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Navigating to safety: Necessity, requirements, and barriers to considering safety in route finding

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ABSTRACT

Automotive navigation systems are one of the driver assistance technologies with the primary objective of directing drivers to their desired destinations. Although recent versions of automotive navigation systems help users minimize their travel time, there are certain situations in which the shortest route is not necessarily the safest one. Navigating through local roads that carry higher risks of crashes—roads with poor geometric designs, drainage problems, lack of illumination, wildlife crossing danger, and interruptions in traffic flow—is an example of the unintended consequences of routing to ensure minimum travel time. This study is designed to examine the safety of the fastest routes suggested by navigation systems. Road network connecting five metropolitan areas in Texas, including more than 29,000 road segments, is studied. The results of comparing the safest and shortest route between pairs of origins and destinations showed that the shortest route can differ from the safest, where taking a route to decrease travel time by 8% was associated with a 23% higher risk of being involved in a crash. The findings indicate the safest route varies according to different weather conditions. To incorporate safety in route-finding, a centralized, predictive algorithm is introduced for static and dynamic safe route-finding that can complement the existing navigation systems. The requirements for implementing such a system are identified as: (1) availability of real-time traffic flow and incident data for dynamic route-finding systems, (2) more accurate crash prediction models, and (3) a methodology for dealing with the tradeoffs between travel time and safety to find the optimal route.

1. Introduction

Automotive navigation systems—also referred to as route guidance systems (RGSs)—are one of the driver assistance technologies and have been part of the intelligent transportation system (ITS) since the 1960 s (Auer et al., 2016). RGSs, which rely on the Global Positioning System (GPS), were initially introduced as in-vehicle technology—either built-in or nomadic devices—and are now widely used in the form of smartphone applications, commonly known as “apps.” The RGS application has evolved since its beginnings, from providing drivers with turn-by-turn route information to finding the shortest route between sets of origins and destinations (mainly the route with minimum travel time) (Schmitt and Jula, 2006). Thus, the benefit of using RGS is not limited to guiding drivers who are unfamiliar with their routes: it also helps to minimize travel times, alleviate traffic congestion, and reduce energy consumption and air pollutant emissions (Huang and Hu, 2018).

As would be expected from driver assistance systems, RGSs are shown to have the potential to improve traffic safety (Kulmala,

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2010, Green, 1997). Despite the numerous safety advantages of RGSs, mainly through the turn-by-turn guidance, it provides for drivers who are unfamiliar with routes, there are unintended negative consequences of using RGS that transportation engineers need to consider. The focus of the literature about the safety impacts of RGSs has been on the potential distractions that can hinder drivers' reaction times (Ziakopoulos et al., 2019, Knapper et al., 2016, Lacherez et al., 2019), riskier lane-changing behavior (Yun et al., 2017), and degradation in the performance of older drivers while using RGS (Stinchcombe et al., 2017). Nevertheless, the adverse safety impacts of RGSs go beyond the changes in drivers' behavior. Since RGSs are designed to guide users through the shortest path, there are certain situations that they guide users onto roads with safety issues. In urban areas, cut-through traffic, those that pass through local roads witha higher number of traffic interruptions and conflicts (Vorko-Jović et al., 2006), higher chances of exceeding speed limits (Vorko-Jović et al., 2006, Liu and Chen, 2009), and poorer geometric designs (Hauer, 1999) to minimize the traffic time, are more likely to be involed in crashes. In rural areas, navigating road users through the routes with lower functional classes (rural local and rural collectors)—which are associated with a higher risk of crashes because of poor geometric designs (e.g., median presence and shoulder width) (Hauer, 1999), drainage problems (Omranian et al., 2018), lack of illumination (Jackett and Frith, 2013), wildlife crossings (Hedlund et al., 2004), and higher levels of traffic disruption—is another example of RGS misguidance.

To the best of the authors' knowledge, no study has focused on examining the safety of the suggested shortest path by RGSs. Although safety consideration in route-finding can be found in the literature of hazardous material transportation (Faghih-Roohi et al., 2016; List, 1991), public safety (Galbrun et al., 2016, Pang et al., 2019, de Souza et al., 2019), and pedestrian route finding (Pang et al., 2019), the literature about RGS safety is limited. The objective of this study is twofold: (1) we examine the safety of the shortest route suggested by road navigation apps in a rural area to evaluate the necessity of considering safety in RGSs, and (2) we propose a system architecture that incorporates safety in RGS, as a direct add-on to the shortest route-finding algorithms, and identify the requirements for such a system.

To examine the safety of shortest routes suggested by navigation apps (routes that minimize the travel time for users), we determine the safety of shortest routes between origins and destinations and their alternatives using statistical models. This study contributes to previous attempts to assess the network-level safety analysis (Maher et al., 1993, Lord, 2002, Krumm and Horvitz, 2017) by proposing a new methodology for quantifying route safety. To this end, we suggest estimating the probability of being involved in a crash at a given route, consisting of thousands of road segments, as the complementary probabilities of the union of survival (observing no-crashes) at the road segments. The road segment survival probability is obtained from theoretical probability functions that can be estimated using ubiquitous crash prediction models as a function of weather conditions, traffic characteristics, and road geometry and characteristics (Lord et al., 2021). Finally, we compare the safety of the alternative routes for each pair of origin and destination. This study focuses on the rural road network between five cities. We chose rural roads with (1) greater safety concerns given higher fatalities per vehicle miles traveled (VMT) compared to urban areas (National Highway Transportation Safety Administration, 2017), (2) higher rates of drivers who are unfamiliar with the routes, and a concomitant bolder role of RGS, and (3) less variation in traffic condition, i.e., prevalence of free-flow traffic condition. The second part of the study contributes to the first part by proposing a route-finding architecture for both static and dynamic RGSs that seek the route with the lowest probability of crashes. On the basis of an overview of RGS algorithms and the proposed route-finding architecture, the requirements of and barriers to developing RGS based on safety (S-RGS) are further discussed. The results of this study are aimed at attracting the attention of those developing road navigation systems as well as researchers and practitioners involved in traffic safety. The proposed system architecture could also stimulate dialogue about vehicle routing in smart cities (Nha et al., 2012, Taha, 2017) and the routing of connected and autonomous vehicles (Olia et al., 2016, Houshmand et al., 2019).

