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Impact of Speed Limit Enforcement Cameras on Speed Behavior: Naturalistic Evidence from Brazil

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Abstract

Speeding is widely recognized as a key contributor to the occurrence and severity of road crashes, making studies on speed reduction devices particularly relevant given poor road safety outcomes worldwide. This study investigates the impact of fixed speed cameras on driver behavior and speed reduction in urban arterials using a naturalistic driving study methodology. Data from 13 drivers and 116 trips in Curitiba, Brazil, were analyzed, with a focus on speed cameras placed on arterial roads. Speed data were grouped and analyzed by various categories, including topographic profile, day and week periods, and rain conditions. Mean comparisons were used to compare data sets, revealing an overall speed reduction effect of 0.69 km/h (−1.33%) around the speed camera. The study identified a pattern of punctual speed reduction, known as a "kangaroo jump," a speed reduction followed by an increase in speed, referred to as the "compensation effect," and a new pattern characterized by a non-significant speed reduction at the speed camera site followed by an increase in speed, referred to as the "cobra strike effect" because of its curve pattern. The largest speed reductions were observed for flat topographic profiles (−2.98%), daytime travel (−1.58%), and travel on working days (−1.75%) with rain (−1.80%). Conversely, the speed camera had little impact on vehicle speed for uphill topographic profiles, no rain conditions, and travels during weekend.

Keywords

automated enforcement, general, safety, speeding, traffic law enforcement

Road crashes cause significant human and financial losses, affecting the sustainability of communities (*1,2*). Unfortunately, low- and middle-income countries (LMICs) like Brazil are disproportionately affected by road trauma. Despite this, there is often a lack of high-quality research to support prevention initiatives in these countries (*3*). Therefore, conducting and publishing research studies that can inform effective road safety interventions is crucial for LMICs.

Research has established a positive correlation between increased vehicle speeds and crash risk and injury severity. Even a slight decrease in mean vehicle speed results in a significant reduction in accident rates (*4–7*). For example, when the speed is increased from 50 to 65 km/h in a pedestrian–car crash, the probability of death increases by four to five times (*8*). In response, many countries and regions have reduced their posted speed limits in urban areas to reduce the severity and frequency of collisions. However, relying solely on road rules and on-road police operations is insufficient to

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reduce vehicle speeds (*9*, *10*). Speed cameras (SCs) have therefore become a popular tool for cities around the world to deter speeding drivers through the threat of fines. In Curitiba, the city hall implemented the first SC in 1992, enforcing a posted speed limit of 40 km/h. Since then, local authorities have made extensive use of SCs to control traffic speed, red light running, and disrespect for traffic signage, among other issues. At the time of this study, Curitiba had 252 SCs in operation, with posted speed limits of 40, 50, 60, and 70 km/h. In Brazilian cities, the maximum allowed speed limit is typically 60 km/h.

Numerous studies have evaluated the effect of urban SCs, mainly based on observational field data (*10–21*), official governmental data (*22–26*), Global Positioning System (GPS) data (*27*), and driving simulator experiments (*28*).

In one study by Retting et al. (*19*), the effectiveness of SCs was assessed based on observational field data across three types of roads: those with SCs and warning signs; those with warning signs only; and those with neither warning signs nor SCs. Data collection occurred both before and after the installation of SCs. The findings indicated that the proportion of vehicles traveling more than 10 mph above the posted speed limit dropped significantly, by about 70% at sites with both warning signs and SCs, 39% at sites with only warning signs, and 16% at sites with neither warning signs nor SCs. Another study conducted by Oliveira et al. (*10*) involved speed measurements in two distinct locations: 200 m after the installation of SCs and on roads without SCs but with similar road characteristics (comparison group). A comparison of speed data between these two groups revealed that on sections 200 m after SCs, the proportion of drivers exceeding the speed limit was higher (40%) than on roads without SCs (33.6%). This led to the conclusion that SCs could influence drivers to attain relatively higher speeds compared to roads without such equipment. Similarly, Gonzalo-Orden et al. (*13*) identified an increase in speeds following the installation of SCs. Their study examined various speed reduction devices in several cities in Spain, including three SCs. Data were collected at three different road sections: before (100–150 m) the SC; at the SC site; and after (100–150 m) the SC.

Some studies demonstrated that SCs might reduce speed variance (standard deviation) (*10*, *18*, *22*, *23*, *28*). However, other studies found no significant changes (*16*) or even an increase in speed variance caused by SC usage (*26*).

The reduction in speeds caused by SCs may be greater for some specific vehicles and lower for others. For instance, Chin (*12*) found that trucks, buses, and heavy vehicles have a lower percentage of reduction (−19.43%) compared to cars (−25.65%). Oliveira et al. (*10*) and Gunarta and Kerr (*16*) found a lower mean speed at SC sites for vehicles that were not cars. In contrast, Oliveira et al. (*10*) found that motorcyclists presented the highest mean speed at SC sites compared to other road users. Kumphong et al. (*18*) found a significant decrease in speed V85, while the mean speed did not show a reduction caused by SC usage.

Inconsistent findings in the literature make it difficult to draw conclusions with respect to the impact of the time of day on the effectiveness of SCs. Some studies, such as Retting and Farmer (*20*) and Quistberg et al. (*26*), suggest that the daytime period does not significantly affect SC effectiveness. However, Tankasem et al. (*21*) found that the highest speed reduction caused by SCs occurred during the night (9.8% compared to 9.4% during the day and 9.6% over a 24-h period). The literature on the impact of weather conditions is relatively scarce. Only Gunarta and Kerr (*16*) have investigated this factor and found that SC effectiveness was enhanced during wet road conditions (rain condition) or when visibility is poor.

The objective of the study was to examine the effectiveness of SCs in reducing drivers' speed in an urban context. We employed a naturalistic approach to assess the effectiveness of these SCs. The study evaluated naturalistic speed profiles, descriptive statistics, and driving behavior patterns as the main outcomes. Instantaneous speed data were analyzed based on predefined groups, including global (general analysis), topographic profile (location analysis), day period, weekday, and weather conditions (situational analysis). The use of naturalistic driving studies provides a better understanding of driver behavior in real-world scenarios, facilitating informed decisions about traffic safety measures. To the best of the authors' knowledge, no naturalistic approaches have been employed to investigate the effectiveness of SCs in urban areas. Therefore, the results of this study hold significant implications for policymakers, traffic engineers, and researchers, emphasizing the importance of incorporating naturalistic approaches into transportation research. Furthermore, the impact of confounding factors, such as weather conditions and the topographic profile, remains relatively understudied, while the role of the day period remains a subject of controversy. This approach can ultimately contribute to the development of more effective and evidence-based traffic safety measures, which, in turn, can help reduce the number of crashes and fatalities on our roads.

Therefore, the significant differences between this study and the existing literature can be summarized as follows: firstly, despite the widespread use of SCs for speed control globally, the scientific understanding of their impact on realistic driving scenarios or continuous speed monitoring data is limited. Secondly, the analyses included unexplored influencing factors such as location and situational elements, contributing to a better understanding of the effectiveness of SCs in diverse situations and environmental conditions. Thirdly, this study may

