pollution (especially PM2.5) [4]. Having said that, traffic congestion not only happens in larger economically developed cities but also in small or old cities as the contemporary driving demands outstrip the previous built environment design and planning [5].

The literature has indicated that the design of built environments has direct influences on people's mobility patterns [6–12], and thus directly determines how traffic congestion is formed. Many studies have investigated the impact of land use on traffic behavior in large metropolises such as San Francisco [13]; Beijing [14,15]; Washington, DC [16]; and Hong Kong [17,18]. Sarzynski et al. [16] revealed that housing–job proximity, density/continuity and housing centrality have significant influences on traffic congestion. Litman [19] examined the transport impacts of various land-use factors, e.g., density, regional accessibility and roadway connectivity, and found that such factors tend to exert a cumulative and synergistic effect on the total travel behavior. Zhang et al. [14] modeled the linear correlation between distribution of urban points of interests (*POI*) and congestion time and demonstrated the adverse effects of commercial land use on traffic status. The insights revealed by previous big city-oriented research, however, cannot be readily generalized to the context of smaller urban areas, which are supposed to have less-developed public transit systems and lower population density compared with a large metropolis. For example, Bian et al. [20] used online map data with cluster analysis and categorized 4 levels of congestion among different Chinese cities. Wang [21] identified a housing and job distribution pattern contradictory to that revealed by Cutsinger et al. [22], which can be related to the less-developed transportation facilities in suburban Florida. With the further urban–rural intertwining in future placatory urbanization, smaller urban or rural areas might connect with big cities through immersive infrastructures, house a great proportion of the influx population at a certain situation and represent potential sources of future economic growth. Thus, this paper argues that it is urgent to understand how the physical design of built environments in these areas affects congestion patterns.

The dominant relational study of built environments and traffic congestion is based upon on examining the “land use-congestion” dynamics at a broader city or regional scale, which provides insights for policymakers in regional development strategies. Chinese people used to say, “No road, no economy”. The saying reflects a universal governmental aspiration of road building in modern society as a way of lifting regional economies and releasing urban population density. Many studies, however, have acknowledged the cost of the uncontrolled transportation expedition that happens in urban sprawl. More long-distance travel and congestion are generated at the cost of environmental destruction and replacing segregated lands uses [23,24]. Meanwhile, supporters of dispersed city development also criticize compact city development as a trigger of the localized congestion that happens more frequently in current metropolitan areas and that brings unexpected risks to traffic management [16,21]. Nevertheless, macro-level metrics are used in these studies to measure the general traffic dynamics of a region over a long duration through a standard concentric model, including commute time, average daily traffic per lane, and delay per capita [16]. The over-uniform sheds light on a potential niche area of study, that is, investigating neighborhood-level interactions between land use and transportation on a fine-grained scale, e.g., distribution of land use categories, layout of arterial roads, road density and street connectivity [21,25].

Since the development of the time–space geography framework by Swedish geographer Torsten Hägerstrand in the mid-1960s [26], research on transportation pattern and congestion conditions has been closely associated with time changes [27–32]. For instance, frequent traffic congestion happens on weekday mornings and at nightfall as a result of the commuting demands of citizens. This commuting-induced congestion is more centered around school districts, CBD and residential blocks linked by urban arterial roads. At weekends, commercial or recreational areas are frequently congested as well for recreational purposes. Meanwhile, occasional traffic congestion, dispersed in cities, tends to appear at random locations and times. They are caused by emergencies such as car accidents, large-scale exhibitions and/or concerts. There are different ways to analyze and tackle these contextual congestion issues. Early studies fall into a travel survey data approach that collects travel destinations, travel time, travel purposes, and means from individuals, like the first extensive personal travel (PT) survey in the Hiroshima metropolitan area in 1967 [33]. However, the recent proliferation of big data, specifically as localization services and smart phone-enabled navigation, is forming hyperlocal travel data. Transportation studies have been applying this new perspective and fine-grained data to the movement of people in time and space [34,35]. For instance, Di et al. [36] have developed a deep learning-based congestion prediction model based on a real-life dataset in a road segment of Finland, while Song et al. [31] detected the factors of traffic congestion in Beijing with multi-source data fusion and mining techniques. However, it is not surprising that these studies are currently focusing on big city contexts, which leaves uncertainty about how time-variant traffic conditions are influenced by spatial land use forms in smaller-scaled cities in China, and we are motivated to fill this gap.

Using a small valley city, Xining, in West China as a case study, this research aims to investigate the spatial–temporal dynamic pattern of traffic congestion in smaller cities in China. The utilization of emerging high-resolution and high-frequency social sensing data set in hyperlocal travel makes this paper stand out among previous research in several aspects. First, different from the extensive research on travel behavior in big cities, our study is particularly concerned with smaller Chinese urban areas with expected economic and population growth in the future. Second, instead of macro-scale analysis, our study looks at the micro-interplay between neighborhood-level urban forms and traffic behaviors, providing insights for the further deployment of urban design and street-scale planning strategies. Third, the temporal factors at different scales (e.g., daily, weekly, and holidays) considered in this research allow for a more thorough understanding of the design of built environments and the formation of congestion. The study contributes to the discourse of traffic behaviors and sheds light on the spatial–temporal pattern of traffic congestion in small cities in China's context. The findings have significant policy implications, providing urban planners with new insights that can help optimize land use, transportation facilities and human resources to improve resilient transportation and healthy urban environment.

