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A Comprehensive Review of GIS-Based Spatial and Spatiotemporal Approaches in Road Traffic Accident Analysis

Muqdad Al Hamami[1], Salam Ridha Aletba[1], Norhidayah Abdul Hassan[2], Hashim Al-Sumaiday[3]

[1]Civil Engineering Department, Wasit University, Kut 52001, Iraq
[2]School of Civil Engineering, Universiti Teknologi Malaysia, 81300, Skudai, Johor, Malaysia
[3]College of Civil Engineering, Tikrit University, Tikrit 34001, Iraq

Corresponding Author Email: mmunthir@uowasit.edu.iq

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ABSTRACT

Different factors may cause Road Traffic Accidents (RTAs), which adversely impact daily lives of people and cause significant economic, human, and social losses worldwide. These factors can be related to the roadway characteristics, driver behavior, and traffic demand. It is crucial to comprehend the spatial and temporal patterns of RTAs for an effective road safety planning and policy formulation. Geographic Information Systems (GIS) is a powerful tool to investigate RTA datasets throughout participating spatiotemporal and attribute information within a combined analytical framework. Thus, this study presents an inclusive review of GIS-based spatiotemporal approaches applied for RTA dataset. Some of frequently GIS approaches that have been utilized by literature such as Kernel Density Estimation (KDE), spatial autocorrelation measures, hotspot detection metrics, and network-based studies are reviewed in this study. By highlighting their limitations and assets, this study examines the resources of dataset that are utilized in RTA studies, such as datasets of hospital, police, and emerging GPS-and sensor-based. The review of this study highlights the main analytical challenges, like inadequate data quality, sensitivity to geographical scale, adjustable issues of area unit, temporal resolution limitations, and adaptability of limited model over domains. Besides, the scarcity of dataset in developing nations, artificial intelligence and machine learning integration, spatiotemporal modeling, and gaps in research, all of which are discussed in this research. The review of this study is an excellent tool for transportation planners, researchers, lawmakers for safety improvement by GIS-driven accident analysis for more predictive with combining prior research.

Keywords: Hotspot detection, Spatiotemporal analysis, Spatial autocorrelation, Network analysis, Machine learning integration

1. Introduction

The Impact of RTAs occurrence is regarded as one of the major global public health issues when it results severity, high economical cost, and bad social impact. World Health Organization (WHO) reported that accidents of road are now the leading resource of people fatality aged between 5 and 29 years [1]. Besides, millions of people have suffered from severe injuries that lead to disability, worse life quality, and more cost of healthcare. Thus, to identify optimal safety measures and policy decisions, assessment is vital due to the intricate consequences [2, 3]. The analysis of RTAs plays a crucial role in comprehending of spatial and temporal dynamics of severity hot spots. Thus, patterns identification of RTA severity and occurrence allows authorities and planners to assign hot spot zones and develop strategic countermeasures. Moreover, thorough evaluation allows decision makers reducing future cost and enhancing overall safety [4].

In order to visualize, analyze, and model spatial data, utilizing GIS offers robust capabilities in RTAs analysis. Within a unified geospatial framework, GIS combines and integrates multiple data sources such as RTA points, road networks attributes, traffic volumes, and environmental factors [5, 6]. Also, the techniques of GIS aid revealing patterns and trends that cannot be detected by traditional statistical approaches of analysis. These techniques such as hot spot mapping, spatial autocorrelation, clustering, and other spatial analysis strategies. Besides, GIS analyses can be utilized for safety planning by inspecting the high concentrated spots of RTAs (hot spots), evaluating of spatial risk factors, and simulating of potential impacts of upcoming infrastructure improvements. By using spatiotemporal GIS techniques, the evolve of accident patterns over time enabling engineers, decision-makers, and planners to remedy performance and inspect emerging hot spot trends [7, 8]. Thus, related agencies worldwide have adopted GIS as an integral advanced systems for road safety management. GIS entails sophisticated spatial analytical tools. These techniques go beyond fundamental visualization [9-11]. For instance, Kernel Density Estimation (KDE) is one of these tools for spatial autocorrelation and clustering analysis [12, 13]. It identifies areas of high and low hot spots without underlying the distribution of dataset [14]. Integration of GIS with different tools is another technique of geospatial analysis of RTAs. For example, by integrating both GIS and algorithm of machine learning, identifying of hot spot areas can be predicted from utilizing historical data and dynamic road conditions [15-18].

Though the growing bunch of researches in this area, RTAs modelling utilizing GIS has a diverse methodological indication, such as uneven standards of reporting and multiple contexts of application [19-21]. Different sorts of data sources have been used with different spatial techniques, different temporal scales, and multiple ways of results interpretation [14, 22, 23]. Some challenges have been faced by researchers and decision-makers when seeking to comprehend the current state of practice, replicate techniques, or assess study findings [24, 25]. Though several researches have reviewed aspects of RTA analyses, still there is a need for more thorough analysis that focuses on spatiotemporal techniques based on GIS. Due to the rapid rise of GIS analytical techniques, such as machine Learning (ML) utilization, real-time data applications, and spatial analysis network-based, there is a crucial need for an organized review to guide future efforts. It is worth mentioning that this study illustrates different methods of GIS-based techniques in analysis of accidents widely rather than introducing some methods and neglecting others.