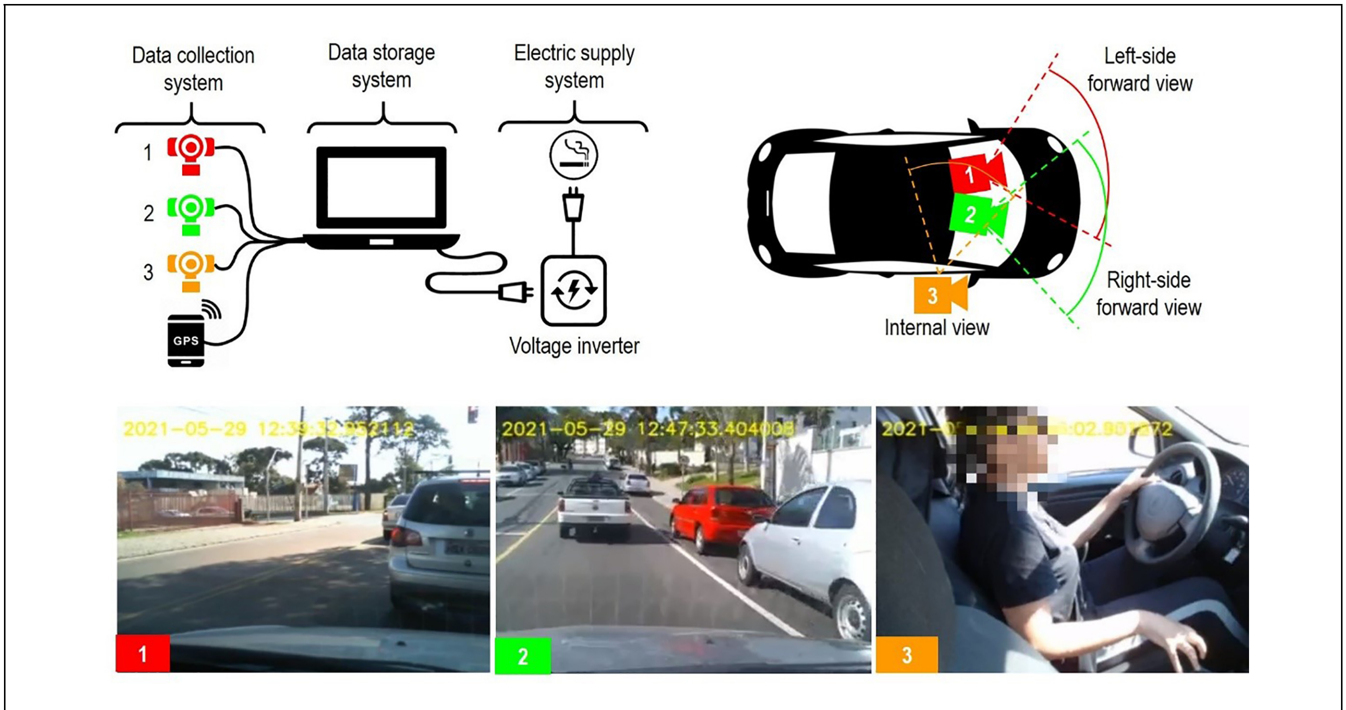

Figure 1. Naturalistic data collection platform configuration, positions of each of Cameras 1, 2, and 3, and some images collected by them.
Note: GPS = Global Positioning System.

be the first naturalistic investigation conducted in South America, representing a pioneering exploration of driver behavior integrated into local cultural patterns.

Methodology

Empirical Data Collection

The Brazilian Naturalistic Driving Study (NDS-BR) is the first research on natural driving in Brazil. The study area was the metropolitan region of Curitiba, located in southern Brazil and characterized as a predominantly urban area. A naturalistic data collection platform (NDCP) was designed to collect the data used in the present study. This NDCP followed the principle of "minimum value prototype," and comprised 10 elements, described as follows: (1) three USB cameras and one USB GPS, which work as a data collection system; (2) one laptop that acts as a data storage system; (3) one voltage inverter for electric supply; (4) one plastic box to accommodate the laptop; and (5) three suction clasps to fasten the cameras. Figure 1 describes the system configuration, the horizontal view angles of each camera, and some images collected by these cameras.

All cameras were installed inside the car. Cameras 1 and 2 were fixed on the windshield and were used to film outside the car. Camera 1 films the left-side forward view, and the Camera 2 films the right-side forward view. Camera 3 was installed in the passenger front window and faced the driver. The GPS device collects the position, time, instantaneous speed, and instantaneous acceleration of vehicles. The video analysis and data treatment showed that the GPS device had a precision of approximately 5 m. Both the video and positioning were synchronized and recorded each second. The NDCP was programmed to turn on as soon as the vehicle started. The equipment was designed with non-intrusive instrumentation to facilitate the instrumentation and not damage the vehicle. To provide some privacy to the drivers, the equipment did not record sound. Two NDCPs were used concomitantly.

A test period was conducted before the data collection began. The NDCP was installed in the car of one of the researchers. We aim to analyze and determine any necessary adjustments in the NDCP. A total of 14 days, 20 trips, and 300 km were analyzed in this phase. No adjustments were identified.

A total of 32 drivers participated in the study. They were recruited using online advertising. For participating in the NDS-BR, drivers received an amount equivalent to 50 USD. Table 1 shows some demographic information and the collection period for each driver.

Drivers' ages varied from 19 to 60 years, and they had held a driver's license for between 1 and 35 years. Most

Table 1. Demographics and Collection Period for Each Driver

Driver	Demographics			Collection period		
	Age	Gender	Driver license experience (years)	Begin	End	Duration (days)
C_1	31	F	9	August, 24 2019	September 6, 2019	13
C_2	38	M	<1	September 7, 2019	September 19, 2019	13
C_3	19	M	<1	September 22, 2019	September 30, 2019	9
C_4	23	M	4	October 29, 2019	November 13, 2019	16
C_5	38	F	21	August 24, 2019	September 6, 2019	13
C_6	25	M	7	September 7, 2019	September 20, 2019	14
C_7	43	M	16	September 23, 2019	September 29, 2019	7
C_8	31	F	8	September 30, 2019	October 8, 2019	10
C_9	28	M	7	November 21, 2020	December 8, 2020	18
C_{10}	60	M	35	November 23, 2020	December 5, 2020	13
C_{11}	27	F	9	January 25, 2021	February 6, 2021	13
C_{12}	45	F	25	February 15, 2021	March 1, 2021	15
C_{13}	21	F	1	February 19, 2021	March 13, 2021	23
C_{14}	32	M	14	December 12, 2020	December 20, 2020	9
C_{15}	47	F	22	January 10, 2021	January 24, 2021	15
C_{16}	26	M	2	January 10, 2021	January 24, 2021	15
C_{17}	27	F	8	July 5, 2021	July 25, 2021	20
C_{18}	41	F	7	July 29, 2021	August 12, 2021	14
C_{19}	61	F	23	July 31, 2021	August 14, 2021	14
C_{20}	33	M	9	August 15, 2021	August 30, 2021	15
C_{21}	48	F	28	May 24, 2021	June 6, 2021	13
C_{22}	22	F	1	May 24, 2021	June 7, 2021	14
C_{23}	20	M	9	June 9, 2021	June 24, 2021	15
C_{24}	29	M	9	June 22, 2021	July 9, 2021	17
C_{25}	29	F	10	August 19, 2021	September 2, 2021	14
C_{26}	31	F	12	September 2, 2021	September 17, 2021	15
C_{27}	26	F	6	September 14, 2021	September 29, 2021	15
C_{28}	29	M	2	October 11, 2021	October 27, 2021	16
C_{29}	32	M	10	October 12, 2021	October 25, 2021	13
C_{30}	27	F	6	October 28, 2021	November 16, 2021	19
C_{31}	35	F	6	November 9, 2021	November 25, 2021	16
C_{32}	47	F	11	November 20, 2021	December 6, 2021	16

of them were female (*18*). The collection period was initiated in August 2019 and ended in December 2021. Each driver used his/her own vehicle to guarantee his/her usual performance and realistic driving behavior. Also, to avoid study bias, information with respect to the objective of the research was not provided to drivers. All vehicles had manual gear transmission and were manufactured between 2001 and 2019. The first trip of each driver was discarded as the drivers were familiarizing themselves with the NDCP. The NDCP collected position data every second. The collection period varied from 7 to 23 days for each driver. In total, 992 trips, 381.45 h of driving tasks, and 9443.83 km of distance traveled were recorded.

Naturalistic Data Screening

We used four types of data to perform the analysis: (1) video data and (2) GPS data (both recorded by the NDS-BR); (3) SC localization (supplied by Curitiba's City Hall); and (4) a road system database (data combination from OpenStreetMap and the Institute for Research and Urban Planning of Curitiba [IPPUC]). The analysis carried out using QGis software. A 400 m control buffer (200 m before and 200 m after the SC) was used to analyze the drivers' instantaneous speed.

We used an element selection scheme (ESS) to select all elements to be to be analyzed. Figure 2 describes the criteria used to select streets, SCs, and trips and the total sample of each element included in the analysis.

It is important to highlight that there were trips that passed through more than one device or passed more than one time through the same device. In this sense, the number of trips passing through the SC (passes) is higher than the total number of trips. We considered the number of trips passing through the SC (passes) to apply the ESS.

