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Safe route-finding: A review of literature and future directions

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ABSTRACT

While road navigation systems seek to determine the shortest routes between a given set of origin and destination points, there are certain situations in which the fastest route increases the risk of being involved in road crashes. This implies the necessity of integrating safe route-finding into road navigation systems. This study is designed to synthesize the literature on safe route-finding and identify the gaps in the literature for future research. Specifically, a scoping literature review methodology is applied to understand how safety is incorporated in route-finding, even beyond motor vehicle navigation systems. Three databases (Scopus, Web of Science, and IEEE Xplore) are explored, and controlling for inclusion criteria, 40 studies are included in this review. The findings of this review indicated five areas through which safety was considered in route-finding: motor vehicle navigation, public safety, public health, pedestrian and cyclist navigation, and hazardous material transportation. The measurement of safety was found challenging with inconsistencies in safety quantification approaches. The safe route-finding algorithms were investigated based on their predictive/reactive, static/dynamic, and centralized/decentralized characteristics. Based on the critical review of the safe route-finding algorithms, availability of real-time data sources, accurate real-time and disaggregated crash risk prediction models, trade-off between time and safety in road navigation tools, and centralized safe route-finding are highlighted as the requirements and challenges in considering safety in road navigation systems. This study outlines a research agenda to address the identified challenges in safe route-finding.

1. Introduction

Navigation has a long history that allegedly started with seafaring and later found its way into land, aeronautics, or space navigation. In all cases, the navigator's position was located in comparison to known locations or patterns, either in the form of dead reckoning or celestial navigation. Later, due to limitations in road signage, navigation systems naturally became appealing to drivers. The first car navigation system, which could direct drivers from specific locations on a rolling map, was introduced in 1909 (Company, 1910). Since then, the car navigation system has evolved, and several built-in or nomadic devices have been introduced. Not only have the devices themselves been evolved, but also the capabilities of the system and the algorithms behind it have been modified. The invention of the Global Positioning System (GPS) in 1973 (Bray, 2014, Canales, 2018), for instance, drastically affected the car navigation industry as the car navigation systems switched from dead reckoning to satellite-based navigation (although, evidently, almost two decades after the introduction of GPS). Adding route-finding and route-planning features was another significant improvement to in-car navigation. With the introduction of smartphones and navigation apps, advanced road navigation systems became nearly ubiquitous. Another innovative feature was calculating the travel time based on traffic conditions and directing users to the shortest route, i.e., the route that minimizes travel time. The route planning was based on the shortest route-finding algorithms (Gallo and Pallottino, 1988). Nowadays, road navigation systems' route planning goes beyond finding the shortest route, but rather includes the most fuel-efficient and environmentally friendly routes (Ding et al., 2017, Holden et al., 2020, Zeng et al., 2017).

Since the 1960s, road navigation systems have been considered a driving assistant technology that promotes safety (Auer et al., 2016). The preliminary versions of road navigation systems could provide users with turn-to-turn guidance that helped drivers to make safer driving (maneuver, lane changing, etc.) decisions. More recent versions of road navigation systems alert drivers of road dangers such as lane closures, speed limits, flood events, crashes, etc. Despite these advances in road navigation systems, safety is not yet considered in route planning.

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Sohrabi and Lord (2022) designed a study to examine the safety of suggested routes by navigation apps and concluded that the fastest route is not necessarily the safest route. This study showed that an 8% increase in travel time could be associated with a 23% reduction in the likelihood of being involved in a crash (Sohrabi and Lord, 2022). They argued that road navigation seeks to minimize the traveler's travel time, sometimes with the cost of navigating them through local roads with poor geometry design, limited road marking and signage, higher interactions with vulnerable road users (cyclists/pedestrians), and higher traffic conflicts, to name a few (Sohrabi and Lord, 2022).

This study is designed to address the gap in incorporating safety in route planning by exploring and synthesizing the literature about safety in route-finding. A scoping literature review methodology is employed to (1) systematically identify safe navigation systems, their applications, and the methodologies behind them, (2) classify safe route-finding algorithms, and (3) recognize requirements and research gaps for future investigations. This review goes beyond motor vehicle navigation systems and explores the safety of various types of navigation applications, namely, pedestrian route planning, hazardous material (HAZMAT) routing, and social safe route finding, with the rationale that safe route-finding algorithms and methodologies can be transferable to road navigation. As environment-friendly route-finding has eventually found its way after a decade of research, this review is expected to accelerate the integration of safe route-finding into navigation apps. Such a system can promote safety by preventing crashes and saving lives. In addition, this study proposes a research agenda for future research on incorporating safety in road navigation systems. Incorporating safety in route finding can promote safety by preventing road crashes.

2. Literature review methodology

A scoping review framework is employed in this study (the scoping review method was previously proposed by Arksey and O'Malley (2005)). The rationale behind choosing a scoping review is based on the fact that the safe route-finding literature is broad rather than deep. According to definitions scoping reviews have a larger scope, characterized by a broader research question and more inclusive eligibility criteria (Munn and Peters, 2018, Sargeant and O'Connor, 2020). The scoping review provided a preliminary literature review to identify areas where there may be a sufficient depth of literature to warrant a systematic review (Sargeant and O'Connor, 2020). This review does not aggregate, describe the concepts and methods, or assess the quality of literature, but maps the literature about safe route-finding and identifies key concepts, gaps, and limitations (Munn and Peters, 2018).

The first step in a scoping review is to identify the research question to be answered (Arksey and O'Malley, 2005). This review aims to find the answer to the fundamental question: "How is safety incorporated in safe route-finding literature?" Specifically, this study was interested in identifying the algorithms and methodologies behind safe route-finding.

A search strategy was developed to retrieve relevant research evidence from three electronic research databases—Scopus, Web of Science, and Institute of Electrical and Electronics Engineers (IEEE) Xplore, and reference lists of the retrieved publications. IEEE Xplore is a research database that covers more than 5 million journal articles, conference proceedings, standards, and related materials on multiple disciplines, including, but not limited to, computer science, electrical engineering and electronics, and allied fields.[1] IEEE Xplore is sponsored by the IEEE and other partner publishers. Scopus is Elsevier's research database, which covers more than 75 million records from 50,000 publishers in four core areas: life sciences, social sciences, physical sciences, and health science[2]. The Web of Science, sponsored by the Institute of Scientific Information, is a publisher-independent research database that covers more than 79 million records from several areas, such as life sciences, biomedical sciences, engineering, social sciences, arts and humanities, natural sciences, health sciences, engineering, computer science, and materials sciences.[3]

The databases were searched to identify published and indexed articles, letters, reports, book chapters, and books using any combination of a set of keywords in their title, abstract, and keywords. The keywords are summarized into two groups in Table 1. All material considered in the review was published as of October 2021.

After screening the titles and abstracts of the identified records, the full text was assessed based on the inclusion criteria. The inclusion criteria were designed to ensure the literature answers the review questions. Three inclusion criteria were defined:

1. Must discuss safety in route-finding as a system, and studies which only discuss route-finding algorithms are not included.
2. Must investigate the route-finding in land transportation as opposed to aviation and maritime transport.
3. Must propose an algorithm or quantification methods rather than commentary publications.

3. Results

3.1. Search results

Overall, 5,955 publications were found–2,246, 989, and 2,720 publications from the Web of Science, IEEE Xplore, and Scopus, respectively. Among those, 40 publications met the inclusion criteria and were reviewed. Fig. 1 summarizes the implemented scoping review using the PRISMA scoping review flow diagram (Tricco et al., 2018). Fig. 2 depicts the annual number of publications since 2010. An increasing number of publications were observed, which implies higher research attention to safe route-finding in recent years.

In the subsequent sections, the results of this review are reported, summarizing the literature based on the definition of safety, the measurement of safety, and the safe route-finding algorithms (Table 2 summarizes the literature).

3.2. Definition of safety

The literature shares a common objective: to maximize the safety in route-finding. Nevertheless, the objective of the optimization problem varied based on their definition of safety. The context of safe routing is also based on different travel modes. Consideration and context of safe routing for vehicles, non-motorists, and public transportation vary widely. Safe routing for vehicles mostly depends on time, distance, safety, and associated critical factors. Safe routing for non-motorists also includes time, distance, and safety, however, there is a need for additional information such as walkability and crime scores of the networks,

Table 1
Keywords summary.

