Spatial Big Data and Analysis Strategies Supporting Geographic Information System for Transportation (GIS-T) in Conceptual Design, Modelling, and Decision-making: A Review

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Abstract

Transportation is a key component in urban design for cities' efficiency and residents' life quality, and GIS has the capability of handling data management, model design, and scientific decision-making for transportation studies. This article reviews how spatial big data and analysis strategies help GIS-T studies from the phases of conceptual design, modelling, and decision-making. In this research, we firstly summarized categorizes of data objects and relevant information for real-world issues from transportation applications in the conceptual design phase. In the modelling phase, optimization strategies for transport planning and accessibility measures through network data were also summarized. Finally, we reviewed spatial analysis methods in supporting transport decision-making, and how spatial methods take advantage of geography features of transport variables in previous studies. Our research primarily focuses on geography research with transportation topics as applications, and this work can help transport experts to have a better understanding of GIS values for transportation modelling and planning.

1. Introduction

Planning, modelling, and analysis in transportation play a vital role in urban design and land use management to improve living quality (Shahumyan and Moeckel, 2017). A smart transportation management strategy can help improve residents' accessibility to facilities (Karou and Hull, 2014), road safety (Kamel and Sayed, 2021), and transportation infrastructure asset management efficiency (White and Stewart, 2015). Spatiotemporal traffic data interpretation and management can support good transportation planning strategies (Basse et al., 2016; Fang et al., 2017). Geographic information system (GIS), as an integrated computer system for geographical data storage, manipulation, analysis and visualization (DeMers, 2011), coordinates with the technical requirements of transport planners well (Lopes et al., 2014). Dating back to the 1990s, the pilot practice of geographic information systems for transportation (GIS-T) started with transportation decision-making with the support of computation on topology relationships from different mapping layers (Niemeier and Beard, 1993). Through decades of development in GIS-T, the capability of GIS in assisting transportation studies has been proven with various practical applications and advanced extensions in functionality, including but not limited to digital transport network management (Djurhuus et al., 2016), route planning with visual navigations (Fang et al, 2012), transport development plan assessment (López and Monzón, 2010), and emergency evacuation plans (Fahad et al., 2019).

Despite new functionalities and case study applications varying from case to case, summarizing how GIS is supporting current transportation innovation in general at the phases of conceptual design, modelling, and decision-making can be a help to future professionals. How spatial databases for objects, optimization models, and spatial analysis are assisting GIS-T is illustrated in Figure 1. At the preparation stage, spatial databases help in setting up data management schemes for research problem understanding and real-world simulation. Tomasiello et al. (2019) summarized four key categories of components for a transport network database model, including the transport infrastructure component, temporal component, land use or geography component, and individual component. These four types of elements are commonly present in databases for transportation and can be specifically represented by objects showing information on 'How', 'When', 'Where', and 'Who' in transportation applications as databases proposed by Koncz and Adams (2002) and Huang (2019).

At the modelling stage, optimization strategies, by abstracting complicated real-world problems into network models using GIS, are commonly utilized to formularize the transportation problem into research targets, decision variables, and constraints (Delmelle et al., 2012). Typical optimizing targets in transportation include minimizing relevant costs (Pamučar et al., 2016), guaranteeing reasonable network flow (Lim and Lee, 2013), and maximizing transport accessibility (Tahmasbi and Haghshenas, 2019). Correspondingly, several common constraints cover transport infrastructure physical capacity, general road network properties (Brachman and Dragicevic, 2014), and features of detailed transport planning activities (Saeheaw and Charoenchai, 2017). Computer science algorithms for network analysis, such as Dijkstra's algorithm (Etherington, 2012) and K-shortest path algorithm (Chen et al., 2021), can be solutions for these formularized models.

At the decision-making stage, spatial analysis methods from GIS, with the consideration of spatial autocorrelation of transport-related factors locally or spatial disparity of variables' relationship in a distance, provide scientific supportive advice for smart urban planning and transport system performance assessment (Álvarez et al., 2016; Brown and Affum, 2002). Considering the spatially clustering feature of traffic variables on the roads, the spatial analysis method can be used to interpolate traffic data and improve data quality for similar tasks in the next lifecycle (Zou et al., 2012).

