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Transportation Research Procedia 60 (2022) 592–599

Transportation Research Procedia

www.elsevier.com/locate/procedia

XXV International Conference Living and Walking in Cities - New scenarios for safe mobility in urban areas (LWC 2021), 9-10 September 2021, Brescia, Italy

Effects of urban road environment on vehicular speed. Evidence from Brescia (Italy)

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Abstract

Inappropriate speeds are key factors that may affect the occurrence and the severity of road crashes. Although rural roads are influenced by more severe crashes than urban roads, perhaps due to the higher vehicular speeds, the latter suffer from a higher frequency of crashes. Therefore, exploring factors affecting the vehicular speed in the urban area is crucial. The literature provided several models to usually estimate the operating speed (i.e., V_{85}) in rural roads. However, further investigations are needed to provide these estimations in the urban areas. In addition, these models often estimate the 85th percentile of the speed distribution, that cannot represent the entire distribution. Therefore, the problem of the speed prediction distribution is also a challenge in urban roads. This paper addresses this challenge by exploring the effects of some road factors on the vehicular speed along segments of urban roads. First, this speed is modelled as a random variable with a normal distribution. Next, by using 11,466 car spot speed data collected along a portion of the urban road network of city of Brescia (Italy), two multiple linear regression models were run for the estimation of the speed mean and the related standard deviation, respectively. Preliminary results showed that the presence of median, the bus stop density, the presence of curb and the type of adjacent land are significant predictors of the vehicular speed distribution on urban roads. These results may support road management agencies to set proper actions on speed management, especially for existing roads and/or critical section roads in urban areas.

Peer-review under responsibility of the scientific committee of the Living and Walking in Cities

Keywords: urban road segments; mean speed; standard deviation speed; normal distribution; multiple linear regression

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Peer-review under responsibility of the scientific committee of the Living and Walking in Cities
10.1016/j.trpro.2021.12.076

1. Introduction

Speed is a key factor for road safety, as it can affect the occurrence and severity of crashes. An inappropriate vehicular speed (or speed) is responsible for a high quota of fatalities and disabilities. For instance, in 2019 in Italy, more of 70% of total crashes occurred on urban roads and speeding represented the 13% of all possible causes (ACI, 2019). This value is surprisingly still too high, given the maximum posted speed limit in urban areas (generally equal to 50 km/h) and considering the repeatedly presence of traffic calming elements (*e.g.*, road narrowing, chicanes), which are primarily intended to reduce speed and protect vulnerable road users (*i.e.*, pedestrians and cyclists).Therefore, further investigation should be carried out to provide safer urban roads. Treatments facing unsafe speed have been at the core of the road safety policy for decades, and a significant progress has been made. However, there is still large potential for addressing this longstanding issue at the EU and national levels (ETSC, 2019). Therefore, with a strong political support and an effective coordination between responsible authorities, speed management strategies can significantly contribute to achieve road safety targets.

Studying the relationship between drivers' speed choice and road environment, could be a useful tool to improve speed management (Bassani et al., 2014). For instance, the development of speed prediction models could help designers both to improve the urban road environment and to increase the safety of all users, with particularly attention to vulnerable users. The literature provided relevant models to explain drivers' speeds as a function of several predictors (variables, factors, or determinants) such as roads geometric characteristics, vertical signs, pavement conditions, land use, speed and traffic data (e.g., Bassani et al., 2014; Thiessen et al., 2017). So, the analysis of road characteristics can promote a safer speed's choice, which are consistent with road functions, and improve road safety performance (Bassani et Sacchi, 2012), in addition to traditional measures (e.g., traffic calming devices). Therefore, the relationship between speeds and driving environment could help to reach possible solutions to speeding. In this way, this procedure facilitates the selection of street layout and roadside elements to obtain the desired traffic result (Kubota, 2013).

Currently, the literature has mainly focused on rural road speed models because driver behaviours in the rural environments seem to be less complex to explain that in urban areas (e.g., Kubota, 2013; Thiessen et al., 2017). Indeed, in urban areas several factors contributed to increase the chance of a crash, such as major traffic volume, coexistence of multiple vehicles' categories and vulnerable users, a high quota of activities and different land use along the roadsides (Barabino et al.,2021; Bassani et al., 2012; Bassani et al., 2014, Bonera & Maternini, 2020; Porcu et al., 2020; 2021). Therefore, urban roads are more challenging compared to rural roads (e.g., Kubota, 2013).