2. Background

While the collected RTA datasets are very dependent on the related spatial autocorrelation (i.e., their road segments and intersections), there is some complexity of analyzing. For instance, research in Jordan revealed around 75 hot spots of accidents due to significance of alignments and intersections as attributes for accidents frequency analysis [26]. Also, over various geometric road categories, the analysis of RTAs reveals that the rate of RTAs fluctuates significantly among road categories, with high correlation between the lower design standards and high severity [27, 28]. Wada et al., [29] concluded that factors like angle of intersections and junction spacing majorly impact RTAs severity. Other researches approached RTAs assessment by GIS from different aspects. For instance, construction has spatially influenced by RTAs frequencies [30]. Besides, the type of structure is significantly impact on hot spot clusters of RTAs over different temporal periods [31]. Literature revealed that the age of drivers is also triggers the severity of RTAs, when the teenage group emphasizes behavioral and socioeconomic risk factors [32]. In addition, Multimodal sensors allocation throughout road networks demonstrates the importance of both GIS and real-time sensing integration in prediction and detection of RTA hot spots [33].

2.1. Overview of Accident Data

The spatial, quality, and accuracy resolution of RTA dataset are essential in assessing the efficiency of GIS-based modeling analysis [34-37]. Different researchers from various areas have utilized different GIS techniques for RTAs analysis as in Table 1. These models consist inspecting patterns, examining spatial distribution, and identifying high-risk spots of RTAs.

Table 1. GIS-based spatial analysis techniques comparison for RTA evaluation

Technique	Typical Use	Strengths	Limitations	Sources	Methodological Synergy
Planar Kernel Density Estimation (KDE)	City-scale or regional assessment of crash concentrations	Straightforward implementation; produces smooth density	Does not incorporate road geometry; may exaggerate	[38]	Often applied as an exploratory step before local spatial statistics

	using point-based accident data	surfaces that clearly highlight accident concentration zones	densities due to spatial smoothing		such as Local Moran's I
Network-Based Kernel Density Estimation (NKDE)	Accident intensity analysis constrained to road centerlines and transport corridors	Accurately reflects linear road structure; improves spatial realism for roadway-related events	Higher computational demand; results depend strongly on bandwidth selection	[39]	Commonly used prior to Getis-Ord Gi* to define statistically robust linear hotspots
Getis-Ord Gi*	Identification of statistically significant clusters of high- and low-frequency crashes	Provides confidence-based hotspot detection using z-scores and p-values	Performance declines with sparse datasets; sensitive to spatial scale	[35, 40]	Frequently combined with KDE or NKDE to validate visually detected hotspots
Moran's I (Global & Local)	Measurement of spatial autocorrelation in crash frequency or severity	Quantifies clustering tendencies and reveals local spatial anomalies	Global index may obscure localized effects; Local Moran's I sensitive to spatial weight matrices	[41]	Integrating Moran's I with KDE enhances hotspot reliability and interpretability

In order to identify the main factors that contribute the occurrence of RTAs, the utilized dataset should be reliable, accurate, and high quality. Multiple studies gathered their set of RTAs from different size of areas. Table 2 illustrates different studies with different spots. For instance, four researches collected dataset from suburban areas, motorway, metropolitan, rural, and highway. However, six studies collected their dataset from only metropolitan areas. The utilized set of RTAs varied in spatial coverage, volume of data, and quality of reporting. Four of the ten evaluated studies had diverse dataset encompassing rural corridors, highways, and urban towns. The dataset of macroscopic areas consists 15,000 to 45,000 RTA records and is generally obtained from local transportation authorities or police departments with a collected resolution of equal to or less than10 meters. However, highway and rural dataset is considerably smaller and ranged between 2000 and 8000 records. This sort of dataset is lacked some attributes such as socioeconomic contexts, classification of vehicles, or data of speeds. For GIS-based detection of hot spot, techniques like KDE, Getis-Ord Gi*, Moran's I were utilized for hot spot zones identifications. However, over macroscopic areas, techniques like KDE frequently reveal exceptionally dense clusters of RTAs

Table 2. GIS-based spatial analysis techniques comparison for RTA evaluation

Study Scope	Contributions and Limitations	Methodological Approach and Key Findings	References
Metropolitan	Integration both GIS and statistical techniques empowered accurate identification of RTA hotspots. Yet, the approach may not sufficiently capture long-term	In order to depict spatial locations and examine spatial trends of RTA, GIS was utilized by employing Getis–Ord Gi* and Global Moran's I for clusters detection. Also, KDE was used	[42]