Given the importance of transport management to urban planning, the capability of GIS in supporting smart transportation innovation, and various advanced functionalities extended by GIS-T over years of development, a review article summarizing data models and spatial analysis methods supporting GIS-T at the stages of conceptual design, modelling, and decision-making can help transport planners, GIS analysts, and researchers working in transport geography fields understand the competence of geospatial tools and theories in improving transport models and future development of GIS-T (Shaw, 2010). The purpose of this review article is to provide a summary of technical milestones of the GIS-T brief development history by reviewing and concluding data models and spatial analysis methods from research cases.

The rest of the article is organized as the follows, section 2 reviews spatial databases’ support in GIS-T at the conceptual design phase by summarizing key transport objects and their relationships in different research cases; section 3 shows optimization models for public transport planning, accessibility measurement, and transport vulnerability formularization; section 4 concludes spatial autocorrelation and spatial heterogeneity methods in supporting transport decision-making, followed by discussion and conclusion.

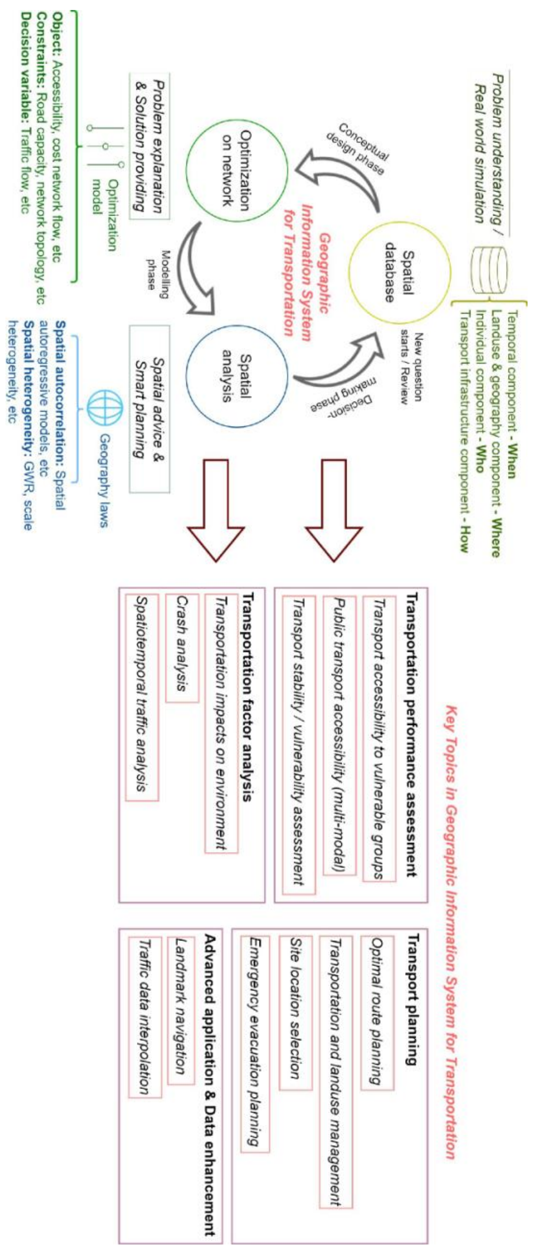

Figure 1. Spatial database, optimization model, and spatial analysis supporting key topics in GIS-T at the phases of conceptual design, modelling, and decision-making

2. Spatial data management at the conceptual design phase

2.1 Key objects in transportation conceptual design

The geospatial features of real traffic conditions on roads and relevant infrastructure information are usually digitalized and abstracted as points, lines, or polygons with key attribute variables in spatial databases for further modelling and analysis (Dong et al., 2019; Peng, 2005). Apart from topology relationships and mapping layers, there are other statistical and temporal data demonstrating users’ information or other traffic-related information shown in featured objects within data models to achieve advanced functionalities (Andris, 2016; Jin et al., 2018; Ding et al., 2021). In general, data objects in conceptual design models would have multiple features, which can be summarized into the following categories:

Where – Information telling geographical locations of transport-related objects, including but not limited to points of interests (POIs), land uses, household locations, road intersections, and building locations.

