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A Comparative Analysis of Surrogate Safety Indicators for Road Hazard Assessment Using Smartphone GPS Data

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Road Safety Assessment (RSA) can be conducted through two primary approaches: (1) the reactive approach, which relies on historical crash data; and (2) the proactive approach, which employs Surrogate Safety Indicators (SSIs). In the reactive approach, hazard potential is evaluated directly by measuring accident frequency, whereas in the proactive approach, SSIs must be validated against actual safety measures. However, few studies have systematically compared multiple SSIs to determine which indicators provide the most reliable correlation with actual crash occurrence, particularly in rural contexts where data collection is challenging. The purpose of this research is to compare 39 SSIs within the proactive RSA framework to identify potential hazards on rural road segments. An observational study was conducted employing Pearson correlation analysis, using vehicle velocity data collected via GPS-enabled smartphones from 100 vehicles across 125 km of rural roads. The analysis divided the road network into uniform 5-km segments and evaluated various crash severity levels, including fatal, injury, and total crashes. Among 39 proposed indicators, the deceleration frequency indicator (DNM1, counting all decelerations during braking without predefined thresholds) demonstrates the strongest correlation with crash data (r = 0.803 for property-damage crashes), establishing it as a highly robust proactive safety measure for rural road networks. Additionally, results revealed that traditional metrics like average vehicle velocity alone were poor predictors of safety compared to comprehensive deceleration-based measures, emphasizing the necessity of granular kinematic data. The findings enable transportation agencies to implement cost-effective, smartphone-based safety monitoring systems for real-time identification of high-risk rural road segments.

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1. Introduction

Road traffic accidents remain a major global public health concern, resulting in approximately 1.19 million fatalities and 20-50 million injuries annually worldwide. They currently stand as a leading cause of death, particularly among younger age groups. In Iran, traffic-related injuries similarly constitute a primary cause of mortality. The recording of over 16,700 fatalities in 2022 (Iranian calendar year 1401), which significantly exceeds both global and regional averages, highlights a severe crisis in road safety [1].

In recent years, Iran has experienced a simultaneous increase in the number of vehicles, travel speeds, population, and overall volume of road trips. However, the development and quality of road infrastructure have not improved proportionately. For instance,

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studies of two-lane rural highways in Iran show that geometric design elements, such as intersection angles and the existence of spiral curves, significantly influence accident ratios [2]. Furthermore, vehicle safety standards remain sub-optimal, and critically, there is a lack of adequate public education to foster a culture of safe driving. Consequently, the frequency, severity, and associated socio-economic costs of crashes have surged, underscoring the urgent need for effective preventive and mitigative measures [3].

Smart monitoring of road conditions and crash events by tracking vehicles via GPS and transmitting data to emergency services when necessary is an efficient approach to reducing traffic fatalities [4]. Some studies recommend adding modules equipped with various sensors that can record critical road parameters and pavement conditions while also detecting crash events [5].

The measure of road safety is often deduced from crash statistics. However, because crashes are accidental in nature, crash data are typically considered "rare events" in statistical terms. Consequently, at least three years of data are required to draw reliable conclusions about crash patterns. This represents a key limitation of this approach [6].

There are several methodologies that consider historical crash data in order to identify potentially high-risk locations [7]; however, the use of crash data in road safety analysis is sometimes hindered by logical and statistical problems such as small sample sizes, a lack of sufficient details to improve understanding of crash failure mechanisms [8], and unavailability [9]. To address these limitations, researchers have attempted to employ other parameters as surrogate measures for the identification of hazardous road locations, including safety inspections [10], traffic simulations [11, 12], traffic conflict techniques [13-15], and studies based on speed profile variation [15, 16]. These proactive approaches rely on observable traffic behavior and road characteristics rather than historical crash records.

Methods based on vehicle speed variations can be divided into three main categories: a) comparing the speed before a crash with the prevailing speed (event-based) [17]; b) comparing the speeds of drivers involved in a crash with those of drivers not involved in a crash (driver-based) [18]; c) comparing speed variations across different road facilities (facility-based) [19].

To proactively assess road safety, these approaches employ surrogate safety measures rather than relying solely on historical crash statistics. Among these measures, speed parameters have been widely adopted as reliable indicators. Following this rationale, the present study introduces a proactive safety evaluation framework based on continuous speed data collected via smartphone GPS.

2. Literature review

The review of prior investigations shows that most drivers exhibit strong reactions when encountering a hazardous situation. These reactions typically involve braking, steering, accelerating, or a combination thereof. Due to the correlation between crashes and near-crash events, researchers have attempted to prevent crashes through near-crash analysis [20]. In fact, classical naturalistic driving studies have firmly established near-crashes as valid crash surrogates for evaluating driving behavior [21]. Since braking constitutes the majority of near-crash events, many researchers have attempted to identify crash risks by measuring speed reduction using GPS technology.

As highlighted by recent reviews, relying solely on historical crash data has critical limitations, as it is fundamentally a reactive approach. In contrast, Surrogate Safety Measures (SSMs) provide sustainable, proactive indicators that allow researchers to investigate high-risk areas before crashes actually occur [22]. Surrogate Safety Measures can be broadly categorized into two main groups. The first category includes time-based, deceleration-based, and energy-based SSMs, such as Time-to-Collision (TTC), Post Encroachment Time (PET), Time-to-Crash/Accident (TC/TA), and Deceleration Rate to Avoid the Crash (DRAC). These measures are widely used across road safety literature and are typically based on predefined thresholds for traffic conflicts. The second category aims to directly associate each traffic conflict with either a crash or non-crash outcome by estimating its crash probability [23].

