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Credible Variable Speed Limits for Improving Road Safety: A Case Study Based on Italian Two-Lane Rural Roads

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Abstract: In an ever-changing driving environment where vehicles are becoming smarter, more autonomous, and more connected, a paradigmatic change in signals for drivers might be required. This need is correlated with road safety (social sustainability). There are several factors affecting road safety, and one of these, especially important on rural roads, is speed. One way to actively influence drivers' speed is to intervene with regard to speed limit signs by providing credible and effective limits. This goal can be pursued by working on variable speed limits that align with the boundary conditions of the installation site. In this research, an analysis was conducted on the rural road network within the Metropolitan City of Bari (Italy) that involved collecting the speeds on each of the investigated two-way, two-lane rural roads of the network. In addition to the speeds, all the most relevant geometric details of the roads were considered, together with environmental factors like rainfall. A generalized linear model was developed to correlate the operating speed limits and other variables together with information about rainfall, which degrades tire–pavement friction and thus, road safety. After the development of this model, safety performance functions, depending on the amount of rain or number of days of rain, were calculated with the intent of predicting crash frequency, starting with the operative speed and rain conditions. Operative speed, speed limit, percentage of non-compliant drivers, traffic level, and site length were found to be associated with all typologies and locations of crashes investigated.

Keywords: variable speed limit; operative speed; statistical models; road safety; rainfall

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1. Introduction

The driving context is facing a drastic revolution: new vehicles are now ready to be deployed as society moves towards an ever-increasing rate of connection and automation [1], including such safety solutions as the massive implementation of Advanced Driver-Assistance Systems (ADAS) on vehicles. On the infrastructural side, roads are becoming smarter and simplifying driving tasks [2]. Such changes in the state-of-the-art driving environment are aimed at reducing fatalities on roads to target the zero deaths goal, Vision Zero, which is set as a worldwide primary goal [3,4]. In recent years, several other minor road-related countermeasures have been implemented to mitigate the crash occurrence on roads, including road marking improvements, traffic calming devices, roundabouts at intersections, and so forth. Among the available solutions to improve road safety, intervening in both vertical and horizontal signal improvement was found to be crucial in both urban [5] and rural environments [6]. At the rural level, one of the main effective solutions involving the simple modification of the signals is to switch from static posted speed limits to variable or differential ones [7]. In fact, speed, combined with other factors, may highly impact crash frequency and severity [8]. For instance, higher speed limits may have contributed negatively to the severity of single-vehicle crashes [9]. Thus, intervening in speed limits can significantly contribute to better driving environments. Such a result was highlighted by [10], which found a correlation between safe speed limits and the typology of severe crash reduction. For example, setting an 80 km/h limit was found to be a safe speed for right-angle, right-turn, run-off-the-road, and rollover crashes, while 110 km/h proved safer for rear-end crashes. The two former variables, speed limit and fatality rate for crash typology, were linked by an exponential function. However, the positive impacts of setting adequate speed limits and the subsequent compliance with them can be achieved only in cases of credible posted speed limits, those which are in line with the road's geometric elements [11,12].

To be credible, speed limits should not only be aligned with operating speeds that drivers can achieve thanks to the geometric features of roads [13] but also be modifiable in response to changes in the boundary conditions, such as traffic density [14,15]. Thus, a variable speed limit (VSL) which would have a positive impact on road safety should be both credible, since it would be in line with the drivers' expectations according to the road geometry, and changeable, because it would account for any major variations occurring on the road.

One environmental variable strongly related to speed, friction, and safety is the weather. In fact, rainy/snowy conditions can drastically alter the perception of drivers and their speed regimes. However, even if static speed limits are usually set based on wet pavement conditions, they do not tend to account for the variability of surrounding conditions that can alter drivers' safety. Some studies in the literature have dealt with this topic from different angles, from the traffic efficiency perspective [16,17] to the identification of hotspots [16,18] and other safety-related concerns [19,20], by finding different responses to the same problem. Rama [19] provided an analysis detailing how reducing the speed limit under unyielding, bad weather conditions can improve the speed reduction up to 3.4 km/h. This reduction is more than drivers can achieve solely by adapting their behaviors to the environmental conditions without any external suggestion. A correlation among weather, road parameters, vehicle status, and stopping sight distance in order to increase the safety and comfort of driving was also investigated more recently, utilizing the Internet of Things and connected roads [20]. These two studies are examples of safety-related research about the possible relationships between bad weather and VSLs.

Considering the above, firstly, the proposed research aims to contribute to the state-of-the-art conversation about VSLs by defining a statistical model to predict the operating speeds on two-way, two-lane rural roads under rainy conditions. The developed model relates the operating speed (V_{85}) to geometric parameters, traffic variables, and weather conditions. In this way, relying on sensors for detecting real-time parameters on the road, it is possible to use the proposed model to substitute "not credible" posted speed limits (i.e., associated with low driver compliance) with constantly updated speed limits, making them credible and aligned with the boundary conditions.

Secondly, to assess safety implications, the development of safety performance functions for different crash types and locations, accounting for rain and the posted speed limit, was attempted. The aim was to predict crash frequency for specific crash locations and types based on speed and environmental conditions. This model could provide an indication of the actual safety performance according to the current conditions detected on roads in real time through sensors at the VSL implementation location.

Several other studies have provided statistical models for V_{85}, demonstrating their value [21]. For instance, the prediction of V_{85} by means of a generalized linear model [22] has been used in the road design process, to model traffic emissions, and to ensure design consistency. Recently, two different regression models were used to understand the influence of road category, road design, and posted speed limit (the credibility of the limit) on V_{85} [23]. Moreover, another recent analysis tried to correlate different speed measures with safety on city streets, finding a positive correlation between crash occurrence and speed variability [24]. The same was performed on freeways, using a fully Bayesian analysis to predict the positive impact of VLSs [25], providing encouraging results.

Thus, the effort of developing models to predict speed based on data collection and then safety conditions based on speed has been extensively made in previous research. However, the twofold goal of predicting updated posted speed limits according to environmental conditions and coupling them with safety models based on speed and different continuously detected and collected boundary conditions has still not been deeply investigated. Therefore, the main contribution of the proposed research is to address the issue of setting variable speed limits, ensuring road safety benefits in real time, according to the ever-changing environmental conditions on roads. This twofold perspective can have important implications for practitioners, because several safety issues on minor roads could be tackled by equipping roadsides with sensors to collect environmental data and posting variable speed limits to reflect the most appropriate real-time speed to drive safely and reduce crash risks.

The remainder of this paper is organized as follows: the methodology used in the research is presented in Section 2, highlighting the context of analysis, the procedures used, the variables, and how the data collection was conducted. The statistical analysis is then shown, followed by the presentation of results. The results are commented on and discussed in the next section before concluding the main findings, limitations, and future scenarios for the research in Section 4.

2. Methods

2.1. Data Collection

The sample of roads used for this study is the two-way, two-lane rural road network managed by the Metropolitan City of Bari (MCB), Italy. Data about the road network of the MCB were available in the context of the Sustainable Urban Mobility Plan (SUMP) (https://www.pumscmbari.it/download/, last accessed 7 October 2024) developed for the MCB. Within the overall road network, the study was particularly focused on the two-way, two-lane rural road network because of the highlighted safety issues [26]. The crash dataset used for this specific assessment was the one provided by the Italian National Institute of Statistics (ISTAT) for the years 2015–2019 related to fatal and injury crashes (F+I crashes) (https://www.istat.it/microdati/rilevazione-degli-incidenti-stradali-con-lesioni-a-persone-3/, last accessed 7 October 2024). Thus, further investigations were needed to study recurrent patterns and the circumstances of the crashes that occurred, intending to target dedicated countermeasures. The data about crashes needed to be integrated with other types of data for the twofold intent of the study, which is predicting VSLs based on environmental issues and providing safety-related outcomes. Therefore, in the absence of available data, a more recent (2023) monitoring campaign diffused over the entire undivided two-way, two-lane rural road network was conducted to acquire data about traffic volume, traffic composition, and speeds.