When – Temporal information of objects. These are common in preparing transit plans or multi-temporal traffic studies, and these temporal data are usually associated with spatial information of objects.

Who – Personal information on individuals, users, or person-related objects in data models. Detailed information can be age, sex, working industry, working status, car ownership, and household information.

What – Information on an individual’s event or activity, which is transport-related. Examples of activities can be residents’ travelling to work or users’ visiting places listed as POIs.

How – Information showing transport modal of activities. It shows how people travel from the origin to the destination. Typical types of transport modal include private cars, biking, walking, buses, trams, or other kinds of public transport.

In this literature review, we selected key objects in GIS-T practical applications and summarized their properties and key information telling ‘Where’, ‘When’, ‘Who’, ‘What’, or ‘How’ in Table 1. In Table 1, objects are categorized by their corresponding entity type, together with possible representations of their spatial information, and the compatibility with temporal information.

Common infrastructure objects include public traffic routes and stops, road segments, walking paths, and POIs (Frihida et al., 2002; Tomasiello et al., 2019). Transport routes and road segments can be stored with an additional Z-value field, indicating the height of infrastructures, supporting 3D modelling and accurate transport planning (Koncz and Adams, 2002). Furthermore, public transport routes and roads can also be linearly referenced in the database systems of some organizations. A practical example of linear referencing systems (LRS) for roads is ‘ArcGIS Roads and Highways’ designed for transportation industry companies and government agencies. In the LRS, rather than using coordinate systems for recording geographic information, relative positions along a polyline are utilized (ESRI, 2004).

Individual information showing details of a person or household can be concluded from government census data or organizationcollected data (Johnston and De La Barra, 2000; Huang, 2019; Price et al., 2021). These data objects are especially useful in simulating traffic flows and other transport indicators. In terms of temporal information in transportation, transit and activity plans made by users, real-time traffic flow, and hourly-based traffic attributes require temporal data analysis and management for advanced functionalities (Tomasiello et al., 2019).

Key objects	Entity type	Spatial	Temporal
Public transport route	Infrastructure	Linear; 2D; 3D	-
Public transport node	Infrastructure	2D; 3D	-
Road segment	Infrastructure	Linear; 2D; 3D	-
Walking path	Infrastructure	2D; 3D	-
Point of interests (POIs)	Infrastructure	2D	-
User / Person	Individual	-	-
Household	Individual	2D	-
Census information	Individual	2D	-
Transit plan / Trip	Event	2D	√
Activity	Event	2D	√
Traffic value	Transport	2D; 3D	√

Table 1. Features of key objects in transportation conceptual design.

2.2 Object relations shown in featured practical applications

This section aims to demonstrate and summarize transportation object relationships in practical applications, including route planning and navigation, multi-temporal transport network management, and agent-based individual transport activity simulation. It is no doubt that road segments and public transport features play fundamental roles in every GIS-T application as shown in Figure 2, while different functionality extensions need changes in entities and data relations to set up.

Real-time visual landmark navigation is one of the most state-of-the-art transport applications. The goal of real-time visual navigation is to design an application for analyzing and showing a visual route towards a landmark destination after receiving a request from the user. The key outputs are visual route instructions towards landmarks with supportive information from road segments and walking paths showing possible routes; and visual, semantic, and geometric features of landmarks. POIs data also play a role in providing ancillary information for target destinations. Route instructions objects are solutions to users' requirements, and this type of spatial object is associated with transport routes, the image library, and landmark objects (Fang et al., 2012).

Multi-temporal transport network management is also an important topic in transport planning. Tomasiello et al. (2019) proposed a conceptual design based on an object-oriented data model for geographic applications (OMT-G) (Borges et al., 2001). This transport network management strategy managed to combine data from heterogeneous sources showing different temporal granularity of traffic information and laid the foundations for accessibility analysis with temporal dynamics. With spatial features of road networks and transport infrastructures included, temporal information on traffic can also be managed through database relations. In spatiotemporal transport data model studies, temporal traffic data and relevant validity on roads are linked to the road network object with RoadID as the key. Similarly, spatial point-based traffic records over a period can also be linked to the corresponding node objects for integration.