Early research employing GPS technology focused on extracting velocity profiles to establish a link between driving behavior and road crash occurrences. Pioneering work in this area by Jun [18] revealed that driving behavior, particularly the speed pattern, is a significant factor in crash potential by comparing drivers with and without recent crash histories [18]. This approach was further developed by Boonsiripant et al. [24], who formalized the technique as the “speed profile” to demonstrate the relationship between its extracted parameters and crash numbers [19]. In their subsequent studies, Boonsiripant et al. [9], Boonsiripant et al. [24] refined this model by identifying “acceleration noise” and “frequency of stops”, both correlated with deceleration, as key predictive parameters [9, 24]. In a similar application of this concept, Camacho-Torregrosa et al. [25] also utilized the speed profile from GPS data to analyze estimated crash rates, specifically for determining average operating speeds and evaluating design consistency parameters [25].

Fontaine and Chun [26] also used GPS probes to estimate the speed differential between adjacent TMC (Traffic Message Channel) segments on freeways. They introduced deceleration events as a surrogate safety measurement for crash data. These events were defined as the number of 15-minute periods where the speed differential between adjacent TMCs exceeded specific thresholds (10, 15, 20, and 25 mph) [26].

Historically, SSM data collection relied heavily on roadside observation techniques, which were labor-intensive and limited in spatial coverage. However, the advent of GPS-enabled devices and smartphone sensors has revolutionized this field by enabling widespread, continuous, and cost-effective data collection under real-world driving conditions [8].

With smartphone GPS accuracy having improved to positioning errors typically within 5 meters [27], their application in safety research has expanded. These devices can determine the geographic coordinates of a vehicle in real time, from which instantaneous speed can be calculated and reported [28]. The built-in sensors of smartphones, particularly GPS and accelerometers, have emerged as cost-effective and reliable tools across various smart transportation domains, from pavement condition monitoring to driver behavior analysis [29]. Furthermore, the rapid advancement of sensor technology has significantly increased reliance on these built-in sensors in naturalistic driving studies. They are now widely utilized to extract critical kinematic SSMs, specifically harsh braking and harsh acceleration events, directly from real-world driving environments [22, 30]. Unlike traditional crash records, which require extensive periods for reliable sample collection, smartphones enable widespread, ongoing, and cost-effective data gathering under real-world driving conditions, providing more timely insights into traffic dynamics. Leveraging this capability, Strauss et al. [31] used smartphone-derived data to examine bicyclists' deceleration rates as a surrogate measure for injury crashes. The correlation coefficient between injury crash frequency and deceleration rate in road sections was found to be r = 0.57 [31].

Stipancic et al. [32] also reviewed the utilization of vehicle manoeuvres as a surrogate measure for crashes. Using smartphone data, they observed that hard braking and hard acceleration events showed a good correlation with the frequency of crashes [32]. The broader literature increasingly supports this positive correlation between harsh driving behaviors, such as harsh braking and acceleration, captured via SSMs, and actual crash risks. Utilizing these harsh events as proactive variables offers a robust alternative to solely relying on reactive historical crash data, allowing for more pre-emptive safety interventions [30].

Further exploring the potential of smartphone telematics, Ziakopoulos [33] utilized high-resolution data to analyse the occurrence of harsh driving events, such as harsh braking (HB) and harsh acceleration (HA). By employing the XGBoost algorithm and SHAP explainability analysis, the study demonstrated that road network characteristics, specifically the number of lanes and speed limits, do not significantly influence the likelihood of these harsh events. Instead, more dynamic factors, including the vehicle's speed and traffic occupancy, were found to be the primary predictors of HB and HA occurrences [33].

In a complementary line of research, Nikolaou et al. [34] introduced spatial analysis to account for geographical dependencies in smartphone-based Surrogate Safety Measures (SSMs). Their study, which focused on harsh braking events, demonstrated that spatial models, such as the Spatial Zero-Inflated Negative Binomial (SZINB) and Spatial Random Forest (SRF), outperform their non-spatial counterparts. The findings identified variables like the number of trips, segment length, speeding, and mobile phone use as significant predictors [34].

While the aforementioned studies confirm the potential of using smartphone-based data for safety analysis, much of this research relies on identifying safety-critical events through the application of predefined and often arbitrary deceleration thresholds. This approach may overlook the cumulative safety implications of more frequent, lower-magnitude speed adjustments, which are particularly relevant on interurban roads. Furthermore, recent comprehensive reviews indicate a critical research gap: future studies must examine how various surrogate indicators correlate with historical road crashes across different severities and regional contexts, moving beyond single-indicator analysis. The present study addresses this gap by introducing and empirically evaluating 39 distinct SSIs, encompassing deceleration frequency and magnitude (across multiple thresholds), as well as indicators derived from velocity, acceleration, and jerk. The primary objective is to systematically correlate these indicators with historical crash data to identify the most robust measure of road safety.

3. The study area

The study area encompassed a two-way, two-lane undivided rural road spanning a total length of 137 km. This finalized route comprised three distinct segments: the first segment traversed level terrain for 20 km. The second segment predominantly passed through rolling terrain for 50 km, while the third segment navigated through mountainous terrain for 55 km. Fig. 1 and Table 1 display the geographical locations of the start and end points for each segment, as well as the entire route.