2.1.1. Traffic Survey Campaign

Data were collected through traffic counters based on radar detection (Sierzega SR4, Fano, Italy). This equipment provides the necessary quality and precision of data: day, time (with a precision of 1 s), the speed of vehicles and their dimensions, the traveling direction, and the time gap between two consecutive detections. A precise installation methodology was followed to detect accurate data with traffic counters, according to guidance from the manufacturing company: setting the counter installation angle around 30° from the center line of the closest lane and installing the device at least a 1 m distance from the ground and 1.5 m from the road shoulder of the nearest lane. Their calibration requires a perfect match between the passing vehicle characteristics and the detected ones (which were visible on the mobile phone connected to the counter device). An experimental vehicle was tested to look at information about speed, vehicle length, and direction, and compare the known data with the data detected by the traffic counters. Once at least 30 recordings were found to be perfectly in line with the known data about the vehicle and the recording, the traffic counter was considered to be well-placed and was left in position. Then, a 30′ in-place analysis of the recordings was performed for each installation to see whether the counters correctly detected all the other passing vehicle data. In this way, the comparison was conducted on their length, not knowing a priori their speed. The traffic counters could work under different temperatures (from −20 °C to 60 °C) and weather conditions, being impermeable to water, and they could detect speeds from 2 to 255 km/h with a ±3% accuracy. The memory of the devices can hold over 860,000 vehicle recordings, and the battery can last 14 weeks without losing details.

The counters were placed considering multiple aspects, starting from the accessibility of streetlight poles (where counters should be physically placed) to the most crash-prone locations in the road network. The final disposition of the counters is represented in Figures 1 and 2. Of course, because of the limited availability of counters, they were turned over to the identified locations. Each data collection lasted one week (of continuous recording) for each location. The monitoring campaign covered the entirety of 2023, excluding all the vacation periods that are necessarily impacted by irregular traffic conditions. The one-week monitoring period for each location started on a Tuesday and ended the following Tuesday, covering both weekdays and weekends, to detect the possible differences that can occur between these types of days. The entire campaign was also conducted during school-traffic and non-school-traffic periods. In this case, to account for the possible distinctions in traffic and driving behaviors, the main approach was to monitor different roads in the same area, at different periods of the year, to obtain homogeneous data. The one-week observation period, albeit short, was deemed sufficient to cover the variability of the traffic flow each day (hourly variations) and throughout the week (daily variations). Moreover, the rationale of the monitoring phase was to cover several roads close to each other in different periods of the year to get the variability of the same area in school-traffic and non-school-traffic periods, or winter versus spring. This rationale was useful for a primary comparison among data derived from the same investigated area to obtain their variability. Another comparison was made between the recorded data and the available ADT data from previous periods (as highlighted in Section 2.1.2). This comparison allowed us to confirm the quality of the recorded data in the most recent period, since they expressed the same variability found in previous analyses.

The MCB is characterized by a Mediterranean climate, with warm summers and mild winters. The average temperature in 2023 was around 17 °C, with peaks during the summer of up to 40 °C. The average rain amount during the year was 48 mm, with peaks during winter. On average, in the MCB, there are six days of rain per month. The relative humidity is always high, with a mean value equal to 62.5% (https://protezionecivile.puglia.it/bollettini-meteorologici-regionali-mensili, last accessed 7 October 2024). In general, adverse weather conditions like fog and snow events are very rare in the study area, and when they happen, they are more frequent and intense in locations far from the coast. Considering their rarity from historical data and their absence within the monitoring campaign, apart from rain, other adverse weather conditions (i.e., fog, snow) could be neglected for the specific scenario and this investigation. The main weather conditions, besides sunny or cloudy days, were characterized by rain. Regarding temperatures, these are relatively high and do not represent a real concern for the area being investigated. In the case of significant temperature fluctuations with remarkable peaks and valleys, the habits of drivers could differ, as could their driving behaviors [27,28]; therefore, this variable could be taken into account in the models developed or calibrated for other regions, together with other adverse weather conditions.

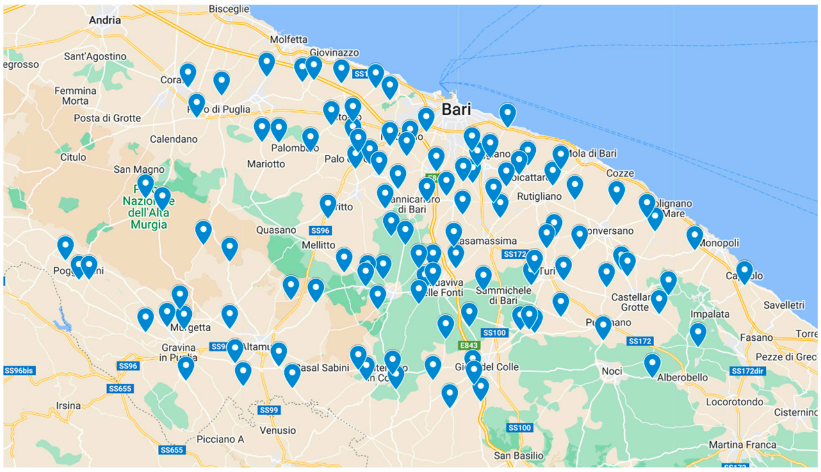

Figure 1. Locations of the traffic counters over the two-way, two-lane rural roads in the MCB, highlighted by blue pins.

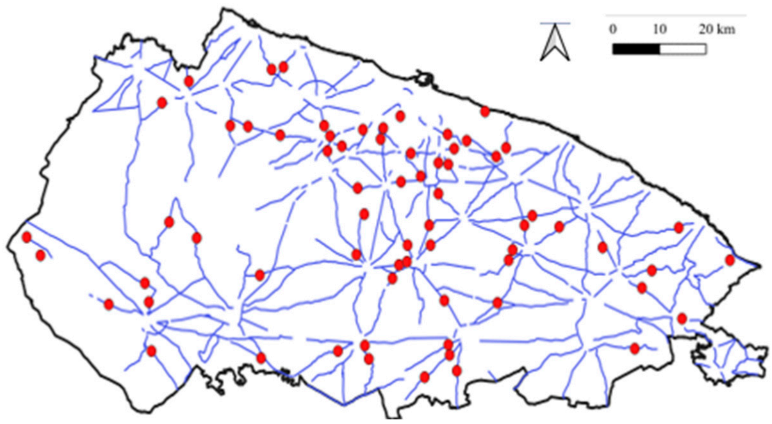

Figure 2. Definition of the monitoring sites and roads where they are located (red dots) and the MCB boundaries.

It is evident that the proposed approach can be extended to all other contexts, but the results of the models are deeply influenced by the selection of the site, which influences not only the values associated with the variables but also the types of roads and the elements to consider for the prediction. Of course, the structure of the proposed models, as will be later highlighted, is adaptable to other conditions and contexts.

2.1.2. Definition of Variables

At each site, the collected data were extracted and elaborated, defining the average daily traffic (ADT), the percentage of heavy vehicles, the mean speed (V_m), and the operating speed (V_{85}), calculated considering isolated vehicles, i.e., those with at least 5 s time gaps from each other. The latter values were compared with the posted speed limit at each location in order to calculate the credibility and the compliance of drivers with the speed limits. On two-way, two-lane rural roads in the investigated area, the speed limits are posted to induce cautious behaviors from drivers, according to several boundary conditions (like the presence of accesses or very sharp curves not consistent with the tangent lengths) present on roads. Therefore, several speed limits may also appear to be lower than the speeds strictly required by geometry. This aspect could induce drivers to disrespect them, as has emerged from an independent random data collection about speed and traffic available (https://webapps.sit.puglia.it/freewebapps/Mobilita/index.html, last accessed 7 October 2024).

After the data collection and categorization, a recognition of all the geometric parameters of the roads was performed. In this sense, the definition of the curvature change ratio (CCR) was crucial. This value can be obtained for each curve, but in this specific case, the average CCR measured over each of the investigated rural road sections proved to be fundamental to account for the overall variability of the horizontal alignment. The horizontal alignment strongly influences driving behavior, especially in the presence of long straight segments, where users tend to speed up. Thus, defining a global CCR for each of the investigated rural roads could provide a strong correlation with the operating speed, as highlighted by several studies [23,29–33]. Among them, one related to the rural roads was used as a benchmark for defining the CCR of the roads [34], expressed as follows:

$$CCR = \frac{\sum \alpha_i}{\sum L_j} \tag{1}$$

where

- CCR is the curvature change ratio (gon/km).
- α_i is the i-th angle of deviation of the i-th curve (gon). The angle of deviation can be related to a single curve or multiple curves on the road layout.
- L_j is the length of the j-th road element (km). This formula can be applied to a single element included between two consecutive tangents or to the entire road. In the latter case, the sum of all the j-th L elements is the total length of the investigated road. In this second case, the CCR provides an overall idea of the tortuosity of the road.