Category	Keywords
Route-finding	Navigation system; Routing; Phone navigation; Car navigation; Bicycle navigation; Vehicle navigation; Automobile navigation; Pedestrian navigation; Road navigation; Route finding; Path finding; Road finding; Road guidance; Route guidance; Vehicle guidance; Car guidance; Navigation device; Route planning; Urban navigation; Vehicle information system; Navigation device
Safety	Safe; Crash; Collision; Accident; Crime; Hazard

[1] Source: https://innovate.ieee.org/about-the-ieee-xplore-digital-library/.
[2] Source: https://www.elsevier.com/solutions/scopus/why-choose-scopus.
[3] Source: https://clarivate.libguides.com/webofscienceplatform/coverage.

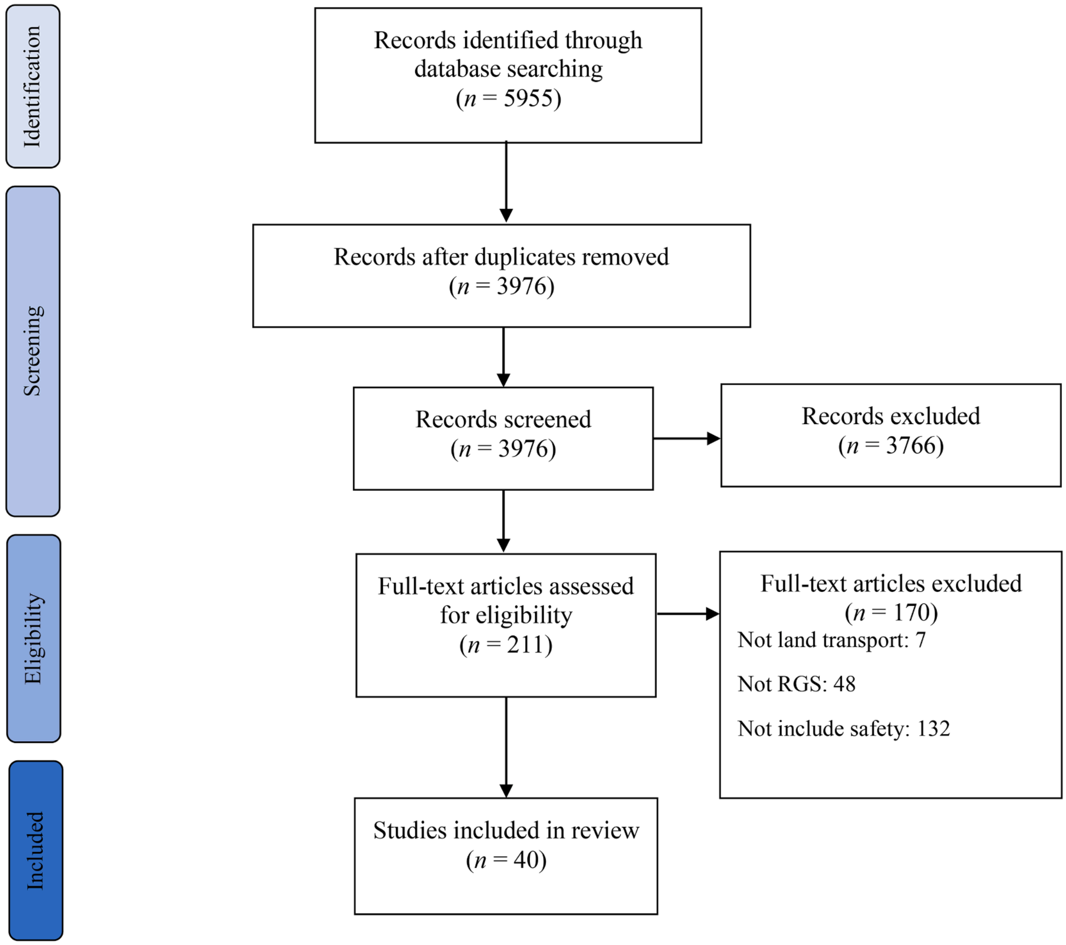

Fig. 1. Study identification and selection mechanism of the implemented scoping review.

trails, bike paths, and sidewalks. Five definitions for safety were found in the literature: Crime risk, health risk, vehicle crash risk, pedestrian or cyclist crash risk, and HAZMAT transportation risk (Fig. 3).

The frequency and distribution of the defined categories across the literature is shown in Fig. 4a).[4] Roughly 41% of included studies are related to the vehicle crash risk, and 21% discussed the pedestrian/cyclist crash risk. The next major category is the crime risk-related studies which account for 25% of total studies. The health risk and HAZMAT transportation risk accounts for 7% of the literature. Fig. 4 (b) depicts an increasing trend in the number of records that vary over time.

Safe route-finding was found in public safety literature. Finding a route (mainly in an urban setting) with minimum risk of being a victim of a crime is studied in the literature (Utamima and Djunaidy, 2017, Byon et al., 2010, Mata et al., 2016, Kaur et al., 2021, Radojičić et al., 2018, Bura et al., 2019, Soni et al., 2019, Alpkoçak and Cetin, 2020, Levy et al., 2020, Puthige et al., 2021, Galbrun et al., 2016). Mainly, the route with the minimum number of historical crimes was introduced as the safest route (Alpkoçak and Cetin, 2020, Byon et al., 2010, Kaur et al., 2021, Mata et al., 2016). Some studies, however, differentiate the type of crimes and target a specified crime for their safe route-finding analysis, e.g., robbery (Radojičić et al. (2018) and crimes that might cause injury or death (e.g., shooting, sex crime, robbery, etc.) (Galbrun et al., 2016, Levy et al., 2020, Puthige et al., 2021, Soni et al., 2019, Utamima and Djunaidy, 2017).

The safe route through which the risk of being exposed to COVID-19 is minimized was studied in the literature (Mishra et al., 2021, Cantarero et al., 2021, Khanfor et al., 2020). The general rule to reduce the risk of exposure to COVID is to maintain social distancing and avoid crowded communities or zones. Several methods were used in the literature to identify the high-exposure hotspots and avoid them. Mishra et al. (2021) identified COVID-19 exposure hotspots such as medical zones, high-density residential areas, and roads with a higher potential for connectivity of people. Khanfor et al. (2020) developed a pedestrian route-finding approach to avoid areas where social distancing is not well-practiced. The proposed framework is backed up by the data from internet-of-thing devices in smart cities (Khanfor et al. (2020). Cantarero et al. (2021) defined high-exposure areas as an area with a high density of population and occupations.

The literature is dominated by studies that explore the route that minimizes the risk of vehicle crashes (Ito and Koji, 2020, Li et al., 2014, Sarraf and McGuire, 2018, Abdelhamid et al., 2016, El-Wakeel et al., 2018, He and Qin, 2017, Hoseinzadeh et al., 2020, Zhou et al., 2017, Abdelrahman et al., 2019, Hayes et al., 2020, Krumm and Horvitz, 2017, Li et al., 2016, Takeno et al., 2016, Kamal Alsheref, 2019, Soni et al., 2019, Liu et al., 2017, Puthige et al., 2021, Chen and Lou, 2021). The safest route is usually considered to be the route with lower historical crash rates (Li et al. (2016), but the severity of crashes was also considered in some studies. Like the safe routes for vehicles, the safety of pedestrian and cyclists are studied in the literature. The pedestrian and cyclist safe route seeks to maximize the safety of pedestrians and cyclists

[4] Two studies double-counted in Figure 5a, as they target both crime risk and vehicle crash risk Soni, S., Shankar, V. G. & Chaurasia, S. 2019. Route-the safe: A robust model for safest route prediction using crime and accidental data. *Int. J. Adv. Sci. Technol,* 28, 1415-1428;Puthige, I., Bansal, K., Bindra, C., Kapur, M., Singh, D., Mishra, V. K., Aggarwal, A., Lee, J., Kang, B.-G. & Nam, Y. 2021. Safest Route Detection via Danger Index Calculation and K-Means Clustering.

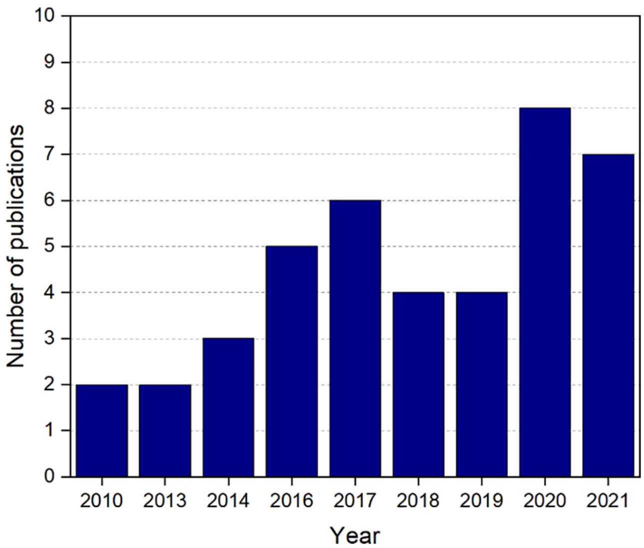

Fig. 2. Publications by year (as of October 2021).

in terms of the risk of road crashes (Santhanavanich et al., 2020, Shah et al., 2020, Bao et al., 2017, Ouyang et al., 2014, Yew et al., 2010, Kusano and Inoue, 2013, Chandra, 2014, Shubenkova et al., 2018, Lozano Domínguez and Mateo Sanguino, 2021). The safe routing for non-motorists generally considers additional data inputs such as sidewalk presence, the network of sidewalks, trails, and walkability scores. The risk of crashes has been associated with lighting (Ouyang et al. (2014) and weather conditions (Shah et al., 2020), among others.