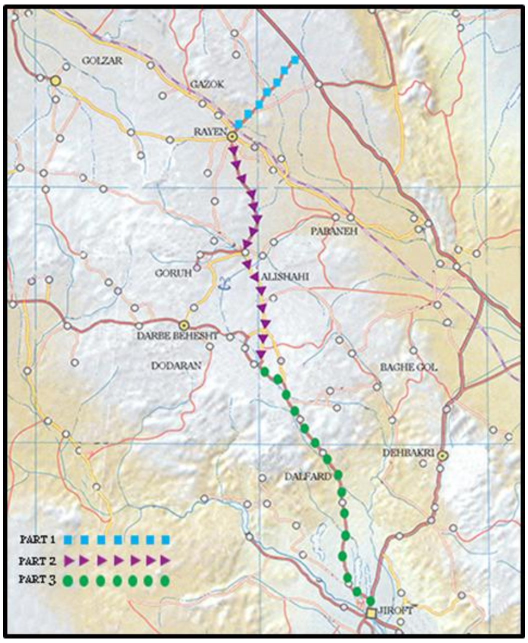

Fig. 1. The study area.

Table 1. Coordinates of the study area.

Part No.	Start point		End point	
	Latitude	Longitude	Latitude	Longitude
Part 1	29.759029°	57.585329°	29.608432°	57.442195°
Part 2	29.585696°	57.442669°	29.138452°	57.499041°
Part 3	29.131210°	57.504835°	28.747257°	57.758172°

4. Data collection

The total number of road crashes for three years was obtained from the Iranian Road Maintenance and Transportation Organization (RMTO). It should be noted that during this specific three-year period (March 21, 2011, to March 21, 2014), no major infrastructural modifications, geometric realignments, or policy changes (e.g., speed limit alterations) occurred along the studied route. This consistency ensures that the historical crash data provides a stable and reliable safety baseline, unskewed by external interventions. Vehicle GPS data were collected from a sample of cars traversing the route. To control for environmental variables and isolate the effect of road geometry, data collection was exclusively conducted under clear weather and dry pavement conditions, which accurately reflects the region's predominantly warm and dry climate with low rainfall. Furthermore, to ensure that the dataset captures a comprehensive representation of naturalistic driving behaviors, the data collection campaigns encompassed both daytime and nighttime driving under these clear conditions.

The AndroSensor mobile application was utilized in this study to record the vehicles' instantaneous speeds and geographic coordinates at one-second intervals with a 5-meter positional accuracy. During the drives, the smartphones were consistently placed on the vehicle dashboards to maintain a clear line of sight to the sky, thereby maximizing GPS signal reception and ensuring data quality. To prevent the Hawthorne effect and ensure naturalistic driving conditions, the data collection was conducted without the drivers' knowledge. The passengers carried out the recording while the drivers were kept completely unaware that their vehicle kinematics were being monitored. This approach ensures that the collected velocity profiles genuinely reflect natural driving behavior in response to the road geometry rather than altered behavior due to observation. A one-second sampling interval (1 Hz) was specifically chosen as it optimally captures macroscopic vehicle kinematics necessary for segment-level safety evaluation. Unlike higher-frequency data (e.g., OBD-II scanners), which are typically suited for microscopic driver behavior analysis and tend to introduce high-frequency sensor noise, a 1 Hz interval aligns with established literature to provide reliable and manageable velocity profiles [27, 35].

Since raw GPS data can be prone to signal fluctuations and sensor noise, which might be falsely interpreted as sudden speed changes, a Kalman filter was applied during the data post-processing phase. This filtering technique effectively smoothed the raw trajectory data and mitigated sensor noise, allowing for the accurate distinction and extraction of true deceleration events (Eq. 1).

$$\mathrm{n} = \frac{z_{1-\alpha/2}^{2} \times p \times (1-p)}{d^2} = \frac{1.96^2 \times 0.5 \times 0.5}{0.1^2} = 96.04 \tag{1}$$

where,

z = 1.96 is the critical value for the 95% confidence interval from the standard normal distribution,

p = 0.5 is the estimated proportion of the population with the characteristic of interest (yielding the maximum variance),

α = 0.05 is the significance level (Type I error rate), and

d = 0.1 is the acceptable margin of error.

A 10% margin of error (d = 0.1) was selected due to the extensive scope of the field study and the inherent logistical constraints of naturalistic data collection. In the context of this study, the calculated minimum sample size of n = 96.04 refers to the number of individual continuous vehicle trips required along the studied route. To account for potential data loss, signal dropouts, and recording errors (dropout rate), data collection was initially conducted for approximately 300 vehicle trips. After a rigorous data screening and quality control process to exclude corrupted, interrupted, or incomplete records, a final set of exactly 100 usable and high-quality vehicle trajectories was successfully extracted. This final sample size effectively accounts for the dropout rate while safely satisfying the statistical requirements for the analysis. The Surrogate Safety Indicators (SSIs) were extracted within 5-km spans, and then the SSIs of all sample vehicles were aggregated in each road segment.

5. Methodology

Following the data collection and sample size determination, this section details the analytical framework employed to evaluate the proposed SSIs. First, a comprehensive set of 39 SSIs is explicitly defined and categorized into two main groups: deceleration-based indicators and other metrics. Next, the procedure for extracting these indicators from the continuous GPS trajectories across the designated 5-km road segments is explained. Finally, the section outlines the statistical approach, utilizing the Pearson Correlation Coefficient (PCC), to establish and quantify the linear associations between these extracted SSIs and historical crash frequencies categorized by severity.