Initially, we decided to analyze SCs located on arterial streets, which are streets with a larger traffic volume and the highest speed limit (except urban highways). So, in

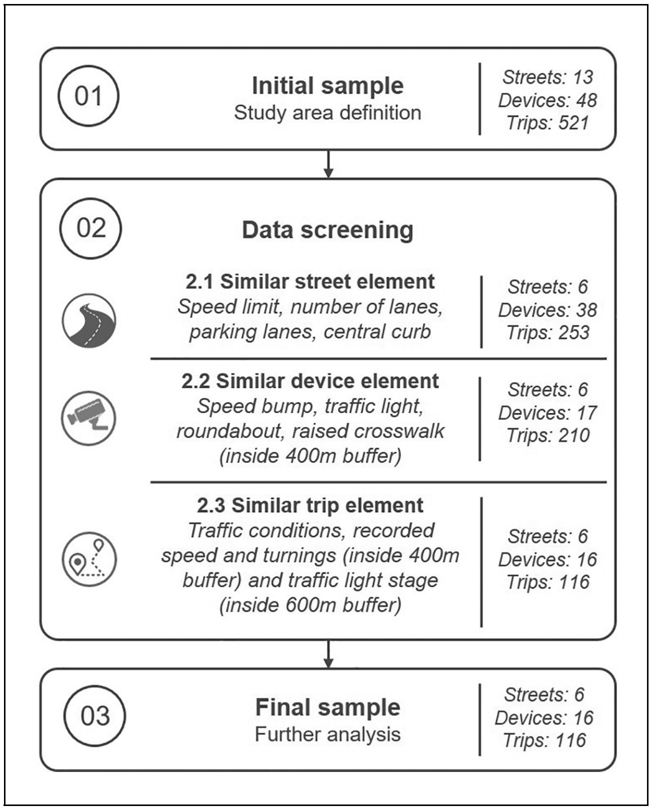

Figure 2. Element selection scheme.

the initial sample (step 1 in Figure 2) we considered all the arterial streets in the city (13), all SCs deployed in these streets (48), and all trips passing through these devices (521).

To have a reliable analysis of the impact of SCs, we had to exclude any driver behavior influence factors. These factors were clustered according to three elements: street (step 2.1); device (step 2.2); and trip (step 2.3). In the first screening step, we selected the most similar streets based on the speed limit (60 kph), number of lanes (4), parking lanes (0), central curb (0), and number of directions (1). We found a total of six streets that meet these criteria. Consequently, the number of devices and trips included also decreased, to 38 and 253, respectively. The second screening step (2.2) was performed excluding SCs deployed up to 200 m before or after other traffic devices (speed bumps, traffic lights, roundabouts, raised crosswalks, etc.). The number of devices analyzed decreased to 17 and the number of trips to 210. In the last screening step (2.3) this same 400 m buffer control was used to control for factors related to road traffic conditions. Similar to Richard et al. (*30*), we used speed data to exclude those trips in which the driver did not have the opportunity to speed with respect to the percentage of the posted speed limit. Thus, we excluded trips that presented some instantaneous speed less than half of the posted speed limit (30 kph). This step provides a preliminary data cleaning by excluding situations where the vehicle was stopped, trapped in traffic congestion, slowing because of a traffic light, or turning to or from another street. In addition, we used a larger control buffer (300 m before and 300 m after) to classify the trips with respect to traffic conditions. Video data were used to identify car-following situations. These events represent situations in which the driver did not have a chance to speed and, therefore, they were excluded. In some cases, although some traffic lights were not located inside the 400 m buffer control, the car queues caused by heavy traffic and red lights influenced drivers' speed outside the 400 m buffer control. Therefore, we also used a 600 m buffer control to exclude those trips in which the traffic light (located between 200–300 m before and 200–300 after the SC) was in the red or yellow stage. This third screening step focused exclusively on trip characteristics. However, all trips recorded in a SC were excluded, and then this device was also excluded. Finally, the total sample included was 6 streets, 16 SCs, and 116 trips.

Naturalistic Data Clustering

Speed data were clustered for further analysis. This process was carried out by covering three analyses: global (considering all data recorded); location (considering differences in topographic profile); and situation (considering day period, weekday, and weather conditions). Figure 3 shows the three analysis, sub-cluster, and comparison groups of each one considered.

Global Analysis. For global analysis, we considered all speed data and no sub-clustering was made. Some 13 drivers, 6 streets, 16 SCs, and 116 trips were considered in this analysis.

Location Analysis. For location analysis, speed data were clustered according to the topographic profile of the SC site. We classified the 400 m control buffer of each SC as flat (<3% inclination), downhill (>3% downward inclination), or uphill (>3% upward inclination). We also used topographic data from the IPPUC database. Among the 16 SC stretches, we classified four of them as flat (with inclination varying from 0.54% to 2.95%), ten of them as downhill (with inclination varying from 3.2% to 25.3%), and finally, two as uphill (with inclination varying from 9.25% to 10.05%). Once each topographic profile has a different number of SCs associated, we also have a different number of trips included for each one. Respectively, flat, downhill, and uphill profiles had 21, 80, and 15 trips included.

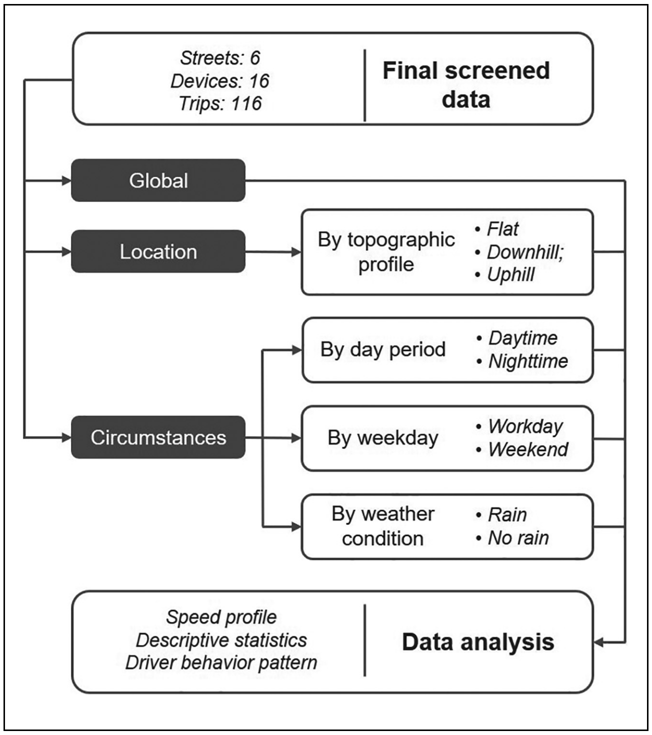

Figure 3. Criteria, analysis, and comparison groups.

Situational Analysis. We considered three main situations for the situational analysis: for the daytime analysis, we considered the sunrise and sunset time to group the speed data in the daytime and nighttime comparison groups, respectively. For weekday analysis, the trips were grouped into workday (Monday, Tuesday, Wednesday, Thursday, and Friday) and weekend (Saturday and Sunday). Finally, for the weather condition analysis the video data was used to classify the trips into rain and no rain.

Data Analysis

Speed Profiles. Considering the screening and clustering processes, we performed one speed profile for each analysis. We extracted speed data within the 400-m buffer control. The speed profiles were plotted considering the distances from the SC site.

Descriptive Statistics. To determine SC impact on driver behavior we analyzed speed data before, during, and after drivers pass through the SC site. For this, three speed analysis ranges (SARs) were established:

- SAR 1: 100–150 m before the SC location;
- SAR 2: 25 m before and 25 m after the SC location;
- SAR 3: 100–150 m after the SC location.

Figure 4 shows some generic speed profiles and their instantaneous speed data included in each SAR.

For each SAR of each speed profile, it was possible to produce three indicators, mean speed, standard deviation, and the mean error, as introduced by Taylor (*29*).