The other critical application in assisting smart transport planning is agent-based traffic simulation. The agent-based model for transport aims at simulating or predicting traffic-related conditions in cities considering individual activity and preference. The estimated results would provide insights for public policymaking. Considering the sensitivity of personal data and the difficulty in private data collection in a wide spatial range, census data released by the government are good sources providing raw materials. To establish the agent-based model, private information on individual residents and households can be roughly extracted from the census. With transit activity specified and road spatial data provided, a transit plan covering details of the itinerary for users can be generated. Given a pilot data model study summarized in Figure 2, the transit plan object is linked to the user object and the activity object for managing simulated personal details of each transition. The transit plan object is also associated with the itinerary object, which summarizes spatial information representing the user's transportation plan (Motieyan and Mesgari, 2018).

3. Optimizations for transport performance assessment and planning at the modelling phase

An optimization model, consisting of a research target, constraints, and decision variables, is a method to describe a real-world problem in a quantity measure (Martins and Ning, 2021). By setting up an optimization model by abstracting and simulating real-world conditions, researchers are able to understand the nature of the issue, the required materials to solve the issue, and practical solutions to conquer the problem (Boyd and Vandenberghe, 2004; Antoniou et al., 2008). Optimization is a commonly used strategy in transport planning, helping engineers and researchers to simulate traffic demands, assess traffic conditions, and predict future trends (Herty and Klar, 2003). Optimization models for transportation are mainly based on nodes and arcs with traffic attributes representing the road network (Lei, 2021). In this section, we summarized featured research targets and constraints in describing research problems in public transport planning, accessibility measures, and traffic vulnerability.

3.1 Optimizations in public transport planning

Traffic flow control, prediction, and management are some of the most important tasks in transport planning. Regardless of daily traffic control or the maximum efficiency of an emergency evacuation, transport planners wish to guarantee passable roads throughout the network as shown in Equation (1).

$$Minimize\ Z = sum(C_{ij} * x_{ij}) , \qquad (1)$$

where C_{ij} is the travelling cost from node '*i*' to node '*j*' (*i* and *j* are directly connected nodes in the network), and x_{ij} is the traffic flow. For any kind of road network, Equation (1) is subjected to fundamental constraints from the nature of traffic flow and road design, and maximum road capacity from Equations (2) to (4).

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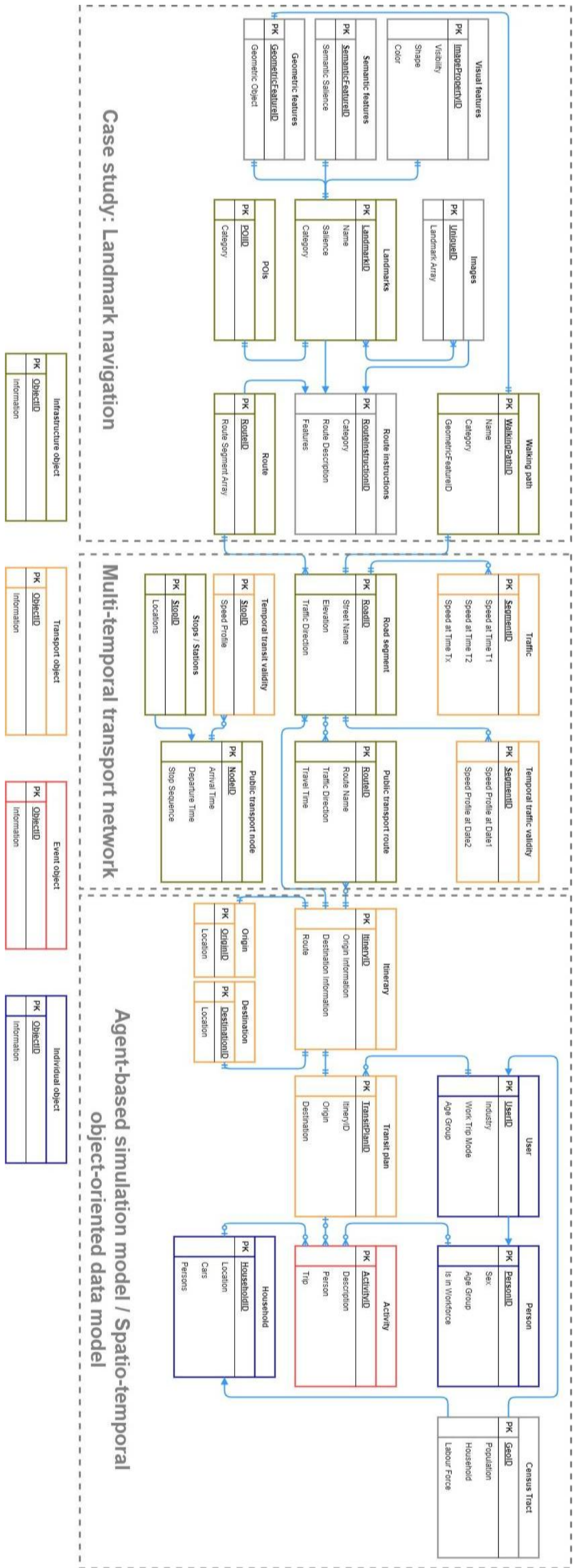