5.1. Suggested indicators

Previous studies on Surrogate Safety Indicators (SSIs) were first reviewed. Subsequently, three road sections were selected according to the study area conditions and road transport regulations. Crash statistics for these three sections were obtained for a 3-year period. Statistical reports on crashes (fatality, injury-causing, damage-causing, total observed, and equivalent property damage only) were extracted for 25 road segments of 5 km length, along with 39 SSIs. GPS-enabled smartphones and appropriate applications, which report the geographic location and the vehicle velocity at one-second intervals, were used to derive SSIs for 100 vehicles on these three road sections. Table 2 indicates the classification of crash types.

Table 2. Crash types (classified by severity).

No.	Crash type	Description
1	Fatality	Crashes leading to the death of at least one person up to 30 hours after their occurrence
2	Injury	Crashes leading to disability, severe injury, light injury, or possible injury
3	Fatality + injury	Fatality + injury crashes (row 1 + row 2)
4	Damaging only	Crashes that lead to financial losses only
5	Total observed	Total fatality, injury, and damaging crashes
6	Equivalent property damage only (EPDO)	In this method, each fatality crash and each injury crash is counted as 9 and 3 damaging crashes, respectively.

The SSIs were divided into two general categories: deceleration-based indicators and indicators.

5.1.1. Deceleration-based indicators

Deceleration-based indicators encompass two groups:

A) Deceleration frequency-based Indicators,

B) Deceleration values-based indicators.

Notably, unlike many urban studies that employ specific deceleration thresholds to isolate safety-critical braking events [18, 32], this study deliberately did not impose a predefined threshold for interurban road segments. In uninterrupted rural traffic flows, drivers typically maintain a steady speed; therefore, even minor but sustained decelerations often reflect essential driving adaptations to roadway geometry, sightline limitations, or potential hazards. By omitting a predefined threshold, the study aimed to prevent bias and empirically evaluate which indicators (including those accounting for all decelerations) yield the highest correlation with actual crash data. Furthermore, applying the Kalman filter during data post-processing ensured that minor signal fluctuations and high-frequency sensor noises were not mistakenly counted as low-magnitude decelerations.

A) Deceleration frequency-based Indicators;

1) The Deceleration Numbers of Mode 1 (DNM1), represent the total count of all decelerations occurring throughout the entire braking duration, recorded at one-second intervals.

2) In contrast to the first mode, the Deceleration Numbers of Mode 2 (DNM2), represent the count of braking events, recording only a single deceleration per event and assigning its spatial coordinates to the onset of braking.

3) An analysis of the deceleration values during braking events revealed that they do not strictly follow an ascending or descending trend, but rather exhibit fluctuations. Consequently, the Deceleration Numbers of Mode 3 (DNM3) represent the count of local maximum decelerations within a braking event, with the spatial coordinates of each local maximum recorded as needed.

4) Similar to DNM, the Deceleration Numbers of Mode 4 (DNM4) records only a single deceleration per braking event; however, its spatial coordinates are assigned to the location of the maximum deceleration rather than the onset of braking.

B) Deceleration values-based indicators;

A pertinent question arises as to why the frequency of decelerations is emphasized over their magnitudes. Recognizing that count-based indicators disregard the numerical value of deceleration (unless classified by a minimum threshold), incorporating the magnitude of each deceleration across the 4 aforementioned modes could potentially improve analytical outcomes. Consequently, this approach may yield an indicator with superior performance in assessing road safety compared to relying solely on historical crash statistics. To investigate this hypothesis, 4 additional indicators are proposed as follows:

5) Corresponding to DNM1, the Value of Deceleration Mode 1 (VDM1) utilizes the sum of deceleration magnitudes rather than their frequency of occurrence. Essentially, this indicator represents the approximate area under the acceleration-time curve for each braking event.

6) The sixth indicator, the Value of Deceleration Mode 2 (VDM2), considers the initial deceleration magnitude during each braking event. This indicator is of particular significance as it may reflect the driver's perception of hazard; consequently, it is investigated as a potentially viable surrogate safety indicator.

7) Corresponding to DNM3, the seventh indicator, the Value of Deceleration Mode 3 (VDM3), utilizes the sum of the

magnitudes of the local maximum decelerations during a braking event, rather than their frequency. This indicator is introduced as it may provide a more accurate representation of the hazard level, making it a potentially more suitable surrogate safety indicator.

8) Determining the maximum deceleration magnitude during each braking event is critical, as it may reflect the severity of the hazard rather than the severity of a crash. Therefore, the eighth indicator, the Value of Deceleration Mode 4 (VDM4), is defined as the sum of the maximum deceleration magnitudes occurring across all braking events. This measure is proposed as a potential candidate for a surrogate safety indicator to replace historical crash statistics.

Upon determining the values of the 8 aforementioned indicators for each braking event, the values were summed across all 90 vehicles for every 5-km road segment. The resulting aggregate served as the representative value for the respective indicator within that segment.

5.1.2. Other indicators

Another pertinent question is why only the frequency or magnitude of decelerations (aggregated within the aforementioned categories) are considered appropriate SSIs in RSA studies. While an SSI is often associated with a braking event, it does not necessarily need to be defined by the cumulative sum or count of decelerations. Instead, it could be related to other parameters, such as velocity or variations in acceleration (both positive and negative). Consequently, the following new indicators are proposed:

9) Average velocity; the velocity-crash association has been extensively investigated. Here we aimed to find whether there is an association between average velocity (Vave) and the number of crashes on each road segment of 5 km length.

10) Average velocity to the second power (Vave2); as with some references, here the association between Vave2 and the number of light injury-causing crashes was investigated.