2. Shortest route vs. safest route

2.1. Study setting

This study focuses on road network connecting five metropolitan areas in Texas, US—Dallas-Fort Worth (DFW), Waco, Austin, Houston, and Bryan-College Station (BCS)—with a population higher than 100,000. The rationale behind selecting this area was threefold. First, a spectrum of road functional classes (minor arterials to fully controlled-access arterials or interstates) can be found in the area. Second, a wide range of variety in travel times between origins and destinations (1–4 h) is covered that helps with the generalization of the results. Third, the studied road network passes through the areas with low population density and less urbanized areas, and therefore, with lower unobservable contributing factors to the risk of crashes, such as land-use impacts. The studied region and the road network are shown in Fig. 1.

Our analysis of road safety and its comparison with the shortest route can be explained in four steps. In Step I, first, we collected and combined the required datasets, including road and traffic characteristics, weather conditions, and historical crash data. Then, we divided the roads into homogeneous road segments. In Step II, crash-frequency prediction models were developed to estimate the expected value of crashes as the road segments. In the next step, the risk of crashes was calculated for each road segment and accumulated for each route. Finally, the safest and shortest routes were compared in Step IV. Fig. 2 shows the study framework and the steps mentioned above. In the subsequent sections, each step is discussed in terms of data sources, assumptions, and methodologies.

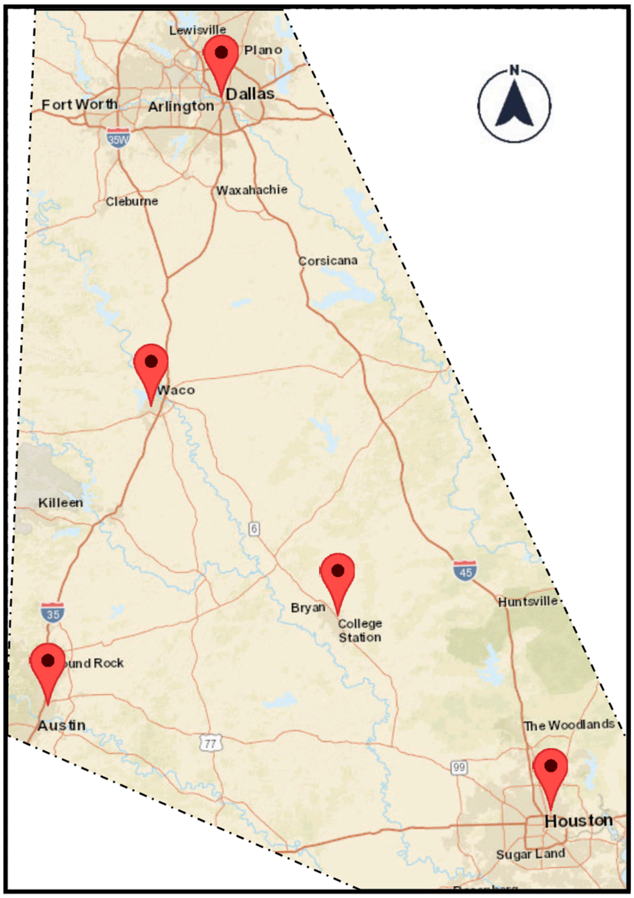


Fig. 1. Studied area.

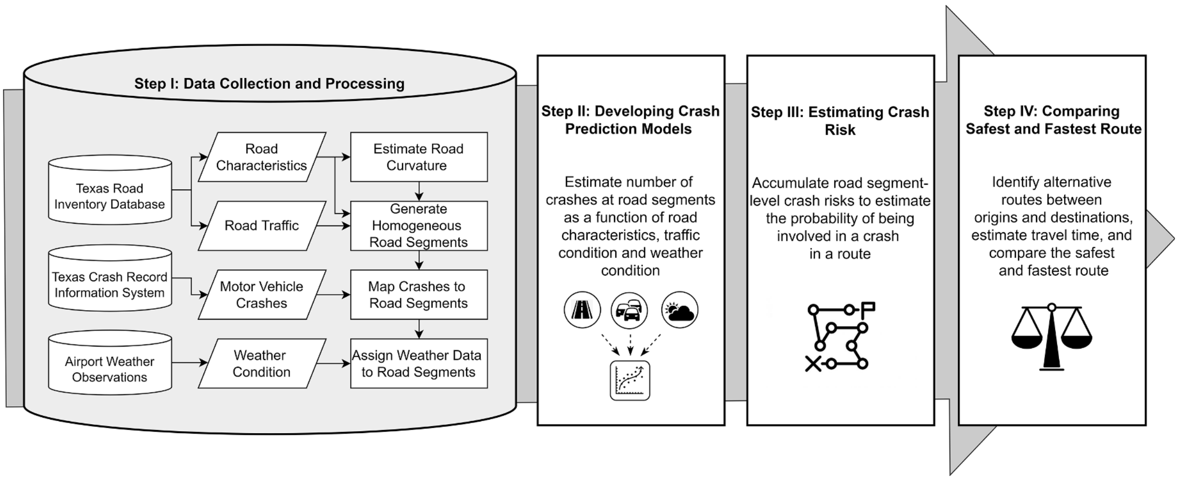


Fig. 2. Study framework.

2.2. Step I: Collecting data

2.2.1. Road and traffic data

The roadway data were extracted from the Texas Department of Transportation (TxDOT) roadway inventory system[1]. The roadway inventory data contain roadway characteristics, including road geometry design characteristics, road cross-section characteristics (e.g., number of lanes, lane width, shoulder width, and median), road structures, illumination, road functional classifications and averaged daily traffic (ADT). The yearly VMT passing through a road segment was further estimated as a product of road segment length in miles and ADT. The studied road network consists of both urban and rural road segments with four rural functional classes including interstate, freeway/expressway, principal arterial and minor arterial, and three urban functional classes including interstate, freeway/expressway, and principal arterial. Fig. 3 shows the studied roads' functional classification and their length in the dataset. We collected the roadway data for the year 2017.