Moreover, existing urban speed models estimated a specific speed percentile, generally the 85^{th} percentile speed, i.e. the operating speed - V_{85} (e.g., Fitzpatrick et al., 2001; Fitzpatrick et al., 2005; Wang et al., 2006; Bassani & Sacchi, 2012). However, V_{85} estimating could not represent the entire speed distribution because it does not enable to distinguish between the mean speed and the speed dispersion factors contributions. Indeed, two percentile speed curves can have the same 85^{th} speed percentile but different mean speed and speed standard deviation (e.g., Medina and Tarko, 2005; Bassani et al., 2014). Therefore, to better explain speeds' data variability, it could be useful to study the entire distribution of speed instead of V_{85} to possible address this concern. In addition, the entire speed distribution representation could be useful to infer possible correlation with accident indicators (Bassani et al., 2014). Studies have demonstrated that an increase in mean speed increases crash severity, while an increase in speed variability increases the frequency of interactions between vehicles (Medina and Tarko, 2005). Furthermore, in urban roads, the free-flow traffic conditions (base to V_{85} determination) are difficult to be maintained, due to high traffic flow and frequent presence of traffic signals/traffic control devices (e.g., Bassani et al., 2014). Finally, since urban streets flow is interrupted, the interpretation of high-volume observations is not as straightforward as for uninterrupted-flow facilities (TRB, 2000).

The contribution of this paper is the evaluation of the effects of some road environment characteristics on the urban speed along an urban road segment, that were not completely analysed in the previous studies. More precisely, at first, this speed is modelled as a random variable with a normal distribution. Next, by using 11,466 car spot speed data collected along a portion of the urban road network of city of Brescia (Italy), two multiple linear regression models were specified, calibrated and validated for the estimation of the mean speed and the its standard deviation, respectively.

This paper aims to contribute to both theory and practice. From a theoretical perspective, this paper covers a research area that has not completely addressed. On the practical side, the identification of roads' characteristics that may affect the driver behaviour could be useful to possibly adjust the road design more consistent with driver expectancy (i.e., applying the self-explaining road criteria) and traffic condition, to increase user's safety.

The remaining paper is organized as follows. Section 2 presents material and methods for the data collection and for the construction of the speed prediction model. Section 3 shows and discusses the results. Finally, Section 4 draws conclusions and provides future perspectives.

2. Materials and methods

2.1. Research context

The research was performed in the city of Brescia, which is in the eastern side of the Lombardy Region (Italy). Brescia has 194,990 inhabitants (ISTAT, 2021), with an area of 90.34 km^2 and a density of about 2,158 inhabitants per km^2. It's the second largest city in the region and the fourth in the northwest Italy. The urban area of Brescia extends beyond the administrative city limits and has a population of 672,822, while over 1.5 million people live in its metropolitan area.

Brescia represents one of the most important industrial, commercial, and social hubs in Italy, so that it originates/attracts major vehicular traffic daily (RL, 2016). However, the urban road network is undersized if compared to the traffic volumes and the territorial extension, as proven by the frequent congestions during peak hours. This fact is also confirmed by the relevant number of road crashes. Over 2019, in Brescia, more than 20% of total crashes occurred in whole Province were located in the urban area (ACI, 2019). Therefore, the development of a real data-driven model to estimate the speed distribution could contribute to identify the variables that may be changed to possible adjust wrong drivers' behaviours owing to lack of good road environment.

2.2. Road surveyed and segmentation

A sample of sections were surveyed along the main urban road network and belonging to collector roads (type E according to MIT, 2001). Moreover, these sections enable the traffic distribution within the metropolitan area and are characterized by the highest traffic flows.

Next, each road has been divided into homogeneous segments, defined as a portion of road comprised between two consecutive signalized intersections or roundabouts. The surveyed segments are located inside the urban area on a flat terrain and cross residential, commercial, hospital and industrial zones. The surveys were conducted during April and May 2021, on weekdays, under daylight and good weather conditions. A total of 37 locations on 24,7 km of urban road network was surveyed. The surveyed roads are shown in Fig. 1.