	changes in dynamics of traffic or accident patterns emerging.	also for RTA density illustration and detect the hot spot areas.	
Metropolitan	This study addressed factors of social equity in safety evaluation by ensuring the incorporation of people with disadvantages. Yet, the outcomes may be influenced by accuracy level and the extent of accident dataset.	In order to examine correlations between RTA occurrences and vulnerable communities, spatial analysis with GIS mapping were conducted followed regression modeling. The main objective of the study was to reveal the crucial need for safety strategies that consist aims of traffic safety and equal opportunity	[43]
Mixed	The study examined both spatial and temporal characteristics to improve the identification accuracy of hot spots. Also, the lack of real-time set of data diminished the predictive and preventive of the study usefulness.	The GIS spatiotemporal analysis, was combined with detection of hot spot and clustering techniques to identify hazardous hot spot areas. Also, Statistical analysis was utilized for RTA trends and associated risks examining. It is concluded that the behavior of drivers is the main cause of RTAs in Qatar.	[44]
Metropolitan	The circumstances of traffic and road geometry were examined to determine the frequency of RTA, revealing significant insights for evaluation of safety.	In order to determine the relevant variables impacting frequency of accidents, Poisson regression analysis was utilized. The outcomes offered reliable recommendations for urban safety measures enhancement.	[45]
Metropolitan	By combining both GIS and HDBSCAN clustering, this study enhanced the detection of hot spots. However, this approach requires considerable computer resources at the case of using vast databases.	In order to arrange and enhance RTA dataset, GIS-based was performed before identifying hot spot areas. Later, HDBSCAN clustering was utilized, which is more accurate and flexible.	[46]
Mixed	In order to assist the targeted safety measures implementation, electronic screening framework was utilized to pinpoint potential spots of RTA. One of the limitations that using of third-party records, which consists some missing of segment-level characteristics.	The rate of RTAs was performed by utilizing negative binomial regression. The study used R programming language for NB model parameters measurements. Also, the study employed models of Empirical Bayes to identify hot spot areas.	[47]
Metropolitan	The study examined two analytical approaches and presented an extensive GIS spatiotemporal analysis. It can be noticed some lacks of prediction and correlation of real-time	In order to determine the RTA frequency, the study combined both density-based approaches and spatial clustering for detecting hot spot areas and temporal analysis to explore the RTA trends.	[48]

	accident beyond geographical patterns.		
Metropolitan	In terms of reliability and accuracy, different identification methods of hot spots have been examined. to enhance with road safety planning. The complexity of methodology, variance of performance, and limitations of dataset, all of which are challenges.	The identification techniques of hot spots including Getis–Ord Gi*, Global Moran's I, mean center, KDE, and average nearest neighbor were evaluated utilizing hit rate, index of predictive accuracy, and index of capture rate. The findings supported the selected effective techniques for high-risk spots detection.	[49]
Mixed	The research strengthened reliability in the association rule mining by maximizing the effectiveness of parameter threshold and the integrating the spatial analysis of GIS-based to provide the practical information for decision-makers. The study approached the occurrence of RTAs in Australia.	The mining of the association rule was developed by optimizing the elements of context. Spatial analysis of GIS-based enhanced the assessment of RTA severity. The combined method enhanced the analysis of severity and revealed the benefits for traffic safety choices.	[50]

In general, RTA studies depend frequently on different sources of data, such as police reports, emergency services and hospitals, and GPS or sensor based. Though each data source presents unique insights, but still has limitations that would impact spatiotemporal analysis. The accident reports of police represent the most primary source of GIS-based dataset for accident RTA analysis [7, 41, 51-53]. These records frequently incorporate vital attributes such as spatial location, date, time, severity of accidents besides other contributed factors [54, 55]. Due to their reporting format consistency and the scope of their regional coverage, multiple researchers have utilized from police records for hot spot spatial clustering recognition. However, police datasets have some limitations. For instance, neglecting to report minor accidents is commonly occurred due to the lack of law enforcement over some regions. Besides, the accuracy of spatial locations of RTAs may differ due to using approximate coordinates or informative descriptions of recording instead of precise GPS measurements. These shortcomings can impact hot spot detection and the results of spatial autocorrelation, especially when the assessments are performed over limited geographical scales.

Both hospital and emergency service records can offer an additional information that may not be provided by police reports [56]. For instance, injuries further details that may not entirely incorporated into the initial investigations. This detailed medical information consists severity of injuries, outcome of treatments, and characteristic of victims. Hence, integrating both GIS-based models and hospital dataset enables recognition of RTA severity hot spot trends across various geographical regions [57, 58]. Though the valuably statistics of hospitals, there is a lack in the precise RTA spatial locations, when the records are typically linked to the residential addresses or the medical facility location rather than the coordination of accident occurrence. Besides, limitations with accessibility, regulations of privacy, and variance of formats make explicit geographical incorporation challenging. Therefore, combining both hospital and police records are much valuable as a spatial dataset, rather than using hospital records alone.

An additional newest source of RTA datasets analysis has been introduced by progressions in sensing technologies [59, 60]. These techniques like phone data, traffic sensors, GPS records, and car tracking. Due to their high-temporal resolution as well as ability to record conditions of traffic in real-time or near-real-time traffic conditions, these techniques enable dynamic spatiotemporal investigations [8, 61, 62]. As advanced simulation methodologies, both predicted risk assessment and real-time hotspot detection can be implemented by GIS using such data [63, 64]. However, some issues are derived from GPS and sensors, such as accessibility of dataset, complexity of processing, and volume of data. Their limited use is a consequence of concerns like privacy of dataset and geographical variations. In addition, such database may significantly depict certain road users, like passenger car drivers, whilst ignoring bicycles or pedestrians.

Though the diverse availability sources of RTAs, there are multiple challenges that impact GIS-based RTA analysis. For instance, inadequate reporting tends to be a significant concern, specifically at the case of non-fatal RTAs and hazardous road users. Moreover, the bias of analytical results may be occurred due to spatial inaccuracies. This is because of geographical coding mistakes, incompatible coordinate systems, and inconsistent levels of resolution. Aggregated reporting intervals and missing dates, both of which are regarded as further limitations for spatiotemporal assessment. In addition, the integration of multiple datasets from different sources poses some challenges related to uniformity of data, variation of scales, and dispersion of ambiguity. In order to mitigate these limitations, there is a crucial need for systematic data collection, verification, and methodological transparency. Thus, in order to enhance both reliability and applicability of GIS-based RTA analyses, there is a crucial need to emphasize the integration of data methodologies and establish of reporting frameworks for future research.