2.2.2. Road segmentation

Since the basis of our analysis is at the road segment level, we needed to define homogeneous road segments in terms of geometry, cross-section characteristics, and illumination. Given the limitations in the existing road characteristics data, we used the ROad Curvature Analyst (ROCA) tool proposed by Bíl et al. (2018) for extracting the road curvatures and their characteristics. This geographical information system (GIS) -based tool identifies the horizontal curves and tangents using machine learning techniques and computes the horizontal curve radii and the azimuth of tangents. Next, we divided roads into segments with homogeneous characteristics, including road alignment, number of lanes, median type and width, shoulders type and width, lighting, and lane width.

2.2.3. Weather data

The weather data for the years 2015 to 2017, including rainfall, hail, and snow events, were collected from the Iowa Environment Mesonet[2] , which archives the automated airport weather observations. We identified five weather stations located in major airports within the studied area. The data is collected from these airports and is assigned to the closest road segments, based on the Euclidean distance.

We classified the weather conditions into two groups, adverse weather conditions, and clear weather conditions. The adverse weather condition represents fog, hail, rain, and snow events, while the clear weather condition group includes clear and cloudy weather with no precipitation. For each road segment, we calculated the total number of hours with adverse and clear weather conditions.

2.2.4. Crash data

The crash data was collected from TxDOT Crash Report Information System (aka CRIS)[3]. We collected data for 2015, 2016, and 2017 for the studied region. Given the fact that crashes are rare events and vary from year to year, crash data from three years are used for our analysis to consider the fluctuations in the number of crashes in years. The crash data includes the time-of-crash, exact coordinates of the crash scene, and whether the crashes happened at, or are related to, an intersection. We assumed the roadway characteristics did not change from 2015 to 2017, and so crashes that occurred in 2015 and 2016 can be attributable to road characteristics in 2017.

2.2.5. Final dataset

We spatially joint crashed with the road segments resulting from the road segmentation process and combined it with the weather data. The dataset consists of yearly crash frequencies for 2015 to 2017, road segment alignment and cross-section characteristics, and ADT. We approximated the traffic volume in various weather conditions using the number of hours of adverse and clear weather conditions in a year, assuming a uniform distribution of hourly traffic flow in a day. After cleaning the dataset for missing values, a total number of 29,382 road segments were included in the dataset. A summary statistics and distribution of continuous and categorical data are reported in Tables 1 and 2, respectively.

Two separated datasets, for adverse and clear weather conditions, were built. Explanatory analyses of crash data from 2015 to 2017 showed the role of adverse weather conditions in increasing the rate of crashes (Fig. 4). In the studied area, the average yearly rate of crashes in terms of the number of crashes per 1-million VMT in adverse weather conditions was observed 2.7 times higher than the rate of crashes in clear weather. About 53% of crashes were related to intersections, which implies a higher risk of crash occurrence at the intersection, with more traffic conflicts. The roadway curvature is detected as a potential hotspot for crashes where the rate of crashes is higher in road curves. A more significant impact of road curvature on crash rates was observed in the adverse weather condition with a 30% higher rate of crashes at road segments located in curves compared to others.

2.3. Step II: Crash prediction models

Crashes are *rare events* and were associated with several factors such as driver characteristics, road, traffic, and weather conditions,

[1] Retrieved from: https://www.txdot.gov/inside-txdot/division/transportation-planning/roadway-inventory.html

[2] Retrieved from: https://mesonet.agron.iastate.edu/request/download.phtml?network=TX_ASOS

[3] Retrieved from: https://cris.dot.state.tx.us/public/Purchase/app/home/welcome

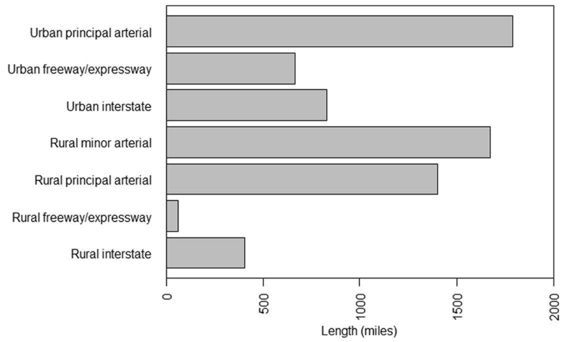


Fig. 3. Road segments functional classifications.

and vehicle characteristics (Lord et al., 2005). Given that, we chose to evaluate roadway safety using the expected value of crashes rather than the historical crash frequency. Lord et al. (2005) showed that the crashes are independent events with an unequal probability of occurrence, which can be approximated with the Negative Binomial (NB) distribution. The NB distribution can handle the overdispersion, which is ubiquitous in crash data. NB regression is employed to estimate the expected value of crashes (Lord and Mannering, 2010, Lord and Geedipally, 2018). The significant differences in crash rates in adverse and clear weather conditions urged us to develop two separate models for each weather condition.

The goodness-of-fit (GOF) of the models was compared using the log-likelihood of the fitted model and the Akaike information criterion (AIC). The AIC was estimated using Eq. (1):

$$AIC = -2(log - likelihood) + 2K \tag{1}$$

where K is the number of model parameters.

We also evaluated the prediction power of the model in terms of Mean Absolute Error (MAE) and Root Square Mean Errors (RSME) (Eqs. (2) and (3)):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i| \tag{2}$$

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \tag{3}$$

where n, y_i and $\widehat{y}_i$ represent the sample size, observed number of crashes, and predicted number of crashes at road segment i, respectively.

Table 1
Summary statistics of continuous variables.