2. Conceptual Framework

A conceptual model was developed in this study to investigate the spatial–temporal dynamics of traffic congestion in smaller urban areas (Figure 1). The model considers both spatial and temporal dimensions. The spatial dimension refers to the physical design of urban built environments, including land use and the distribution of transportation networks. Land use factors are measured based on the distribution of different types of *POI* in the research areas, e.g., shopping malls, education facilities and tourist sites. The transportation network includes factors such as density of roads, public transit accessibility, and distance to arterial roads. To reveal the latent correlation among various factors, statistical analysis such as bivariate correlation and principal component analysis (PCA) was performed to select and (or) transform representative metrics in order to effectively characterize smaller urban forms. The temporal dimension examines the effects of temporal factors in three scales, i.e., daily cyclic pattern, weekly cyclic pattern, and influence of national holidays. The aforementioned factors serve as independent variables of a comprehensive spatial–temporal model to predict the level of traffic congestion in the region of interest. The model reveals which and how urban form factors affect traffic conditions.

The conceptual spatial–temporal model can be summarized in mathematical ways, as follows:

$$C_t = f(L, [t]) \tag{1}$$

$$L = f_l(POI_1, POI_2, \ldots, POI_m) \tag{2}$$

where C_t is the traffic condition at time t; L is a metric that characterize the land-use patterns; $[t]$ represents the temporal factor that serves as a control variable, which can ensure only traffic conditions occurring at the same time are considered. To investigate time-variant effects, the congestion model is compared at different time C_t. The land use metric L is extracted based on an analysis (e.g., bivariate correlation and PCA) of the density of m types of *POI* in the research area.

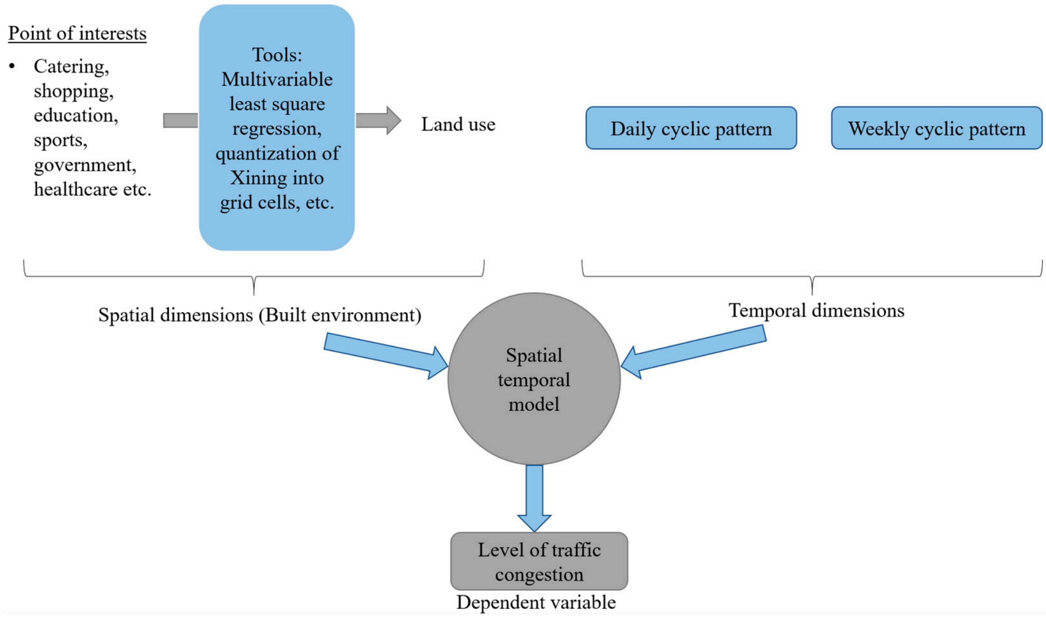

Figure 1. Conceptual framework to understand traffic congestion patterns in smaller urban areas.

3. Materials and Methods

3.1. Data Sources and Materials

Xining, a capital city of Qinghai province, China, was selected as the modelling area in this study. The city has a development history of more than 600 years dating back to the Ming Dynasty. As shown in Figure 2, Xining City is located in the northeast of the Qinghai–Tibet Plateau, and is divided into 5 municipal districts, 1 county, and 1 autonomous county, among which the four old, developed districts, i.e., Chengbei, Chengxi, Chengzhong and Chengdong, are included in this study area. In total, the study area occupies a land space of 457.52 km^2 and housed more than 1.32 million residents by 2019 [37]. The urbanization rate and gross domestic product (GDP) of Xining reached 75% and CNY 137.298 billion, respectively, in 2020, which ranks top of Qinghai Province [38,39]. However, compared with big cities with a population of over 10 million in China, such as Beijing, Shanghai, Guangzhou and Shenzhen, Xining is still largely lagging behind [40]. Different methods have been applied globally to define the size of urban areas, such as population, urbanization rate, sectoral employment and provision of infrastructure and services [41–44]. By these criteria, Xining belongs to a typical smaller city in current China. While under the latest one-belt–one road national strategies, Xining is also expected to become a big city in northwest China which plays a key role in regional trade and tourism [45]. The contested city visions of Xining bring a unique opportunity, in the context of China, for this research to generate distinctive findings that are different from the previous metropolis-focused transportation studies.

The social sensing materials used in this study were collected from AutoNavi Map https://lbs.amap.com/ (accessed on 7 December 2021), a leading Chinese mapping and navigation service provider. For land use information, we used the application programming interface (API) provided by the AutoNavi Map to extract 12 categories of *POI* within the boundaries of the study area, which includes catering, shopping, life services, sports, healthcare, hospitality, tourist attraction, residence, government institution, education, financial services and company. Specifically, the *POI* data provided by AutoNavi Map is at the building level, containing information on *POI* ID, building coordinates and *POI* type code.