Multiple safety interventions that can be taken into consideration by law-makers, but each with a distinct impact. Figure 1 illustrates the comparative analysis for the United States and Canada from 1990 to 2021 [65]. Though both nations almost have the similar degrees of technological advancement and economic, the dataset reveals that the records of severity of road traffic accidents evolve in contrasting directions. The rate of injuries per 1 million in the US peaked at approximately 13,029 inhabitants, compared to 9486 in Canada. After 2000, there is a relatively steady to continuous drop in Canada, reaching to its lowest rates at the end of the period. On the other hand, the US illustrates more variation when there was a sharp drop from the late 1990 to 2010, followed by temporary boom and fluctuations around the middle of 2010. These outcomes reveal a different performance of safety and exposure levels, besides the success of adopted safety regulations between the two nations.

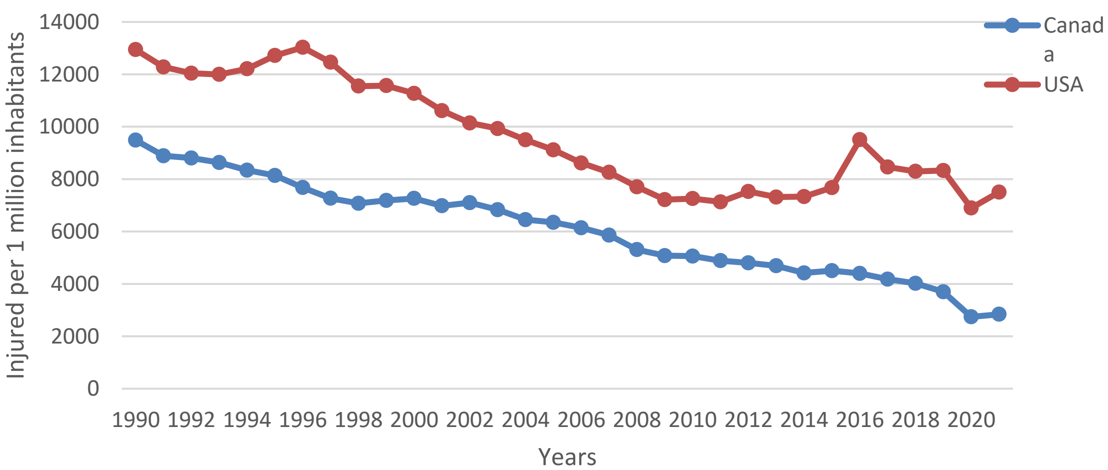

Figure 1. Comparison of vehicles injuries per 1 million inhabitants between the United States and Canada (1990-2021). Data source [65]

Differences of trends in the rates of injuries (the fluctuations and temporary rises in the US compared to the continuing decrease in Canada, indicating the impact of systematic variables and policy actions on the findings of road safety. The high rates of injuries in the US reveals the impact of manageable systematic and cultural variables rather than considering high mobility or environmental levels. It is worth mentioning that the collected dataset emphasizes the significance of targeted safety measures, rigorous regulation, and infrastructural enhancements in mitigating traffic injuries. Additionally, for the design, safety, and assessment purposes, these findings have major implications, especially with regard to developing technical methodologies and data safety managements.

2.2. GIS RTA Assessment

Due to its combination ability of spatiotemporal and data attribute within an integrated context, GIS is a fundamental analytical platform that has been widely utilized for RTA studies. To identify hot spot areas and characterize RTA pattern of distribution, different researchers have extensively utilized using GIS for spatial

methods, like KDE, metrics of spatial autocorrelation (e.g., Moran's I) and hot spots identification (e.g., Getis–Ord Gi). These models enhance safety planning by identifying spatial clustering and systematic risk patterns.
Besides the spatial analysis, spatiotemporal analysis has attracted fascination with researches of RTA. For instance, emerging hot spot analysis and space-time cube have been utilized by multiple researchers to identify the temporal emergence of RTA hotspots and to estimate risk levels over multiple time scales. Conducted study in Columbia, MO developed the emerging hot spot tool of GIS by creating an algorithm for a clear and thorough definitions of clustering emergence over different temporal scales [66]. This contribution advances the identification of persistent and emerging of high-risk areas. In addition, other bunch of research illustrated that GIS is not only enables the integration of urban planning by different road attributes with RTA, but also enhances the efficiency of safety measures [67].
Other usage of GIS over some developing countries has been widely utilized. In order to measure the spatial distribution of RTAs, a bunch of studies selected some urban areas in Saudi Arabia like in Bisha and Abha using spatial statistical models (i.e., mean center, directional distribution, and standard distance) [68, 69]. The findings of these researches highlight the crucial role of GIS in promoting required safety measures over various urban zones. Besides, other studies have concentrated on anticipated and preventive traffic safety applications. By combining GIS with artificial intelligence (AI), a supreme identification of hot spot areas forecasting of RTA has been utilized by facilitating immediate visualizing and emergency response planning [17, 18].
In general, the recent studies concluded that the GIS extends beyond merely simulation when it serves as robust analytical technique for spatial or spatiotemporal analysis of RTAs. However, challenges like dataset limitation, spatial scale sensitivity, constraints of temporal scale, and data scarcity of dataset, all of which are still persisted [48, 63]. Therefore, addressing these constraints along with emerging data sources integration with powerful modelling technique signifies an essential path for future GIS-based studies of RTAs.