The HAZMAT transportation risk was also included in route-finding (Eren and Tuzkaya, 2021, Preda et al., 2013). Preda et al. (2013) developed a HAZMAT transpiration route-finding for various types of HAZMAT. Eren and Tuzkaya (2021) proposed safe route-finding for COVID-19-related HAZMAT. The safest route for HAZMAT is usually considered to be a route with less risk of HAZMAT exposure and emissions.

3.3. Safety measurement

In the reviewed studies, there is a large variation in how safety is measured and quantified. In a nutshell, the safety was measured based on (1) data-driven analyses of the crash frequency, crash rate, or probability of incidents or crashes, (2) a scoring technique, and (3) safety-indicator variables as a proxy of risk.

3.3.1. Data-driven measurement of safety

In the first group, historical crash data was commonly used for the analyses. Takeno et al. (2016) used the dangerous point and degree of risk to measure safety. The suggested safe route avoids dangerous locations with higher crash frequencies. The degree of risk is served as a

Table 2
A summary of the reviewed studies.

Study	Definition of Safety	Measurement of Safety	Algorithm		
			Predictive/ reactive	Static/ dynamic	Centralized/ decentralized
(Santhanavanich et al., 2020)	Pedestrian or cyclist crash risk	Data-driven	Reactive	Dynamic	decentralized
(Sarraf and McGuire, 2018)	Vehicle crash risk	Scoring	Predictive	Static	decentralized
(Mata et al., 2016)	Crime risk	Data-driven	Predictive	Dynamic	decentralized
(Kaur et al., 2021)	Crime risk	Scoring	Reactive	Dynamic	decentralized
(Radojičić et al., 2018)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Takeno et al., 2016)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Bao et al., 2017)	Pedestrian or cyclist crash risk	Scoring	Reactive	Static	decentralized
(Chen and Lou, 2021)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Khanfor et al., 2020)	Health risk	Safety indicator	Predictive	Static	decentralized
(Mishra et al., 2021)	Health risk	Scoring	Predictive	Static	decentralized
(Ito and Koji, 2020)	Vehicle crash risk	Scoring	Reactive	Dynamic	decentralized
(Utamima and Djunaidy, 2017)	Crime risk	Data-driven	Reactive	Static	decentralized
(Li et al., 2014)	Vehicle crash risk	Data-driven	Reactive	Dynamic	decentralized
(Cantarero et al., 2021)	Health risk	Safety indicator	Predictive	Dynamic	decentralized
(Shah et al., 2020)	Pedestrian or cyclist crash risk	Scoring	Reactive	Dynamic	decentralized
(Abdelhamid et al., 2016)	Vehicle crash risk	Data-driven	Predictive	Dynamic	decentralized
(Preda et al., 2013)	HAZMAT risk	Scoring	Predictive	Static	decentralized
(El-Wakeel et al., 2018)	Vehicle crash risk	Safety indicator	Reactive	Dynamic	decentralized
(He and Qin, 2017)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Byon et al., 2010)	Crime risk	Scoring	Predictive	Static	decentralized
(Hoseinzadeh et al., 2020)	Vehicle crash risk	Data-driven	Predictive	Dynamic	decentralized
(Zhou et al., 2017)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Abdelrahman et al., 2019)	Vehicle crash risk	Data-driven	Predictive	Dynamic	decentralized
(Hayes et al., 2020)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Bura et al., 2019)	Crime risk	Data-driven	Predictive	Static	decentralized
(Krumm and Horvitz, 2017)	Vehicle crash risk	Data-driven	Predictive	Static	decentralized
(Li et al., 2016)	Vehicle crash risk	Data-driven	Predictive	Dynamic	decentralized
(Kamal Alsheref, 2019)	Vehicle crash risk	Scoring	Predictive	Static	decentralized
(Soni et al., 2019)	Vehicle crash risk/Crime risk	Scoring	Predictive	Static	decentralized
(Eren and Tuzkaya, 2021)	HAZMAT risk	Scoring	Predictive	Static	decentralized
(Alpkoçak and Cetin, 2020)	Crime risk	Data-driven	Predictive	Static	decentralized
(Ouyang et al., 2014)	Pedestrian or cyclist crash risk	Safety indicator	Predictive	Dynamic	decentralized
(Yew et al., 2010)	Pedestrian or cyclist crash risk	Data-driven	Predictive	Static	decentralized
(Liu et al., 2017)	Vehicle crash risk	Data-driven	Predictive	Dynamic	decentralized
(Levy et al., 2020)	Crime risk	Data-driven	Predictive	Static	decentralized
(Puthige et al., 2021)	Vehicle crash risk/Crime risk	Data-driven	Predictive	Static	decentralized
(Chandra, 2014)	Pedestrian or cyclist crash risk	Data-driven	Predictive	Static	decentralized
(Lozano Domínguez and Mateo Sanguino, 2021)	Pedestrian or cyclist crash risk	Safety indicator	Predictive	Static	decentralized
(Shubenkova et al., 2018)	Pedestrian or cyclist crash risk	Safety indicator	Predictive	Static	decentralized
(Galbrun et al., 2016)	Crime risk	Data-driven	Predictive	Static	decentralized

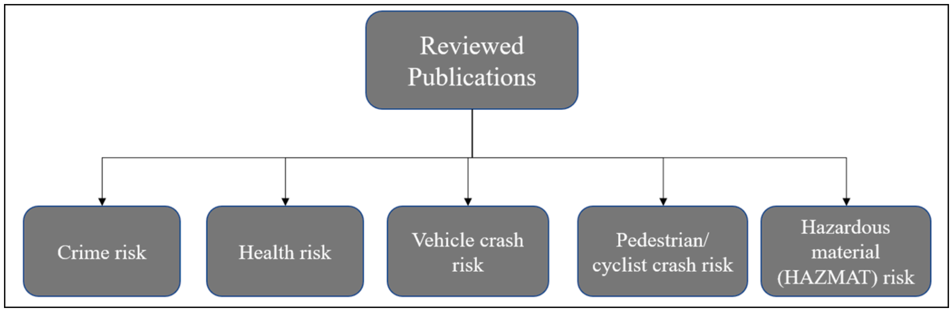

Fig. 3. Risk categories.

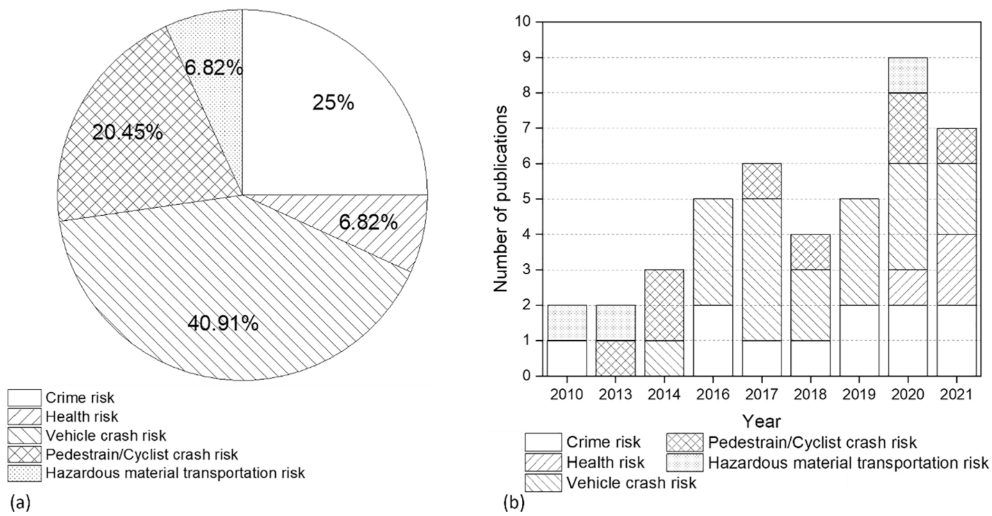

Fig. 4. Illustration of grouped safety objectives: (a) Frequency of publications by objectives; (b) Frequency of yearly publications by objectives.