For the traffic conditions, the AutoNavi Map API was used to collect real-time road traffic status in the study area. The AutoNavi real-time road traffic data are constructed from GPS-based information uploaded by map service users to the computing platform combined with data collected from video cameras and induction coils. The level of congestion was measured by a score hierarchical system, where the values of 0, 1, 2, 3 and 4 represent "unknown", "smooth", "slow", "mild congestion" and "heavy congestion", respectively. Each piece of traffic status data is associated with its corresponding coordinates. In order to characterize the temporal involvement of congestion, the traffic condition data were collected every hour each day. The data were recorded for 9 consecutive days, from 7 December 2021 to 15 December 2021, covering weekdays, a pre-weekend (Friday), and a weekend as holiday.

Figure 2. The geographic location of Xining in China.

3.2. Quantizing the Study Area into Grid Cells

The entire study area was divided into grid cells to aggregate the land use and traffic condition data on the basis of each area unit. The application of this approach was considered suitable due to its prevalence in relevant studies, such as Cutsinger et al. [21], Martínez et al. [46] and Salomons and Pont [47]. As shown in Figure 3, the geographical center of the study area was designated as the center of one cell, starting from which a mesh of cell grids was subsequently expanded outward. The determination of cell size is a debatable issue [48]. While some researchers, e.g., Cutsinger et al. [22] and Sarzynski et al. [16], used a cell size of 1.0 × 1.0 miles; the others, e.g., Wang [21] and Mendel et al. [49], argue a size of 2.5 × 2.5 miles is more stable for urban form measurement. As we are interested in the transport impact of neighborhood-level urban form in a relatively small region, the cell size was set to 1.3 × 1.3 miles in this study, which can characterize the land-use pattern in Xining with sufficient resolution. The quantization resulted in a total of 118 cell grids in the study area.

3.3. Variable Definition and Quantification

Based on the collected data, variables can be defined in order to quantify the land use, transportation network and traffic condition in each cell grid.

Land use is characterized by the density of different *POI* categories in a cell, as illustrated by Equation (3):

$$DPOI_i = \frac{N^i_{POI}}{cell\,Area} = \frac{N^i_{POI}}{2.59} \tag{3}$$

where $DPOI_i$ is the *POI* density of category *i* ($i \in [1, 12]$), which corresponds to one of the 12 categories mentioned in Section 3.1; N_{POI}^{i} is the number of category *i POI* in a cell; and *cellArea* is the area of the cell, which equals 2.59 km^2 in this study.

The traffic condition in a cell is measured by the mean traffic status, *MTS*, which is defined as follows:

$$MTS_t = \frac{\sum_{i=1}^{N_{TS}} TS_t^i}{N_{TS}} \quad (4)$$

where MTS_t represents the average traffic status of the cell of interest at time *t*; TS_t^i is the traffic status at time *t* at *i* location; and N_{TS} is the total number of sample locations with traffic status data in the cell.

According to the above definition, variable values for all 118 cells can be calculated. Table 1 lists statistics of the calculation results.

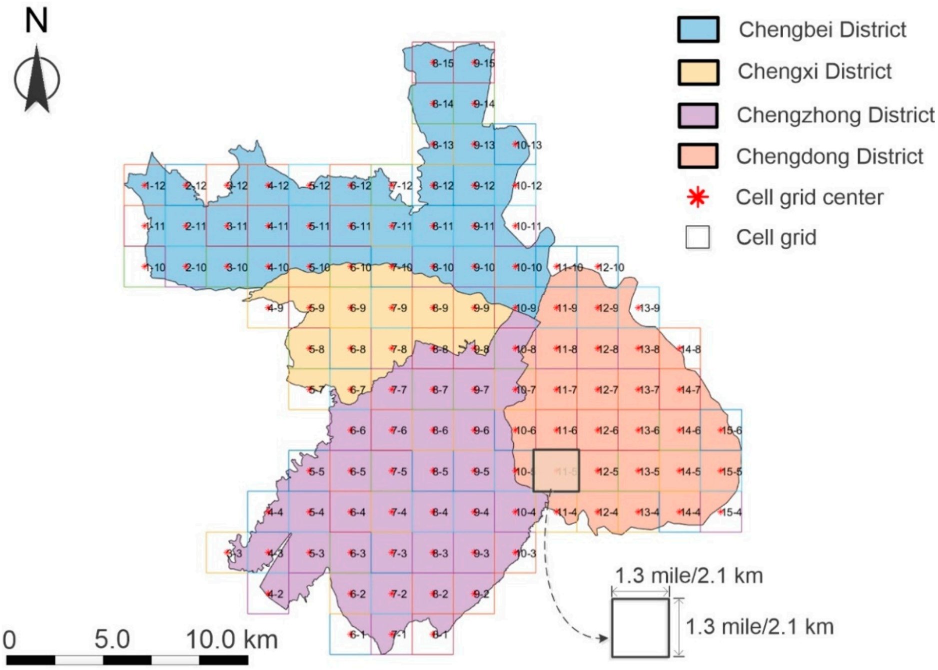

Figure 3. The study area consisting of 118 square-mile cells by quantization.

Table 1. Statistics of the defined variables.

Variables	Mean	St. Dev.	Maximum	Minimum
Land Use (Independent Variables)				
Catering	15.4	37.5	235.6	0
Shopping	31.6	75.2	479.7	0
Life services	15.0	38.2	248.6	0
Sports	2.0	5.4	34.5	0
Healthcare	5.0	12.7	76.8	0
Hospitality	4.1	13.1	101.8	0
Tourism	0.5	1.1	6.2	0
Residence	3.4	7.8	49.7	0
Government	4.1	10.4	73.3	0
Education	3.7	9.0	62.4	0
Financial	1.9	5.8	38.1	0
Company	7.0	13.4	76.4	0
Traffic condition (Dependent variables)				
MTS *	1.03	0.10	3.75	1.00

* Note: the statistics of *MTS* in the table took into account the traffic condition of all the 9 days of investigation.