Figure 2. An illustration of data conceptual designs transport planning practical applications: real-time visual landmark navigation, multi-temporal transport network, and agent-based simulation model.

$$sum(x_{ij}) - sum(x_{ji}) = b_i \,, \qquad (2)$$

where b_i is the net traffic flow at node i.

$$0 \leqslant x_{ij} \leqslant u_{ij} \,, \qquad (3)$$

where u_{ij} is the maximum road capacity from node ‘i’ to node ‘j’. The traffic volume in each arc should not exceed the road capacity.

$$sum_k(x_{ki}) = sum_j(x_{ij}) \,, \qquad (4)$$

where node ‘k’ and node ‘j’ are directly connected to node ‘i’. If the road intersection does not allow car parking, for this node, the total traffic flow incoming is equivalent to the total traffic flow outgoing.

Equations (1) to (4) are based on the traffic flow x_{ij} as the decision variable. This optimization model is a foundation form in transport planning, and variations in the research target or constraints can be applied to fit different cases. Take emergency evacuation planning as an example, Equations (1) to (4) are common physical variables working as the basis of a network optimization model (Yamada, 1996). Biological response variables and social variables simulating the real-world scenario can be further introduced to fit cases. For instance, adjustments to the travelling cost C_{ij}, by simulating biological responses of self-preservation from the danger, can be made by adding more travel costs on arcs close to the hazard. Furthermore, the road capacity value can be changed correspondingly to reflect emergency response actions as social variables, including firefighters and police actions, which make changes on roads (Brachman and Dragicevic, 2014).

3.2 Measures of transport accessibility

Travelling accessibility through the transportation system is another primary concern from the view of transport experts. In supporting a wider team of sustainability and humanity, transport accessibility can be an indicator telling the urban performance and infrastructure effectiveness (Saghapour et al., 2016; Cheng et al., 2019; Zannat et al., 2020). Furthermore, spatially visualizing transport accessibility and land uses of interests can help policymakers have a better understanding of the vulnerable population of a region (Wang and Chen, 2015). A formula for multi-modal transport accessibility is shown in Equation (5) (Hansen, 1959). In general, planners tend to increase transportation utilization by maximizing Equation (5).

$$A_{ijm} = sum_j(a_j * f(C_{ijm})), \qquad (5)$$

where A_{ijm} is the accessibility from location ‘i’ to ‘j’ using a mean of transport ‘m’ (bus, tram, bike, underway, and others); a_j is the attractiveness factor for the location ‘j’; $f(C_{ijm})$ is the cost function of travelling from ‘i’ to ‘j’ using ‘m’ transport. The cost functions are usually the impedance function of the generalized cost between two locations.