parameter when calculating the cost function of a route development algorithm. Hoseinzadeh et al. (2020) measured safety in terms of average crash number, route volatility, and driving style. They defined an impedance index that combines safety and time in route finding. Zhou et al. (2017) defined the danger index to represent the collision density of the street and illustrate the danger intensity in a certain street. The danger index is calculated as the count of the collision number divided by the street length. Puthige et al. (2021) first defined the crash score based on the severity of a crime and then gave each type of crime a rated weight and further calculated the crime score. The final danger index is used for measuring overall safety. The danger index is defined as the summation of the crash score and crime score divided by the path distance, and the index is further considered as the weight of a multi-objective shortest-path model. Santhanavanich et al. (2020) mapped the historical traffic crash data to the geodatabase, then found the high-risk areas (crash hot spots). The developed route planning algorithm plans to circumvent these hotspots of the risk area. Utamima and Djunaidy (2017) defined the dangerous point with a certain radius based on the crime data (i.e., type, location, description). The dangerous area is further developed based on the crime point and surrounding radius. The developed route selection algorithm avoids these dangerous zones. Yew et al. (2010) measured safety based on the ratio of the number of reported incidents to the amount of exposure. Risk rate can be regarded as a probability and further used in the route-finding algorithm. Hayes et al. (2020) used the crash rate to represent the safety level. It is calculated as the number of crashes that occur on a given road in the past 12 months divided by the maximum number of crashes that happened on a single road in the selected region. The driver customized weight is applied to the crash ratio and further considered as a part of the cost function for the route-finding algorithm. Levy et al. (2020) added safety into the reward function of the reinforcement learning algorithm[5]. Safety is defined as a function of the average distance from previously known crime spots during the learning step. Based on the crime-related reward function, the reinforcement learning algorithm generates the routes avoiding the crime point. Alpkoçak and Cetin (2020) used the crime rate to measure and compare the safety of the regions. In this research, the crime rate is defined as the ratio of the number of incidents occurring in the region to the number of populations of this region. Bura et al. (2019) used the number of crime records to measure safety. The crime records are mapped to the corresponding region and used for finding the route with fewer crime records along the route.

More advanced data-driven models estimated the probability of an incident using prediction models. Mata et al. (2016) applied the Bayes model to cluster the types of crime. Based on the Bayes clustering

[5] Reinforcement learning contains several components contains agent, environment, state, rewards, policy, and value function. The agent is the decision-maker; Environment is the physical world where the agent learns the action; Action is a set of actions that which agent performs; State is the agent's current situation; Reward is the feedback that the environment gave to the agent after an action; Policy is the method to map agent's state to action; Value function is the future reward that agent will obtain after a certain action. Reinforcement learning is a machine learning technique that an agent keeps learning in an interactive environment from the agent's action based on a series of trial and error methods.

algorithm[6], the probability of an event occurring on a given day and time and at a specific location was calculated. The generated probability can be used for measuring safety. Additionally, if there is no available crime data in an area, the Bayes model will make an estimation to find the safety points in this area. The weight of these points will be assigned and serve as the parameters for the safe route algorithm. Radojičić et al. (2018) defined risk as a probability of an event occurring along the defined route. The risk probability changes as the vehicle travel distance increase. The cumulated risk index for a route is formed with various safety-related parameters and travel distance information. This cumulated value is included in the objective function, which is used for route determination. To measure safety, Li et al. (2016) and Li et al. (2014) defined the risk index as follows:

$$RRI(i) = F\left(\sum_{j=1,2,3} n_{ij} S_j / AADT_i\right) \tag{1}$$

where i is the road segment number, $RRI(i)$ is the risk index for the i th segment, $j = 1, 2, 3$ denotes the severity level of fatality, injury, and property damage only, respectively, n_{ij} is the predicted number of levels j to occur over road segment i in a certain period, S_j represents the cost of a crash type, $F(\bullet)$ is a function that scales the cost of most homogenous segments to an index between 0 and 10, and $AADT_i$ represents the annual average daily traffic on the road segment i. The weighted sum of the cumulative travel time and *RRIs* were used for the cost function for safe route-finding. Abdelhamid et al. (2016) estimated the probability of being involved in crashes based on the characteristics of the road segment and the behavior of the vehicle driver. Abdelrahman et al. (2019) used the number of crashes, near-crash, and baseline events captured in the driving environment for calculating the probability of crashes. Krumm and Horvitz (2017) estimated the probability of a single-vehicle crash on a certain road segment over a given hour. Then, the crash probability of a route is defined as a set of independent Bernoulli trials[7], with one trial for the crash road segment. Galbrun et al. (2016) assigned a risk score to each edge that is proportional to the probability of crime events happening on the corresponding road segment. The spatial density for the crime event is first estimated via the Gaussian kernel density estimation[8], then the estimated density function is summed up to obtain the crime activity density, which is proportional to the probability of observing a crime event on the given edge. The final risk score is obtained by normalizing the crime activity density. Liu et al. (2017) measure the crash probability as:

$$p_{(s_i)} = 1 - p_{(c_i)} \tag{2}$$

Where $p_{(s_i)}$ is the crash probability of the road i and $p_{(c_i)}$ is the crash probability of the road i. The no-crash probability for the entire route is estimated as the product of the crash probability of all the segments within a route. The safest route score is further determined based on the crash probability of the route; a higher safety score represents a safer route.

3.3.2. Scoring technique

In the second group, safety is measured based on a scoring technique, mainly in the form of a scaled value. Kaur et al. (2021) measured safety based on scoring the relative parameters. Each segment has a safety score which ranges from 0 to 15. They defined several rules to change the safety score for each segment based on the safety-related parameters. For instance, the safety score increases if there is a police station along the road, or, if a road segment passes through a deserted region, the value decreases by two. The safest route includes road segments with higher scores. Bao et al. (2017) analyzed the impact of each safety factor. After evaluating the impact of parameters, each segment is assigned a safety score. The higher the safety score value, the safer a route can be. The overall route safety score is the summation of the sub-route safety score. These safety scores will be served as the weight of the shortest route-finding algorithm to determine the route. Mishra et al. (2021) measured the safety based on several hazard factors and each hazard factor was assigned a numerical value. Proximity to the containment zone was one of the factors considered in this study, and it decreases with every 100 m as the distance increases up to 300 m. The second hazard factor was proximity to the medical facilities, which is assigned as 0.08 for the edges with the proximity of 100 m near the medical facilities and decreases as distance increases. The last hazard factor considered was the traffic risk and the betweenness centrality, which was normalized and scaled into the range of 0 to 0.06 to represent the traffic risk. The final safety score was calculated as the summation of all of these factors. Byon et al. (2010) targeted the crime risk and counted the number of death cases associated with each zone. The zone with the highest counted deaths received a rating of 5. The zone with the lowest death count received a rating of 1. The safest route passes through the zones with lower crime scores. Soni et al. (2019) measured safety using an overall numeric risk score. Specifically, the crime and crash score for a certain point was calculated first by assigning the different weights for different types of crime and crashes. Then, the averaged crime and crash were estimated based on all the considered points and regions. The risk score was further calculated as the summation of the averaged crime and crash score. Shah et al. (2020) targeted pedestrian safety and incorporated traffic and weather data to measure safety. They defined the safety factor as a scoring value (i.e., High, Medium, Low) based on the traffic and weather condition. Eren and Tuzkaya (2021) obtained the Medical Waste Management (MWM) safety score (valued between 1 and 10). Kamal Alsheref (2019) selected traffic crashes as the safety parameter. The intensity of importance to safety is measured by Saaty's 9-point scale[9] (Zanakis et al., 1998). Then, the safety intensity was further used in the weight calculation in the route selection algorithm.

3.3.3. Safety indicator

In the last group, safety is measured based on the indicators of safety. Khanfor et al. (2020) measured safety as a part of the weight of edges of the road map graph used for developing the safety route. The safety weight is a numeric value that combines the impact of the surrounding co-location/co-work-based relation (CLOR) communities and devices belonging to the same social friendship and ownership relation (SFOR) community of the pedestrian's device. The SFOR and CLOR can be regarded as indicators of safety considering the social distance issue of COVID-19. Cantarero et al. (2021) developed an approach that identifies the density of citizens and level of occupation and combines this information with the behavior of citizens. The level of danger is defined based

[6] The Bayes clustering algorithm is a Bayes algorithm used for the purpose of clustering. The Bayes algorithm considers specific features that are identified and assigned to a specific cluster. Particularly in this research, the clustering approach obtains some probabilities that represent the estimation for specific crimes that were previously classified semantically. Also, the Bayes algorithm can be used for obtaining a likelihood of an event occurring with several given conditions based on the Bayes theorem.