3.4. Traffic Congestion Modeling

Based on the traffic condition characterized by the *MTS*, typical traffic peak hours were identified in order to model the intercorrelation between smaller urban built environments and congestion. Among various statistics modeling methods, multivariable least-squares regression (MLSR) is well-known for its simplicity and efficiency, and it has been used in various scenarios such as construction machine trajectory prediction [50], waste composition estimation [51,52] and building inspection [53]. MLSR also has wide applications in transportation research [14,16,54]. In this study, we employed the MLSR to construct the traffic congestion model.

The MLSR searches for a function $y = f(x)$ that can best fit the mapping relationship from a list of independent variables x to the dependent variable y. This is achieved by iteratively updating the model $f(x)$ so as to minimize the square error between the predictive and observation values. In the context of traffic congestion modeling, suppose the traffic condition at time t is to be predicted, then the corresponding traffic condition and prediction model can be represented as y_t and $f_t(x)$, respectively. The independent variable x here characterizes the built environment patterns, encompassing both the land use and transportation network indices mentioned in Section 3.3 for each cell. Let $T_t = \left\{ \left(x^1, y_t^1\right), \left(x^2, y_t^2\right), \ldots, \left(x^N, y_t^N\right) \right\}$; ($N$ = 698) denotes the data samples of all 118 cells. The modeling process can be mathematically expressed as follows:

$$\begin{cases} y_t = f_t(x) \\ \text{s.t. } \min\limits_{f_t} \sum\limits_{i=1}^{N} \left[y_t^i - f_t\left(x^i\right)\right]^2 \end{cases} \tag{5}$$

Note that the built environments can be deemed as unchanged under the timescale of our research (i.e., weeks or months). Thus, the independent variable x does not have a subscript t. Traffic data collected at different t will result in different congestion models $f_t(x)$. By comparing the importance or contribution of different built environment factors to the model at different times, we will gain insights into how land use or accessibility to transportation networks affects traffic conditions with the involvement of time.

4. Results and Findings

4.1. Time-Variant Effects of Traffic Condition

The built environment in smaller-scaled cities affects traffic conditions in different ways as time passes. The time-variant pattern of traffic status in Xining has been explored in this section, with the goal of identifying the most likely congestion time for later land-use distribution and correlation analysis. It has been acknowledged that urban roads are particularly needed for people's commuting purposes during weekdays. The roads deemed necessary at weekends or holidays (referred to as "weekend" hereafter if not specifically mentioned) may vary in different situations. Additionally, scholars have also revealed that travel demand is higher on the day before weekends or holidays (referred to as "pre-weekend" for simplicity) than normal workdays [29,55].

As a result, in subsequent analysis, traffic condition data are classified into three date categories, i.e., weekdays, weekends and pre-weekends.

Figure 4 reveals the average *MTS* at typical time points during weekdays (i.e., average of traffic data from 7–9 December and 13–15 December 2021), pre-weekends (i.e., average of data from 10 December 2021), and weekend (i.e., average of data from 11~12 December 2021). A common observation among the three date conditions is that the rush hour with the most traffic pressure is around 6 pm, although the level of congestion on weekends is lower than that on weekdays (or pre-weekend). This is not a surprise, as the weekday evening congestion is related to the off-work traffic, while during weekend, families may also go out to have dinner at 6 pm, which enhances the traffic congestion [55].