11) Average velocity to the third power (Vave3); as with some references, here the association between Vave3 and the number of light injury-causing crashes was investigated.

12) Statistics on road crashes in Iran do not separate light and severe injury-causing crashes, and only three general groups of crashes (fatality, injury-causing and damaging) are mentioned. We therefore defined the average velocity to the second plus third power (Vave2+ Vave3), aiming to examine the association between this indicator and crashes.

13) Fatal crashes are a critical component of RSA studies, as they result in significant property damage, severe bodily injuries, and substantial compensation costs, in addition to the loss of life among vehicle occupants. Among crashes of varying severities, fatal crashes occur with the lowest frequency. This low frequency increases the likelihood of random occurrences, making it significantly more difficult to identify a proper SSI that exhibits a strong correlation with these events. Furthermore, fatal crash outcomes are highly dependent on numerous exogenous factors. For instance, the presence of vehicle safety features (e.g., airbags) and occupant compliance (e.g., seatbelt usage) are critical determinants. Additionally, the efficiency of post-crash emergency medical services plays a vital role. These confounding variables, combined with the highly random nature of such crashes, make it exceedingly difficult to derive an appropriate SSI solely from velocity or acceleration data, whether analyzed individually or in combination. Nevertheless, it is still possible to identify the indicator that demonstrates the highest relative correlation with these crashes. Consistent with the existing literature, this study investigates the association between Vave4 and the frequency of fatal crashes.

14) The velocity variance (Vvar), which represents the difference of average velocity to the second power, can be an appropriate SSI, since the vehicle's average velocity may not be the crash's cause, but it may be influenced by inconsistency and turbulence in the vehicle's movement, which can be better expressed in the difference of average velocity.

15) Standard Deviation (SD) of velocity (Vstdv), which indicates the vehicle's velocity difference from the average. This parameter represents inconsistency and turbulence in the vehicle's movement.

16) The average vehicle acceleration on roads (Aave). Vehicles can move more quickly and evenly on a straight road with light traffic; consequently, the Vave increases, and Aave decreases. In contrast, on a winding or mountainous road, vehicles move at a lower velocity and more acceleration changes inevitably occur. Therefore, negative or positive average acceleration is likely to be an appropriate SSI. Variance and SD were also controlled.

17) The variance of acceleration (Avar) for each road segment.

18) The standard deviation of acceleration (Astdv) for each road segment.

19) Average deceleration (Dave) for each road segment. The sum of deceleration numbers and values was expressed as the SSI for deceleration value and number. However, the average, variance, and/or SD of deceleration values may be a more appropriate SSI.

20) The variance of deceleration (Dvar) for each road segment.

21) The standard deviation of deceleration (Dstdv) for each road segment.

22) Average of a jerk to the second power for each road segment (Jave2). Acceleration is a derivative of velocity with respect to time, while jerk is the time derivative of acceleration. In the former, the driver brakes and velocity decreases gradually

with a steady rate over braking. But in the latter, the velocity is suddenly reduced, and the acceleration rate is not constant over braking, where the crash risk is higher. Therefore, the average of a jerk to the second power is probably a more suitable SSI, because, in the second power, the jerk's positive and negative modes cannot neutralize each other's effect.

23) The variance of a jerk to the second power for each road segment (Jvar2).

24) The standard deviation of a jerk to the second power for each road segment (Jstdv2).

25) The average product of the velocity with the deceleration in the DNM1 (SDM1ave) for each road segment. It should be assessed whether the risk level can be greater when braking occurs at a high rather than low velocity, even under the same deceleration. The product of the deceleration with velocity (SD) is therefore considered a possible SSI. Considering this indicator with all four deceleration number modes would probably lead to appropriate SSIs. In each case, we can assess the average, variance, or standard deviation of the product of the velocity with the deceleration.

26) The average product of the velocity with the deceleration in DNM2 (SDM2ave) for each road segment.

27) The average product of the velocity with the deceleration in DNM3 (SDM3ave) for each road segment.

28) The average product of the velocity with the deceleration in DNM4 (SDM4ave) for each road segment.

29) The variance of the product of the velocity with the deceleration in DNM1 (SDM1var) for each road segment.

30) The variance of the product of the velocity with the deceleration in DNM2 (SDM2var) for each road segment.

31) The variance of the product of the velocity with the deceleration in DNM3 (SDM3var) for each road segment.

32) The variance of the product of the velocity with the deceleration in DNM4 (SDM4var) for each road segment.

33) The standard deviation of the product of the velocity with the deceleration in DNM1 (SDM1stdv) for each road segment.

34) The standard deviation of the product of the velocity with the deceleration in DNM2 (SDM2stdv) for each road segment.

35) The standard deviation of the product of the velocity with the deceleration in DNM3 (SDM3stdv) for each road segment.

36) The standard deviation of the product of the velocity with the deceleration in DNM4 (SDM4stdv) for each road segment.

37) Average difference of velocity to the second power (at one-second intervals) in the deceleration modes for each road segment (ΔSD2ave). The length of the brake line is proportional to the changes of velocity to the second power during the braking time. This could therefore be an appropriate SSI.

38) The variance of the difference of velocity to the second power (at one-second intervals) in the deceleration modes for each road segment (ΔSD2var).

39) The standard deviation of the difference of velocity to the second power (at one-second intervals) in the deceleration modes for each road segment (ΔSD2stdv).

The value of each of the indicators and the statistics of observed crashes (classified by severity) were calculated on each of the road segments of 5 km length. The Pearson correlation coefficient (PCC) was used to measure the linear correlation between SSIs and crash statistics.