2.3. Data collection, pre-processing and data cleaning

Since the estimation of the speed distribution required several components i.e., spot speed measurements and road characteristics for each segment, different data types were collected from different sources.

As for the spot speed measurements, these were conducted by using a laser traffic counter provided by a reputable manufacturer. This device is based on the laser beams emission and reception that perpendicularly crosses the road axis. It was located on the roads' edge parallel to the travel direction, at about 1m from the road surface, and at know distance from the beginning of the selected segment. Moreover, the device was carefully hidden to avoid changes of driver's behaviour owing to its presence. The device recorded time (i.e., date, hour, minutes, and seconds), spot speed [km/h], vehicle length [m] and travelling direction (i.e., ascending and descending) for each passing vehicle. Surveys lasted at least 30 minutes to have a representative data sample. The device enabled speeds registration in both directions (for roads with one lane in each direction) or in single direction (for roads with multiple lanes in each direction). A total of 21,084 vehicles' spot speed was recorded. Moreover, since spot speed data were automatically collected, some data cleaning was applied before calibrating the speed models.

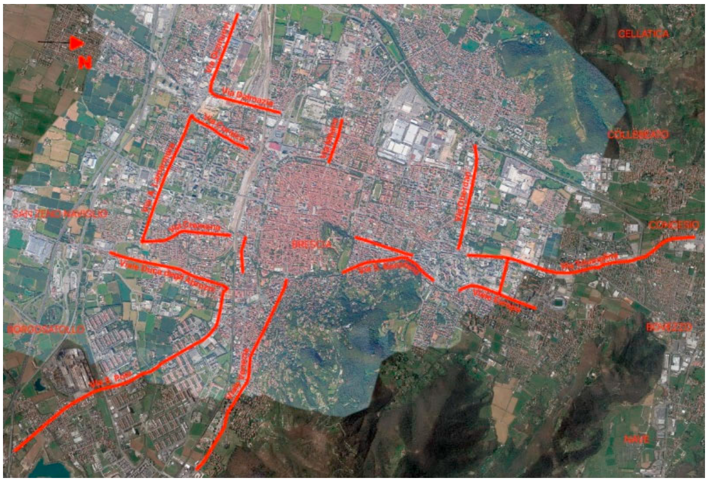

Figure 1: Surveyed roads considered for the study

Bicycles, motorcycles and commercial vehicles speeds were excluded (according to a length-based criterion), because the main goal was to provide speed models for cars, that represent the highest quota of traffic. Next, the literature provides different gaps to evaluate free-flow conditions in urban area (Fitzpatrick et al, 2001; Bassani et al., 2014; Thiessen et al., 2017). In this paper, a 2-s threshold was used to exclude congestion effects but at the same time to avoid excessive alterations of the real speed distribution. Finally, data cleaning returned 11,466 car spot speed records, that generated 52 values of mean speed and speed standard deviation over 37 locations.

As for the road characteristics, firstly drawing on the previous literature, road axis, cross section, roadside, marking roads, traffic data and land crossed were identified as possible factors affecting the operating speeds. Next, data on these factors (and sub factors) were collected for each segment by using several sources, such as on the field measurement, direct measurement, and digital cartography.

2.4. Data analysis method

Let N be the set of surveyed locations and let assume that the speed observed at location $i \in N$ is a normally distributed random variable with mean μ_{v_i} and standard deviation σ_{v_i}.

Let:

- z be the standard normal random variable, i.e., a normal distributed random variable with mean $\mu_z = 0$ and standard deviation $\sigma_z = 1$;
- $\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2}\, du$ be the cumulative distribution function of z.
- $z(p) = \Phi^{-1}(p)$ be the z value associated to a certain fixed percentile p.