2.3. Statistical RTA Assessment

In order to improve transportation safety, forecast methodology, risk assessment, and spatiotemporal methodologies, multiple strategies have been emphasized in GIS-based RTA analysis. There is a crucial need to identify the fundamental factors that causes of RTAs by assessing the likelihood of RTAs, backing up treatments like human factors, heuristic learning algorithms, fuzzy logic models, and probabilistic frameworks [70]. Numerous researchers in the road safety discipline assessed the impact of data segmentation models on RTA severity and concluded that size of sample was not an adequate indicator of model accuracy, which reflects the need for a robust statistical validation [71]. Jiao, Y. et al., [72] advocated an interaction context of integration, statuses mobility, and elements of environment to identify traffic conflict. For safety investigation of heavy trucks, some authors concluded that utilizing active and passive technology might reduce around 59% of fatalities among road users [73]. Other researchers determined that there is a crucial need for a developed statistical models for RTA severity mitigation to enhance drivers vision systems, emergency braking systems, and information systems for blind spots [74, 75]. On the other hand, a study in Denmark [76] raising that the regularity of inspection does not reduce the chance of RTAs. By utilizing machine learning techniques (XGBoost and hybrid SHAP-based models) for risk assessment, a researcher [77] identified the associated risks of driving over urban collector and arterial roads by creating a risk assessment matrix. These sorts of studies highlighted the crucial need for a particular measures of safety and spatially adapted policies of road safety [78]. Focusing on emergency breaking systems has the major impact towards mitigation of RTAs for bicycles and pedestrians, when they characterized by inadequate visibility or elevated speeds [79]. Adopting images of drone-based to assess conflicts of near-accident with high accuracy established a unique alternative for traffic safety measurement for RTA prevention [80]. The outcome illustrated the usage of safety systems for RTAs mitigations besides the crucial need to increase their efficacy in practical conditions.

2.4. Aim of the Review

The aim of this review is to provide a methodological combination of the literature on GIS-based methods for RTA analysis with emphasis on spatiotemporal techniques of analysis. Hence, the objectives are:

1- To summarize the GIS-based range of spatiotemporal techniques, which employed in RTA Researches and consist clustering, hot spot detection, spatial autocorrelation, network-based analysis, and space-time emerging approaches

2- To evaluate the data source sorts, analysis scales, contexts of study that reported in the literature. In order to help identifying limitations and opportunities in the current research practice, there is acrucial need to comprehend both analytical scales and data characteristics.
3- To propose guidelines for researchers' future recommendations and practical applications in safety planning and formulation of policy. Hence, it seeks for supporting researchers, planners, decision-makers in enhancing RTA analysis by GIS for further superior safety strategies.

3. Methodology of GIS Techniques Used in Accident Analysis

The clusters distribution of RTA hot spots and the intensity analysis have been widely applied by techniques of GIS-based. These models allow researchers categorizing spatial correlations, identifying high-risk spots, and supporting safety strategies. A bunch of GIS techniques are widely employed in RTA analyses, such as spatial density estimation, spatial autocorrelation, hotspot detection, and clustering models.

3.1. Spatial Analysis Methods

3.1.1. Kernel Density Estimation (KDE)

KDE is frequently employed in GIS-based RTA detection to identify hot spot areas [13]. This tool identifies the spatial intensity of RTA occurrence by normalizing data of points over a continuous plane, hence identifying areas with higher intensities of RTAs [14]. This approach is exceptionally competent to demonstrate spatial patterns and facilitate the detection of hot spot in roads and urban areas [12]. Besides, it generates maps of density that reveal road segments or intersections with high-risk. It is worth mentioning that the kernel function and bandwidth value significantly impact the results, as excessive bandwidths might conceal local patterns, while narrow bandwidths could boost disturbance. Though its highly sensitive to the selection of parameters, the easy interpretation and simple application in GIS platforms let KDE remains popular. Multiple researches utilized planar KDE approach, which basically determines the kernel function by a circular searching area. Equation 1 is used the intensity of a specific position.

$$f(s) = \sum_{i=1}^{n} \frac{1}{\pi r^2} k\left(\frac{d_{is}}{r}\right) \quad (1)$$

Where $f(s)$ is the specific location intensity, r searching radius, k kernel density, and d_{is} distance between s and i^{th}.

Nevertheless, planar KDE lacks to consider the fundamental topologies of road network or the visibility of traffic. This can lead to bias of interpolations when the RTAs are distributed along the road networks. Therefore, NKDE is appropriate when it provides a non-parametric approach to assess RTA intensity constrained by road networks [39]. While the accidents are occurred along the road segments, NKDE is more robust in identifying hotspot of accidents by calculating density along these segments and avoiding density spreading out of roads areas. However, NKDE has some limitations when it has high complexity in computation with a strong dependance.

3.1.2. Moran's I Statics

One of the initial spatial statistical autocorrelation tools in GIS, Moran's I, has extensively utilized for inspecting of spatial clustering, weather the RTA hot spots are clustered, discrete, or randomly distributed over spatial area [81]. It comprehends both local and global statistical analysis. Equation 2 is used for global Moran's I index.