6. Results

6.1. Results of deceleration-based indicators

The results of the correlation of indicators related to the number or total of decelerations are presented in Tables 3 to 10. Classification of the acceleration number or value in these values is based on the lower limit of deceleration values with steps of 0.5 m/s^2. For example, NMD1 > 1 means the deceleration number in the first mode, but the deceleration value must be greater than 1 m/s^2. The analysis of Tables 3 to 10 showed that in all modes, the deceleration numbers were consistent with the number of crashes (of any severity). The (corresponding) indicators of total deceleration values showed a better correlation. The best results were obtained in Table 3. Among the eight indicators, the frequency of DNM1 (where all the decelerations (deceleration) at the whole braking time (a deceleration per second) were counted) showed the highest correlation with crashes, especially damaging ones (and thus total crashes).

6.2. Results of other indicators

An SSI may be associated with deceleration, but it may not be associated with the sum of the deceleration amount or number, or even deceleration itself. Here, the indicators were defined first, and the results of the correlation test on these indicators and the number of crashes were then presented in Table 11.

7. Discussion

As shown in Table 11, contrary to common assumption, average speed does not exhibit a significant or direct correlation with total crashes or specific crash severities. This observation holds true for the second, third, and fourth powers of average speed as well. Where a correlation does exist, it tends to be inversely proportional. Furthermore, when speed is combined with another parameter into a composite index, such as the product of speed and deceleration, it diminishes the parameter’s correlation with crash frequencies. This phenomenon likely stems from the topographical characteristics of mountainous segments; due to steep gradients and numerous horizontal curves, the average vehicle speed is inherently lower, yet the frequency of crashes in these areas is higher.

Conversely, the standard deviation of speed exhibits a moderate correlation (0.4 to 0.6) with observed crashes. Deviations from the mean speed within a segment induce traffic turbulence and increase overtaking maneuvers, ultimately leading to collisions.

While average acceleration showed no correlation with crashes, the variance and standard deviation of both acceleration and deceleration demonstrate a moderate correlation. These parameters serve as measures of “acceleration noise” (turbulence), indicating the deviation of vehicle acceleration from a normal state. High acceleration noise signifies greater traffic disruption, which consequently leads to increased crash rates. Notably, the average deceleration indicator yields better results, surpassing the 0.6 correlation threshold.

Jerk represents the rate of change of acceleration over time. A higher jerk implies more abrupt acceleration changes, which may indicate the severity of the hazard perceived by the driver (rather than the crash severity itself). To prevent positive and negative values from cancelling each other out, the correlation of the squared jerk with crashes was examined. However, results indicated that the average squared jerk also has only a moderate correlation with crashes. Additionally, the indicator representing the average difference of squared speeds during deceleration, which correlates with braking distance during a braking event, demonstrated an adequate correlation (approximately0.6) with Equivalent Property Damage Only (EPDO) crashes.

Table 3. The correlation coefficient of the deceleration numbers indicator (first mode-DNM1) with the number of observed crashes (classified by severity).

Crash type	NDM1 > 0	NDM1 > 0.5	NDM1 > 1	NDM1 > 1.5	NDM1 > 2	NDM1 > 2.5	NDM1 > 3	NDM1 > 3.5
Fatality	0.376	0.325	0.280	0.235	0.234	0.137	0.153	0.142
Injury	0.102	0.148	0.172	0.165	0.156	0.185	0.140	0.147
Fatality + injury	0.232	0.253	0.257	0.234	0.226	0.215	0.181	0.183
Damage only	0.803	0.681	0.664	0.628	0.617	0.579	0.555	0.526
Total observed	0.741	0.642	0.628	0.592	0.580	0.546	0.517	0.492
EPDO	0.601	0.535	0.514	0.473	0.464	0.412	0.391	0.374

Table 4. The correlation coefficient of the deceleration numbers indicator (second mode-DNM2) with the number of observed crashes (classified by severity).

Crash type	NDM2 > 0	NDM2 > 0.5	NDM2 > 1	NDM2 > 1.5	NDM2 > 2	NDM2 > 2.5	NDM2 > 3	NDM2 > 3.5
Fatality	0.222	0.309	0.293	0.252	0.244	0.162	0.168	0.140
Injury	0.091	0.137	0.159	0.151	0.122	0.163	0.138	0.146
Fatality + injury	0.164	0.237	0.251	0.228	0.199	0.206	0.185	0.182
Damage only	0.713	0.702	0.683	0.649	0.630	0.608	0.584	0.538
Total observed	0.647	0.656	0.643	0.608	0.586	0.568	0.542	0.502
EPDO	0.482	0.533	0.524	0.486	0.463	0.429	0.411	0.379

Table 5. The correlation coefficient of the deceleration numbers indicator (third mode-DNM3) with the number of observed crashes (classified by severity).

Crash type	NDM3 > 0	NDM3 > 0.5	NDM3 > 1	NDM3 > 1.5	NDM3 > 2	NDM3 > 2.5	NDM3 > 3	NDM3 > 3.5
Fatality	0.300	0.316	0.295	0.253	0.245	0.155	0.168	0.140
Injury	0.100	0.146	0.167	0.158	0.128	0.168	0.137	0.145
Fatality + injury	0.201	0.248	0.258	0.235	0.205	0.207	0.184	0.181
Damage only	0.771	0.700	0.685	0.650	0.632	0.604	0.586	0.543
Total observed	0.706	0.657	0.647	0.611	0.588	0.565	0.544	0.506
EPDO	0.549	0.539	0.530	0.490	0.466	0.426	0.411	0.381

Table 6. The correlation coefficient of the deceleration numbers indicator (fourth mode-DNM4) with the number of observed crashes (classified by severity).