4. Spatial analysis methodologies at the decision-making phase

Spatial analysis methods, capturing geographical features of traffic variables, have the capability to provide informative results in supporting transportation decision-making (Hackl et al., 2019; Liu et al., 2017). Spatial analysis methods usually consider spatial features of variables or spatial variation of the relationship across the space by introducing specific terms or computing strategies into a statistical model (Özbil Torun et al., 2020). It has been widely acknowledged that transport-related features follow the laws of geography through decades of research development in GIS-T (Lopes et al., 2014). In this literature review, we categorized spatial analysis models into the ‘spatial autocorrelation’ and the ‘spatial heterogeneity’ as shown in Table 2. Methods on spatial autocorrelation consider the existing clustering effects of traffic variables, especially observations that are geographically close enough, and these methods can be used to predict transportation demands or interpolate missing data (Zou et al., 2012). Furthermore, transport-related variables’ relationships can be different from place to place when objects or relationships are summarized in regional statistics or measured at a distance (Kamel and Sayed, 2021). Thus, methods of spatial heterogeneity can help in capturing the spatial variation and provide insights into transport decision-making (Brown and Affum, 2002).

Analysis models	Geospatial phenomenon	Featured transport study
Kriging method	Transport features (e.g. traffic volume) on the roads are similar in closer areas.	Interpolation of missing transport data (Zou et al., 2012).
Spatial autoregressive model	Spatial autocorrelation pattern of transport-related features by regional statistics.	Transportation demand forecast (Lopes et al., 2014).
Spatial expansion model	The average travel distance or mobility of residents may vary spatially.	Transport accessibility by measuring average travel distance (Cheng et al., 2019).
Gravity model	The decrease in residents’ tendency to travel outside with the increase in distance.	Transportation accessibility assessment and analysis (Celik, 2010; Geurs and Van Wee, 2004; Meyer and Miller, 2001).
Spatial error analysis for linear regression	Minor variance of variables’ relationship supporting transport planning can be shown by linear residuals.	Decision-making for active mobility planning (Hackl et al., 2019).
Geographically weighted regression	Spatial variation on transport-related variables’ relationship in a distance.	Recreational walking relationship with land use and social factors (Özbil Torun et al., 2020).
Poisson lognormal model with regional statistics	The statistical distributions of some transport variables follow the Poisson distribution.	The relationship between bike-vehicle crash and network indicators (Kamel and Sayed, 2021).

Table 2. Spatial analysis models in supporting transport planning

Transport variables may follow the geography law of autocorrelation (spatial dependence) in general cases, which means observation of transport variables at a place is highly likely at the same level as observations nearby. Some of the spatially correlated transport variables can be average annual daily traffic (AADT) and average vehicle speed on roads. Kriging, is a spatial interpolation method utilizing the feature of the variable’s autocorrelation over the space and also presenting spatial variance. Kriging and its variant methods have been practised in traffic data prediction with acceptable accuracy (Zou et al., 2012).

Furthermore, there are also indicators quantifying spatial autocorrelation levels, which can be applied to linear regressions to improve model performance. Moran’s I and LISA are two important indicators showing spatial dependence globally and locally, by measuring how the target area is different from its surroundings (Fischer and Wang, 2011). Spatial autoregressive models are series of regressions by adding spatial terms once the strength of spatial dependence on variables is verified (Venkadavarahan et al., 2023). A more complicated spatial regressive model can be shown with the combination of two or three spatially-lagged terms of dependent variable, selected independent variables, and residual. In transport-related studies, relevant socio-economic variables demonstrate a comparatively strong spatial dependence when statistically summarized by traffic analysis zones (TAZs) or administrative boundaries. Thus, multiple regression models in transport-related research could perform better by introducing spatial dependence terms on variables or residuals (Lopes et al., 2014).