Speed Behavior Patterns. To identify the speed behavior patterns of each analysis we first used the Anderson–Darling test to check the normality of the data. The result indicated that the data presented non-normal distribution ($p < 0{,}005$). Then we used the Mann–Whitney test to check if the differences between each SAR were statistically significant. These tests were performed in MiniTab software. Once there were three SARs, we tested nine hypotheses for each speed profile:

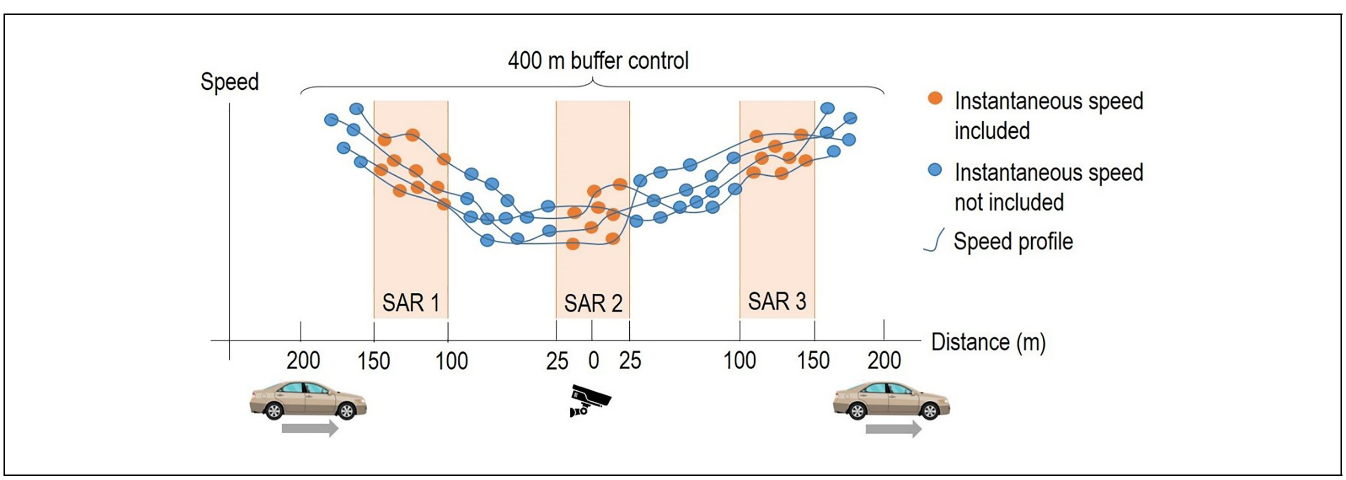

Figure 4. Instantaneous speed data included and not included in descriptive statistics.
Note: SAR = speed analysis range.

I. speed in SAR 2 is less than speed in SAR 1;
II. speed in SAR 2 is less than speed in SAR 3;
III. speed in SAR 1 is different from speed in SAR 3;
IV. speed in SAR 2 is greater than speed in SAR 1;
V. speed in SAR 2 is greater than speed in SAR 3;
VI. speed in SAR 2 is different from speed in SAR 1;
VII. speed in SAR 2 is different from speed in SAR 3;
VIII. speed in SAR 1 is less than speed in SAR 3;
IX. speed in SAR 1 is greater than speed in SAR 3.

All tests were performed considering a 95% confidence level.

Results

Characteristics of the Trips Recorded and the Screening Process

Table 2 shows the individual contribution of each driver to the trips recorded.

A total of 992 trips were recorded, resulting in 7305.087 km traveled and 237.22 driving hours. The number of trips, the traveled distance, and the driving hours ranged from 3 to 97, 10.13 to 821.09 km, and 0.55 to 59.56 h, respectively. This variability was caused by different patterns of driving schedules, commuting distances, and usual trip duration. Furthermore, some data recorded from drivers C_{14}, C_{16}, and C_{17} has been corrupted because of a NDCP malfunction, resulting in a smaller data sample for these drivers.

Because of the complexity of the urban environment, in the screening process, we sought to isolate the impact of SCs as much as possible. Table 3 presents the data included in each analysis, and Figure 5 shows the devices included, the driver's routes, and the road system in Curitiba.

Table 2. Total Number of Trips, Traveled Distance, and Driving Hours by Each Driver

Driver	Total number of trips	Traveled distance (km)	Driving hours (h)
C_1	29	227.61	12.08
C_2	15	263.56	12.85
C_3	19	207.40	7.72
C_4	56	235.23	9.96
C_5	58	287.00	12.38
C_6	38	129.75	5.77
C_7	29	389.53	56.14
C_8	44	271.66	59.56
C_9	29	389.54	14.12
C_{10}	35	271.64	9.17
C_{11}	11	72.86	3.25
C_{12}	97	821.09	21.5
C_{13}	12	25.53	1.42
C_{14}	6	23.22	0.64
C_{15}	25	126.90	4.78
C_{16}	7	115.76	4.44
C_{17}	3	10.13	0.55
C_{18}	20	151.20	6.43
C_{19}	32	219.55	10.82
C_{20}	24	708.47	15.89
C_{21}	17	80.61	3.11
C_{22}	77	478.22	14.81
C_{23}	23	202.60	8.70
C_{24}	15	77.62	2.78
C_{25}	25	23.95	6.65
C_{26}	45	42.97	11.94
C_{27}	35	56.59	15.72
C_{28}	48	39.09	10.86
C_{29}	44	34.60	9.61
C_{30}	53	34.56	9.60
C_{31}	10	15.54	4.32
C_{32}	11	20.71	5.69
Total	992	7305.087	237.22

Global Analysis

Figure 6 shows the outcomes of the global analysis.

The speed profile shows that most of the instantaneous speed values were below the posted speed limit. In SAR 2, for example, only two trips recorded some data higher than 60 kph. The mean speed presented values in ascending order for SARs 2, 1, and 3: 50.2 ± 0.2, 50.9 ± 0.3, and 51.6 ± 0.4, respectively. These values represent a speed reduction in SAR 2 by 1.4%, followed by an increase of 2.8% in SAR 3. In contrast, considering the same order (SARs 2, 1, and 3), the sample of instantaneous speed data (N) presented descending values: 424, 410, and 402, respectively. This was an expected result, since speed data are recorded every second and the three SARs had the same length (50 m), the lower the speeds practiced the greater the amount of data collected (N). The standard deviation also presented a decrease–increase pattern: there was a reduction from SAR 1 to SAR 2, followed by an increase in SAR 3.

The differences between each SAR were statistically corroborated by driving behavior pattern results. Table 4 shows the statistics of the Mann–Whitney test for global analysis.

In summary, the test results show that speed data in SAR 3 was higher than in SAR 1, which was higher than in SAR 2 (confirmation of hypotheses I, II, III, VI, VII, and VIII). This pattern is known as the "compensation effect" as the driver, after reducing speed because of the SC, tends to compensate for the time and speed lost and achieve a higher speed than the previous one (*10*, *13*). Clique ou toque aqui para inserir o texto.

Location Analysis

Figure 7 shows the outcomes of the location analysis. The driver behavior pattern included only the statistically significant results.

Table 3. Data Included in Each Analysis

Analysis		Groups	Number of speed cameras	Number of trips	Number of drivers
Global		NA*	16	116	13
Location	By topographic profile	Flat	4	21	10
		Downhill	10	80	13
		Uphill	2	15	9
Situation	By day period	Daytime	NA*	41	13
		Nighttime	NA*	67	12
	By weekday	Workday	NA*	82	13
		Weekend	NA*	26	12
	By weather condition	Rain	NA*	22	10
		No rain	NA*	86	13

Note: *NA = Not available.

The uphill profile did not present any instantaneous speed data above the posted speed limit in the 400 m buffer control. The flat profile, in turn, presented some instantaneous speed above the speed limit. The downhill profile showed some instantaneous speed data above 60 kph, and the mean speed was above 50 kph for all three SARs. There was a mean speed reduction between SARs 1 and 2 for flat and downhill profiles (−2.98% and −1.88%, respectively), and a mean speed increase for uphill profiles (3.41%). Relating to mean speed variation between SARs 2 and 3, the flat and downhill profiles presented an increase (3.27% and 4.41%, respectively), while the uphill profile presented a decreasing rate (−6.43%). In this sense, the flat and downhill profiles presented a decrease–increase pattern associated with mean speed. Furthermore, all variations, whether of increase or decrease, were higher between SAR 2 and SAR 3 than between SAR 1 and SAR 2.