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{i,j} Z_i}{\sum_{i-1}^{n} Z_i^2} \quad (2)$$

Where

Z_i & Z_j—deviations from mean

w_{ij}—spatial weight between feature i and j

n—quantity of features

S_o—aggregate of all the spatial weights

For overall spatial autocorrelation, Global analysis can be utilized, while local provides a thorough assessment to identify areas with high or low rates of RTA severity, frequency, and temporal variation over road segments [41]. This tool is crucial to establish a theoretical basis for further hotspot analysis. However, Moran's I requires a thorough assessment of spatial weight weights due to local boundaries, which significantly influence results. Equation 3 illustrates local Moran's I index

$$I_i = Z_i \sum_{j=1}^{n} W_{i,j} Z_j \quad (3)$$

Where
Z_i & Z_j—deviations from mean
w_{ij}—spatial weight between feature i and j
n—quantity of features

3.1.3. Getis-Ord Gi*

Unlike Moran's I, Gi* statistic identifies the clusters of hot spots or cold spots of RTA that are statistically significant. This technique is crucial to provide statistically robust results for infrastructure enhancement and decision making. However, Gi* sensitivity to neighborhood definitions and spatial scale is obvious. Hence, selection of wrong criteria would cause deceptive of hot spot detections [82].

3.1.4. Spatial Clustering Methods

Based on spatial proximity and similarity of attributes, spatial clustering technique organizes spatial location of RTAs into coherent classifications. These methods have utilized in GIS-based RTA analysis comprise K-means clustering, hierarchical clustering, and density-based spatial clustering of applications with noise (DBSCAN) [83, 84]. These models allow researchers identifying the patterns of RTAs that might not be observable merely by the estimation of density or the assessment of correlation. Besides, distinguishing noise from significant spatial patterns, DBSACN is efficient in identification of RTA clusters that irregularly shaped. Methodologies of clustering are frequently integrated with GIS simulation to enhance comprehension and facilitate decision-making.
However, the lack of uniform standards to determine cluster amounts or thresholds of distance would cause inaccurate results. Thus, these clustering algorithms needs for a careful thorough modifications and parameter verifications. As a result, outcomes of clustering are frequently verified by other statistical measurements or incorporated with other techniques of hot spot detection.

3.2. Spatiotemporal Analysis Methods

Multiple spatiotemporal methodologies have been applied for RTA hot spot detections, utilizing attributes of RTAs. For instance, both DBSCAN and K-means are broadly approached for RTA clustering examination over spatial and temporal scale [84-86]. Additionally, planar KDE and Network KDE (NKDE) are also used to estimate the intensity of spatiotemporal distribution of RTAs across geographic area or road networks. These models apply kernel functions to calculate the density of local events of RTAs, which can be categorized into hot spot classes, then arrange incident points into raster cells or segments of road network. Techniques like Gi*, Moran's I, and Ripley's K-function have also been utilized to investigate both clustering and autocorrelation of RTAs [8, 51, 87]. These methods evaluate the spatial dependency by investigating the adjacent incidents. Also, for clustering analysis over different time scales, temporal aspect can be implemented [88]. Besides, ESRI's Emerging Hot Spot Analysis tool obviously association space–time dynamics [89].
If we compare among the above-mentioned spatiotemporal techniques, there is a need to mention that KDE with both planar and network sorts differentiate from Gi* Morans' I with surface representing of density or intensity points.

4. Review of application results

RTA analysis based on GIS techniques has been broadly adopted for practical support of managing of traffic safety, planning facilities, and formulating policies. By narrowing the gap between practical management and academic research, GIS offer significant insights into spatiotemporal patterns. For instance, a study in Harbin, China for the selected set of RTA data from 2016 to 2018, and investigated the spatiotemporal distribution or RTAs by utilizing statistics of GIS [90]. The study focused on severity and frequency of RTAs. The collected dataset was processed to identify the exact coordination of accidents and categorize them as per seasonal classification. Later, two methodologies were considered, both density and cluster analyses. If the roads network density is regarded as a concern, the results depicted that the RTAs is highly occurred in the Central Business Districts (CBD). Besides, cluster analysis has revealed that these areas are mainly indicated with clusters of low-severity RTAs.

Hot spot identification by Global Moran's I was also carried out for the selected RTA dataset. The dataset comprehends 44,724 RTA records during 2014 and 40,098 during 2015, which collected by the police department of Mashhad, Iran [91]. Besides, the study utilized Gi*, average closest neighbors, and mapping cluster methods of analysis. The reliability was determined by hit rate, recapture rate, and forecast accuracy. The outcomes revealed that Moran's I showed the highest accuracy and the most effective in hot spot detection of RTA. Though it was more reliable, but Gi* had less accuracy. Thus, Moran's I offers the optimal balance of reliability and efficiency.

By using a set of RTA data between 2015 and 2017, a recent study [92] used KDE to identify hot spots and estimate the spatial autocorrelation of RTAs in Hanoi, Vietnam. In order to signify the hot spot clustering, Moran's I was utilized while KDE was for detection. Also, Gi* was used to confirm high-high clusters, while PDO was employed for hot spot ranking. KDE's limitations were tackled by avoiding statistically irrelevant or non-critical clusters via this combined method.