Then, the speed associated to the p percentile, which helps investigate the overall speed distribution, observed at location $i \in N$ is given by:

$$v_i(p) = \mu_{v_i} + \sigma_{v_i} \cdot z(p) \qquad \forall i \in N \tag{1}$$

The distribution parameters μ_{v_i} and σ_{v_i} observed at location $i \in N$ can be assumed as response variables for two multiple linear regression (MLR) models. More formally, let: $\widehat{\mu_{v_i}}$ and $\widehat{\sigma_{v_i}}$ be the predicted mean speed and the speed standard deviation at location $i \in N$ respectively; X_{ik} and X_{iq} be the values of the kth and qth predictors for the mean speed and the speed standard deviation at location $i \in N$ respectively; α_k and β_q be the regression coefficients associated with the kth and qth predictors, respectively; A and B be the hyperplane intercepts for the mean speed and the speed standard deviation, respectively; m and n the total number of explanatory variables considered in the MLR models for the mean speed and the speed standard deviation respectively. The MLR models for the mean speed and the speed standard deviation predictions are given by:

$$\widehat{\mu_{v_i}} = \sum_{k=1}^{m} \alpha_k X_{ik} + A \qquad \forall i \in N \tag{2}$$

$$\widehat{\sigma_{v_i}} = \sum_{q=1}^{n} \beta_q X_{iq} + B \qquad \forall i \in N \tag{3}$$

These models were estimated by the ordinary least squares' method. Moreover, they were evaluated by the following goodness-of-fit statistics: the R^2 and the linear correlation between predictors and the response variable, indicated by global F-test and the corresponding significance value. The sign of the coefficients and their significance were also evaluated.

Once the models have been estimated, by substituting equations (2) and (3) in (1), the model to predict the speed associated to the p percentile, observed at location $i \in N$, is obtained as a function of the explanatory variables:

$$\widehat{v_i(p)} = \sum_{k=1}^{m} \alpha_k X_{ik} + A + \left(\sum_{q=1}^{n} \beta_q X_{iq} + B \right) \cdot z(p) \qquad \forall i \in N \tag{4}$$

3. Results and discussion

In this study, μ_{v_i} and σ_{v_i} are considered as response variables to look for a better estimate of mean (Model 1) and standard deviation (Model 2) of the speed, by using data collected on a sample of urban road segments.

Table 1 and Table 2 show the results at the best fits of Model 1 and Model 2, respectively. Moreover, Tables 1 and 2 report both the full and the refined model, for Model 1 and Model 2. The full model was estimated with all the variables, whereas the refined one was estimated considering the most significant variables once a stepwise regression procedure is applied (i.e., backward or forward) to provide a compact model. The coefficients (Estimate) and their significance (p-value) -which is bold-edited when <.001- are shown for each model. Finally, the last part of tables 1 and 2 reports the summary statistics.

Model 1 and Model 2 acceptably fit data. However, as shown in Table 1 and 2, two models show different results. First, the number of significant variables differs (*i.e.,* 10 for mean, 5 for standard deviation of speed). In addition, as for R^2, Model 1 and Model 2 explain 81% and 36% of mean speed and speed standard deviation variance by the selected predictors, respectively. The low R^2 for Model 2 might be due to the small variability or to the need of a larger number of observations. Of course, it deserves further investigation in the future. However, as for the Standard Error (where a smaller value ensures better precision of line of best fit) Model 2 returns, however, acceptable results. Similarly, as for F-test, the results ensure acceptable significance of the selected model (p-value <.001). Therefore, we can reject the null hypothesis that all the regression coefficients are zero.

The physical meaning and the sign of the variables for Model 1 are discussed in what follows.

As for the horizontal and vertical alignment, the results show that a 1 m increase in the segment length increases mean speed and confirm previous research (Thiessen et al, 2017).

As for the cross section, a 1 m increase in the lane width increases mean speed and confirms previous results (Bassani et Sacchi, 2012; Thiessen et al, 2017). This result is realistic because drivers could consider wider roads safer, and hence the driving speed would be higher. Unlike Fitzpatrick et al. (2005), the presence of median (painted, raised or divided) affects drivers' behaviour compared to absence of median. One interpretation for this impact is that the presence of median avoids potential collisions with vehicles passing in opposite direction, and hence the mean speed would be higher. Unlike Thiessen et al. (2017) and our expectations, an increase of bus stop density increases mean speed. Effectively, a major bus stop density could generate interruptions to traffic and hence reduce speeds and mobility. Probably, this result could be due to a major bus stop density on multilane roads, where speeds are found higher and more consistent with remaining traffic flow.