[7] A Bernoulli trial is a test that can result in one of two outcomes: success or failure. In one of these trials, "success" indicates you got the result you were looking for. Here, the "success" trial can be treated as the trial with the crash in a single road segment.

[8] Kernel density estimation is a non-parametric method for estimating an unknown probability density function using a kernel function. Here, the Gaussian kernel is selected which means the data points follow a Gaussian curve.

[9] Saaty's 9-point scale is the standard measurement scale used for the analytic hierarchy process (AHP). AHP is considered a multi-criteria decision-making technique using psychology and math. The steps of AHP include: (1) defining the problem, options, and criteria; (2) Creating a matrix based on the pairwise comparison; (3) Compute the importance weight of each criterion; (4) Selecting the best option. Here, the AHP is used for modeling the route selection problem in a hierarchical form and further recommending the route.

on vulnerability, transmission risk, and level of occupation. The output of the Danger Model contains a numerical danger index that serves as a measurement of safety. Shubenkova et al. (2018) investigated multiple safety parameters, including both the objective parameters (e.g., unregulated crossing) and subjective parameters (e.g., health condition). All the safety parameters were given a numerical value and a corresponding weight. The overall complex indicator was used for measuring safety by summing up the product of the value of each safety parameter and its corresponding weight. Ouyang et al. (2014) measured the safety of cyclists based on slope, road type, road width, signs on the road, and road lighting. Each factor was broken into multiple levels and safety weights are assigned to each level. All weights were set between 0 and 1, with 1 meaning the safest condition and 0 meaning the least safe condition. The single unified safety coefficient was further estimated as the product of the weights. El-Wakeel et al. (2018) detected and categorized road surface types and anomalies. The average road quality, which represents the safety, is labeled qualitatively and further used for route-finding. Rain events on roads were considered a risky situation by Ito and Koji (2020), and numerical traffic risk, scaled from 1 to 10 to the roads, was defined on the basis of historical rain events. He and Qin (2017) incorporated the ratio of the deceleration rate to avoid a crash to the maximum available deceleration rate as the proxy for traffic safety. A safety hazard index was further defined for roadway segments and intersections. Chandra (2014) developed crash indicators for cyclists and older drivers as a function of traffic attributes such as speed and density, driver attributes such as perception-reaction time, and street attributes of length and the tire-to-road friction coefficient.

3.4. Route-finding algorithms

The Dijkstra algorithm and its variants were mainly used in the literature to find the optimal routes (Santhanavanich et al., 2020, Mishra et al., 2021, Utamima and Djunaidy, 2017, Cantarero et al., 2021, Sarraf and McGuire, 2018, Abdelhamid et al., 2016, Byon et al., 2010, Zhou et al., 2017, Mata et al., 2016, Krumm and Horvitz, 2017, Takeno et al., 2016, Yew et al., 2010, Liu et al., 2017, Galbrun et al., 2016). The original Dijkstra algorithm was designed to solve the shortest route-finding problem. The cost function is modified to incorporate safety in route-finding. The modified Dijkstra algorithm aims to minimize the cost function to find the path with the minimum cost from a single source vertex to all other vertices in a weighted, directed graph. The inputs for the modified Dijkstra algorithm usually contain a single or multiple safety-related parameters and the geographic data, and the output usually will be several routes recommendation. Byon et al. (2010) modified the Dijkstra algorithm by incorporating safety parameters (e.g., crime rate, road slope, scenic view, and elevation of a ground surface) into the cost functions. By minimizing the modified cost functions, the output of this algorithm is the safest route with less crime and better road conditions. A* algorithm was also utilized in the literature with a modified heuristic function (Hayes et al., 2020, Alpkoçak and Cetin, 2020). Similar to the Dijkstra algorithm, the input parameters contain the geographic information for the origin and destination points and the safety-related parameters.

Another approach for finding the safest route is to rank the shortest path and its alternatives based on safety (Ito and Koji, 2020, Hoseinzadeh et al., 2020, Bura et al., 2019, Bao et al., 2017, Liu et al., 2017, Puthige et al., 2021, Chandra, 2014). Also, machine learning (ML) can be used not only for generating the safety measurement but also for predicting a safe route. The deep reinforcement learning algorithm is one of the ML-based techniques that was used in the literature to find the shortest path (Levy et al. (2020). The input parameters are usually coordinate information about the route start point and endpoint and the safety-related parameters (e.g., crime events, vehicle speed, road condition). The output of the ML algorithm is the safest path.

The safe route-finding algorithms can be categorized on their predictive/reactive, static/dynamic algorithms, and centralized/decentralized designs. The subsequent sections summarize the literature based on the characteristics of the algorithms.

3.4.1. Predictive vs reactive algorithms

Route-finding algorithms can be classified according to the reactive or predictive nature of the algorithm (Schmitt and Jula, 2006). Fig. 5a shows the frequency of the predictive and reactive algorithms in the reviewed studies. Predictive algorithms account for 78.05 % of literature, while 21.95 % of the reviewed studies used reactive algorithms. A distribution of predictive/reactive algorithms over time is depicted in Fig. 5b.

The reactive algorithm determines the path based on observed data without employing any future information (Schmitt and Jula, 2006). The predictive algorithm employs a predictive model to predict the future conditions of the route. Galbrun et al. (2016) used the gaussian kernel density estimation to estimate the probability of observing the crime event in the given segment. Krumm and Horvitz (2017) estimated the future crash probability via the Bernoulli trials. Mata et al. (2016) used the Bayes algorithm to predict the probability of a crime event occurring on a given day and time and at a specific location. Abdelrahman et al. (2019) predicted the risk based on the joint effect of detected behavior and environmental context. Besides the conventional statistical predictive models, the machine learning models can also be used to predict the safety conditions for the future route. For instance, Levy et al. (2020) developed a deep reinforcement learning algorithm to generate the path, indicating the future safety of the route with a given time and start and end points. Also, the input of a predictive algorithm might contain several safety parameters, and the output will be an overall safety index for the segment or the route to represent the safety (Li et al., 2014, Li et al., 2016, Radojičić et al., 2018).

3.4.2. Static vs Dynamic algorithms

Depending on whether or not the route-finding system reacts to real-time information, the route-finding algorithm can be divided into two types: static and dynamic (Schmitt and Jula, 2006, Herbert and Mili, 2008, Dong, 2011, Khanjary and Hashemi, 2012). Fig. 6 (a) shows the frequency of static and dynamic algorithms in the studied papers. 63.41 % of the reviewed studies are static algorithms (Mishra et al., 2021, Utamima and Djunaidy, 2017, Sarraf and McGuire, 2018, Preda et al., 2013, He and Qin, 2017, Byon et al., 2010, Zhou et al., 2017, Mata et al., 2016, Radojičić et al., 2018, Hayes et al., 2020, Bura et al., 2019, Krumm and Horvitz, 2017, Takeno et al., 2016, Kamal Alsheref, 2019, Soni et al., 2019, Bao et al., 2017, Eren and Tuzkaya, 2021, Alpkoçak and Cetin, 2020, Yew et al., 2010, Levy et al., 2020, Puthige et al., 2021, Chandra, 2014, Chen and Lou, 2021, Khanfor et al., 2020, Shubenkova et al., 2018, Galbrun et al., 2016, Lozano Domínguez and Mateo Sanguino, 2021). The other 36.59 % of the total reviewed publications are the dynamic algorithms (Santhanavanich et al., 2020, Ito and Koji, 2020, Li et al., 2014, Cantarero et al., 2021, Shah et al., 2020, Abdelhamid et al., 2016, El-Wakeel et al., 2018, Hoseinzadeh et al., 2020, Abdelrahman et al., 2019, Kaur et al., 2021, Li et al., 2016, Ouyang et al., 2014, Liu et al., 2017, Kusano and Inoue, 2013). Fig. 6 (b) demonstrates the time series of the publications showing the static and dynamic algorithms. Except for the year 2010, there are both static and dynamic algorithms in each year. The difficulties of processing the real-time data might explain the lower number of publications with the dynamic algorithms compared to the static algorithms.