However, several other conditions can impact the speed of drivers and, consequently, their safety. Therefore, other boundary conditions, such as the number of intersections and accesses on the roads investigated and their typology (three-legs, four-legs, roundabouts), were defined. The variation of the cross-section of the roads along the route was assessed as well, as the difference between the maximum dimensions of the cross-sections reached along the route and the minimum ones, expressed in meters. This variable was considered important for the scope of the research, since the cross-sectional dimensions can impact the drivers' perception of roads and, consequently, their speed. This condition becomes extremely important, especially in the absence of (or in the case of very limited) shoulders, which is a usual condition on the roads in the considered sample.

Since the collection of data was conducted in different periods over the entire covered area, the weather conditions could have been different, with, in turn, a different influence on the driving behavior. Thus, the speed could also have varied due to intense rainy conditions. Hence, pluviometric data, such as the number of rainy days and the amount (in millimeters) of rain that fell, were acquired. These latter pieces of information were obtained from two different sources: the regional hydrological annals for the period 2015–2019, to overlap crash data and weather data (the amount and days of rain were collected year-by-year within the selected time interval); and the rainy bulletin of the Civil Protection Department, to get the data for the specific week of monitoring at each location. Not all the investigated roads were associated with a pluviometric station that collected rain data. In these cases, data from the closest pluviometric station, within 5 km, were assigned to the road. As regards snow and fog, neither of these atmospheric phenomena was present during the collection of data in the monitoring phase.

Another seasonal factor considered to be influential on the possible driving conditions for road users was the traffic associated with home–school trips. Therefore, a parameter was introduced to highlight if the data collection happened during an in-school period or when school was over/closed. The importance of this information was obtained from the SUMP report of the MCB. This document highlights how, of all the daily travel of users with their vehicles or using public transport, schools attracted 5.2% of all travel by the population of the MCB. Hence, if the detection happened during an in-school period, traffic volumes may have increased. To summarize, the variables considered for the models are the following:

- Traffic, "ADT", is a continuous variable, representing the average daily traffic obtained from one week of data recording with the speed counter. Traffic data were obtained by the 2023 monitoring campaign and compared to historical data. A stability in the ADT values was found from 2017 to 2023, to use the values obtained during the monitoring phase for crash predictions as well. Thus, there is just one ADT value for each road, no matter what timeframe is considered.
- Vehicle composition, "VLegg", is a continuous variable. This variable represents the percentage of light vehicles recorded during the monitoring phase by the speed counters. It is expressed as a percentage of the total vehicles recorded at each monitoring station. The heavy vehicles are a complement to 100 of the provided number. The same consideration made for the ADT about its time stability is applicable to the percentage of light vehicles. It remained stable through the years studied, so it was possible to rely on one value only for both operating speed and the safety model, no matter what timeframe was considered.
- Speed Limit, "Limit", is a factor variable. The posted speed limits were collected during the monitoring phase. Thanks to Google Street View, the current speed limits were compared with the ones between 2015 and 2019 to define whether they have been constant through the years. No variations were detected. The recorded and posted speed limits are 50 km/h, 60 km/h, 70 km/h, 80 km/h, and 90 km/h, depending on the characteristics of the roads. On the same road, the posted speed limit varies according to different conditions. Thus, for the purpose of the analysis, only the posted speed limit preceding the use of the counter was used. Thus, the speed limits were categorized as follows:
    - 0 = 50 km/h—Limit50
    - 1 = 60 km/h—Limit60
    - 2 = 70 km/h—Limit70
    - 3 = 80 km/h—Limit80
- Vehicle traveling at speeds greater than the posted speed limit, "SupL", is a continuous variable expressed as a percentage of vehicles traveling at speeds greater than the posted speed limit. The data came from the monitoring phase with the speed counters. Thus, this variable could have been applied just for the operating speed model, because no clues were available about this behavior in the period 2015–2019.
- School day, "Scholastic", is a binary variable. The numeral 0 indicates that the recorded values happened during an in-school period, and 1 signifies that the monitoring phase happened outside an in-school period. Thus, this variable could have been applied just for the operating speed model, because no clues were available about this behavior in the period of 2015–2019.
- L is the length of each of the investigated sites/roads expressed in km.

- CCR is intended as a synthetic measure of the variability of the horizontal alignment of the road, as expressed in Equation (1). The values of the CCR represent the complex/tortuous alignment with several sharp curves. This variable could be applied to all the desired time spans since it is constant throughout time, expressing a geometric condition.
- Rmax is intended as the maximum radius of curvature among the curves of the site, measured in meters (m). This variable could also be applied to all the desired time spans since it is constant throughout time, expressing a geometric condition.
- Rain. In this case, also, different measures were alternatively considered during the definition of the models, given their correlation. More details will be provided in Section 2.2.2. The two considered rain variables are the following:
    - Days of rain (GG); that is, a continuous variable representing the count of days with a rain phenomenon during the monitoring period.
    - Amount of rain (mm); that is, a continuous variable, expressed in millimeters, the cumulative amount of rain that fell during the monitoring period.
- Intersection density, "IntDensity", is a continuous variable representing the ratio of intersections on the investigated road over the extent of the road. It is a kilometric frequency of intersections, including minor and major ones. This variable could be applied to all the desired time spans since it is constant throughout time, expressing a geometric condition.
- Intersection typology, "IntTyp", is a factor variable representing the intersection typology on the investigated road (0: three-legged intersections; 1: four-legged intersections or roundabouts; 2: mixed typologies of intersections). This variable could be applied to all the desired time spans since it is constant throughout time, expressing a geometric condition.
- Cross-section variability, "VarSez", is a continuous variable, representing the difference between the maximum and minimum cross-sectional dimensions of the investigated road, measured in meters (m). This variable could be applied to all the desired time spans since it is constant throughout time, expressing a geometric condition.

2.1.3. Description of Variables

For the mentioned variables, a descriptive analysis was performed to determine how the variables are distributed over the entire set of investigated roads.

At first glance, it seems that the variability of traffic (standard deviation of ADT) is significant. This was expected, since roads managed by the MCB belonging to the same typology—two-way, two-lane rural roads—can have different functions: they can either be arterials/collectors connecting several cities or local roads. This aspect is also highlighted by the significant variability in road length (about 10 km on average, with a standard deviation equal to 8.56 km). The traffic composition of the roads seems to be homogeneous for all the investigated roads, made up of a large portion of light vehicles (more than 90%).

Moreover, the aforementioned functional variability of these roads, together with the variable boundary conditions (especially in the case of long sections), is reflected in the detected high variability of road cross sections. All the investigated roads present different geometric layouts and tortuosity. This characteristic is obvious, based on the high standard deviation of the maximum radius of curvature and the CCR.

Regarding intersections, the density fluctuates, also depending on the road function. However, most of the intersections are three-legged, followed by four-legged intersections and roundabouts. Rarely is there a mixture of three-legged, four-legged, and roundabouts on the same investigated segment.

The posted speed limits are mainly between 50 km/h (0) and 70 km/h (2). The maximum possible regulatory limit for this type of road is 90 km/h in Italy, but this was never encountered on the investigated roads. As anticipated, several of the prescribed lower limits in the sample of roads can be explained by the extreme variability of boundary conditions, geometric alignment, and the presence of intersections. Despite these considerations, the first descriptive analysis reveals that the behavior of drivers is far from the speed limit impositions, as is clear from the V_m, V_{85}, and SupL. This tendency can be explained by road geometric conditions, which are not self-explanatory, and by low traffic volumes that can induce drivers to speed up. The posted speed limits take into consideration several aspects, such as the presence of accesses and minor intersections that a regular driver may not consider at the speed selection moment because of driving experience or low traffic volume. All these conditions represent key factors in the selection of possible control strategies for effective VSLs.