As for roadside configuration, the results showed that the presence of curb close to the carriageway contribute to increase mean speed. This is a new result. Indeed, the curb separates the carriageway from the sidewalks, hence drivers might feel safer, adopting higher speeds. Despite of expectation, the presence of pedestrian crossing is not significative to reducing mean speed. This could be due to an inadequate perception of pedestrian crossing by the drivers and may represent a risk factor for vulnerable users.

As for adjacent land-use, unlike Wang et al. (2006), residential, commercial or school areas have the lowest mean speeds, especially close to school. This was an expected result because pedestrian activities are higher in these contexts; hence, drivers may adopt safer mean speeds to preserve vulnerable users' safety.

Table 1. Regression results for mean speed – Model 1.

Explanatory Factors	**Full model**				**Refined model**			
	Estimate	*p-value*	*Lower 95%*	*Upper 95%*	*Estimate*	*p-value*	*Lower 95%*	*Upper 95%*
Constant	25.38	.02	3.44	47.33	22.16	**<.01**	11.96	32.36
Horizontal and vertical alignment								
Segment length	.02	**<.01**	.01	.03	.02	**<.01**	.01	.02
Distance from previous intersection	-1.98	.46	-7.41	3.45				
Cross section								
Number of lanes	1.51	.52	-3.21	6.23				
Lane width	2.35	.06	-.13	4.82	2.48	.01	.52	4.43
Painted or raised median	7.32	.01	1.91	12.74	8.42	**<.01**	5.09	11.75
Divided median	8.11	.02	1.11	15.11	11.14	**<.01**	7.70	14.58
Bus stop density	.73	.03	.07	1.39	.91	**<.01**	.47	1.36
Distance from previous pedestrian crossing	-.002	.86	-.03	.02				
Distance to successive pedestrian crossing	.02	.08	-.002	.03	.02	.02	.003	.03
Pedestrian crossing density	-.08	.77	-.62	.46				
Presence of pedestrian signal light	.66	.63	-2.13	3.45				
Roadside								
Presence of sidewalk	-1.53	.50	-6.11	3.05				
Presence of curb	2.34	.28	-1.96	6.65	4.24	**<.01**	1.89	6.59
Presence of bike route	.63	.75	-3.33	4.59				
Presence of on-street parking	-.84	.72	-5.56	3.89				
Access point density	-.10	.34	-.32	.11				
Adjacent land (reference condition: hospital)								
Residential	-2.53	.11	-5.63	.58	-2.49	.05	-5.00	.02
Commercial or office	-2.87	.08	-6.06	.32	-3.10	**<.01**	-5.37	-.82
School	-5.54	.06	-11.34	.25	-6.80	**<.01**	-10.40	-3.20
Traffic								
Percentage of cars with respect to total passing flow	.01	.92	-.18	.20				

Regression statistics	*DF*	*SS*	*MS*	*DF*	*SS*	*MS*
Regression	12	1732.14	144.35	10	1689.04	168.90
Residual	39	356.24	9.13	41	399.33	9.74
Total	51	2088.38		51	2088.38	
R^2	.83			.81		
Standard Error	3.03			3.12		
Observations	52			52		
F	15.80			17.34		
Significance F	$2.07 * 10^{-11}$			$9.70 * 10^{-12}$		

The physical meaning and the sign of the variables for Model 2 are discussed in what follows.

As for cross section, the presence of painted or raised median decreased the speed standard deviation. This result could be attribute to less speed variability on separate carriageway roads registering during surveys. Unlike from the results of Model 1, an increase of bus stop density decreases the speed standard deviation. Probably, this result could be due to a major bus stop density on multilane roads, where a smaller speed variability was observed. A major distance to previous pedestrian crossing increases the speed standard deviation. This is a novel result and could be due to a minor speed variability nearest the pedestrian crossing induced by a more cautious driving behaviour. Similarly, unlike Thiessen et al. (2017), an increase of pedestrian crossing density decreases the speed standard deviation, perhaps due to cautious drivers that can adapt their driving style (i.e., they could maintain a more consistent speed) when the pedestrian presence is frequent.

As for roadside configuration, the presence of sidewalk on roadsides increases the speed standard deviation. A major standard deviation indicates that the influence of sidewalks exhibits different drivers' behaviour.