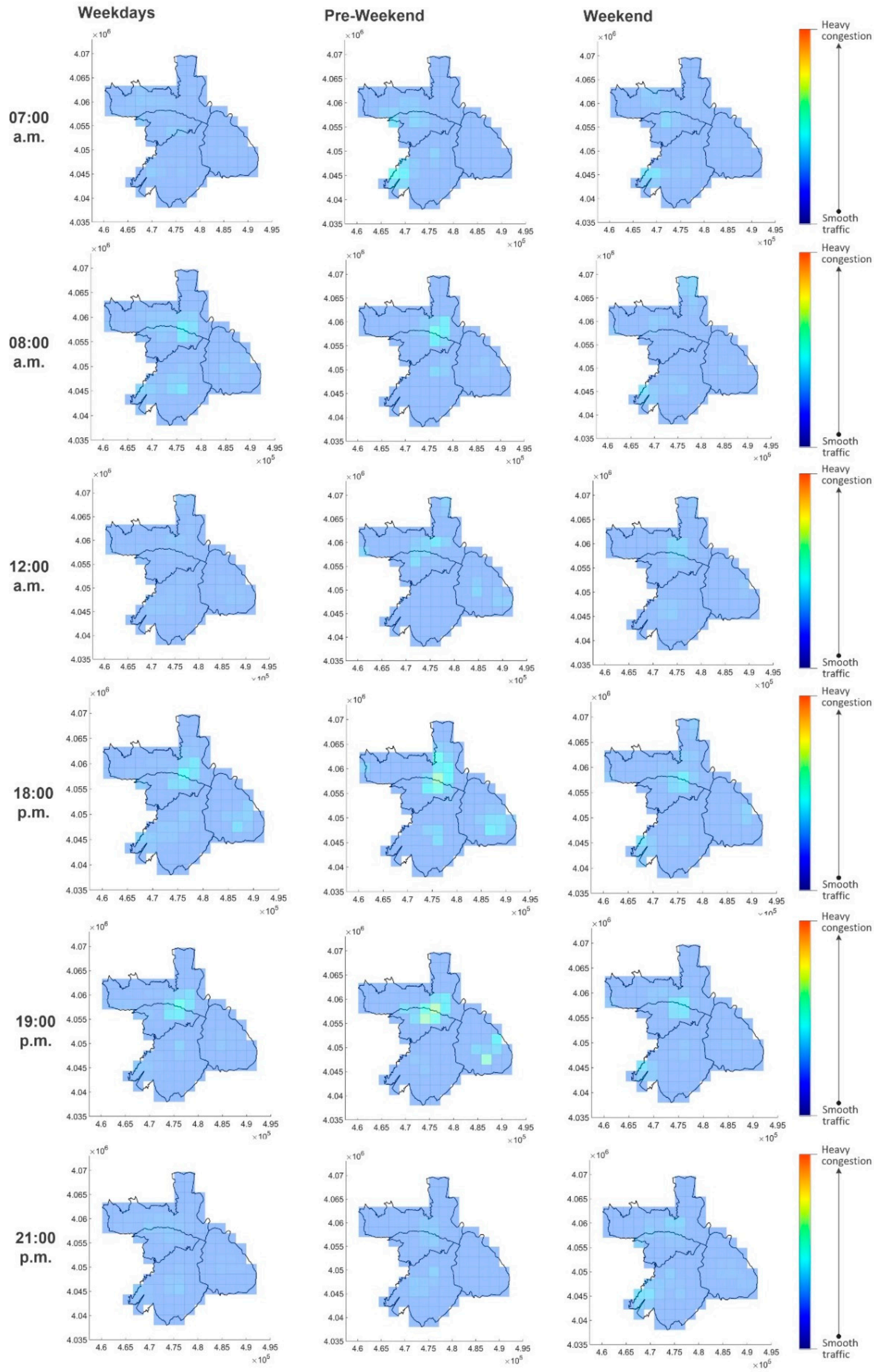

Figure 4. Evolvement of traffic condition during weekdays, the day before weekend (Friday) and weekend.

The commuting-led congestion can be reflected in two traffic peaks a day which appear at both weekdays and pre-weekend. One is at around 8:00 in the morning and one is at around 18:00–19:00 in the afternoon. On the weekend, the morning peak does not normally appear, as fewer people need to commute to work. Even if extra work needs to be done, the office time and place can be flexible [55]. As many economists and traffic analysts predict, work-from-home (WFH] is becoming the new working mode, especially after the outbreak of COVID-19, which may significantly relieve the traffic pressure in the morning peak in the future regardless of whether it is weekends or weekdays [56,57].

Among two commuting-led traffic peaks in a day, the morning traffic peak congestion is usually mild compared with the peak in the evening. During the evening peak around 6:00–7:00 pm, the pre-weekend congestion is much more severe than that of a normal weekday, with nearly half of the study areas being classified as congested. This condition could be attributed to an increase of long-distance travel stimulated by social activities at weekends, as people tend to visit families and friends on holidays [58]. The trend can be further verified in Figure 4, as each district congestion experienced at evening peak hour on the pre-weekend compared with monocentric congestion on normal weekdays. People who are migrant to work in urban areas tend to live near their workplaces while far away from their family houses due to the time and economic savings of daily commuting. When the holidays arrive, dispersed long-distance travel and destinations appear as a result of emotional connections, which causes congestion across districts.

4.2. Land Use Distribution Analysis

The distributions of the 12 *POI* categories in the study area are depicted in Figure 5. From a general perspective, most of these facilities are concentrated in the old city center (intersection of Chengbei, Chengxi, Chengzhong and Chengdong districts) which have been formed by four crossing regional roads since historical Xining. However, if we look into detailed resolutions, there are still some POS categories clustered at a few subcenters in other districts, such as education, sports, shopping and companies.

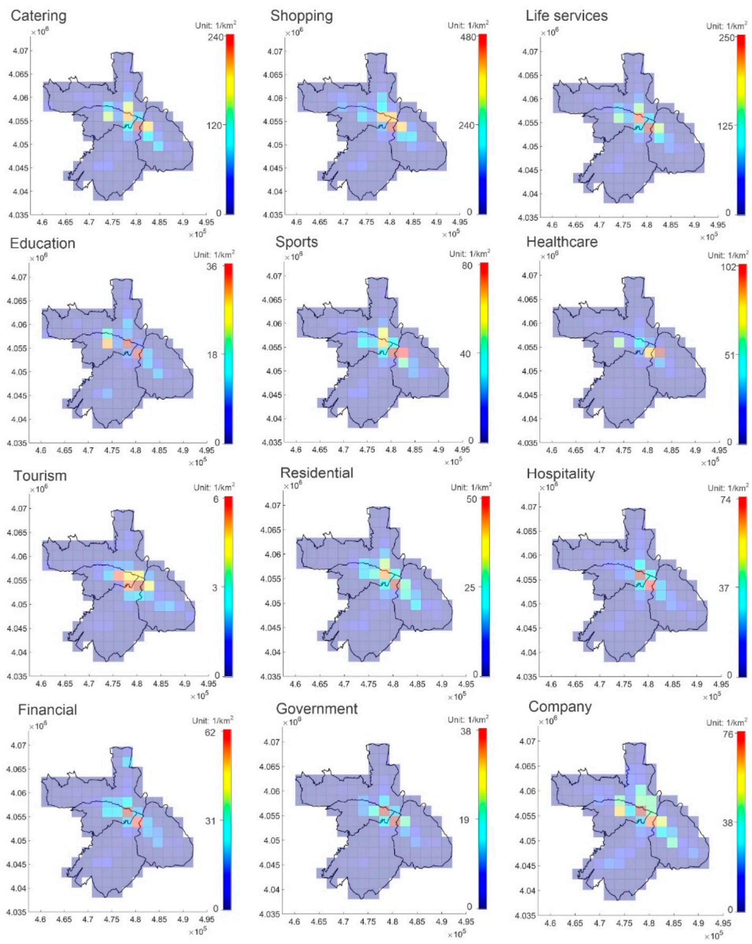

Figure 5. Distribution of 12 categories of points of interests (*POI*) in Xining City.