Moreover, considering weather conditions is important since at least 10 mm of rainfall was recorded per week during the traffic surveys, as emerges in Table 1. However, in terms of rainy days during the monitoring period, the overall frequency was sporadic, since it rained most of the time for one or two days out of seven (two days on average).

Table 1. Descriptive statistics of the considered variables.

Variable Name (Numeric)	Mean Value	Standard Deviation	Variable Name (Categorical)	Count	Percentage
ADT (veh/day)	4258.32	3630.14	Posted speed limit—0 (50 Km/h)	50	48.5
VLeg (%)	92.18	5.97	Posted speed limit—1 (60 Km/h)	12	11.7
L (km)	10.27	8.56	Posted speed limit—2 (70 Km/h)	39	37.9
VarSez (m)	1.53	2.06	Posted speed limit—3 (80 Km/h)	2	1.9
Rmax (m)	721.62	385.92	Intersection typology—0 (3-legged)	53	51.5
CCR (gon/km)	38.25	37.88	Intersection typology—1 (4-legged)	39	37.9
IntDensity (N int/km)	1.07	0.98	Intersection typology—2 (mixed)	11	10.7
Vm (km/h)	74.72	9.93			
V85 (km/h)	90.12	11.94			
SupL (%)	77.75	20.55			
Days of rain	2.07	1.70			
Amount of rain (mm)	10.33	14.49			

2.2. *Statistical Analysis*

In the context of the current investigation, two different statistical analyses were conducted: one for predicting the operating speed and the other for modeling crash frequencies.

2.2.1. Operating Speed Model

The first model, aimed at predicting operating speed (V_{85}), was developed considering the road design, traffic, and environmental conditions by relying on a generalized linear model. As suggested in the Introduction, operating speeds predicted from such a model, fed by real-time data coming from traffic counters and pluviometers, could enhance credible and variable posted speed limits.

With this intent in mind, the variables were selected and the model form was defined. In particular, a generalized linear model was developed based on the available data [22]. This model was developed with the intent of providing a basis for VSLs; hence, real-time data was used for the model. For this purpose, the most recent available data useful for determining the operating speed was used. The model was not intended to rely on historical data for calibrating the output. This approach is slightly different from the ones used and highlighted in the next section, since the premises and the type of model and procedures are different.

The statistical analysis was run in an R environment. The dependent variable was the operating speed (V_{85}). All the independent variables useful for the analysis were retained in the model only in cases where the *p*-value associated with the estimated coefficients was lower than 0.10 (10% significance level). Several combinations of the variables previously introduced were attempted in the model, though we avoided using correlated variables in the same attempt, based on the calculation of a Spearman correlation matrix. In detail, a couple of variables showing Spearman correlation coefficients greater than 0.5 were not included together in the tentative models. Alternative candidate models showing statistically significant predictors were compared by looking at the coefficient of determination and results from likelihood ratio tests to select the final model.

2.2.2. Safety Performance Function Model

The second modeling effort was dedicated to defining a crash prediction model (defined as the Safety Performance Function—SPF—in the Highway Safety Manual, 2010, [35]) that accounted for the influence of the operating speed and other factors, such as rain-related measures, on the crash frequency.

This analysis builds on Intini et al. [36], which has already investigated the safety performance of the Metropolitan City of Bari at the macro level. In this study, the goal of the SPF is to find a relationship at the road section level of undivided two-way, two-lane rural roads between the crash frequency and other measures such as the operating speed and rain-related measures. Therefore, the developed SPFs were based on the same variables introduced in the previous section. However, in this case, different dependent variables (crash frequencies) were separately used in the models, defined as follows:

- Total F+I crashes occurring, derived from the count of F+I crashes recorded between 2015 and 2019 on the investigated roads by the ACI-ISTAT dataset. This category is further divided into the following three sub-categories, separately used as outcome variables:
    - Intersection (Int) is a continuous variable counting the number of F+I crashes occurring at the intersections.
    - Segment (Seg) is a continuous variable counting the number of F+I crashes occurring on the tangent segments of the road sections.
    - Curve (Cur) is a continuous variable counting the number of F+I crashes occurring on the curved parts of the road sections.
- Multi-vehicle crashes, including rear-end, sideswipe, side crashes, and front crashes, "MultiVeic". This variable derives from the count of multivehicle F+I crashes that occurred between 2015 and 2019 on the investigated roads (ACI-ISTAT dataset).
- Single-vehicle crashes, including run-off-road and hit-obstacles crashes, "SingVeic". This variable derives from the count of single-vehicle F+I crashes occurring between 2015 and 2019 on the investigated roads (ACI-ISTAT dataset).

The 2015–2019 timeframe was selected to obtain a historical series to rely on, considering at least three years of observed crashes [35]. Starting from these observed data, the future prediction of the model can be extended to the entirety of the desired period, depending on the availability of data to use as input for the model.

The model was calibrated for the case study in the province of Bari. It can be applied to other contexts, but some coefficients could vary based on the different boundaries and driving conditions. Some calibration coefficients could be applied, or the variables could be reconsidered for a different context, as also suggested by HSM 2010 [35].

The aim of the proposed approach is to provide a first attempt to combine VSLs and safety assessment in real time and to make secondary rural roads smarter. The proposed procedure can be applied to all other contexts in an attempt to define the local model. The absence of a wide generalizability of the model could represent a limitation of the study.

Considering that these data belong to the timespan 2015–2019, rainfall data retrieved from the pluviometric annals are in this case adjusted to the same period (2015–2019) as well. To account for this difference with respect to the operating speed analysis, the rainfall amount is labelled as mm_P (instead of simply "mm"), while the days of rain are labeled as GG_P (instead of simply "GG"). Data obtained by this source were extremely precise and associated with a specific point. Within a radius of 5 km, the road was selected as belonging to one pluviometric station or to another.

Among the different alternative models for predicting crash frequencies [37], the consolidated negative binomial count data model (NB) was used to obtain the SPF [35]. The procedure for selecting the final model was the same as that used for the operating speed model.

The model was created based on at least three years of observed crashes, as suggested by HSM 2010 [35]. According to this need, the crash dataset for 2015–2019 was used because of its availability and robustness, as already highlighted by previous investigations in this area [26–36]. The selection of this time period did not affect compatibility with the V_{85} model since the two proposed models were calibrated with different sources and predict different future scenarios. Therefore, independently of the calibration data, the goal of prediction can be achieved by integrating the required data into the model. Moreover, the V_{85} model and the SPF do not interact directly by means of a specific variable. They interact in a post-process phase: the V_{85} can be predicted based on the detected real-time environmental conditions. Then, the obtained V_{85} can be used in considering a suitable speed limit according to the boundary and environmental conditions. This new speed limit could then be used to predict crash frequencies in an offline process to understand the safety implications. Based on this further assessment and on the analysis of the geometric and operational conditions (which are not specifically treated in this study), the variable speed limit could eventually be tested. This should be the integrated framework to rely on and to provide for road managers.

3. Results and Discussion

The results of the two groups of models are detailed in this section.

3.1. Operating Speed Model: Results and Discussion

In the Table 2, results derived from modeling operating speeds (V_{85}) are provided.

Table 2. Results from the generalized linear model used to estimate V_{85}.

Explanatory Variables	Coeff. Estimate	Std. Error	t-Value	*p*-Value
ADT	-3.927×10^{-4}	2.750×10^{-4}	−1.428	<0.001
VLegg	−0.865	0.148	−5.835	<0.001
SupL	0.258	0.045	5.678	<0.001
mm	−0.110	0.065	−1.713	0.043
IntType1	−5.276	1.892	−2.789	0.006
IntType2	*−4.564*	*3.260*	*−1.40*	*0.104*
CCR	−0.064	0.024	−2.680	0.008
Likelihood ratio test (reference: null model): $\chi^2(8) = 491.86$, $p < 0.001$, $R^2 = 0.62$				

In italics are all the variables with an associated coefficient showing a *p*-value greater than 0.10.