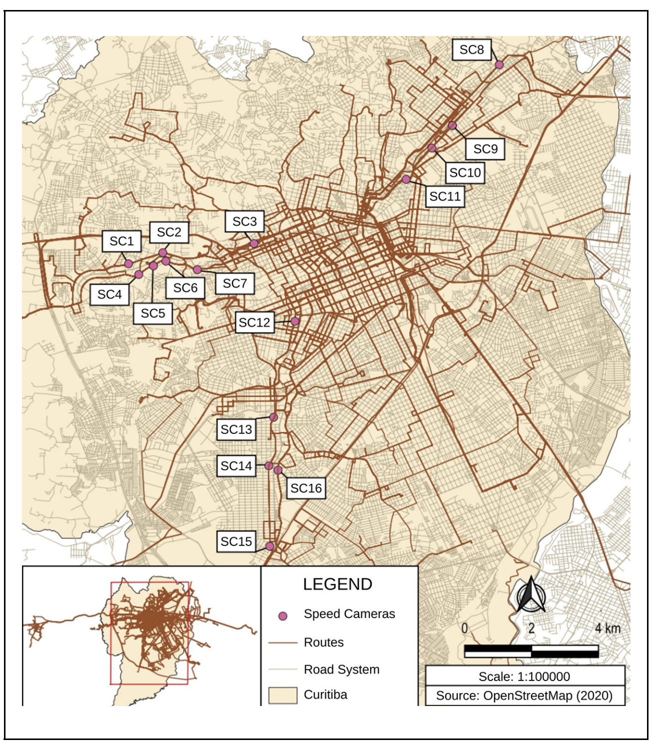

Figure 5. Speed cameras included and drivers' routes.
Note: SC = speed camera.

The standard deviation was higher for SAR 3 followed by SAR 1 and SAR 2 for all three topographic profiles (decrease–increase). The greatest standard deviation reduction occurred for the downhill profile between SAR 1 and SAR 2 (−38.8%), and the greatest increase occurred for uphill between SAR 2 and SAR 3 (69.4%).

Table 5 shows the statistics for Mann–Whitney test for all topographic profiles.

With respect to the driving behavior pattern, the flat profile presented a speed reduction in SAR 2 followed by a speed increase in SAR 3 to a level similar to SAR 1. This is a well-known pattern called a "kangaroo jump" (*10*, *13*, *23*, *23*, *28*) and reveals a punctual speed reduction effect. The downhill profile presented the compensation effect (SAR 3 is higher than SAR 1, which is higher than SAR 2). On the other hand, the uphill profile presented the highest speed in SAR 2 followed by SAR 1 and SAR 3, which were equal. These results showed the pattern of the kangaroo effect but inverted.

Situation Analysis

Day Period. The outcomes of this analysis are shown in Figure 8.

Only two trips for nighttime presented speed data above the speed limit. In addition, daytime had more divergent instantaneous speed data than nighttime. The standard deviation corroborates this behavior since the values from all daytime SARs are higher than the nighttime ones. For both groups (daytime and nighttime), the decrease–increase pattern can be observed for mean speed, with an increase in SAR 3 to a higher level compared to SAR 1. Daytime presented a speed reduction of

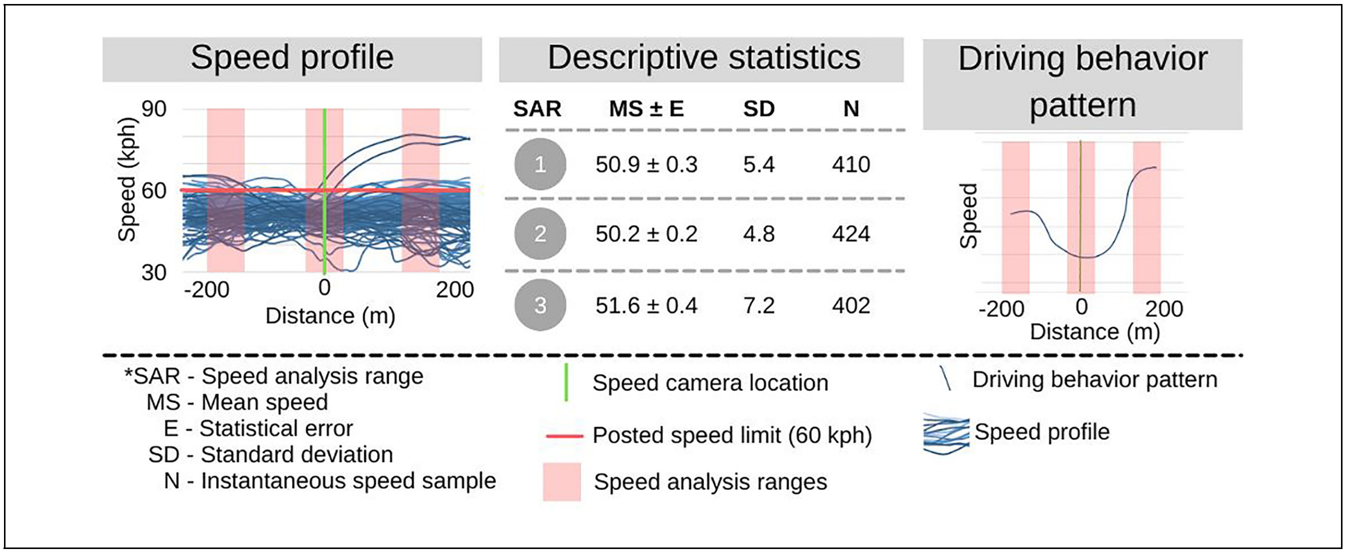

Figure 6. Outcomes for the global analysis.

Table 4. Statistics of the Mann–Whitney Test for Global Analysis

Hypothesis	*W*	*p*-Value
I	171,174.50	0.046
II	162,064.00	0.000
III	160,329.50	0.049
IV	171,174.50	0.954
V	162,064.00	1.000
VI	171,174.50	0.050
VII	162,064.00	0.000
VIII	160,329.50	0.029
IX	160,329.50	0.971

−1.58% followed by an increase of 3.29%. Nighttime, in turn, presented a speed reduction of −0.98% followed by an increase of 1.78%. The standard deviation also presented the same pattern (decrease–increase) for nighttime, while for daytime, this parameter was equal for SAR 1 and SAR 2. Nighttime had the greatest instantaneous speed data, 244, 252, and 242 for SARs 1, 2, and 3, respectively.

Table 6 shows the statistics for the Mann–Whitney test for both day periods.

The results from driving speed behavior patterns were the same for daytime and nighttime periods. The relationship between SAR 1 and SAR 2 or SAR 3 was inconclusive because of contrasting hypothesis results. On the other hand, SAR 3 was higher than SAR 2 in both groups.

Weekday. The outcomes of this analysis are shown in Figure 9.

Because of the different number of days considered for each group, for this analysis, the majority of the speed data was for the weekday group. Differently from the day period analysis, we had a different mean speed variation between each group considered. For the workday group, there is a mean speed reduction from SAR 1 to SAR 2 (−1.75%) followed by an increase in SAR 3 (2.78%). In contrast, in the weekend group mean speed presented ascending values for SARs 1, 2, and 3, respectively, representing two subsequent speed increases: 0.2% and 3.94%. The standard deviation showed the same pattern of mean speed for both groups: a decrease–increase for workdays (−13.5% and 60.0%, respectively) and two subsequent increases for the weekend (5.5% and 27.6%, respectively).

Table 7 shows the statistics for Mann–Whitney test for both weekdays and the weekend.

The driving behavior pattern concerning the workday group presented the kangaroo effect: SAR 2 was the only one that was different and was lower than the other ones. In contrast, for the weekend group the driving behavior showed that there was no difference between SARs 1 and 2, but there was a significant increase in speed data for SAR 3.

Weather Conditions. The outcomes of this analysis are shown in Figure 10.

For this analysis, we had the greatest data variation between the groups. For the rain group the speed sample data varied from 54 to 57. In contrast, for the no rain group, this sample varied from 344 to 366 instantaneous speed data. This difference can also be noticed in the speed profiles. A potential explanation for this is that