Additionally, the datasets used in the static algorithms and dynamic algorithms are different. Fig. 7 summarizes the datasets used in the literature for static and dynamic route-finding. The datasets can be classified into three groups: geographic information datasets, historic datasets, and real-time datasets. The geographic datasets were incorporated in both static and dynamic route-finding. The geographic database includes information about the start and endpoints of the route and the road network. Geographical datasets are sourced from OpenStreetMap, Bings map, and Google map (Santhanavanich et al., 2020,

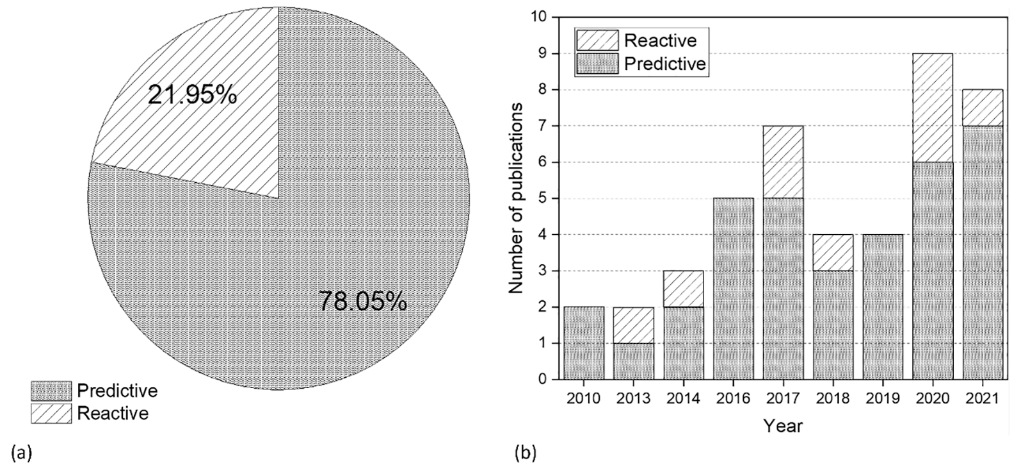

Fig. 5. (a) Study frequencies by predictive and reactive algorithm; (b) Yearly study frequencies by the predictive and reactive algorithm.

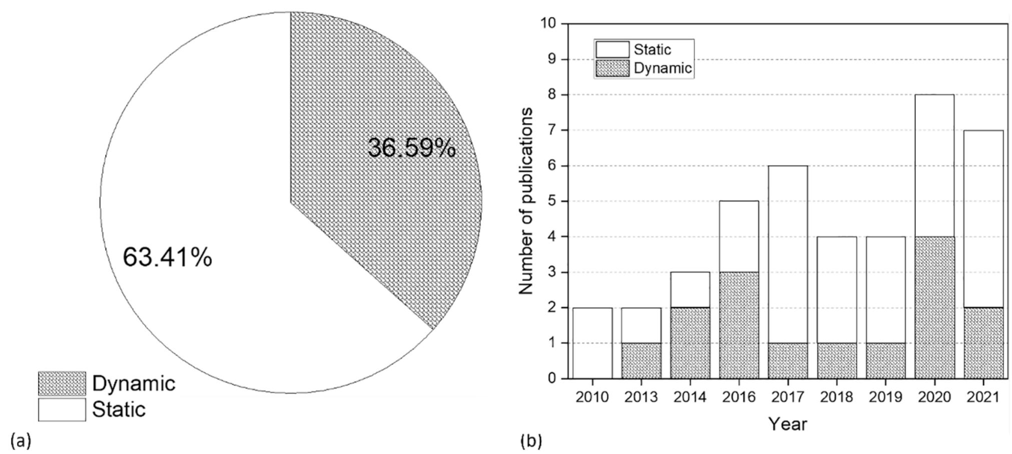

Fig. 6. (a) Study frequencies by static and dynamic algorithm; (b) Yearly study frequencies by static and dynamic algorithm.

Mishra et al., 2021, Utamima and Djunaidy, 2017, Cantarero et al., 2021, Shah et al., 2020, Sarraf and McGuire, 2018, El-Wakeel et al., 2018, He and Qin, 2017, Zhou et al., 2017, Hayes et al., 2020, Bura et al., 2019, Krumm and Horvitz, 2017, Takeno et al., 2016, Soni et al., 2019, Alpkoçak and Cetin, 2020, Liu et al., 2017, Levy et al., 2020, Puthige et al., 2021, Khanfor et al., 2020, Galbrun et al., 2016, Lozano Domínguez and Mateo Sanguino, 2021), among others. Besides geographical datasets, the static algorithm also used historical data for safety measurements. For example, the static algorithm-related studies in the crime risk category used historical crime records (see Fig. 7 for more examples), whereas the dynamic algorithms incorporate real-time data. Various real-time datasets are found in the literature- namely, the news websites (Mata et al., 2016, Kaur et al., 2021), the official report (Li et al., 2014, Hoseinzadeh et al., 2020, Li et al., 2016), various sensors and GPS data (Ito and Koji, 2020, El-Wakeel et al., 2018, Abdelrahman et al., 2019, Ouyang et al., 2014, Kusano and Inoue, 2013), and data from APIs (Santhanavanich et al., 2020, Cantarero et al., 2021, Shah et al., 2020, Abdelhamid et al., 2016, Liu et al., 2017).

3.4.3. *Centralized vs Decentralized algorithms*

Route-finding algorithms can be distinguished according to their objectives. In the decentralized algorithm, the decision-making is made by an individual user, and, therefore, the system maximizes the users' benefit (Schmitt and Jula, 2006, Khanjary and Hashemi, 2012). In a centralized system, however, the algorithm aims to optimize the benefit of all users (or society) (Schmitt and Jula, 2006, Khanjary and Hashemi, 2012). The safe route-finding literature is dominated by decentralized algorithms (all papers included in this review were using a decentralized algorithm).

3.5. *Publications after the review time*

While missing the most recent publication in review studies is inevitable, we updated our search with a focus on road safety to include the most recent literature. As a result, four publications were found (Huang et al., 2022, Sohrabi and Lord, 2022, Jiang et al., 2022) that meet our inclusion criteria.

Huang et al. (2022) proposed a conflict-based approach for travel route safety estimation. This approach measures safety in terms of traffic conflicts at the road segments and intersections. A dynamic, predictive algorithm was used in this study. The traffic conflicts are predicted using machine learning techniques, including road and intersection characteristics and dynamic traffic characteristics. The safe route is then found using a fuzzy logic method, calculating the risk level of taking a route with regards to the intersection and road segment conflict rates.

Sohrabi and Lord (2022) measured safety in terms of the theoretical probability of being involved in crashes, as a complement of no-crash (survival) probability. They assumed crash events are a result of a Poisson process, and the crash frequency at a road segment can be characterized by a negative binomial distribution. The distribution, which provides the probability of crashes, is estimated based on the road characteristics and aggregated traffic conditions. They also developed models for adverse and clear weather conditions, which make their algorithm a semi-static, predictive algorithm.