Results deriving from this first model highlight the strong effect of several of the mentioned variables. Especially crucial for this manuscript's goal of providing real-time speed estimates for VSLs is the correlation between the amount of rain (mm) and the operating speed. Increased rain causes the operating speed to decrease.

Moreover, although the operating speed only includes isolated vehicles, the effect of the ADT is still present. The justification for this result could reside in the mutual influence that vehicles have on each other traveling along the same paths, even with large time gaps: drivers are influenced by other drivers' behaviors (see e.g., ref. [38]). While, as expected, the ADT is inversely correlated with the V_{85}, the presence of light vehicles is also surprisingly inversely correlated with the V_{85}. This means that the massive presence of light vehicles led to reducing speed more than the presence of heavy vehicles. This can be justified by the cross-sectional arrangement of the road. The presence of just two lanes with almost absent shoulders enables the passing of one heavy vehicle at a time, without impacting the opposite direction's vehicle flow. But, in the case of multiple slow vehicles, the possibility of passing all of them is very low. Thus, the flow slows down. Moreover, as found by [38], drivers have a mutual influence on each other. In this scenario, the presence of similar types of vehicles had a greater influence on generating homogeneous behaviors like slowing down. This effect is similar to that of the intersection density. With an increase in density, first, the chance of conflicts increases, and second, driving speed decreases. This can be associated with drivers tending to be more cautious if they are aware that the higher intersection density could endanger their travel.

As expected from the previous literature [23,29–32], the effect of the CCR on operating speed is statistically significant. As the CCR increases, the speed decreases. Obviously, these are averaged values of the CCR over the entire road. This finding is consistent with the data about the percentage of drivers traveling at speeds higher than the limit, because when the road contains long tangents after an insidious road path, drivers are more prone to speed up to reduce their travel time [39].

The percentage of vehicles driving faster than the posted speed limit is positively linked to the V_{85}. While this result seems obvious, it should necessarily be analyzed together with the following figures (Figures 3 and 4), which report on the relationships among operating speed, the posted speed limit, and the percentage of vehicles moving faster than the speed limit (SupL).

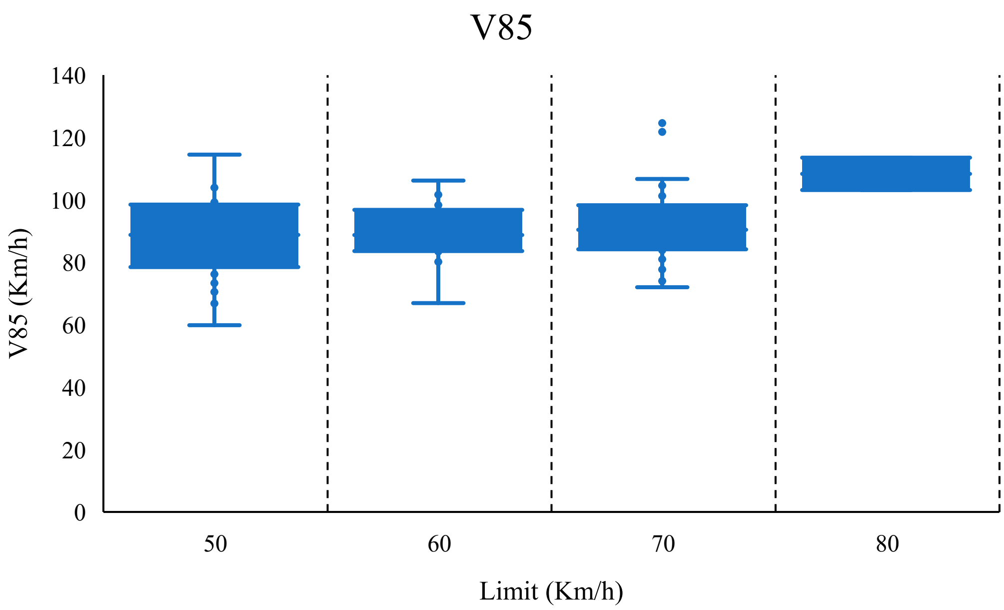

Figure 3. Whisker plot for V_{85} according to different speed limits.

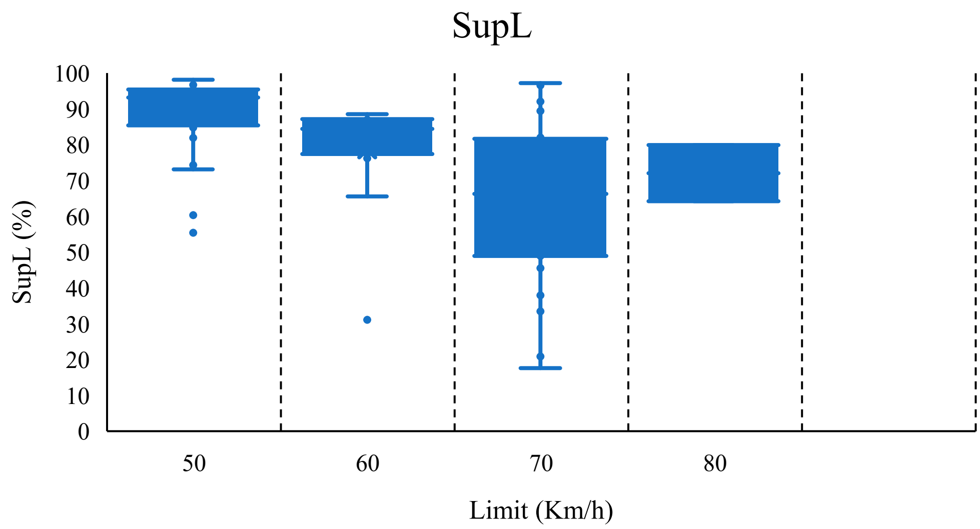

Figure 4. Whisker plot for SupL according to different speed limits.

The previous figure shows that the operating speed V_{85} is practically independent of the speed limit, apart from cases in which the speed limit is higher than 70 km/h (which, however, account for only 2 of 103 in the sample). Moreover, the analysis of operating speed boxplots reveals that the highest variability in operating speed corresponds to the case of the lowest speed limit (50 km/h). This should be analyzed in parallel with the SupL boxplots. In fact, in this case, it is evident that the percentage of vehicles traveling faster than the posted speed limit (SupL) is maximum (on average about 90%) in cases of the lowest speed limit (50 km/h). Moreover, on average, the SupL decreases with the speed limit, showing a clear correlation (in fact, the two variables were not simultaneously retained in the model). Another interesting aspect is that the highest variability in the SupL is noted for a higher limit (70 km/h). Hence, on average, it seems that drivers operate their speed independently of the speed limit and that the lower the speed limit, the more they are consistent in their noncompliant behavior. This supports the need for credible speed limits and for implementing technological innovations such as dynamically variable speed limits (VSLs).

In fact, current speed limits are compulsorily set based on particular geometric and/or boundary conditions to prevent risky situations and usually take into account worst-case scenarios (e.g., wet conditions). However, in cases where the geometric and boundary conditions allow for adapting the speed limit, setting VSLs according to the ever-changing road conditions becomes crucial. This approach could possibly lead to real-time adjustments, thanks to the knowledge of road geometry and the collection of traffic and environmental data in some spots of the road. These data can be used as input in the presented model, which can be used to continuously calculate the operating speed and thus adapt the VSL accordingly (e.g., 10 km/h lower than the V_{85}). This approach, in the absence of constraining low-speed conditions (clearly, adjusted VSLs should always be compatible with safety requirements based on the geometric and boundary conditions apart from the V_{85} predicted in real time), might increase the reliability and the credibility of the speed limit, making drivers more prone to set their speeds according to VSLs. There is no certainty about the acceptance of VSLs, but their variability and their adaptability to the varying driving conditions could increase the rate of credibility, which could in turn enhance drivers' responses. Moreover, there is also a strategy involving the frequency of the variable message and how to deliver the message such that it influences the response of drivers, as will be discussed later. A testing period would be beneficial to understand the impact and drivers' responses directly and then adjust and optimize functionalities according to the recorded behaviors.

3.2. Safety Performance Functions (SPFs): Results and Discussion

The results of the different estimated safety performance functions (for different crash locations and typologies) are presented as follows in Table 3. The effects of the independent variables on the different crash estimates are summarized in Table 4.