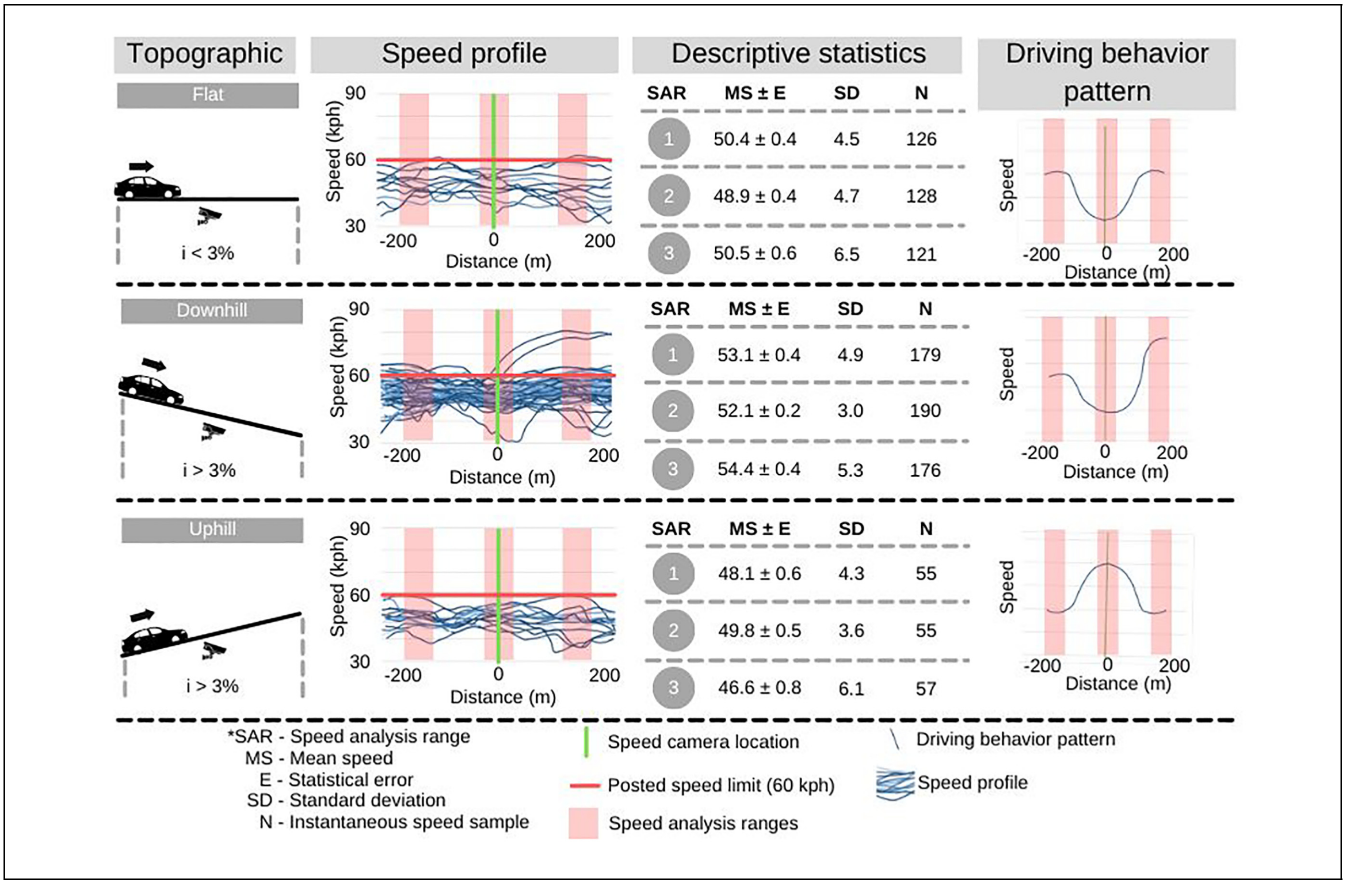

Figure 7. Outcomes for topographic profile analysis.

rain episodes are less common than those with no rain (sunny or cloudy). In addition, in rainy situations, the traffic tends to be more congested, and in the screening process, we excluded those trips in car-following situations.

No speed profile presented speed data above the posted speed limit for the rain group. On the other hand, we had instantaneous speed data above 60 kph in all three SARs for the no rain group. Nonetheless, the mean speed for the rain group was lower than for the no rain group for all three SARs. The decrease–increase pattern was observed for both groups for the mean speed and standard deviation. The rain group had the greatest decrease in mean speed (−1.8%) compared to the no rain group (−0.8%). In contrast, this same group had the greatest increase as well (4.1% for rain and 2.4% for no rain).

Table 8 shows the statistics for the Mann–Whitney test for both weather conditions.

For the rain group, the driving behavior pattern shows contrasting hypothesis results between SAR 1 and SAR 2 or SAR 3. However, speed in SAR 3 was higher than in SAR 2. For the no rain group, the identified pattern was the same for the weekend group from the previous analysis: there is no significant difference between SARs 1 and 2, but there was a significant increase in speed data for SAR 3.

Discussion

In this study, we utilized a naturalistic approach to assess the effectiveness of SCs in an urban setting. We collected data from 32 drivers and 992 trips in Curitiba, using equipment that adhered to the minimum value prototype principle and included video and positioning recording. Our findings suggest that naturalistic data collection is an adequate method for investigating speed behavior in specific regions, such as Brazil. We developed a methodology that helps minimize the impact of confounding variables on the analysis. The analysis considered three key outcomes: the speed profile, descriptive statistics, and driving behavior patterns. The speed profile provided instantaneous speed plotting based on distances from the SC locations. Most trips exhibited instantaneous speed values below the posted speed limit within the 400-m control buffer, indicating a positive local effect of SC enforcement on the city's arterial roads. In fact, all tested groups maintained a mean speed below 60 kph.

Table 5. Statistics of the Mann–Whitney Test for All Topographic Profiles

Topographic	Hypothesis	*W*	*p*-Value
Flat	I	14,815.00	0.005
	II	14,384.00	0.002
	III	15,161.00	0.410
	IV	14,815.00	0.995
	V	14,384.00	0.998
	VI	14,815.00	0.010
	VII	14,384.00	0.004
	VIII	15,161.00	0.205
	IX	15,161.00	0.796
Downhill	I	31,830.00	0.001
	II	28,918.50	0.000
	III	29,263.50	0.007
	IV	31,830.00	0.999
	V	28,918.50	1.000
	VI	31,830.00	0.001
	VII	28,918.50	0.000
	VIII	29,263.50	0.004
	IX	29,263.50	0.996
Uphill	I	3444.50	0.991
	II	3608.00	0.998
	III	3292.50	0.283
	IV	3444.50	0.010
	V	3608.00	0.002
	VI	3444.50	0.019
	VII	3608.00	0.004
	VIII	3292.50	0.860
	IX	3292.50	0.141

Furthermore, we observed a mean speed reduction between SARs 1 and 2 for almost all groups, except for the uphill profile and weekend groups, which exhibited an increase during this range. Consequently, the mean speed variation rate between SARs 2 and 3 increased, except for the uphill profile. The local effect of the SCs on speed behaviors underscores their utility as local interventions for high-risk areas within the road network.

Although the findings from this research support the mean speed reduction effect caused by SCs, the change in speed found here was significantly smaller than in other studies. Table 9 presents the mean speed reduction associated with SCs found in previous studies. The data collection method described as "In loco" means that the researchers collected the data, and "Supplied by authorities" means that the researchers used data collected and provided by the local transit authorities.

The global analysis shows a reduction of 0.70 kph (1.38%) in driving speed. Among the studies presented in Table 9, the one that comes closest to the results of this research is Kumphong et al. (*18*), which presented a mean speed reduction of 1.30 kph (2.41%) in Thailand. Furthermore, only one study has investigated the effectiveness of urban SCs through GPS data (*27*), which again has a speed variation higher than the values found here. The contrasting results from the present study may be explained by two reasons: firstly, the speed limit enforced by the SCs analyzed here is relatively high for