To avoid the influence brought by the different scales, all variables were normalized to the range of [0, 1] based on the following equation:

$$DPOI_i{}' = \frac{DPOI_i - \min_i(DPOI_i)}{\max_i(DPOI_i) - \min_i(DPOI_i)} \tag{6}$$

$\max_i(DPOI_i)$ and $\min_i(DPOI_i)$ calculate the maximum and minimum of the $DPOI_i$ among all cells, respectively.

4.3. Spatial–Temporal Traffic Congestion Modeling

The aforementioned 12 land use factors (e.g., D_{cat}, D_{shp}, and etc.) are considered as independent variables. Then traffic conditions at different time are used as dependent variables to modeling spatial–temporal traffic dynamics through several multivariable regression models. According to the findings in Section 4.1, we considered traffic conditions in five typical temporal scenarios: (a) the morning peak in a normal weekday (Wd-mn-peak); (b) the evening peak in a normal weekday (Wd-en-peak); (c) the morning peak in a pre-weekend day (pWe-mn-peak); (d) the evening peak in a pre-weekend day (pWe-en-peak); and (e) the evening peak in a weekend day (We-en-peak).

Table 2 shows the results of multivariate regression in the five mentioned scenarios, which includes the standardized coefficients of the independent variables and their significance and the mathematical formulas of the resulting regression models. The absolute values of the standardized coefficients reflect the predicted relative importance of the corresponding variables to the dependent variable (i.e., traffic status). The larger of the coefficients, the more important of the variables to the traffic congestion, and vice versa. The significance reflects confidence in the given coefficients at a 95% level, and a significance value lower than 0.05 means the assertion is statistically significant. In Table 2, the built environment factors that are both important and statistically significant are marked with bold font style.

Table 2 provides useful information on the ways different land uses in smaller urban areas influence traffic conditions differently at different time periods. In all of the five investigated temporal scenarios, D_{edu} is obviously the most frequent positive factor related to traffic congestion, while D_{gov} is often negatively correlated. This finding indicates that street blocks in small cities with denser educational land use and remote to governmental institutional land uses are likely to experience serious traffic congestion in peak hours universally across weekdays, pre-weekends, weekends and holidays. Cross-referencing with Figure 4 and educational land use distribution in Figure 5 verifies this trend vividly, where on average the most severe congestion clusters are around the different clusters of educational land use in Xining City. This finding marks a significant difference in traffic congestion between big cities and small-scaled cities. Most of the studies in the literature analyzing land-use and traffic congestion correlations have identified commercial land use as the most positive influential factor leading to urban congestion [14,16]. However, our results indicate that educational land uses in small urban areas like Xining seemingly play a more important role in the formation of traffic jams among all built-environment factors.

During an average weekday, the morning peak hours are only influenced by D_{edu} and D_{com}. During the evening rush hours, however, the proportion of life services land use (D_{lif}) and residential areas (D_{res}) also have different levels of positive influence: the higher the D_{lif} and D_{res}, the more severe the traffic congestion that occurs. This correlation is consistent with daily experience, especially with small, old cities like Xining, where traditional Danwei community systems still exist in urban forms. Xining City preserves several Danwei communities in old urban areas where basic working places, life services and residential areas are close to each other. A Danwei community (also called a "work unit") is a unique urban typology developed in the 1950s in which state-owned enterprises (SOE), factories, schools, health care and cultural facilities were grouped together for the efficiency of urban management and increasing employment rate [59]. After the opening reform and modern development of cities in China, most of the Danwei system collapsed. Due to the lack of large-scale urban regeneration in less-developed middle and western China, Xining City might still preserve certain land-use functions in its old city center, while companies, schools and hospitals have certainly expanded out of the system. Thus, the denser distribution of residential areas with life services land uses means more commuting happens, especially at evening peak hours when employees and children return to their homes.

Table 2. Regression results of traffic congestion in weekday scenarios.