All crash frequencies, whether classified by type or by location, can be predicted as a function of the ADT and the length of the site (see, e.g., refs. [35,40,41]). The ADT is always linked to an increase in crash frequency, as suggested by Table 4. The ADT is, in fact, a risk exposure variable.

The length of the site ("L") is not correlated with the crash frequency prediction in only two cases, in the intersection and curve crash models. In fact, intersection crashes usually do not depend on the length of the site but more on intersection density and typology. On the other hand, curve crashes are more relatable to the geometric issues of the specific curves than to the entire length of the site. Even if the wrong coordination between tangents and curves can affect the perceived safety on a curve, the entire length of the investigated site seems to have negligible effects on crash prediction in curves. Regarding site length, its influence on crashes is positive (i.e., an increase in length leads to an increase in crash frequency) for the overall crash prediction and the type of crash (single- or multi-vehicle). This correlation is typical of crash prediction models (see, e.g., refs. [35,40,41]) because the length is another risk exposure variable.

The percentage of light vehicles ("VLeg"), i.e., the traffic composition, seems to have an impact on the total crash frequency and the multi-vehicle crash frequency. Results reveal that increasing the percentage of light vehicles increases the crash frequency for both models. Apart from what was previously stated about the relationships between light vehicles and riskiness, this result can be interpreted considering that slow speeds, especially those due to traffic conditions, induce greater perception and reaction time [42]; therefore, reacting to external inputs becomes more challenging for drivers. Moreover, reduced speeds can lead to aggressive behaviors for overtaking maneuvers, associated with a greater likelihood of head-on crashes but also a greater likelihood of rear-end crashes in cases of different speeding behaviors [43]. This result seems particularly emphasized by model results that highlight positive and statistically significant coefficient values. This means that with an increase in the percentage of light vehicles, multi-vehicle crashes and the total number of crashes are more likely to increase, for the reasons explained. No other crash frequency variables seem to be statistically significantly affected by the traffic composition.

The other independent variable, always (except for curves) associated with the developed models, is the speed limit ("Limit"), i.e., the posted speed limit. This latter result, more than the others, is crucial in the context of discussing variable posted speed limits, because it can provide meaningful information about the correlation between crash frequency and speed limits. Based on the discussion in the previous paragraph about speeds, posted speed limits that are not perceived as credible may lead to dangerous situations and increase the chance of noncompliance by drivers (see also [44,45]). The first consideration is that curve crashes do not depend on speed limits, assessing that the driving behavior on curves is strictly related to specific curve driving conditions. This can be justified since drivers would adjust their speeds and trajectories according to the perceived risk of the specific curve conditions. Considering the speed limits correlated to crashes, their influence varies depending on the speed limit and the specific crash prediction model. They are positively correlated with a crash occurrence for the total crash model. However, further considerations are needed. In fact, for the total crash model, the 60 km/h speed limit was not statistically significant, and the 80 km/h limit is not representative, since only two sites exhibited that speed limit. Therefore, results show that the 70 km/h speed limit is relatively more dangerous than the 50 km/h speed limit. This result can also be interpreted by looking at Figure 2, focusing on the high variability of noncompliant drivers at 70 km/h. It appears that a 50 km/h speed limit encourages almost all drivers to be noncompliant; on the other hand, the 70 km/h limit generates variable behaviors that lead to uncertain driving conditions on roads. The latter phenomenon could well explain the reason why the 70 km/h speed limit is associated with a greater total crash occurrence.

Regarding the other speed limits, it seems that in going from 60 to 80 km/h, the probability of crashes compared to the 50 km/h speed limit almost doubles. A 70 km/h limit is three times more dangerous than one of 60 km/h, if compared to the baseline scenario, and 80 km/h is five times more dangerous than 60 km/h (always considering the baseline of 50 km/h as the benchmark), all other conditions being equal.

Table 3. Results from the negative binomial model used to estimate the crash frequency. In bold, the dependent variables (Ntot, MultiVeic, SingleVeic, Curve, Rett, Int) estimated by the independent ones.

Ntot = Number of Crashes = Dependent Variable				
Explanatory Variables	**Coeff. Estimate**	**Std. Error**	**z-value**	***p*-value**
(Intercept)	−2.916	1.020	−2.858	0.004
ADT	1.192×10^{-4}	1.344×10^{-5}	8.868	<0.001
VLegg	0.031	0.014	2.324	0.020
Limit60	*0.340*	*0.225*	*1.513*	*0.130*
Limit70	0.938	0.229	4.100	<0.001
Limit80	1.649	0.525	3.141	0.002
L	0.008	0.007	1.113	0.026
Rmax	-5.041×10^{-5}	1.413×10^{-5}	−3.567	<0.001
Dispersion parameter: 2.58, AIC = 1237.1; Likelihood ratio test (reference: null model): $\chi^2(8) = 84.659$, $p < 0.001$, $R^2 = 0.26$				
MultiVeic = number of multi-vehicle crashes = Dependent Variable				
Explanatory Variables	**Coeff. Estimate**	**Std. Error**	**z-value**	***p*-value**
(Intercept)	−4.214	1.347	−3.129	0.002
ADT	1.511×10^{-5}	1.754×10^{-5}	8.613	<0.001
VLegg	0.017	0.010	1.748	0.008
Limit60	−0.012	0.280	−0.042	0.097
Limit70	0.390	0.206	1.888	0.005
Limit80	0.260	0.596	0.436	0.007
CCR	−0.004	0.002	1.688	0.009
L	0.003	0.010	0.320	0.047
Dispersion parameter: 2.32, AIC = 886.0; Likelihood ratio test (reference: null model): $\chi^2(8) = 295.49$, $p < 0.001$, $R^2 = 0.27$				
SingleVeic = number of single-vehicle crashes = Dependent Variable				
Explanatory Variables	**Coeff. Estimate**	**Std. Error**	**z-value**	***p*-value**
(Intercept)	−1.552	0.494	−3.143	0.002
ADT	4.425×10^{-5}	2.380×10^{-5}	1.860	0.006
Limit60	0.068	0.311	0.219	0.008
Limit70	0.306	0.196	1.561	0.012
Limit80	0.452	0.641	0.705	0.048
CCR	−0.002	0.003	−0.685	0.049
L	1.401×10^{-4}	0.011	0.012	0.009
mm_P	4.414×10^{-4}	7.178×10^{-4}	0.615	0.050
Dispersion parameter: 0.82, AIC = 831.3; Likelihood ratio test (reference: null model): $\chi^2(8) = 308.43$, $p < 0.001$, $R^2 = 0.23$				
Curve = number of crashes happening on curves = Dependent Variable				
Explanatory Variables	**Coeff. Estimate**	**Std. Error**	**z-value**	***p*-value**
(Intercept)	−2.753	0.646	−4.263	<0.001
ADT	5.337×10^{-5}	2.864×10^{5}	1.863	0.036
CCR	0.007	0.002	2.812	0.005
mm_P	0.002	0.001	1.583	0.011
Dispersion parameter = 0.63, AIC = 645.2; Likelihood ratio test (reference: null model): $\chi^2(4) = 447.48$, $p < 0.001$, $R^2 = 0.39$				

Table 3. *Cont.*

Rett = number of crashes on straight tangents = Dependent Variable				
Explanatory Variables	**Coeff. Estimate**	**Std. Error**	**z-value**	***p*-value**
(Intercept)	1.103	0.383	−2.877	0.004
ADT	1.723×10^{-4}	2.178×10^{-5}	7.912	<0.001
Limit60	−0.153	0.290	−0.526	0.599
Limit70	0.151	0.172	0.877	0.038
Limit80	0.142	0.679	0.210	0.083
IntTyp1	−0.509	0.185	−2.749	0.006
IntTyp2	−0.814	0.275	−2.967	0.003
mm_P	-5.449×10^{-4}	5.837×10^{-4}	−0.934	0.035
L	−0.021	0.012	−1.899	0.052
Dispersion parameter = 4.50, AIC = 788.77; Likelihood ratio test (reference: null model): $\chi^2(9) = 70.336$, $p < 0.001$, $R^2 = 0.37$				
Int = number of crashes happening at intersections = Dependent Variable				
Explanatory Variables	**Coeff. Estimate**	**Std. Error**	**z-value**	***p*-value**
(Intercept)	−2.694	0.291	−9.256	<0.001
ADT	1.322×10^{-4}	2.947×10^{-5}	4.4484	<0.001
Limit60	−0.715	0.477	−1.497	0.013
Limit70	*−0.087*	*0.254*	*−0.346*	*0.730*
Limit80	0.520	0.642	0.809	0.042
IntTyp1	0.566	0.270	2.094	0.036
IntTyp2	0.511	0.373	1.368	0.017
IntDensity	0.066	0.116	0.565	0.051
Dispersion parameter = 1.17, AIC = 509.67; Likelihood ratio test (reference: null model): $\chi^2(8)$: 567.51, $p < 0.001$, $R^2 = 0.38$				

In italics are all the variables with an associated coefficient showing a *p*-value greater than 0.10. The referenced type of intersection, IntType, is IntType0, i.e., the three-legged intersections. Results are expressed accordingly, highlighting the impact of IntType1 and IntType2 compared to the baseline IntType0.