Crash type	NDM4 > 0	NDM4 > 0.5	NDM4 > 1	NDM4 > 1.5	NDM4 > 2	NDM4 > 2.5	NDM4 > 3	NDM4 > 3.5
Fatality	0.222	0.291	0.293	0.252	0.240	0.157	0.173	0.136
Injury	0.093	0.131	0.143	0.140	0.114	0.155	0.124	0.153
Fatality + injury	0.165	0.225	0.237	0.218	0.191	0.196	0.175	0.186
Damage only	0.712	0.691	0.683	0.647	0.628	0.604	0.592	0.531
Total observed	0.647	0.644	0.640	0.604	0.581	0.562	0.547	0.498
EPDO	0.482	0.517	0.519	0.481	0.457	0.422	0.412	0.376

Table 7. The correlation coefficient of the sum of the deceleration values indicator (VDM1-correspondent with first mode) with the number of observed crashes (classified by severity).

Crash type	VDM1 > 0	VDM1 > 0.5	VDM1 > 1	VDM1 > 1.5	VDM1 > 2	VDM1 > 2.5	VDM1 > 3	VDM1 > 3.5
Fatality	0.326	0.301	0.259	0.217	0.206	0.124	0.126	0.098
Injury	0.152	0.159	0.178	0.177	0.179	0.211	0.196	0.230
Fatality + injury	0.257	0.254	0.255	0.238	0.235	0.233	0.221	0.240
Damage only	0.700	0.669	0.649	0.616	0.600	0.562	0.528	0.475
Total observed	0.659	0.632	0.614	0.583	0.568	0.535	0.504	0.463
EPDO	0.546	0.521	0.499	0.463	0.451	0.407	0.386	0.359

Table 8. The correlation coefficient of the sum of the deceleration values indicator (VDM2-correspondent with second mode) with the number of observed crashes (classified by severity).

Crash type	VDM2 > 0	VDM2 > 0.5	VDM2 > 1	VDM2 > 1.5	VDM2 > 2	VDM2 > 2.5	VDM2 > 3	VDM2 > 3.5
Fatality	0.229	0.223	0.222	0.205	0.202	0.162	0.160	0.069
Injury	0.124	0.127	0.118	0.141	0.112	0.176	0.268	0.286
Fatality + injury	0.195	0.195	0.188	0.202	0.175	0.217	0.297	0.279
Damage only	0.650	0.620	0.592	0.573	0.520	0.501	0.466	0.277
Total observed	0.602	0.576	0.550	0.537	0.485	0.480	0.469	0.303
EPDO	0.466	0.450	0.433	0.424	0.386	0.382	0.397	0.270

Table 9. The correlation coefficient of the sum of the deceleration values indicator (VDM3-correspondent with third mode) with the number of observed crashes (classified by severity).

Crash type	VDM3 > 0	VDM3 > 0.5	VDM3 > 1	VDM3 > 1.5	VDM3 > 2	VDM3 > 2.5	VDM3 > 3	VDM3 > 3.5
Fatality	0.299	0.297	0.272	0.233	0.217	0.139	0.137	0.137
Injury	0.150	0.155	0.171	0.169	0.156	0.200	0.200	0.200
Fatality + injury	0.245	0.249	0.254	0.237	0.219	0.229	0.228	0.228
Damage only	0.704	0.686	0.669	0.637	0.617	0.586	0.556	0.556
Total observed	0.659	0.645	0.631	0.600	0.579	0.555	0.529	0.529
EPDO	0.534	0.526	0.513	0.478	0.456	0.421	0.406	0.406

Table 10. The correlation coefficient of the sum of the deceleration values indicator (VDM4-correspondent with fourth mode) with the number of observed crashes (classified by severity).

Crash type	VDM4 > 0	VDM4 > 0.5	VDM4 > 1	VDM4 > 1.5	VDM4 > 2	VDM4 > 2.5	VDM4 > 3	VDM4 > 3.5
Fatality	0.266	0.278	0.270	0.231	0.213	0.141	-0.016	0.090
Injury	0.137	0.140	0.152	0.153	0.144	0.190	0.234	0.245
Fatality + injury	0.221	0.228	0.235	0.222	0.207	0.221	0.200	0.251
Damage only	0.689	0.678	0.666	0.634	0.613	0.585	-0.150	0.478
Total observed	0.640	0.633	0.624	0.594	0.572	0.552	-0.080	0.468
EPDO	0.507	0.508	0.503	0.470	0.448	0.418	0.005	0.363

Table 11. Results of the correlation test on SSIs and the number of crashes (classified by severity).