Variable	Mean	SD	Minimum	Maximum
Curve radius (feet)	496.8	246.8	43.3	2003.9
Median width (feet)	19.2	37.2	0.0	500.0
ADT (vehicle/day)	34021.2	44733.0	360.0	329766.0
Truck Percentage	10.6	8.4	0.7	63.5
Lane width (feet)	12.3	1.4	8.0	25.0
# of traffic flow interruptions (ramps, intersections, entrance and exists)	0.1	0.5	0.0	6.0
Averaged daily VMT (veh.mi/day)	3034.9	5525.3	3.5	80258.0
Averaged daily VMT in adverse weather (veh.mi/day)	130.5	247.8	0.1	4028.2
Averaged daily VMT in clear weather (veh.mi/day)	2904.4	5279.7	3.4	76229.8
Segment length (mile)	0.1	0.1	0.0	0.7
# of crashes in 2017 (adverse weather)	0.3	1.0	0.0	32.0
# of crashes in 2016 (adverse weather)	0.3	1.1	0.0	26.0
# of crashes in 2015 (adverse weather)	0.3	1.0	0.0	18.0
# of crashes in 2017 (clear weather)	2.2	5.6	0.0	105.0
# of crashes in 2016 (clear weather)	2.3	5.7	0.0	95.0
# of crashes in 2015 (clear weather)	1.9	4.6	0.0	64.0

Table 2
Distribution of the categorical variables.

Variable	Level	Frequency	Percentage
Curve flag	**Yes**	23572	80.23
	No	5810	19.77
Number of lanes	**2**	9307	31.68
	3	212	0.72
	4	12907	43.93
	5	338	1.15
	6	4809	16.37
	7	124	0.42
	8	1215	4.14
	9	75	0.26
	10	335	1.14
	11	21	0.07
	12	36	0.12
	13	3	0.01
Median flag	**No**	15127	51.48
	Yes	14255	48.52
Inner side paved shoulder flag	**No**	7004	23.84
	Yes	22378	76.16
Outer side paved shoulder flag	**No**	5548	18.88
	Yes	23834	81.12
Speed limit	**20-35**	1359	4.63
	36-50	6012	20.46
	51-60	11321	38.53
	61-70	7808	26.57
	71-85	2882	9.81

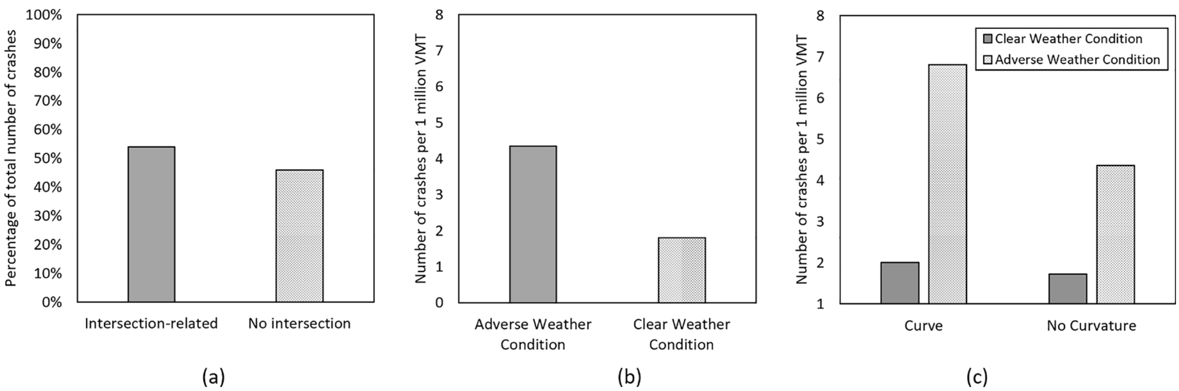


Fig. 4. Explanatory analysis of the data.

2.4. Step III: Crash risk estimation

In this study, we estimated the yearly risk of crashes using the theoretical probability of the complement of observing zero crashes, i.e., survival probability. As opposed to experimental probability, which can be estimated as a ratio of the expected number of crashes and VMT (Lord, 2002), we used the theoretical probability of crashes given that this analysis is based on the data from a limited time (three years). Although theoretical and experimental probabilities can be inconsistent for three years, it is expected that the experimental probability converges to the theoretical probability in a longer period of time. Since we assumed that the crash data could be drawn from NB distribution, the theoretical probability (hereafter, probability) of survival in a year at the road segment i can be calculated by the NB probability density function (Eq. (4)).

$$P(y = y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}}\left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i} \tag{4}$$

where μ and α are the mean (i.e., expected value) and the dispersion parameter, respectively. In the NB regression, the expected value of y at the road segment i (μ_i) is determined by a set of k regressors (x):

$$\mu_i = VMT_i \times \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) \tag{5}$$

Using the NB regression estimates and Eqs. (4) and (5), the probability of observing zero crashes in a year can be estimated for road segment *i*. For the sake of further clarification, three arbitrary NB cumulative distribution functions (CDF) are demonstrated in Fig. 5. The probability of observing zero crashes in a year at road segment *i* where the expected value and the dispersion parameter have been estimated as 3.0 and 1.0, respectively, is equal to 0.66.

The yearly probability of survival in a route can be further estimated by multiplying the survival probability of each road segment. The survival probability at *n* road segments of route *k* can be determined using Eq. (6):

$$S_k = S_{k,1} \bigcap S_{k,2} \bigcap \cdots \bigcap S_{k,n} = \prod_1^n S_{k,i} \tag{6}$$

Respectively, the yearly probability of observing at least one crash in a route can be estimated as the complement of the survival probability, $P(atleastonecrashataroadsegment) = 1 - S_k$. Given the small values of yearly survival probability in a route and to have a more tangible interpretation of the results, we converted the yearly survival probability at a road segment to daily probabilities assuming the equal daily probability of crashes across a year. This assumption is in agreement with the common usage of ADT in the crash frequency models, assuming a uniform distribution of yearly traffic across days.

2.5. Step IV: Comparing the shortest and safest route

We identified alternative routes between pairs of origin and destination considering two criteria. First, we included routes with up to 20% higher travel time than the shortest route between origins and destinations in our analysis. The travel time is estimated for free-flow traffic conditions. Second, the routes consisting of the road functional classification higher than arterials, interstate, freeway/expressways, and arterials are selected. ArcGIS's network analyst tool was used to find alternative routes (Esri, 2020). The classic Dijkstra's algorithm solves a shortest-path problem (Esri, 2021). The alternative routes are schematically shown in Fig. 6. In this step of the analysis, for each pair of origin and destination, we compared the travel time and the daily probability of crashes in the route alternatives.