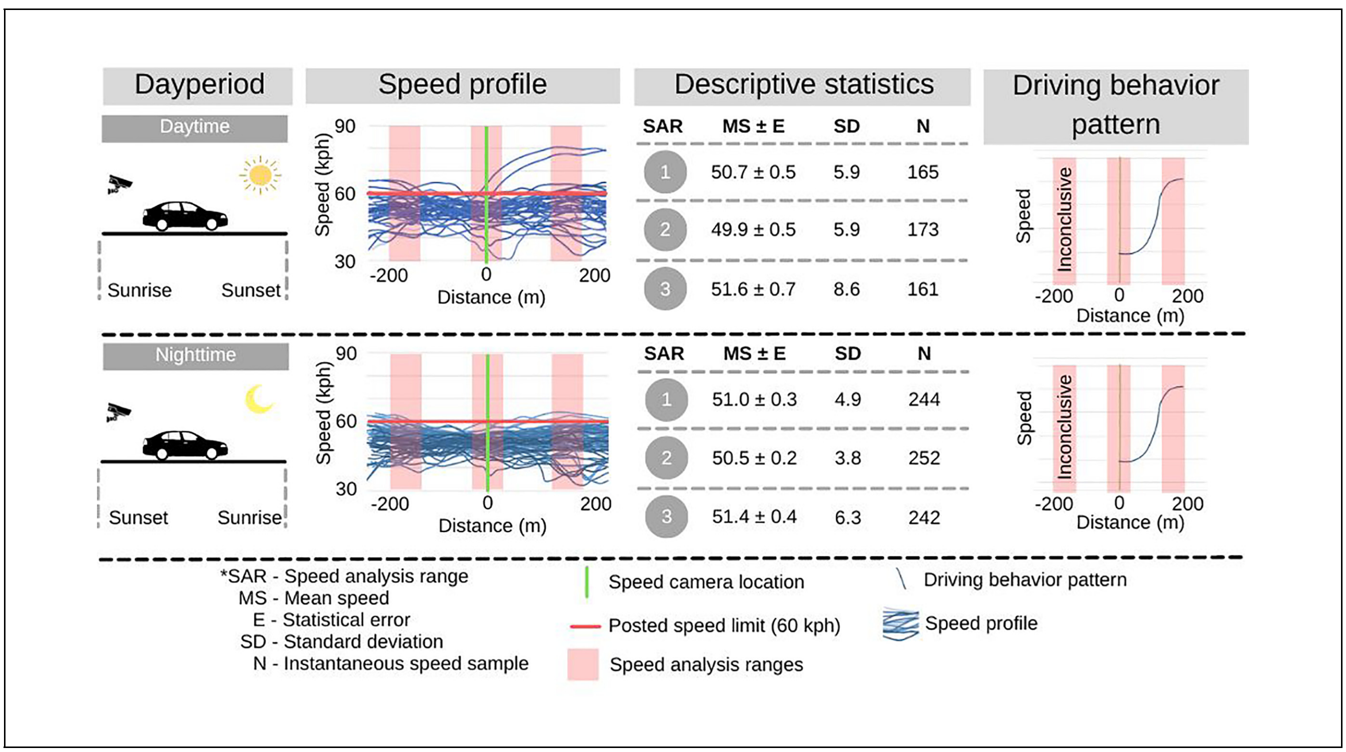

Figure 8. Outcomes for day period analysis.

Table 6. Statistics of the Mann–Whitney Test for Both Day Periods

Day period	Hypothesis	W	p-Value
Daytime	I	28,500.50	0.180
	II	27,208.00	0.022
	III	26,028.00	0.265
	IV	28,500.50	0.820
	V	27,208.00	0.978
	VI	28,500.50	0.360
	VII	27,208.00	0.045
	VIII	26,028.00	0.132
	IX	26,028.00	0.868
Nighttime	I	60,372.50	0.079
	II	56,995.50	0.000
	III	56,942.50	0.110
	IV	60,372.50	0.921
	V	56,995.50	1.000
	VI	60,372.50	0.159
	VII	56,995.50	0.001
	VIII	56,942.50	0.055
	IX	56,942.50	0.945

an urban street (60 kph). It can suggest that these devices produce an effect of maintaining the traffic speeds and not calming it. In other words, the maximum of 60 kph might be a speed that drivers feel comfortable to practice (close to their desired speed), and the enforcement plays a limiting role and not a decreasing one. Secondly, the arterial streets analyzed here have the highest concentration of electronic enforcement in the city. For that, the possibility of a new enforcement device ahead can influence drivers to barely uniformly adjust their speed and not to increase it considerably.

The study's findings reveal several patterns in driving behavior, aligning with existing literature. The kangaroo jump effect, documented in previous studies (*10*, *13*, *22*, *28*), was observed in the flat profile and workday groups. Another established pattern is the compensation effect (*10*, *13*), detected in the global and downhill groups. Both patterns are associated with temporary speed reduction effects. Some studies suggest that in urban areas, SCs can lower drivers' speeds after the SC site or even near streets (*12*, *19*, *20*, *31*). However, this study's findings did not confirm such behavior.

The daytime, nighttime, and rain groups showed no significant differences between SAR 1 and SAR 2 or SAR 3, followed by a speed increase between SAR 2 and SAR 3. The weekend and no rain groups presented no significant differences between SARs 1 and 2, followed by a speed increase in SAR 3. In other words, this pattern represents a compensation effect without a punctual speed reduction at the SC site. The high compliance level observed may be related to minor speed adjustments between SARs 1 and 2. However, drivers might believe

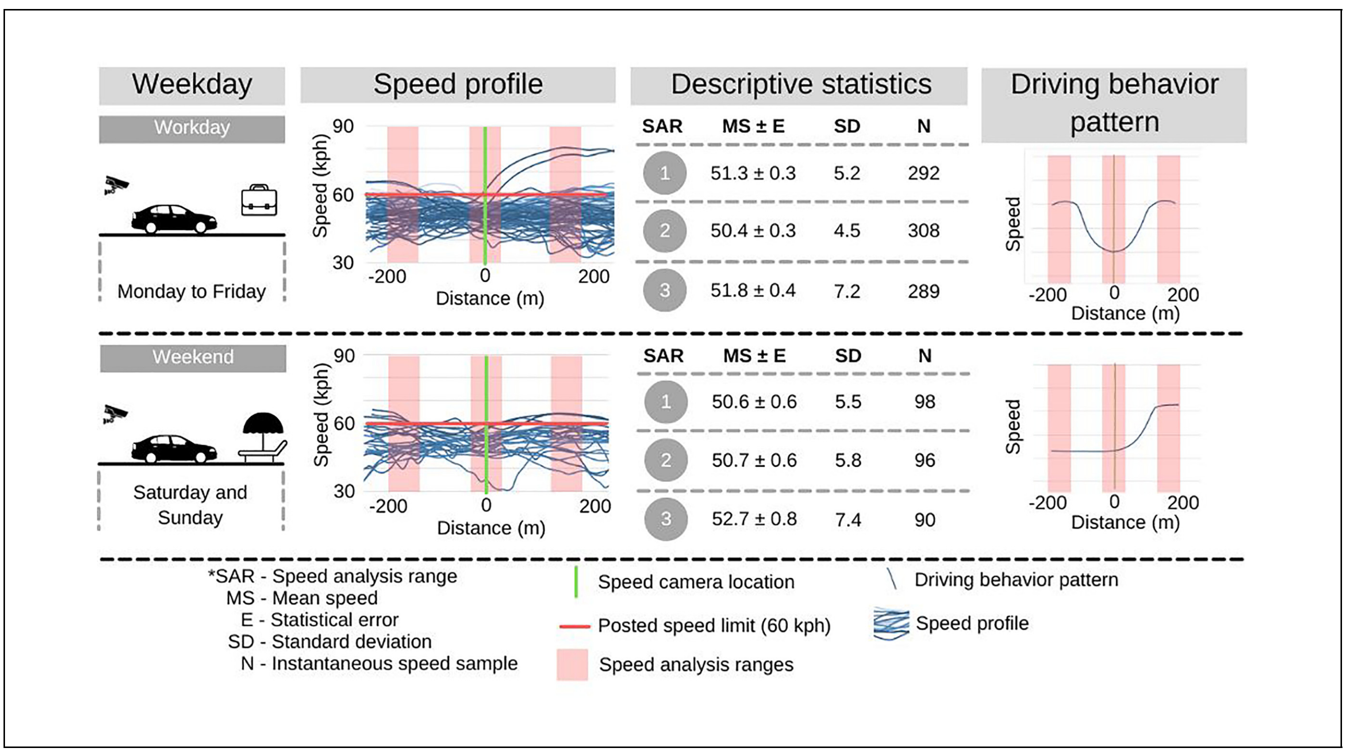

Figure 9. Outcomes for weekday analysis.

Table 7. Statistics of the Mann–Whitney Test for All Days of the Week

Weekday	Hypothesis	W	p-Value
Workday	I	86,729.00	0.003
	II	84,527.00	0.000
	III	82,253.50	0.179
	IV	86,729.00	0.997
	V	84,527.00	1.000
	VI	86,729.00	0.006
	VII	84,527.00	0.000
	VIII	82,253.50	0.090
	IX	82,253.50	0.911
Weekend	I	9813.00	0.877
	II	8136.00	0.011
	III	8309.00	0.011
	IV	9813.00	0.124
	V	8136.00	0.989
	VI	9813.00	0.247
	VII	8136.00	0.022
	VIII	8309.00	0.005
	IX	8309.00	0.995

that the speed limit enforcement has ended, leading to increased speeding because they think there are no more SCs ahead. We refer to this pattern as the "cobra strike" effect because of its curve-like shape.

In the location analysis, we identified an additional pattern not associated with a speed reduction in SAR 2. Although we aimed to exclude any confounding factors in the screening process, certain situations may influence driver behavior more than SCs in some trips.