The spatial heterogeneity feature in variables’ relationships over the study area can be represented by the discrepancy in weighting coefficients at different regions (Fotheringham et al., 2003). The GWR model has been applied to transportation research in investigating the transport-related relationship between urban form and residents’ walking behaviour with indicated spatial variance over the space (Özbil Torun et al., 2020). Poisson lognormal model in road safety planning is applied with regional statistics, and thus variables’ relationships are different from region to region (Kamel and Sayed, 2021). Furthermore, regional statistics on the Poisson lognormal model also have spatial scale heterogeneity, and modelling based on different spatial units would have different regression results (Abdel-Aty et al., 2013).

5. Discussion

In this article, we reviewed spatial models and analysis methods in supporting conceptual design, modelling, and decision-making phases under the scope of GIS-T. In the conceptual design, spatial databases have the capability to manage and manipulate spatial, temporal, or statistical data showing information regarding ‘Where’, ‘When’, ‘Who’, ‘What’, and ‘How’ for relevant objects and relations in transport planning. We then summarized typical optimization models on the network data with general targets and constraints in the transport modelling phase. Finally, we discussed on spatial models, following two laws of geography and capturing geospatial features of variables and relations in transport planning. These spatial analysis methods can provide insights into decision-making by showing spatial autocorrelation and spatial variation patterns.

Despite decades of development, GIS-T remains a promising field regarding the rigid demand of transport modelling as a key part of smart urban design, and its potential to be compatible with cutting-edge techniques from a broader field. Current GIS-T can get further enhancement from two aspects: smart decision-making with the assistance of advanced exploratory spatial data analysis (ESDA), and extended functionalities in transportation with the integration of explainable Geo-AI.

From the view of ESDA in supporting smart transport decision-making, there are innovative geospatial models showing spatial stratified heterogeneity and indicating new geographic patterns, which have a high potential to be applied to transportation studies. Currently, geographical detector based methods have the capability to show variance of spatial association and interaction of transport-related factors (Liu et al., 2020). These methods can also inform policymakers of the difference in spatial relations by geographical strata (Song et al., 2020; Wang et al., 2016; Zhang et al., 2022). Furthermore, geocomplexity, a new spatial indicator derived from spatial dependence, also has the potential to be applied to transportation fields for spatial pattern identification and model improvement (Zhang et al., 2023).

From the view of explainable Geo-AI integration, statistical machine learning models (SML), such as random forest, have been applied to simulate users’ choices in transport cases. The improved SML method, in supporting decision-making for policymakers, can provide interpretable results along with spatiotemporal features extracted from raw datasets (Kim et al., 2021). Regarding the utilization of similar models in future work, explainable Geo-AI models have advantages in explaining the phenomenon and predicting trends with higher accuracy and clear patterns (Xu et al., 2023).

We acknowledge that there are limitations in this review work. Considering the difficulties in searching satisfied research articles within the scope of tremendous volumes, we primarily focused on innovative geospatial data models and relevant strategies with applications in transportation research during the article selection process. Thus, this research mainly concerns geography research with traffic applications and other transport modelling studies with a minor focus on geospatial values are not the primary focus of this work. Thus, a future review study reviewing how transport modellers understand the geospatial value and improve their models and decision-making by introducing various geospatial features could be a supplement.

6. Conclusion

Transportation management is a key component in urban design for cities’ efficiency and residents’ life quality. GIS has proven its capability in providing solutions for data management, model establishment, and scientific decision-making through decades of development in GIS-T. This article reviews how spatial data and analysis strategies can help GIS-T from the aspects of conceptual design, modelling, and decision-making. Throughout the research, we summarized categorizes of data objects and relevant information reflecting ‘Where’, ‘When’, ‘Who’, ‘How’, and ‘What’ for real-world problem simulation for transportation applications in the conceptual design phase. Furthermore, optimization strategies for transport planning and accessibility measures based on properties of arcs, nodes, and connectivity through network analysis in the modelling phase were also summarized. Finally, we reviewed spatial analysis methods in supporting transport decision-making, and how ‘spatial autocorrelation’ and ‘spatial heterogeneity’ methods take advantage of geography features of transport variables in previous studies. Our research primarily focuses on geography research with transportation topics as applications, and future studies reviewing how transport modellers improve their models and decision-making by introducing geospatial features can be a supplement.

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