	Wd-mn-Peak (8:00 am)			**Wd-en-Peak (19:00 pm)**			**Wd-en-Peak (21:00 pm)**		
	Coefficient	Sig.	R^2	Coefficient	Sig.	R^2	Coefficient	Sig.	R^2
D_{cat}	**−1.514**	**0.046**	0.586	**−1.685**	**0.007**	0.748	−0.805	0.335	0.442
D_{shp}	−0.485	0.121		**−0.582**	**0.024**		0.223	0.517	
D_{lif}	0.685	0.506		**2.455**	**0.004**		0.388	0.733	
D_{spt}	−0.044	0.917		−0.204	0.565		0.799	0.096	
D_{hea}	1.543	0.089		−0.516	0.485		1.327	0.185	
D_{hop}	−0.68	0.074		0.000	1.000		−0.704	0.094	
D_{tou}	0.059	0.790		0.001	0.996		0.417	0.093	
D_{res}	0.572	0.363		**1.878**	**0.000**		−0.555	0.425	
D_{gov}	**−0.987**	**0.032**		**−1.845**	**0.000**		**−1.125**	**0.028**	
D_{edu}	**1.056**	**0.007**		**1.110**	**0.001**		0.685	0.112	
D_{fin}	−0.531	0.289		**−0.827**	**0.045**		−0.935	0.093	
D_{com}	**0.545**	**0.021**		**0.504**	**0.009**		0.408	0.116	
	pWe-mn-peak (8:00 am)			**pWe-en-peak (19:00 pm)**			**pWe-en-peak (21:00 pm)**		
	Coefficient	Sig.	R^2	Coefficient	Sig.	R^2	Coefficient	Sig.	R^2
D_{cat}	**−1.906**	**0.004**	0.707	**−1.464**	**0.021**	0.736	**−2.226**	**0.003**	0.608
D_{shp}	**−0.774**	**0.005**		**−0.526**	**0.045**		−0.178	0.559	
D_{lif}	1.388	0.124		**2.246**	**0.010**		0.206	0.838	
D_{spt}	−0.580	0.126		0.205	0.570		**1.266**	**0.003**	
D_{hea}	0.268	0.734		−0.447	0.554		**2.547**	**0.005**	
D_{hop}	−0.040	0.903		−0.032	0.920		**−0.747**	**0.045**	
D_{tou}	−0.288	0.141		0.298	0.112		**0.612**	**0.006**	
D_{res}	**2.141**	**0.000**		**1.284**	**0.016**		−0.044	0.943	
D_{gov}	**−0.882**	**0.029**		**−1.738**	**0.000**		**−1.709**	**0.000**	
D_{edu}	**1.038**	**0.003**		**0.847**	**0.010**		**1.090**	**0.005**	
D_{fin}	−0.589	0.179		**−1.010**	**0.017**		**−1.007**	**0.041**	
D_{com}	**0.498**	**0.016**		**0.641**	**0.001**		0.408	0.076	
	We-mn-peak (8:00 am)			**We-en-peak (19:00 pm)**			**We-en-peak (21:00 pm)**		
	Coefficient	Sig.	R^2	Coefficient	Sig.	R^2	Coefficients	Sig.	R^2
D_{cat}	1.607	0.058	0.425	−1.112	0.124	0.632	−0.281	0.758	0.186
D_{shp}	0.427	0.221		−0.290	0.331		−0.008	0.982	
D_{lif}	**−2.667**	**0.022**		0.886	0.369		−0.019	0.988	
D_{spt}	0.318	0.509		0.480	0.246		−0.105	0.840	
D_{hea}	1.413	0.162		0.221	0.797		−0.219	0.841	
$\mathrm{D_{hop}}$	−0.530	0.210		−0.226	0.532		0.081	0.859	
D_{tou}	0.299	0.231		**0.447**	**0.038**		−0.081	0.764	
D_{res}	**−1.675**	**0.018**		0.871	0.149		0.381	0.617	
D_{gov}	−0.247	0.629		**−1.929**	**0.000**		−0.277	0.617	
D_{edu}	**1.539**	**0.001**		**0.990**	**0.009**		0.309	0.511	
D_{fin}	−0.479	0.391		−0.500	0.297		−0.125	0.836	
D_{com}	0.031	0.906		0.394	0.080		0.312	0.270	

For the days before weekends (i.e., pre-weekends), it is not surprising that education and residential areas still have a positive influence on traffic congestion. However, Table 2 also shows that catering and governmental land uses appear always to exert a negative influence on the morning or evening peak congestion (no matter whether it is a normal weekday or a pre-weekday). Although we fully realize that correlation does not always reflect true causality [60,61], the negative correlation might be explained by few formal catering activities occurring in big restaurants in a rush weekday morning, as adults and kids need to start their work and studies on time. They might have breakfast mostly at home or on the way to their workplaces. Meanwhile, governmental land uses consist of those public institutions that provide services like real estate transactions. It is reasonable that fewer people will go to these officials too early or too late at peak hours when those institutions might not be open or may have closed. Therefore, the interplay between D_{gov}, D_{cat} and traffic conditions does not suggest that the allocation of more land for restaurants could reduce congestion. Additionally, the congestion in the late evening peak at 9 pm on pre-weekends is mostly influenced by healthcare and sports land uses (D_{hea} and D_{spt}). This observation might indicate that most people in Xining are less overworked and have more free time to exercise and take care of their bodies after work compared with urban citizens in big cities.

In terms of weekend evening peaks, traffic congestion is found to be positively related to educational and tourist land uses. The latter implies a preference of people in Xining going to tourist spots as leisure activities on holiday nights. This might be the opposite of most of the situations in big cities, where people tend to go shopping instead of going to tourist attractions on a short holiday night. However, it can be explained by the fact that Xining is a small-scaled city, and therefore most of its artificial tourist spots, like some heritage buildings and temples, are not located remotely but are still within the accessible range of downtown areas.

5. Discussion

Our research sheds light on the critical issue of the interaction between built environments and travel behaviors, offering valuable insights into the spatial–temporal pattern of traffic congestion in smaller urban areas of China. By analyzing the hyperlocal travel data over a duration of 9 days from Xining City, we identified two traffic peaks on a typical weekday: the morning peak at around 8:00, and the evening peak at around 18:00–19:00. The evening peak is generally more congested than the morning peak, which is consistent with previous research in large metropolitan areas [28,31,55]. As compared to a typical weekday, the evening peak on the pre-weekend has significantly more severe traffic jams, according to previous research [30]. The pre-weekend congestion can be attributed to increasing cross-regional traffic demands prior to the holidays.