The kangaroo and compensation effects provide support for a middle-income country in the existing international literature. The consistent findings between the Brazilian study and other studies conducted abroad demonstrate that drivers' speed choice behavior when passing through SCs is similar in various scenarios. In low- and middle-income nations, where the capacity for timely enforcement tends to be limited, this underscores the necessity for speed enforcement solutions that offer a longer detection zone, such as average speed enforcement and new speed management technology (*32*). In addition, it is worth noting that the use of naturalistic data to analyze elements in the urban environment results in a significant loss of collected data because of the need to isolate the analyzed element and exclude confounders.

Limitations

Because of the recruitment being based on a self-selection process and that the researchers could not coerce individuals or groups to participate, the sample size used is imbalanced, with a higher representation of females compared to males. This imbalance could potentially affect the generalizability of our findings, particularly with respect to gender-related differences in speed behavior.

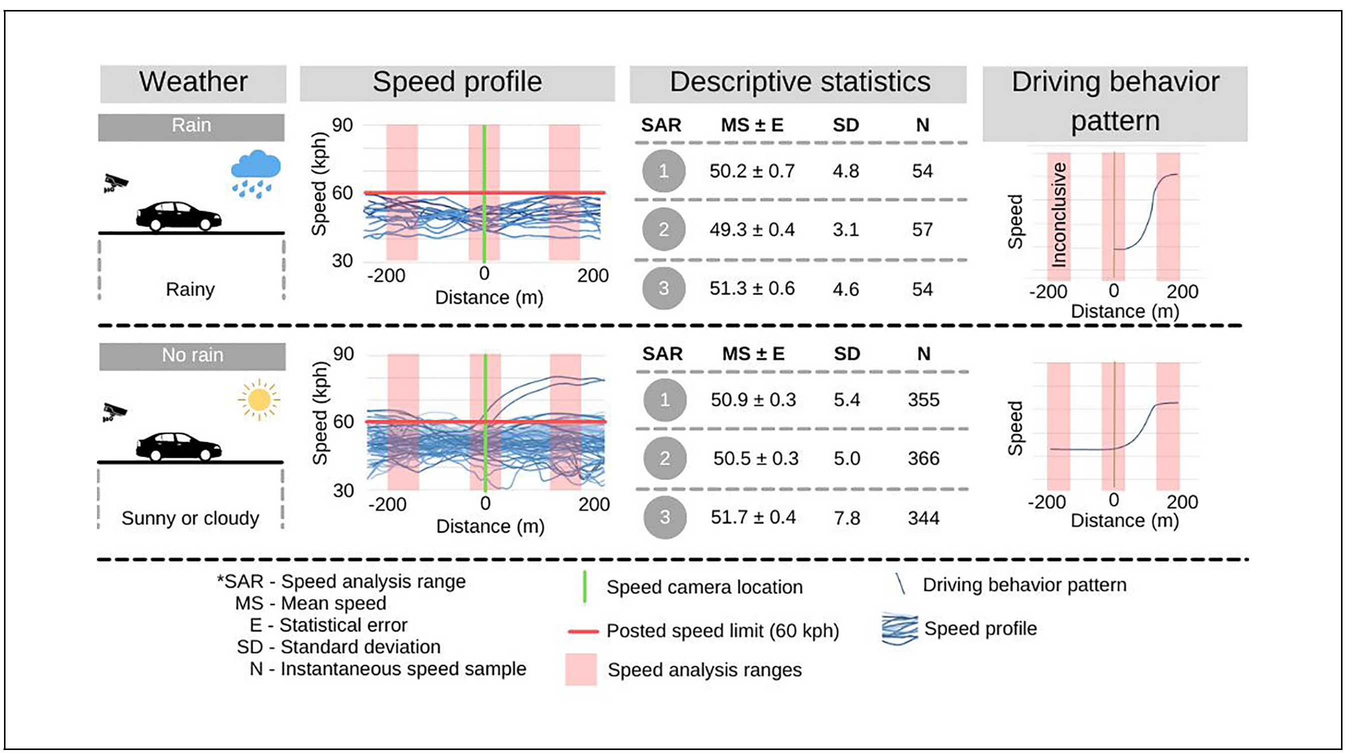

Figure 10. Outcomes for weather condition analysis.

Table 8. Statistics of the Mann–Whitney Test for Both Weather Conditions

Weather condition	Hypothesis	W	p-Value
Rain	I	3012.00	0.145
	II	2700.00	0.002
	III	2783.00	0.327
	IV	3012.00	0.857
	V	2700.00	0.998
	VI	3012.00	0.290
	VII	2700.00	0.004
	VIII	2783.00	0.164
	IX	2783.00	0.838
No rain	I	129,680.50	0.191
	II	120,660.50	0.000
	III	118,500.50	0.031
	IV	129,680.50	0.809
	V	120,660.50	1.000
	VI	129,680.50	0.382
	VII	120,660.50	0.001
	VIII	118,500.50	0.016
	IX	118,500.50	0.984

In addition, the age group of the participants is quite broad. This wide age range may introduce variability in driving behaviors, as younger and older drivers may have different tendencies. Furthermore, it is important to note that we did not consider participants' driving history, including previous crashes and violations. This omission is a limitation of the study, as these factors can significantly influence driving behavior.

Many other unexplored factors could have influenced the results as driving is a complex set of interconnected tasks, and previous studies have shown that factors such as passenger presence (*33*), road advertising (*34*), health-related issues (*35*), road safety policies (*36*), cell phone use (*37*, *38*), and the COVID-19 pandemic (*39–41*) can influence driving behavior and risk choices. The high loss of data collected because of the screening process and isolation of confounding factors can be also mentioned as a limitation. Therefore, when interpreting our findings, it is crucial to keep in mind these limitations and the potential effects they may have on the generalizability and comprehensiveness of our results.

Conclusions

In this study, we utilized a naturalistic approach to assess the effectiveness of SCs in an urban setting. We collected data from 32 drivers and 992 trips in Curitiba, using equipment that adhered to the minimum value prototype principle and included video and positioning recording. Our findings suggest that naturalistic data collection is an adequate method for investigating speed behavior in specific regions, such as Brazil. We developed a methodology that helps minimize the impact of confounding variables on the analysis. The analysis considered three key outcomes: the speed profile; descriptive statistics; and driving behavior patterns. The speed profile provided instantaneous speed plotting based on distances from the SC locations. Most trips exhibited instantaneous speed values below the posted speed limit within the 400-m control buffer, indicating a positive local effect of SC enforcement on the city's arterial roads. In fact, all tested groups maintained a mean speed below 60 kph. Furthermore, we observed a mean speed reduction between SARs 1 and 2 for almost all groups, except for the uphill profile and weekend groups, which exhibited an increase in this range. Consequently, the mean speed variation rate between SARs 2 and 3 increased, except for the uphill profile. The local effect of the SCs on speed

Table 9. Summary of Results from Other Urban Speed Camera Studies

Country (Ref.)	Mean speed reduction (kph)	Mean speed reduction (%)	Posted speed limit (kph)	Data collection method
Canada (*11*)	−2.40	NA*	NA*	In loco
Singapore (*12*)	−16.75	−25.65	50	In loco
New Zealand (*16*)	−2.20	−4.05	50	In loco
U.S.A. (*17*)	−8.53	−10.20	40–56	In loco
Thailand (*18*)	−1.30	−2.41	80	In loco
UK (22)	−7.08	−13.41	48	Supplied by authorities
UK (*23*)	−6.60	−12.42	48	Supplied by authorities
Brazil (*10*)	−9.70	−16.75	NA*	In loco and supplied by authorities
U.S.A. (*26*)	−2.41	−5.84	32	Supplied by authorities
U.S.A. (*20*)	NA*	−14	NA*	In loco
U.S.A. (*19*)	−6.44	−9.53	40–56	In loco
Thailand (*21*)	−7.50	−9.93	80	In loco
Poland (*27*)	NA*	−26.7	50	GPS

Note: GPS = Global Positioning System. *NA = Not available.

behaviors underscores their utility as local interventions for high-risk areas within the road network.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: E.C. Amancio, J.T. Bastos, T.M.C. Gadda; data collection: E.C. Amancio, J.T. Bastos; analysis and interpretation of the results: E.C. Amancio, J.T. Bastos, T.M.C. Gadda, J.N. Corrêa, G. da Costa Bonetti, O. Oviedo-Trespalacios; draft manuscript preparation: E.C. Amancio, G. da Costa Bonetti. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

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