Table 4. Summary of the statistically significant effects of the independent variables on crash frequencies of different typologies estimated using the negative binomial models ("+" for increase; "-" for decrease).

	Ntot	**MultiVeic**	**SingVeic**	**Curve**	**Rett**	**Int**
ADT (veh/day)	+	+	+	+	+	+
VLeg (%)	+	+				
Limit60		-	-			-
Limit70	+	+	+		+	
Limit80	+	+	+		+	+
L (km)	+	+	+		-	
Rmax (m)	-					
CCR		-	-	+		
Amount of rain (mm)			+	+	-	
IntType1					-	+
IntType2					-	+
IntDensity (N int/km)						+

The single-vehicle and multi-vehicle crash prediction models show different effects of the speed limits, again, with all other conditions being equal. For multi-vehicle crashes, the 60 km/h speed limit is associated with a decrease in crash frequency; on the other hand, 70 and 80 km/h speed limits are associated with an increase in crash frequency. The ratio is almost the same as highlighted before, where 80 km/h is the one associated with most crashes compared to 50 km/h, but it increases the likelihood of single-vehicle crashes only by around 0.5 times. The speed limit of 80 km/h is around five times more crash-driving than 60 km/h compared to the benchmark value. In multi-vehicle crashes, the crash reduction in the case of 60 km/h compared to 50 km/h is immediately offset by a crash increase if 70 km/h and 80 km/h are considered in comparison to 50 km/h. Additionally, the 60 km/h speed limit is associated with a decrease in crash frequency for the intersection crash prediction model when compared to 50 km/h. The 70 km/h speed limit is associated with an increase in crashes for tangents when compared with 50 km/h. The 80 km/h speed limit is always associated with a crash frequency increase when compared to 50 km/h conditions. From these results, it is evident that the speed regulation of intersections has valuable effects in terms of safety. All the other models highlight an important aspect with regard to VSLs: slight changes in speed limits can significantly impact safety. This aspect is correlated with the aforementioned considerations, i.e., higher speed limits can increase uncertain driving behaviors and variability in noncompliance. Therefore, speed limits should cohere with the road and environmental conditions to be safe, credible, and reliable, inducing uniform driving behaviors and compliant responses. This consideration can be corroborated by looking at Figure 2: the operative speed is independent of the speed limit, and it is almost constant; hence, the only influencing aspect is related to the variability of driving behaviors. Heterogeneous behaviors imply more risks on the roads. Therefore, a VSL, if adequately installed, could bring about safer and more respectful driving behavior towards posted speed limits.

After the above comments about speed limits, it is worth highlighting that there are just two sites with 80 km/h as the posted speed limit (thus ten counts in the model, two for each investigated year of the crash dataset). In terms of statistical modeling, the 80 km/h limit should have been grouped with another limit due to its rare occurrence, but, from an engineering point of view, each limit has a different meaning and effect on driving behavior and safety [46]. Keeping this in mind, results about the 80 km/h speed limit would require a greater sample to be confirmed.

The maximum radius of the horizontal alignment correlates with crashes only for the total crash prediction model. It means that greater radii imply improved safety.

Another measure for the tortuosity and curvature of the road is the CCR, which seems to correlate more with the different crash frequencies than the radius. This can be explained by the overall indication that the CCR provides about the tortuosity present at the site. The maximum radius is just a measure of a single curve, which could also not align with the overall tortuosity of the road path. Multi-vehicle and single-vehicle crashes are affected by the CCR in that increasing the CCR decreases the crash frequency. With regard to multi-vehicle crashes, an increase in the CCR can lead to driving more safely and thus to reducing potential conflicts among multiple vehicles because of the frequency of sharp curves, where passing is almost impossible. The same considerations can be applied to crashes on tangents. In the case of single-vehicle crashes, the CCR is also inversely correlated to crash occurrence. A low CCR is associated with greater speeds on tangents and large radius curves; therefore, vehicles are at risk when managing unexpected curves, leading to single-vehicle crashes. This could be a possible explanation for the estimated negative coefficient associated with the CCR. Curve crashes are directly proportional to the CCR because sharper curves and greater tortuosity imply riskier curves to drive.

Looking at the rain variable, i.e., the rainfall amount (mm_P), it correlates with the curve, single-vehicle, and tangent crash prediction models only. The result involving curves and single-vehicle crashes is explainable considering the geometric issues with curves: the more it rains, the riskier the driving is on curves due to instability [47]. For the same reason, the frequency of single-vehicle crashes can increase. For tangents, the rainfall amount is inversely related to crashes. Consistent rain may induce drivers to be more cautious;

therefore, on certain road segments, the influence of rain does not seem to be detrimental to safety.

The intersection typology is correlated with the tangent and intersection crash prediction models. For the latter, four-legged intersections and mixed typologies of intersections are positively correlated with crashes. As regards crashes occurring on tangents, four-legged intersections and roundabouts on segments are safer when they occur frequently. This is due to the indirect speed management induced by the presence of intersections on segments.

The intersection density is an independent variable capable of explaining only the intersection crashes. It is positively related to crashes; with increased intersection density, the crash frequency increases, because of the greater number of possible conflicts.