2.6. Crash prediction model estimation results

The dataset was divided into two subsets, testing and training datasets. The training dataset used for developing models and the models' prediction power were examined using the testing dataset. The models were developed to predict the number of crashes in 2017 at the road segment level. The *MASS R package* was used for model estimation (Venables and Ripley, 2013).

The estimated models for adverse weather and clear weather conditions are reported in Table 3. All of the model coefficients were significant, with a 95% confidence interval. As discussed before, the length of the road segment and the ADT were considered as exposure variables. We included the average of the observed number of crashes in the previous two years as an independent variable in the model. This variable can account for unobserved factors that may affect the risk of crashes. A higher number of crashes is expected in adverse weather conditions on urban roads. For an additional traffic interruption (ramp, intersection, exist, and entrance) in the road segment, 22%, and 14% more crashes are expected in adverse weather conditions and clear weather conditions, respectively. The existence of the median and paved outer shoulders will reduce the likelihood of crashes in clear weather conditions. Road curvature is associated with a higher number of crashes.

The GOF of the models indicates that the model for adverse weather conditions is a better fit to the observed number of crashes in 2017 compared to the model for clear weather conditions. For evaluating the prediction power of the model, a random number was drawn from the NB distribution with the estimated expected value and dispersion for each road segment. The MAE of the models for adverse and clear weather conditions is estimated at 0.739 and 5.899, respectively. A closer look at the distribution of the absolute prediction errors indicated that the likelihood of predicting the number of crashes with two marginal errors at the road segment level is equal to 94% for the adverse weather model and 73% for the clear weather model (Fig. 7).

2.7. Comparison between the shortest and the safest route

We compared the cumulative risk of crashes (as the estimation methodology is explained in section 2.4) and the travel time in the free-flow condition in Table 4. The results unveiled inconsistency in the shortest and safest routes between origins and destinations. Taking the shortest route instead of the safest route between DFW and BCS will reduce the travel time by 8%; however, the daily probability of crashes in adverse weather conditions will be increased by 23% compared to the safest route. Results indicate that the safest routes between a pair of origin and destination can vary in different weather conditions. In clear weather conditions, taking the shortest route between DFW and BCS will result in an 8% decrease in travel time and a 20% increase in crash risk. Taking a route

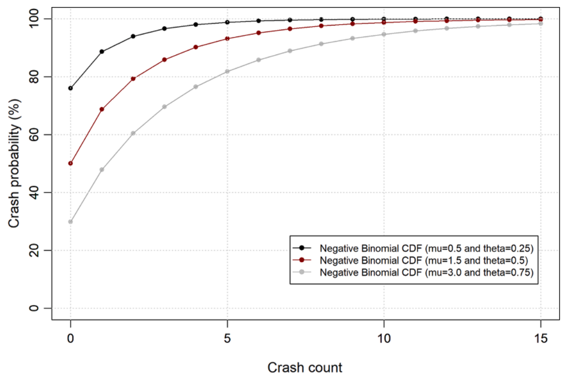


Fig. 5. Demonstration of NB CDFs for crash probability estimation.

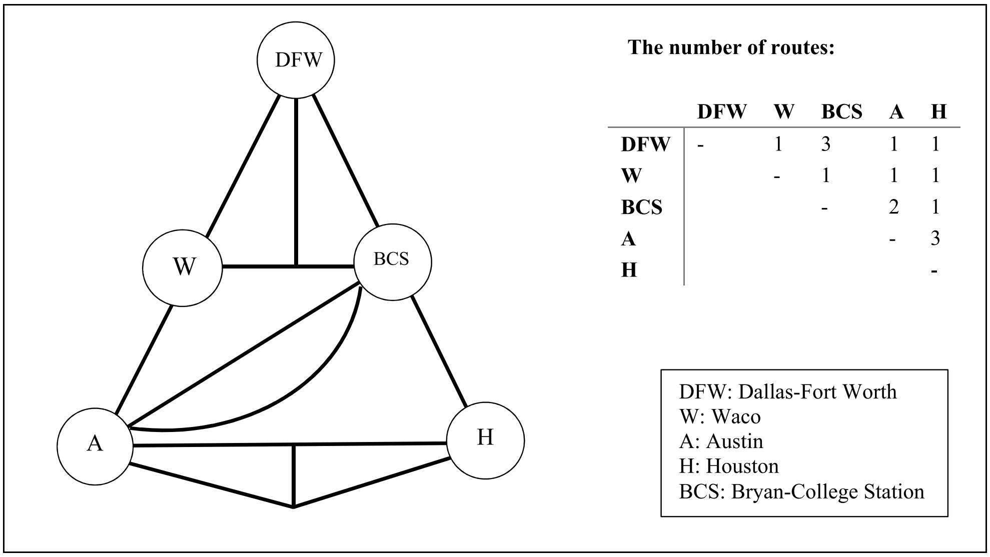
between Austin and BCS with a 1% lower travel time will result in a 6% higher risk of crashes in clear weather conditions. In contrast, the safest route is the same as the shortest route between Austin and BCS in adverse weather conditions. Our analysis suggests that taking the longest route between Austin and Houston with an 11% higher travel time will result in a 1% decrease in the daily probability of crashes.

3. S-RGS route finding

The result of the comparison between the shortest and safest routes between five Texas metropolitan areas shed the light on the need for considering traffic safety in RGS. In this section, we briefly discuss the variation of RGS algorithms, and then propose a route-finding architecture for S-RGS that seeks the safest route. Finally, we highlight the barriers and requirements for developing an S-RGS.

3.1. RGS algorithm classification

Depending on whether or not the RGS reacts to up-to-date information about road and traffic conditions, 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



	DFW	W	BCS	A	H
DFW	-	1	3	1	1
W		-	1	1	1
BCS			-	2	1
A				-	3
H					-

Fig. 6. Schematic demonstration of routes between origins and destination.

Table 3
Estimated models.