5. Thematic Synthesis of Reviewed Studies

Variety of studies have approached GIS-based RTA analysis. Previous sections classified some selected researches using GIS, including Moran's I, KDE, and Gi*. The overall summary of NKDE presents perspectives upon the utilization of such models for accomplishing different analytical objectives. Five main topic areas can be identified: hot spot recognition, prediction RTA estimation, GIS with advancing techniques integration, safety studies for policy and equity-based, and investigations for infrastructure-based. A substantial percentage of the published safety articles focused on hot spot identification and spatial depiction of RTA risk areas. These studies employed KDE, Moran's I, and Gi* [93, 94] for hot spots identification and validation. The main objective was to enhance the overall safety of roads through the designation of key zones for enforcement. These researches reveals that GIS has the ability to visualize RTA clusters and allow planners and lawmakers focusing on road safety improvements.

Another bunch of research explored both risk assessment and forecasting modeling. Rather than merely simulating them, the future prediction of RTAs and comprehend their reasons is the main objective of this group of research. GIS and statistical integrated frameworks were utilized to determine the risk of RTAs [17, 95], but others examined road risks utilizing data-driven models over different environmental and behavioral circumstances. This model demonstrates the trend into preventive RTA management by enabling evidence-based preventative remedies. The growing trend of GIS-based with AI and ML modelling has increased lately by integrating spatial analytics with ML models like XGBoost, neural networks, and hybrid explainable models for RTA prediction of Hot spots besides supporting real-time decision-making [16, 96, 97]. These studies have demonstrated evolution from conventional descriptive to autonomous, adaptive systems that can consider comprehend massive and dynamic spatial data for traffic safety assessments. This integration enhances the accuracy of forecast, systems of early warning, and response speed. Nevertheless, this approach has some technical limitations that restricts its usefulness. For instance, both scale and dispersion of geographical dataset raise significant issues.

Like road networks, GIS dataset has frequently multiple levels. Also, land use, traffic flow, and topography dataset range in spatial resolution, temporal scale, and formatting. The diversity of data restricts preprocessing, validation, and spatial alignment, which lead to computationally demanding and error-prone integration [63, 98]. Also, irregular distributions and spatial autocorrelation restrict ML training of model. The main difference of GIS dataset from traditional one is the spatial dependency, where adjacent places affect each other's characteristics. Therefore, without spatially conscious algorithms such as regionally weighted regression or spatial deep learning, ML models might incorrectly interpret the dependence causing inaccurate predictions [99].

The third theme, high dimensional extraction and representation of spatial data features, still practically demanding. In order to provide organized geographic characteristics, network connectivity, metrics of proximity, and spatiotemporal interactions, sophisticated methods like spatial embeddings, graph neural networks, or tensor-based representations are crucially needed [100]. Moreover, computational limits can be emerged, due to high-resolution or real-time spatial attributes, especially for dynamic applications like prediction of RTA and response of emergency. Spatial dataset and AI models integration often requires distributed processing, GPU acceleration, or cloud-based geographical processing. At last, notwithstanding GIS-based policy and safety planning, ML models act as black boxes [101].

The fourth theme investigate policy and equity analysis utilizing GIS to determine the impact of both demographic and financial variables on the findings of road safety. By using GIS, recent research examined variances of spatial risk of traffic among populations at risk [102]. These studies contribute to sustainable transportation discussion by combining demographic information with spatial safety analysis for inclusive and socially reasonable safety efforts guidance.
The summary of thematic illustrates that GIS based RTA research has advanced from traditional representation to multi-dimensional frameworks, spatial data combination, modelling predictive, and intelligent systems. For supporting transportation safety policies, RTA mapping research is developing from analytical mapping to the analytics of data-driven. Thus, to enhance road safety, future research should focus on sophisticated combining of GIS models with practical application.

6. Review Discussions

For its importance, the spatial analysis methods of RTA have commonly approached by multiple researchers. For instance, the KDE, Moran's I, and Gi* are the most common utilized methods for spatial assessment, when traditional statistical methods cannot provide. These methods are practical to identify spatial clustering besides concentration of RTAs. Hot spot detection is an essential outcome of spatial RTA assessment. Previous researches reveal that sort of vehicles besides some analytical factors substantially impact the patterns of hot spots and spatial distributions. In order to identify hot spots effectively, both hidden contributing factors and analytical models should be considered. A robust data processing of GIS, integration, and visualizing abilities allow precise spatial assessment and interpretation of RTA dataset, thus resulting an essential framework for planners and decision-makers.
Geospatial safety studies are widely utilized in developed nations like in the US, UK, or Canada rather than developing countries. These studies have obtained information from road categories, traffic interaction, trip distance, and speed of vehicle. However, some geometric specifications like slope, lane width, and curvature are remain poorly represented due to the issues of data availability. Spatial RTA analysis is restricted by the lack of high resolution, reliable, and infrastructure dataset. Thus, for better understanding and attempts at intervention, it is recommended for future studies to include comprehensive features of roadway. The evolution of Road safety assessment by GIS-based is obvious. Early researches majorly employed KDE and Moran's I for RTA hot spot clustering identification. Further innovations such as network-based density algorithms and Gi* statistics enhanced statistical accuracy by spatially significance of explicitly analysis. Road safety management has evolved from basic geographical modeling for decision-support systems of data-driven. It is worth mentioning that spatial analysis introduces the geospatial distribution of incidents across specific area or space, while spatiotemporal focuses on integration both spatial and temporal dimensions to allow researchers examining the evolution over places and time occurrences.