One of the most important findings of our study is the discovery of a significant positive correlation between educational land use and surging traffic pressure in a small city in China as compared with previous findings of urban business land use in big cities [14,31]. In Xining, roads along schools and after-school tutoring agencies are likely to experience heavier congestion. Even during the weekend evening peak, coefficients of 0.99 still occur. Furthermore, the positive traffic influence of educational land use (D_{edu}) is intertwined with the distribution of residential land use (D_{res}) in urban areas, and these two factors appear together three times: during the weekday evening peak, the pre-weekend morning peak and the evening peak. The congestion pattern is related to the recent school district housing policy. The 2020 enrollment rate of senior high school entrance examinations in Xining has dropped to 54.5%. Compared with 68% in big cities like Shanghai, this poses great pressure to parents in Xining as the upward mobility for their kids in a less-developed small city seems to have never been harder before. Therefore, acquiring houses in good school districts is competitive and they are full of families. The similar commuting routes to schools pose potential congestion to the traffic.

Having said that, the fewer coefficients of urban business land uses (catering, financial and commercial) in Xining suggest a negligible impact of commercial uses on peak hour congestion. Commercial land use (D_{com}) only appears positive during the weekday morning peak at 8 am, while catering (D_{cat}) shows a negative coefficient during the normal weekday morning peak, morning and evening peak of the pre-weekend and the weekend evening peak at 7 pm. This may be a result of the unique urban forms in Xining, where the catering and shops are relatively small scale and dispersed into different Danwei compounds. Due to their close distance to residential buildings, automobile travel does not need to be generated. This kind of less commercially oriented traffic congestion also suggests that, compared with fully developed shopping malls and cultivated consumption culture, the business circle development in small cities like Xining might be lagging behind.

The practical implications of this study are twofold. From the spatial dimension, the significant joint force of educational land use and residential land use on Xining's traffic congestion suggests a direction for transportation optimization via reasonable urban planning and design. The study of Rothman et al. [62] in Toronto has revealed that traffic congestion around schools is associated with double-parking, reversing and crossing between parked cars. Therefore, at the urban planning level, major urban roads can be directed to bypass educational hotspots in the future. From the perspective of urban design, the streets near major educational facilities should be carefully designed with specific mobile-free locations for kids' drop-off and pick-up [63], contributing to congestion relief and enhanced traffic safety. Shenzhen has already started these kinds of micro transportation regeneration around schools in 2020. At a policy level, school district policy has already faced controversies in China. The capitalization of education quality may be adjusted or canceled soon in order to reach the social justice among different income groups and crack down on exorbitant housing prices [64]. From the temporal dimension, the pre-weekend evening peak is significantly more congested than that of an average weekday, indicating that more human resources or smart transportation monitoring technologies should be allocated during such times in order to consolidate traffic management, especially at roadway intersections.

The current study has a few limitations that necessitate further investigation. First, future research could include more built environment factors, such as public transit networks, geographical and climate conditions into traffic congestion analysis. Although not many public transportation approaches have been developed in Xining, it does have several public bus routes and expanding regional highways [65]. Although the influence of weather factors has been minimized as much as possible by averaging the traffic status from different dates, it is widely projected that extreme weather may significantly affect traffic congestion and travel behaviors in the current global climate change environmental conditions. Besides, Xining has a typical narrow valley city morphology, so its transportation networks and capacity might be different from small urban areas in the flat plains of southeast China. Thus, future research can incorporate such factors as controlled variables or collect more traffic data in order to further reduce their impacts by averaging operations. The second limitation is the administrative coverage of the study areas. Due to a lack of data from other remote districts in Xining, this study only focused on four districts in Xining City. As these four districts are the oldest and most densely populated in Xining, it is interesting to see how divergent social–demographic factors in ages and GDP per capita might affect the traffic behaviors in small-scaled cities in the future. The third limitation is that the study period is relatively short, covering only nine days in December due to data constraints. This would limit the ability of our model to capture seasonal effects on traffic congestion. For this reason, future studies are recommended to include a longer study period. Finally, more case studies could be conducted in other small urban or rural areas in order to form a valuable and comparable database for transportation management in China [66–68].

6. Conclusions

Congestion in traffic is a long-standing contemporary issue that has piqued the interest of the global scientific and practical communities. Particularly in light of the world's ongoing urbanization, traffic congestion has become increasingly severe, resulting in significant negative social, economic and environmental consequences. Past literature has indicated the interrelationship between built environments and traffic congestion while mostly investigating the long-term effects of land use strategies with a focus on large metropolises. Little attention has been paid to time-variant impacts on neighborhood-level traffic conditions in smaller urban areas. Considering the rising significance of small-scale cities in the future in terms of population receiving and equal resources' distribution, developing an understanding of the interplay between built environment factors and traffic congestion patterns is urgent. Therefore, this research aims to apply multivariate least-squares regression analysis to understand the spatial–temporal pattern of traffic congestion in Xining, a typical smaller urban area in China, by extracting its hyperlocal travel data.

The results indicate that smaller urban areas follow a similar temporal pattern but with a different spatial pattern of traffic congestion from that in large metropolises. Xining experiences both morning and evening traffic peaks on the weekdays and pre-weekends and only an evening peak during weekends or holidays. The pre-weekend congestion is significantly worse than on a normal weekday, implying that stronger measures to consolidate traffic management should be implemented during this time. Educational land use and residential areas were both found to contribute significantly to traffic congestion in Xining, and their combined effects tend to exacerbate the situation. Thus, during future urban development of Xining, multi-centric urban planning should be considered. If good educational recourses and residential areas can be rationally allocated in other new towns, traffic conditions in the old urban area can be released. Of course, public transit should always be carefully planned and improved with not only short-distance public buses in the city center but also long-distance public buses connecting different residential hubs and companies in other districts at peak hours.

The main contribution of this study is to enrich the empirical literature on the nexus between built environments and traffic congestion in smaller urban areas in the context of northeastern China, which is often understudied. Our results enhance the current understanding of the spatial–temporal variations in traffic congestion patterns associated with various land use features, providing new insights into efficient transportation management and sustainable land-use planning.

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