Variables	Estimated Model					
	Adverse weather condition			**Clear weather condition**		
	Coefficient	**SE**	**z value**	**Coefficient**	**SE**	**z value**
Constant	−3.802	0.037	−102.345*	−2.448	0.017	−144.708*
log(averaged number of crashes in previous two years + 1)	1.411	0.017	82.397*	1.090	0.005	222.214*
Urban roads (1 if yes, 0 otherwise)	0.439	0.035	12.610*	–	–	–
# of traffic flow interruptions in the segment	0.222	0.017	13.192*	0.139	0.009	15.768*
Paved outside shoulder (1 if the outside shoulder is paved, 0 otherwise)	–	–	–	−0.065	0.016	−3.950*
1/Radius of the curves	1.219	0.265	4.600*	0.499	0.154	3.234*
NB Dispersion parameter	0.455	0.114	3.994*	0.229	0.142	1.617**
Goodness of fit						
2*loglikelihood	−25,421.112			−62,211.218		
AIC	25,833			62,223		
Prediction power						
MAE	0.739			5.899		
RSME	3.157			44.542		

* significant with a 95% confidence interval.
** significant with a 90% confidence interval.

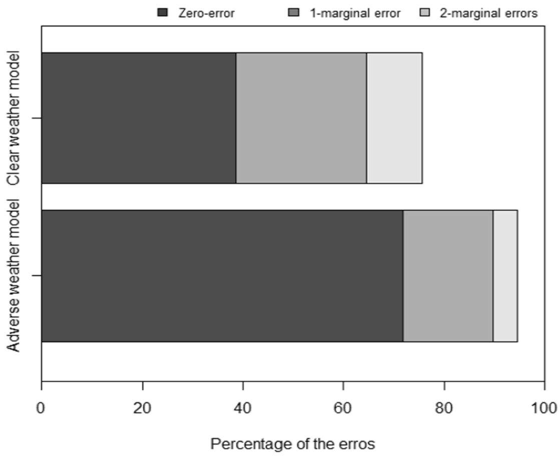


Fig. 7. Distribution of the prediction errors.

Table 4
Comparing travel time and cumulative risk of crashes.

Origin-destination	Routes	Length (mile)	Travel time (minute)	Deviation from the shortest route	Adverse weather condition		Clear weather condition	
					Daily risk of crashes (%)	**Deviation from the safest route** (%)	**Daily risk of crashes** (%)	**Deviation from the safest route** (%)
DFW- Bryan	DB1	166	160	0%	71%	20%	54%	23%
	DB2	171	165	3%	73%	24%	53%	20%
	DB3	175	172	8%	59%	0%	44%	0%
BCS- Austin	BA1	107	112	0%	79%	0%	64%	6%
	BA2	108	113	1%	81%	3%	60%	0%
Houston- Austin	HA1	162	154	0%	57%	0%	41%	1%
	HA2	165	157	2%	61%	6%	41%	4%
	HA3	171	171	11%	59%	4%	40%	0%

Hashemi, 2012). Specifically, dynamic RGS takes into account real-time data on traffic, road closures, and incidents. In addition, RGSs can be classified according to the reactive or predictive nature of the algorithm (Schmitt and Jula, 2006). Reactive route guidance is solely based on the current conditions of the travel network, without insight into future conditions; predictive routing systems, on the other hand, are based on anticipated road conditions resulting from an iterative prediction algorithm. RGSs are also distinguished according to the definition of their ultimate goal: a centralized system aims to maximize benefits for the road network, while a decentralized system aims to optimize benefits for the individual user (Schmitt and Jula, 2006, Khanjary and Hashemi, 2012).

The level of complexity and reliability of RGSs varies according to the algorithm classifications mentioned above. For example, dynamic route finding is a more complex algorithm with a higher level of reliability compared to static route finding. Predictive RGS can give insight into the future condition of a road network and provide users with more reliable guidance, but with the cost of extensive modeling. With regard to commercialized road navigation systems, these are mainly designed as a decentralized algorithm that maximizes benefits for the user (i.e., minimizing travel time), not for the road transport system.

In the context of route-finding based on safety, S-RGSs can be designed as static or dynamic systems. Since the goal of finding the safest route is to prevent crashes, the S-RGS needs to predict the risk of crashes in the future (until the user makes it to the desired destination), and so a reactive algorithm would not be effective. Also, guiding users to a road that carries a higher risk of crashes in order to prevent more crashes would be morally unjustifiable. Therefore, the S-RGS needs to perform as a decentralized system to avoid potential ethical controversy.

3.2. The safest route-finding architecture

Fig. 8 shows the proposed static and dynamic S-RGS architecture. First, once the system receives the trip information—i.e., the origin and destination of the trip in a given time of day—the algorithm identifies the route alternatives utilizing road network data and possible incidents-e.g., road or lane closures due to flooding, and accident(s).

Second, for the sake of crash risk predictions, the road network needs to be divided into homogeneous road segments with similar road characteristics, including road curvature, shoulder type and width, median type and width, pavement, traffic disruption (entrance, exit, and intersection), functional classification, number of lanes, and lane width. Similarly, intersections and their characteristics (number of approaches, geometry design, and control) are identified. In the dynamic system, the information regarding the illumination condition, road closure, and road construction should be implemented in route identification and road segmentation. Third, historical crash data and traffic information are assigned to the road segments of each route and are stored in the system as the crash risk prediction database. For the dynamic S-RGS, real-time traffic data, such as traffic flow and speed, need to be collected in addition to information about weather conditions (e.g., precipitation, wind speed, and visibility), time of day (peak/off-peak), lighting, and potential work construction at the time of the trip.

Fourth, the risk of crashes at the road segments and intersections should be predicted and then accumulated for each route. For the static S-RGS, the risk of crashes can be estimated using types of crash prediction models (an overview of crash prediction models can be found in Lord and Mannering, 2010; Washington et al., 2020; Lord et al., 2021). For estimating the risk of crashes in a dynamic RGS, real-time crash prediction models (RTCPM) need to be employed to predict the risk of crashes in the short term (see (Shi and Abdel-Aty, 2015, Hossain et al., 2019, Li et al., 2020) for more details about RTCPM).