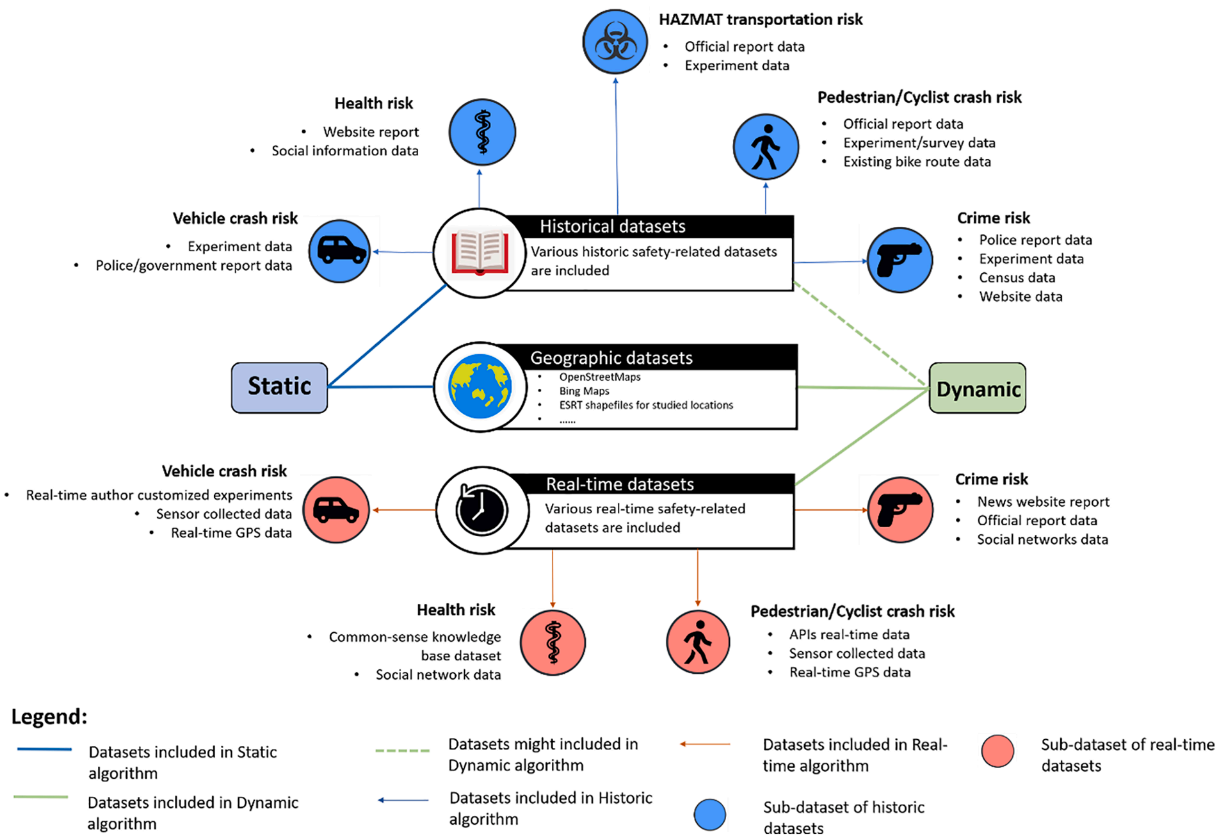

Fig. 7. Datasets used for static and dynamic algorithm.

Jiang et al. (2020) proposed a model that measures the safety of roads, integrating road segment-level crash rates and vehicle-level conflict probability. Road segment-level crash rates are estimated by developing the safety performance functions. Vehicle-level conflict probability is estimated using Neural Network, taking into account real-time data from driver behaviors, roadway characteristics, vehicle queuing status, distance-related measures, and speed-related measures. The safety of the road is further measured as "risk scores," integrating crash rates and conflict probability using fuzzy logic. A follow-up study by Jiang et al. (2022) complements the dynamic, predictive algorithm by proposing a heuristic algorithm to solve a real-time routing problem that minimizes travel time while maximizing the average risk score. The proposed algorithm is tested using real historical crash data and simulated driver-based data.

4. Discussion

4.1. Lessons learned from the literature

This review identified five areas in which safety was incorporated into routing problems. The literature about safe route-finding in road navigation can be traced back to 2014, and since then, not many studies have targeted this topic. An inconsistency was found in the measurement of safety in the literature. Data-driven analysis of frequency, rate, and risk of incidents was widely used in the literature to measure safety. Scoring on the basis of ordinal values was another approach to quantify safety in the literature. As the measurement of safety can be challenging, measurable indicator parameters (surrogate safety measurements) were also used as a proxy for safety. The Dijkstra algorithm, with some modification, was commonly used to find the shortest route, i.e., the route with minimum risk. Depending on whether or not the navigation system reacts to up-to-date information, route-finding algorithms can be divided into two types: static and dynamic. Most of the identified algorithms are static, mainly because of limitations in the availability of data for dynamic route-finding. Safe route-finding algorithms can be based on predicting the state of safety in the system (or route) or observed safety. Reactive route-finding is based solely on the current conditions, without insight into future conditions. Predictive routing systems, on the other hand, can give insight into the future condition of a road network, but at the cost of extensive prediction modeling. Safe route-finding algorithms can also be distinguished according to the definition of their ultimate goals: a centralized system aims to maximize benefits for the road network, while a decentralized system aims to optimize benefits for the individual user. Table 3 summarizes the types of route-finding algorithms for each safe route-finding system.

4.2. Safe route-finding in road navigation

Safe route-finding algorithms aim to inform users about the safety of alternative routes between the desired origin and destination. Road crashes are rare events subject to temporal instability (Mannering, 2018), which implies the limitations of solely relying on historical data for estimating the risk of crashes. Also, the risk of crashes was associated with roadway characteristics, weather conditions, user behavior, and traffic conditions (Petridou and Moustaki, 2000, Lord et al., 2021, Qiu

Table 3
Different types of route-finding algorithms for each safe route-finding system.

Definition	Dynamic/ static	Predictive/ reactive	Centralized/ decentralized
Vehicle Crash risk	Both	Both	Decentralized
Health risk	Both	Predictive	Decentralized
Cyclist/pedestrian crash risk	Both	Both	Decentralized
HAZMAT risk	Static	Predictive	Decentralized
Crime risk	Both	Both	Decentralized

and Nixon, 2008), which can change over time. As such, safe route-finding needs to account for the changes in determinants of crashes during the trip and provide insights into the future for both route-finding and detouring. Ideally, safe route-finding is designed as a dynamic, predictive algorithm. A dynamic, predictive algorithm needs to provide a robust prediction of the risk of crashes in real-time data.

Switching from reactive to predictive algorithms requires employing crash prediction models. Traditional crash prediction models are founded on the assumption that crash events follow a binary trial, and for a large number of vehicles the incidents can be modeled by the Poisson process (Lord et al., 2005). The distribution of crashes during a specific period of time (usually one or multiple years) was shown to draw from a negative binomial distribution, where the expected value of the distribution function represented the expected number of crashes at a specific road segment (Lord et al., 2005). These models take into account the aggregated environmental, behavioral, and traffic information for estimating the expected number of crashes (Washington et al., 2020), which limits their application for dynamic routing. Real-time crash prediction models (see (Hossain et al., 2019) for an overview of the models) have the potential to update in real-time and take into account the volatility of traffic. While the majority of these models aggregate the traffic information in small time intervals (Hossain et al., 2019), new models have been proposed for vehicle-level crash risk predictions (Basso et al., 2021). Vehicle-level models would be able to consider user-specific factors in route selection, namely, driving experience, driver background, and vehicle characteristics, that can elevate the reliability of risk estimations.

In the roadway safety literature, crashes are mainly used as a measurement of safety (Lord et al., 2021). Due to challenges in the availability and quality of crash databases, surrogate safety measures (e.g., time to collision and traffic conflicts) were also used as a proxy for road safety (Lord et al., 2021). Safety measurement based on scoring, however, is prone to subject bias. While a variety of safety measurements can be used to measure the safety of road segments, quantifying the safety of the route (usually consisting of several road segments) is required for identifying the safe route.

For safe route finding related works, it is important to develop a comprehensive database. Two major types of databases are required for incorporating safety in road navigation: 1) road network or road inventory database, and 2) database on operational measures (e.g., operating speed, travel time, historical crash or event information on the roadway segment). Table 4 lists the key data elements and potential sources for each of these data elements. Interested readers can consult Tarko et al. (2021) for a comprehensive list of emerging data sources for improving safety (Tarko et al., 2021). Roadway inventory data usually contains information of roadway features (e.g., segment length, roadbed width, median type, shoulder type, shoulder width). In many cases, the roadway features are provided in separate layers. Many state databases do not provide additional geometric data such as super elevation, curve radius, and posted speed limit. OpenStreetMap and other private data vendors (e.g., HERE) can used by researchers to acquire additional geometric data. For operation measures, researchers need to acquire data on two major metrics, travel time/traffic volume-related features, and recurrent/non-recurrent event-related features (e.g., road incidents). Fig. 8 summarizes the required databases for static and dynamic safe route-finding. Some of the potential open-source datasets can be collected from Departments of Transportation (DOTs), the Highway Performance Monitoring System (HPMS), the Highway Safety Information System (HSIS), the Roadway Inventory Database (RID) and the companion Naturalistic Driving Study (NDS) data (from the 2nd Strategic Highway Research Program or SHRP2), Traffic Monitoring Analysis Systems (TMAS), and National Performance Management Research Data Set (NPMRDS). Researchers can also purchase or acquire data from commercial private data vendors including HERE, INRIX, Wejo, and StreetLight. Some private data vendors (e.g., Wejo) also provide data from vehicle on-board devices. The data elements include trajectory, wiper usage, acceleration, deceleration, hard braking, sudden stoppage, and near collision. While some of these data sources can report real-time data (to support a dynamic algorithm), MapQuest[10] and Bing Map Traffic AI[11] can be used to acquire real-time traffic data. Crowdsourced databases such as Waze can be potential sources for real-time incidents. For safe routing algorithm design, it is necessary to acquire data from both public and private data sources. Table 4 lists some of the key data elements and related data sources.

Table 4
Example data sources for safe route-finding.