Table 2. Regression results for speed standard deviation – Model 2.

Explanatory Factors	**Full model**				**Final model**			
	Estimate	*p-value*	*Lower 95%*	*Upper 95%*	*Estimate*	*p-value*	*Lower 95%*	*Upper 95%*
Constant	14.76	**<.01**	5.31	24.21	9.93	**<.01**	8.52	11.33
Horizontal and vertical alignment								
Segment length	-.002	.31	-.01	.002				
Distance from previous intersection	.26	.83	-2.08	2.59				
Cross section								
Number of lanes	.30	.77	-1.74	2.33				
Lane width	-.51	.34	-1.57	.56				
Painted or raised median	-1.43	.22	-3.76	.91	-1.04	.03	-1.95	-.14
Divided median	-.49	.74	-3.51	2.52				
Bus stop density	-.26	.08	-.54	.03	-.14	.08	-.30	.02
Distance from previous pedestrian crossing	.01	.04	.0004	.02	.01	.01	.002	.02
Distance to successive pedestrian crossing	.001	.77	-.01	.01				
Pedestrian crossing density	-.15	.21	-.38	.09	-.11	.07	-.22	.01
Presence of pedestrian signal light	-.57	.34	-1.77	.63				
Roadside								
Presence of sidewalk	1.25	.21	-.73	3.22	.81	.07	-.07	1.68
Presence of curb	.59	.52	-1.26	2.45				
Presence of bike route	1.20	.16	-.50	2.91				
Presence of on-street parking	.74	.46	-1.29	2.77				
Access point density	.03	.51	-.06	.13				
Adjacent land (reference condition: hospital)								
Residential	.15	.82	-1.19	1.49				
Commercial or office	-.26	.70	-1.64	1.11				
School	.97	.43	-1.53	3.47				
Traffic								
Percentage of cars with respect to total passing flow	-.05	.21	-.13	.03				

Regression statistics	*DF*	*SS*	*MS*	*DF*	*SS*	*MS*
Regression	20	64.57	3.23	5	45.19	9.04
Residual	31	62.68	2.02	46	82.06	1.78
Total	51	127.25		51	127.25	
R^2		.51			.36	
Standard Error		1.42			1.33	
Observations		52			52	
F		1.60			5.07	
Significance F		.12			$8.82 * 10^{-4}$	

4. Conclusions

Speed is a crucial factor of road safety, that may heavily affect the occurrences and severity of crashes on urban roads. An inadequate roads' geometric design combined with a high traffic volume, a coexistence of multiple vehicles' categories and vulnerable users and an inappropriate drivers' behaviour (i.e., speeding) could be potential causes for risk collisions. Therefore, the setting of speed prediction models could be a useful tool to discover the relationship between drivers' behaviour and several road characteristics. To achieve this objective, different speed parameters can be considered as a base parameter for safety evaluation, such as: (i) the 85th percentile of the operating speed (i.e., V_{85}) distributions in free-flow traffic conditions and (ii) the mean speed and the speed standard deviation of a normal speed distribution. Usually, V_{85} estimation is considered as a base parameter for safety evaluation, but even if the computation of V_{85} is quite simple, this parameter cannot represent the entire speed distribution. Indeed, it is possible that two percentile curves have the same V_{85} but different mean speed and speed standard deviation. Therefore, in this study the observed speed is modelled as a random variable with a normal distribution, fully described by the parameters mean and standard deviation. These are assumed as response variables for two multiple linear regression models using car spot speed data collected along the urban road network of the municipality of Brescia (Italy). The regression analysis showed that the parameters segment length, lane width, presence of median (painted, raised or divided), bus stop density, distance to previous pedestrian crossing, pedestrian crossing density, presence of curb, presence of sidewalk and residential, commercial or school adjacent land significantly contribute to explain the vehicular speed distribution in terms of mean speed and speed standard deviation. These results may also be useful for the public administration and road management agencies with the purposes to: (i) address incorrect driving behaviours to encourage more vulnerable users' protection; (ii) adjust the parameters of the urban environment (e.g., improving pedestrian crossing perception by drivers) to enhance urban safety. Further research can be developed to improve the results by using more data and testing the influence of roadside elements even more.

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