Crash type	Fatality	Injury	Fatality + injury	Damage only	Total observed	EPDO
V_{ave}	-0.406	-0.141	-0.277	-0.774	-0.727	-0.959
$V_{ave}{}^{2}$	-0.421	-0.15	-0.29	-0.772	-0.728	-0.943
$V_{ave}{}^{3}$	-0.434	-0.154	-0.3	-0.766	-0.725	-0.924
$V_{ave}{}^{2,3}$	-0.434	-0.154	-0.299	-0.766	-0.725	-0.924
$V_{ave}{}^{4}$	-0.445	-0.156	-0.305	-0.757	-0.719	-0.904
V_{var}	0.241	-0.021	0.072	0.198	0.186	0.2
V_{stdv}	0.244	0.283	0.342	0.559	0.559	0.486
A_{ave}	0.06	0.06	0.002	-0.141	-0.12	-0.11
A_{var}	0.189	0.303	0.339	0.524	0.528	0.452
A_{stdv}	0.244	0.283	0.342	0.559	0.559	0.486
D_{ave}	0.329	0.2	0.3	0.601	0.585	0.516
D_{var}	0.178	0.327	0.356	0.476	0.492	0.432
D_{stv}	0.239	0.306	0.36	0.524	0.533	0.476
$J^{2}{}_{ave}$	0.156	0.332	0.352	0.504	0.515	0.754
$J^{2}{}_{var}$	-0.193	0.461	0.335	-0.09	0.004	-0.017

J^2_{stv}	-0.118	0.505	0.403	0.062	0.15	0.139
$SDM1_{ave}$	0.143	0.225	0.253	0.137	0.178	0.32
$SDM2_{ave}$	-0.369	0.106	-0.044	-0.328	-0.291	-0.178
$SDM3_{ave}$	0.037	0.26	0.243	0.095	0.14	0.286
$SDM4_{ave}$	-0.156	0.251	0.163	-0.007	0.034	0.187
$SDM1_{var}$	-0.129	0.394	0.3	-0.078	0.006	-0.011
$SDM2_{var}$	-0.113	0.202	0.136	-0.277	-0.204	-0.237
$SDM3_{var}$	-0.132	0.405	0.309	-0.061	0.022	0.004
$SDM4_{var}$	-0.154	0.408	0.303	-0.067	0.015	-0.004
$SDM1_{stv}$	-0.085	0.354	0.281	-0.054	0.021	0.010
$SDM2_{stv}$	-0.153	0.177	0.099	-0.315	-0.245	-0.273
$SDM3_{stv}$	-0.088	0.363	0.288	-0.037	0.038	0.027
$SDM4_{stv}$	-0.122	0.362	0.275	-0.052	0.022	0.014
$\Delta S_D{}^2{}_{ave}$	-0.060	0.069	0.038	0.369	0.324	0.595
$\Delta S_D{}^2{}_{var}$	-0.122	0.066	0.013	0.317	0.273	0.498
$\Delta S_D{}^2{}_{stv}$	-0.084	0.125	0.079	0.346	0.314	0.567

8. Conclusions

This study evaluated various Surrogate Safety Indicators (SSIs) derived from smartphone GPS data to assess road hazards, particularly focusing on mountainous terrains. The comparative analysis of 39 indicators across different modes of calculation yielded several critical insights:

First, simplistic indicators such as average speed are inadequate for safety assessment in mountainous topographies. The inherent geometric constraints (steep gradients and sharp curves) naturally lower average speeds in high-risk zones, leading to an inverse or insignificant correlation with actual crash frequencies. Instead, measures of traffic turbulence, such as the standard deviation of speed and acceleration noise, serve as more reliable indicators of crash potential.

Second, indicators associated with deceleration proved to be substantially more reliable than those related to acceleration or composite speed-deceleration indices. Among the 31 indicators categorized in the second group (Table 11), average deceleration (Dave) exhibited the highest correlation with crash occurrences (over 0.6). Furthermore, the average difference of squared velocities during deceleration (ΔSDave2) showed promising results, particularly for EPDO crashes, highlighting the importance of braking dynamics in hazard evaluation.

Ultimately, when comparing the most effective indicators from all groups, the frequency-based indicators significantly outperformed value-based or variance-based metrics. The frequency of type-1 deceleration (DNM1), which assigns one count per second of deceleration across the entire braking duration, demonstrated the strongest overall correlation with both damaging and total observed crashes. Therefore, DNM1 is recommended as the most appropriate and robust surrogate safety indicator for proactive road hazard assessment using generalized GPS data.

9. Limitations and future directions

While this study successfully utilized the Pearson Correlation Coefficient (PCC) as a straightforward metric to initially screen, comparatively evaluate, and rank the proposed surrogate safety indicators, it is important to acknowledge certain methodological limitations. First, the primary scope of this research was the comparative ranking of indicators rather than developing predictive crash count models. For predictive modelling purposes, future studies should employ advanced count-data regression models, such as Poisson or Negative Binomial (NB) models, which are specifically designed to handle the nature of crash frequencies. Second, the current analysis did not account for potential spatial autocorrelation among the adjacent 5-km road segments. Addressing spatial dependencies using spatial econometric models in future research would be a highly valuable extension to refine the accuracy and reliability of the predictive safety models based on these surrogate indicators.

Furthermore, as this study focused on establishing statistical correlations, the identified indicators were not validated on an independent dataset. Future studies should focus on developing predictive models using these indicators and validating their predictive power on external datasets.

Additionally, while this study aimed to identify a generalized indicator across diverse topographies, future studies could perform segregated analyses to develop terrain-specific safety indicators and thresholds.

Statements & declarations

Author contributions

Reza Jalalkamali: Conceptualization, Investigation, Methodology, Formal analysis, Resources, Writing - Review & Editing.

Shahriar Afandizadeh Zargari: Conceptualization, Investigation, Methodology, Project administration.

Mohammad Hossain Jalal Kamali: Investigation, Writing - Review & Editing.

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Data availability

Data available on request due to restrictions, e.g., privacy or ethics: The data presented in this study are available on request from the corresponding author. The data are not publicly available because the researchers intend to retain the dataset for future comparative analyses and extended research purposes.

Declarations

The authors declare no conflict of interest.

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