Fifth, the route with the lower accumulated risk of crashes will be reported as the safest route. In the dynamic system, this process needs to be iterated in real-time and inform the user about the potential alternative safest route.

3.3. Requirement for and barriers to implementing S-RGS

While S-RGSs have promising safety impacts, their implementation is heavily dependent on the availability of data, crash risk prediction precision, and the optimum pathfinding algorithm. The required data for a static S-RGS are limited to road network data—road and intersection characteristics, averaged traffic flow, and historical crashes—that are expected to be available to local or federal government agencies responsible for road transportation. In contrast to static S-RGS, a dynamic S-RGS is developed based on real-time data, including real-time incidents, road construction, illumination, weather condition, and traffic flow characteristics, of which incident and traffic data are more challenging to be collected than the others. Collecting traffic flow and incident data requires expensive equipment (e.g., loop detectors, cameras); however, approximations from crowd-sourced data can be an alternative. Google Maps and Waze are two examples of the commonly used dynamic RGSs (in the form of smartphone apps) that are benefiting from the data collected from users.

S-RGSs are predictive algorithms, and crash risk predictions play a significant role in the accuracy of the algorithm. While the crash risk prediction literature has been usually used for identifying the factors affecting the risk of crashes (from an econometrics point of view), in the context of S-RGS, the prediction power of models needs to be investigated. Meaning et al. (2020) discussed the superior performance of the data-driven methods in predicting crashes. Also, recent applications of machine learning algorithms in traffic safety indicated their potential to predict crash risk with higher accuracy (for real-time crash prediction, see (Theofilatos et al., 2019); for static crash prediction, see (Dong et al., 2018)).

Given the fact that crashes can affect not only those directly involved but also other road users, leaving the choice between safety and time to the users may result in unethical decisions and unfair consequences. For example, drivers with a lower sensitivity to safety may take the route with a higher risk of crashes in order to reduce their travel time. In the case of being involved in a crash, all road users will be affected by this decision. Therefore, the tradeoff between safety and travel time needs to be addressed in the S-RGS algorithm. The recent attempt of Carmody and Sowers (2019) to redefine the routing problem as a bi-objective optimization problem is a starting point for future research in order to address this barrier to S-RGS deployment.

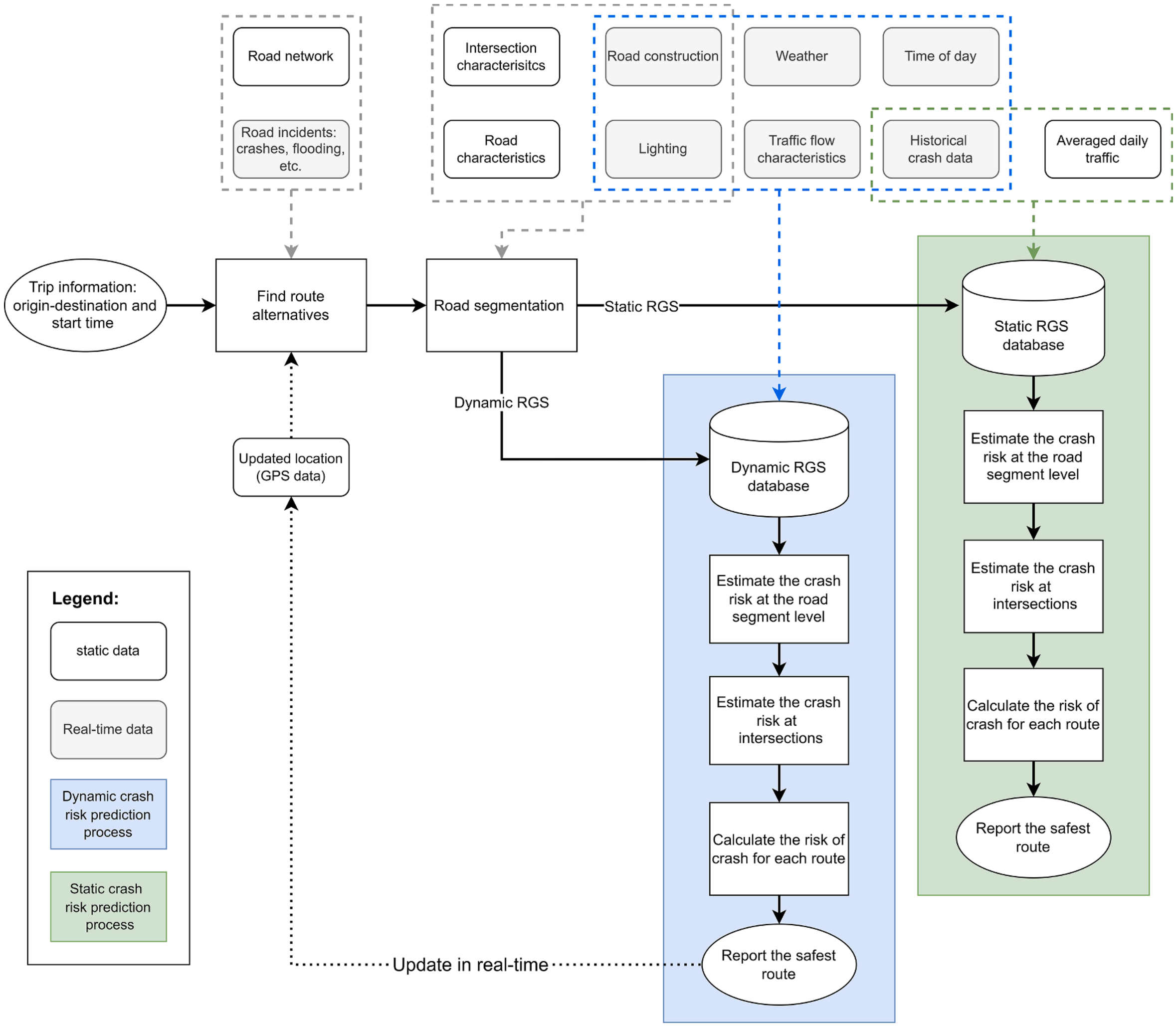


Fig. 8. A scheme of safest route-finding architecture.