All of the outcomes mentioned highlight the importance of considering all the aspects related to the road, from geometry to environmental variables, in order to explain safety performance. Such consideration is aligned with the purpose of the study about the importance of credible and reliable VSLs. First, as highlighted by the mentioned literature, speed limits should be set according to the road geometric features in order to be credible and to allow drivers to comply with them. Moreover, the ever-changing conditions on roads while traveling undoubtedly affect the speed regime for the purpose of safety. With this in mind, setting variable posted speed limits can ensure greater rates of safety for all drivers. Static speed limits are an option in the case of geometric or other specific constraints that should always be accounted for, independently of the boundary conditions. For all other cases, setting a VSL can be a valuable option, with real-time recordings of data and extraction of speed limit values, thanks to the proposed framework and the deployment of traffic and environmental sensors on roads. The necessary equipment is low-cost and enables secondary roads to be smart, helping drivers. Yet despite the benefits of the technologies mentioned, there are other factors to consider for their effective implementation. First of all, installing VSLs would require sensors for monitoring and a data cloud and algorithms to obtain the desired output. Comparing these features to the overall equipment that a smart road could require, the costs seem negligible. However, as previously highlighted, these roads are often subjected to low-cost interventions and maintenance; therefore, deploying VSLs on the overall secondary road network might be a utopian endeavor. Some choices could be made based on selected rationales (such as risk scores [48]) to intervene on a selected set of roads. The cost of the wide implementation of VSLs remains the first obstacle to this innovation. The second obstacle is human drivers and their adaptations. A recent investigation [49] demonstrated that, in adverse weather conditions such as those proposed by this study, a VSL improves car-following behavior, enhancing safety and sight distances. Saha et al., 2015 [50], investigated the different impact that VSLs can have on safety outcomes according to the combination of weather conditions and geometric alignment. Of course, complex alignments combined with adverse weather conditions strongly compromised the safety of travel. Moreover, the presence of VSLs induces greater trust in drivers for suggested speeds lower than 90 km/h, highlighting more cautious behaviors, including reduced speed variability and reduced mean speed values. Both these conditions are crucial for road safety in adverse weather conditions [51]. Moreover, evaluating VSLs under different bends, slopes, and traffic conditions, it emerged that they effectively improve the road capacity, reduce the driving risk of vehicles, and alleviate traffic congestion, especially under such adverse weather conditions as intense rain and foggy or snowy situations [52]. These findings are in line with the expectations of the proposed model, which aims to provide safer speeds under rainy conditions, utilizing the real-time monitoring of data from pluviometric stations and traffic sensors (to detect speeds and traffic volumes). Thanks to these pieces of information, it would be possible to adapt VSLs to the real-time speeds of drivers in an attempt to reduce them. The adaptability of drivers to these technologies might be studied for mid- and long-term situations, not in simulated environments but on real roads, through monitoring strategies to test their effectiveness. This can be a possible further development of the studies on VSLs. But drivers' responses might be nonhomogeneous, and, in that case, some control strategies could improve their effectiveness. Not all drivers are compliant with road signs, whether static or variable; however, a VSL update frequency of 5 min and a maximum speed difference of 10 km/h between successive time steps was found to be the best solution, improving safety up to 50% and mobility to 30% [53]. The importance of control strategies is fundamental, since VSLs are sensitive to the level of driver compliance, and working effectively on the best control strategy can ensure uniform driver compliance [54]. VSLs can introduce benefits in potential crash reduction (5–17%) and total travel time, if adequately managed [55]. The effectiveness of such implementation depends on other factors such as gender, age, road type, visibility conditions, and familiarity, which could undermine their positive effect [56,57]. Ambiguous results about VSLs on freeways were found when comparing alternative control strategies. Standard strategies seemed to improve safety but increase travel times. Hence, it is necessary to accurately work on control strategies (and adjust them in cases of unexpected results) and to work on the type, size, placement, and spacing of VSLs to positively impact driver behavior [58]. The introduction of VSLs has already been considered in the wider context of smart roads, at least from a regulatory point of view (https://www.nhtsa.gov/book/countermeasures-that-work/speeding-and-speed-management/countermeasures/legislation-and-licensing/variable-speed-limits, last accessed on 5 May 2025) (https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=PI_COM:Ares(2021)2243084&rid=1, last accessed on 5 May 2025). Thus, in this regard, their introduction could be easy. Another aspect to consider is effective strategies for implementing VSLs while not inducing aberrant behaviors. In fact, as also mentioned in the study, the introduction of VSLs might be evaluated in light of all the other boundary conditions; they do not have to encourage speeding and/or aggressive behaviors, just to modify the acceptable speed according to several conditions that can influence mobility. The control strategies and the frequency of signal updates can be influential as well [53].

The decision whether to implement a VSL must be supported by a benefit–cost analysis. Such analysis can also be used to prioritize the intervention of VSL technology on roads [59]. According to an economic assessment of VSL systems based on a case study performed on British Columbia provincial highways, results show a high benefit/cost ratio [60]. Furthermore, the use of this system demonstrates that it may be most appropriate for long-term applications in terms of benefit–cost analysis [61]. In fact, as the results underline, the positive effects on the safety of VSLs are consistent. Their implementation is rapid, and they do not directly impede ordinary traffic flow. Other types of intervention, such as road design improvements or traffic calming, are more expensive [62] and force temporary road interruptions. This negatively impacts the benefit–cost ratio. Solutions such as road design improvements are extremely beneficial in the context of a thorough renewal and modification at a network level to create homogeneous and systemic interventions. However, if the intervention is isolated, it is extremely demanding in terms of cost and design requirements. The benefits introduced in terms of safety are not immediate and need to be evaluated by ad hoc functions, such as the one proposed by Donnell et al., 2019 [63]. On the other hand, with regard to such cheaper and more immediate solutions as speed-enforcement strategies, they can impact rural road safety by reducing potential crashes up to 15% (as suggested in [64]). VSLs seem to be an intermediate strategy with regard to cost and ease of implementation, but a valuable solution for crash reduction (e.g., approximately −30% in the case of rural road crashes, as suggested in [60]).

The proposed method can be extremely valuable in light of data-driven strategies and sensors for improving the trajectories and the behaviors of drivers. Some efforts have been made in this direction, and not only for VSLs [65–67]. Once these approaches are widely deployed and coupled with accurate sensor performance, the introduction of VSLs could be optimized and improved for safe implementation.

4. Conclusions

The transportation world is facing several challenges and modifications, starting with autonomous vehicles and smart roads. However, before introducing such wide-ranging changes, we must consider that some types of roads need smaller interventions to provide sustainable improvements in terms of safety and travel comfort. One of these is the rural secondary road, which is often present in demanding driving environments and/or built several years ago, before the introduction of either the self-explanatory road approach or modern standards. These roads could be made safer with simple interventions like variable posted speed limits. In many cases, the posted speed limits are as obsolete as the roads where they were placed and do not account for all the variability of road conditions. The presented manuscript aims to account for these variabilities, attempting to find a model that explains the correlation among vehicle operating speeds and the geometric variables of the roads, together with other environmental factors such as rainy-day conditions or amounts of rain. Vehicle operating speed was selected because it represents the actual speed chosen by drivers, meaning that it should be aligned with the context in which they are traveling. Moreover, the traffic, geometric, and environmental variables are linked to crash occurrence by means of the development of SPFs. This approach was tested on the two-way, two-lane rural roads of the Metropolitan City of Bari, in the context of the drafting of the Sustainable Urban Mobility Plan. These roads were selected as relatively most affected by crashes in the investigated period of 2015–2019.

The two selected models, one for operating speeds and the second for SPFs, were, respectively, a generalized linear model and a negative binomial one. The explanatory variables for this model were CCR, ADT, the percentage of light vehicles, the percentage of speeds greater than the posted speed limits, and the amount of rain. The latter variable is a crucial predictor to set VSLs, correlating data from pluviometric stations with speed limit stations. In this way, it could be possible to alert drivers and to set speeds according to the changing conditions: speed limits can be modified and set as variable in cases where no other constraints for safety are to be applied to the investigated road.

Looking at the outcomes provided by the SPF, the role of the posted speed limit for safety purposes seems crucial. It was found that the total number of crashes, the crash typology, and the location of the crashes were affected by the ADT, road tortuosity, posted speed limits (which are implicitly correlated with the percentage of noncompliant vehicles, see Figure 2), and the length of the site. Curve and segment crashes are also related to rainy conditions. Of course, VSLs can be a solution, but they need to be tested on some selected roads in order to understand also responses from drivers, especially in terms of homogeneity of compliance and thus on potential safety. The VSL should be set as credible; therefore, drivers should be more prone to comply with it. However, it is important to state that more experimental data about the effects of VSLs on compliance and driving behaviors are needed to demonstrate their usefulness and effectiveness.

Despite the proposed study presenting some positive preliminary results, research in this field can be enriched by adding other environmental variables that could have an impact on driver speeds and implementing real-time, data-driven strategies. In this way, the outcome of the proposal for a VSL can be extended to multiple types of conditions. Moreover, a thorough investigation of other road typologies would ensure the applicability of these models to other contexts and to all potential available road typologies. Another limitation of this study is that the coefficient estimate was based on the conditions present at the investigated sites. These coefficients can be calibrated for other contexts just by varying the input data. The mathematical structure of the models may not vary; only the value of some coefficients can vary according to other boundary conditions. Moreover, this study can be constantly updated to provide meaningful results for practitioners with the most recent crash data. Relying on recent years' crash data, the SPFs could be better calibrated to find strong connections between the variability of posted speed limits and crashes.

The outcome of this research can be useful for road managers, who can create VSL stations to post credible and reliable speed limits, correlating the collected data to crash frequency and therefore setting the most suitable posted speed limit, also taking into account all the other road variables (like ADT or rain). This integrated approach can lead to several benefits, not only in terms of safety, but also in terms of cost reduction for post-crash interventions and management. Moreover, posting VSLs can be a starting point in helping drivers become accustomed to interacting with roads, with an eye towards the future deployment of smart roads and helping drivers become more comfortable with and trusting of technology implemented on roadways.

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