7. Scenario Technology Matching and GIS Application Framework

RTA analysis of GIS approaches relies on objectives of research, quality of datasets, and scale of spatial area. Throughout complicated road segments, NKDE identifies concentrated RTA hot spots and effectively represent spatial intensity as hot spot clusters. Their methodologies of analysis making these tools ideal for identification of hot spot clusters, especially in congested urban road networks. Alternately, Moran's I can assess spatial autocorrelation and detect the pattern of risk by presenting robust statistical knowledge with high and low risk spatial clusters. Gi* can identify statistically significant hot and cold spots to determine response areas and enable safety resource allocation. It is worth mentioning that the combination of GIS with ML methods boosts scenario analyses and forecasting solutions. In addition, hybrid methodologies facilitate the simulation of interventions impacts and the prediction of RTA risks. In general, the proposed framework links the gap of methodology between practical decision-making and spatial analysis for supporting data-driven of road safety management efforts.

8. Challenges and Limitations in GIS-Based Accident Analysis

Despite the significant advances in GIS-based RTA, multiple challenges with limitations restrict its efficacy, portability, and practically. Enhancing data reliability and guiding evidence-based safety planning should be addressed for methodological rigor enhancement.

8.1. Data Quality Issues

Factors like dependability, precision, and completeness of dataset are crucial for analysis of RTAs. Datasets collected by local or regional institutes might include errors, missing values, location, timing, or severity categorization deviations. Minor RTAs involving susceptible road users are often neglected, biasing outcomes. Due to the different data formats and geocoding accuracy, spatial trends alteration and RTA hot spot misleading can be resulted.

8.2. Scale and the Modifiable Areal Unit Problem (MAUP)

Spatial analysis scale is crucial for identification of RTA patterns. The analysis results of GIS may vary depending on the accuracy of spatial resolution, characterized by Modifiable Areal Unit Problem (MAUP). This issue may exaggerate or fragment RTA hotspots, which means hiding localized high-risk spots or produce spurious clusters at the case of fine-scale selection. Thereby, reliability and accurate interpretation require selecting an appropriate scale and multi-scale analysis.

8.3. Temporal Resolution

Another drawback of RTA analysis, temporal variations of RTA data when multiple datasets only have recorded the date of incidents without providing of time stamp. This can make the peak hour and seasonal trend assessment is difficult. Also, inconsistent recording intervals along with reporting delays may reduce the accuracy of spatiotemporal modeling and hot spot evolution studies. Therefore, addressing temporal resolution challenges is crucial for traffic safety management and GIS applications.

8.4. Model assumptions

Analytical models utilize simplifying concepts that may not accurately reflect real-world traffic extent, which might bias results and reduce the accuracy of future prediction.

9. Conclusions

This review study has methodically observed the GIS role in RTA assessment among 65 investigated articles. GIS have been utilized by literature to assess the RTA patterns, clustering distributions, and temporal dynamics by models like KDE, Moran's I, Gi*, and space-time analysis. GIS applications cover major approaches, data sources, applications, issues, and future targets. The literature illustrates that GIS can identify the RTA hot spots, assess road safety strategies, and support decision-making and policy procedures. Traffic research with GIS-based are steadily increased, demonstrating methodological development and worldwide endorsement of GIS as an essential analytical framework for safety enhancement.

Multiple significant aspects of GIS-based RTA studies have been highlighted from this review. Initially, a significant variation is considered in the utilized dataset, such as police records, hospital dataset, and other sources like statistics of sensor-generated and GPS. Though these resources contribute significant attributes on RTA occurrences, some concerns like spatial inaccuracies, imprecise reporting, and limitations of temporal scales can adversely impact the reliability of analysis. Second, various techniques are frequently employed for spatial assessment, consisting KDE, Moran's I, Gi*, and spatial clustering techniques. These approaches have proven effective in assisting with hot spot detection, RTA pattern identification, and particular remedy assistance. Nevertheless, there is a crucial need for thorough methodological considerations when the reliability of these techniques can be impacted by the restrictions of sensibility of scale, Modifiable Areal Unit Problem (MAUP), and context-specific. The Third crucial significant aspect when GIS has numerous practical applications in traffic safety. With the application of GIS, policymakers and planners are able to turn sophisticated spatial dataset into feasible options. This feature aids in the hot spot identification of accidents, makes planning of road safety more feasible, and improves policy regulation. Hence, by simulating and assessing distribution of RTAs, GIS offer a robust framework for evidence-based interventions for road safety enhancement. Last but not least, there are multiple potential gaps were recognized. For instance, in developing nations, there is a lack in the use of ML or AI, real-time data integration, and data coverage. It is worth mentioning that enhancing plans of emergency response, boosting early detection of risk areas, enabling preventive road safety measures, and strengthening prediction accuracy are all possible outcomes to fill up these gaps. Thus, the integration of both advanced GIS-based techniques with real-time and AI-driven data analytics implies a viable approach for future studies in traffic safety. Also, combining spatial, temporal, and attribute dataset simplifies planning of evidence-based safety, enables prioritization of high-risk areas, and evaluates interventions. Finally, for assessing, predicting, and mitigating traffic accidents, GIS is crucial to utilize. Hence, using GIS and robust analytics establish safe and efficient road networks.

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