4. Discussion

4.1. Key findings

The comparison between the shortest and safest routes between five metropolitan areas in Texas revealed that commonly used road navigation apps can misguide users toward using a road that carries a higher risk of crashes. Results of the designed case study showed that reducing travel time by 8% can result in a 23% higher risk of being involved in crashes. Our analysis also suggests that the safest route between a pair of origin and destination points can vary depending on weather conditions. This study manifests the necessity of considering safety in RGSs.

A system architecture is proposed for the safest route finding of S-RGSs. We discussed ethical controversies in centralized S-RGSs and concluded that the safest route finding should be designed as a decentralized system. Given that the S-RGS aims to prevent crashes, predictive algorithms are required to find the safest route. S-RGSs can perform as static or dynamic systems; while static systems are less complex than dynamic ones, this comes at the cost of greater vulnerability to temporal changes, including traffic flow fluctuations, illumination, weather conditions, work zones, and incidents. According to the proposed architecture, the requirements of deploying S-RGSs are (1) real-time traffic flow and incident information for dynamic S-RGS, (2) accurate crash prediction models, and (3) acknowledging the tradeoff between travel time and safety in order to find the optimal route.

4.2. Strengths and limitations

This study revealed one of the shortcomings of existing road navigation apps by indicating the inconsistency between the shortest and safest routes. In this regard, for the first time, we compared the shortest and safest routes between a set of origins and destinations after proposing a new method for estimating the probability of crashes. Publicly available data were used for this analysis. We proposed a system architecture that enables drivers to find the safest route. The proposed static safest route-finding architecture was designed to use publicly available datasets, and therefore to be simple to implement in route advisor systems (e.g., RouteWise[4]).

Given the limitations in the availability of traffic data in a rural area, we did not examine the safety of the route in real-time. The extensive literature about incorporating temporal changes in traffic on road safety (Shi and Abdel-Aty, 2015, Peng et al., 2018, Hossain et al., 2019) can be used for real-time crash probability predictions. For more accurate results, travel time and risk of crashes need to be estimated in real-time in dynamic routing and for different times of the day in static routing. Another limitation of this work is estimating the travel time of the routes assuming free-flow conditions in a route. Although this assumption can be close to reality in rural roads, and for static route safety analysis, this assumption needs to be revisited in future studies on urban roads and dynamic routing problems. The road segments represent both directions in this study, as do the historical crash data. Therefore, the estimated risks were attributable to both directions of the road. We did not have access to the detailed characteristics of the intersection and, consequently, did not develop separate crash prediction models for intersections. Instead, we considered traffic flow interruptions as a surrogate measurement of the intersections' impacts on safety in the crash prediction models. We did not distinguish the crashes based on their severity. As discussed by Lord and Mannering (2010), we assumed the probability of crashes at road segments along a route are independent, which means that Eq. (6) can be used to estimate the probability of survival. It is assumed that the goal of S-RGS should be minimizing the number of crashes rather than the severity of crashes, given the significant uncertainties in predicting crash severity. However, several studies have addressed the joint prediction of crashes by severity (Park and Lord, 2007, Alarifi et al., 2018, Shaon et al., 2019). For estimating the VMT in different weather conditions, we assume the ADT is distributed evenly in days and within hours of a day, and approximate the hourly traffic flow using this assumption. Therefore, we approximated the VTM in adverse weather conditions by multiplying the number of hours in the year with adverse weather conditions by the hourly traffic flow. The proposed architecture for finding the safest route seeks to minimize the risk of crashes and did not consider other costs of travel (e.g., travel time). Therefore, this study does not contribute to the previous attempts to modify the cost function of the shortest route algorithms considering road safety (Carmody and Sowers, 2019). Similar to examining the safest and shortest routes, we did not consider the severity of crashes in the safest route-finding architecture.

4.3. Future research and implementations

Future research is required to address the limitations of this study: assumptions regarding the traffic flow, directional crash risks, intersection crash risks, and how spatial correlation could be included to estimate risk at road segments along a route. Also, the severity of crashes needs to be considered for finding the safest route. Addressing the barriers in deploying S-RGSs can be another avenue that can elevate the discussion of this paper. Investigating the possibility and precision of employing crowd-sourced traffic and incident data concerning rural roads as input for crash prediction models and S-RGS route-finding algorithms; improving the precision of the crash prediction models, for both real-time and static S-RGS; and redefining the routing optimization problem and considering multi-objective routing algorithms were identified in this study as the barriers to deploying S-RGS.

As we discussed in this paper, the requirements of the static safest route finding for S-RGS are relatively low and are simple to implement. The S-RGS can at least be used as an advisory planning tool for rural trips, one that can negate some of the potential adverse impacts of existing road navigation apps.

5. Summary and conclusions

This study aims to investigate the necessity of including safety in road navigation and identify the requirements and barriers to incorporating safety in route finding. We designed a study to examine the safety of the shortest route suggested by road navigation apps. To support this analysis, we proposed a methodology for route safety estimations. The results of our analyses on five metropolitan areas in Texas, US, shed light on the salience of considering safety in road navigation apps, where an 8% increase in travel time was associated with a 23% reduction in the probability of being involved in a crash. We further proposed a system architecture for considering safety in route finding and highlighted the requirements for and barriers to implementing safety in S-RGS—namely, availability of data for dynamic road safety estimations, accurate crash prediction models, methods for dealing with the trade-off between safety and time, and potential ethical issues in considering safety in route-finding. Such a system would guide users to—and through—the safest route, and therefore, can improve traffic safety by preventing crashes. It is expected that new generations of road navigation tools will become capable of finding the safest route in the near future.

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[4] A commercialized route advising system that helps drivers to better understand their exposure to traffic crash risk along a specified route, while providing trip feedback and safe alternate recommendations (https://www.tnedicca.com/routewise/).

CRediT authorship contribution statement

Soheil Sohrabi: Conceptualization, Methodology, Data curation, Writing – original draft, Visualization, Investigation, Validation. **Dominique Lord:** Methodology, Supervision, Validation.

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.

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