Data Elements	Data Source
Speed Measures	
Posted speed limit or travel time	State DOT, HERE, SHRP 2-RID
Avg. operating speed, percentile speed, & speed variance	State DOT, INRIX, INRIX XD, HERE, NPMRDS
Continuous 5-minute, 15-minute, hourly, daily, monthly & annual speed	
Vehicle trajectory data or waypoint data	INRIX, Wejo, StreetLight
Percent of vehicles exceeding speed limit	State DOT
Roadway Inventory Data	
Segment length	State DOT, HPMS, SHRP2-RID, GoogleEarth
Number of lanes	
Shoulder and lane width	
Horizontal and vertical alignment	
Median barrier	
Roadside fixed objects (barrier, guardrail, poles)	
Traffic control devices, pavement condition	
Weather Characteristics	
Continuous hourly, daily, monthly and annual precipitation & visibility data	NOAA, Road Weather Information System (RWIS)
Traffic Volume Measures	
AADT	State DOT, TMAS, HPMS, SHRP2-RID, StreetLight Data Inc.
Hourly traffic volume	TMAS, StreetLight
Crash Measures	
Crash time and date	State DOT, HSIS, SHRP2-RID
Crash location	
Crash type and severity	
Crash contributing factors (e.g., speeding)	
Lighting and weather conditions	
Real-Time Traffic Data for the U.S.	
1.70 million cases (2016–2019) [every 90 s]	MapQuest Traffic Application Programming Interface (API)
0.54 million cases (2016–2019) [every 90 s]	Bing Map Traffic API
Real-Time Incident Data	
Crowdsourced data	Waze

Commercialized route-finding systems are mainly designed to maximize benefits for the user (i.e., minimizing travel time), not for the road transport system. To support these systems, a safe route-finding algorithm needs to maximize safety at the user level.

4.3. Challenges and future directions

Based on the comprehensive literature review and the discussion in sections 4.1 and 4.2, this study proposes a research agenda for future research to address the gaps and requirements for developing safe route-finding algorithms.

[10] Source: https://www.mapquest.com/.
[11] https://www.bingmapsportal.com/.

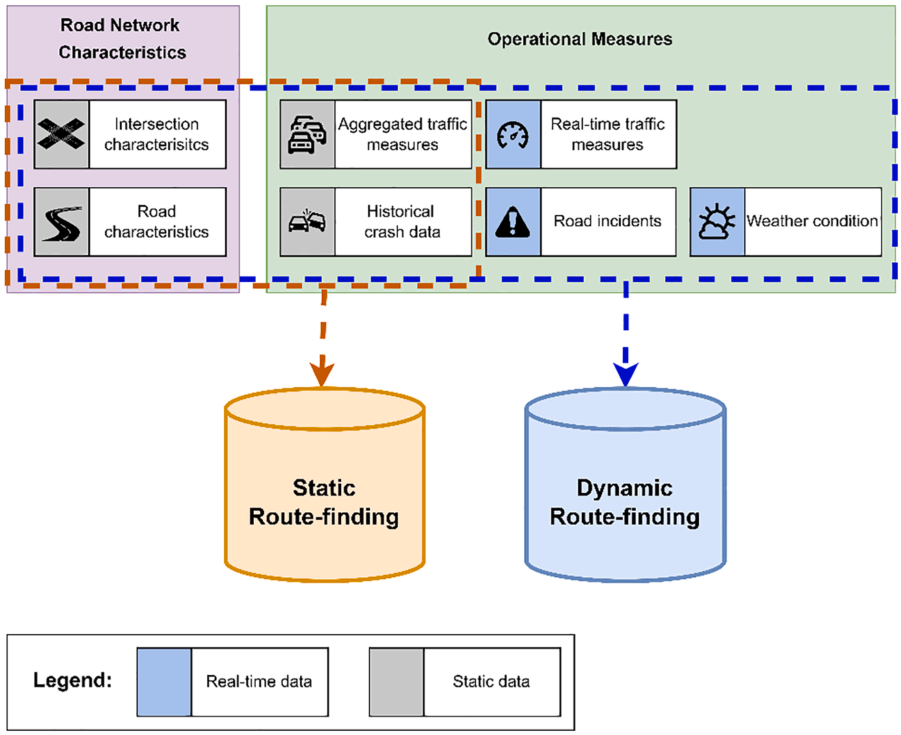

Fig. 8. Static and dynamic safe route-finding data requirements.

The level of complexity and reliability of route-finding varies according to the algorithm classifications mentioned above. For example, dynamic, predictive route finding is a more complex algorithm with a higher level of reliability compared to static route-finding, but to achieve reliable estimations of the risk of crashes and, consequently, the safest route, accurate prediction models are required to estimate the risk of crashes in real-time. Despite the advances in real-time crash prediction models, more research is required to ensure robust, reliable predictions. Also, the vehicle-level crash prediction models can elevate the reliability of safety measurements by including a higher level of granularity in risk estimations. Measurement of route safety and incorporating it into route-finding algorithms is another challenge in safe route-finding algorithms that requires further investigations.

For real-time routing, real-time information about traffic conditions, road incidents (e.g., closures due to flooding, crashes, and maintenance), and weather conditions are required. Such data (traffic condition and road closure) is not publicly available, which makes developing dynamic, predictive safe route-finding algorithms challenging. While collecting real-time information about traffic and road conditions can be costly, crowdsourced data can be considered an alternative data source for real-time data (Amin-Naseri et al., 2018, Lin and Li, 2020).

The trade-off between time and safety is critical. In the case the safest route is not consistent with the fastest route, the users face a dilemma about whether to choose the safest route or the fastest one. While the choice between safety and time is subjective to the driver's sensitivity, it is expected to affect other road users. Understanding the decision-making process of users (to choose between safety and travel time) would help with proactive plans (e.g., educational activities) to promote safety on roads (de Leur and Sayed, 2003).

Unlike route-finding based on travel time, a decentralized, safe route-finding algorithm can harm other users. Crashes usually involve more than one vehicle, and road crashes may cause road closure and traffic congestions that impose delays on other road users. Therefore, incorporating safety in route-finding and egoism decision-making of users can raise ethical concerns. Centralized safe-route-finding algorithms can address this concern; however, one can argue that the centralized system can force drivers to take safer routes, which can invade the liberty of users.

Table 5 summarizes the proposed research agenda.

5. Summary and conclusion

This study addresses the gaps in considering safety in road

Table 5
Proposed Research Agenda.

Problem	Research Topic
Accurate crash prediction models	The safe route-finding algorithm should be designed as a predictive algorithm to account for changes in the risk of being involved in crashes. Future research is required to improve the accuracy of prediction models.
Disaggregated crash prediction models for measuring safety	Developing vehicle-level crash prediction models by providing the users with modified information about their trips based on the user's driving style, historical record of crashes, potential weaknesses, etc.
Short duration crash prediction models	Developing short-duration (e.g., daily, hourly) crash prediction models to provide more real-time aspects of safety on the navigation tools.
Measurement of route safety	Introducing new methods to aggregate road segment and vehicle-level risks at the route level.
Collecting crash and traffic data in real-time to support dynamic, predictive route-finding	Investigate the potential of using crowdsourced data in safe route-finding algorithms
Trade-off between safety and time	Investigate the sensitivity of users to the risk of being involved in crashes and travel time
Centralized or decentralized navigation system	Exploring the potential safety impacts of two types of safe route-finding algorithms, centralized and decentralized, and the

navigation systems and reviews the existing knowledge around safe route-finding (even beyond road navigation). A scoping review methodology was implemented, and 41 studies were included in this review. Based on this comprehensive review, the gaps in the literature were identified, and an agenda for future research were proposed. Addressing the limitations in the availability of data, developing robust safety measurement methods, and addressing the potential challenges in increasing safety in navigation apps are highlighted as major needs for further investigations.

This review has certain limitations. Although safe route-finding has been studied in many domains, the literature about safe route-finding in the context of roadway safety is scarce. We tried to synthesize and map the safe route-finding literature beyond the roadway safety domain to identify transferable knowledge and accelerate incorporating safety in road navigation. The developed review protocol, however, needs to be revisited once more studies are available. A scoping review method was used in this study to map the existing knowledge about safe route-finding and identify the gaps and challenges in incorporating safety in road navigation. Future studies and systematic reviews are required to augment understanding of safe-route findings for different modes (pedestrian, bicyclist, vehicle, and public transport), particularly the measurement of safety and routing methodologies.

CRediT authorship contribution statement

Soheil Sohrabi: Conceptualization, Methodology, Investigation, Visualization, Writing – original draft, Writing – review & editing, Supervision. **Yanmo Weng:** Writing – original draft, Writing – review & editing. **Subasish Das:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing, Supervision. **Stephanie German Paal:** Validation, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

No data was used for the research described in the article.

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