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Red-light running behavior of cyclists in Italy: An observational study

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ABSTRACT

Accident analysis and studies on traffic revealed that cyclists' violation of red-light regulation is a typical infringement committed by cyclists. Furthermore, an association between cyclists' crash involvement and red-light violations has been found across different countries. The literature on red-light running cyclists' behavior in relation to their characteristic is still scarce. The present study, adopted an eye-observational methodology to investigates differences in cyclists' crossing behavior at intersections, with a particular attention to their demographical characteristics. The classification of cyclists' red-light behavior in risk-taking, opportunistic and law-obeying, was adopted and re-adapted to reflect more objective behaviors, eliminating any inference or judgment. Two researchers at a time observed unobtrusively at four different intersections, during morning and late afternoon peak hours, 1381 cyclists approaching the traffic light during the red phase. More than 60% of the observed cyclists violated the traffic control. Results showed that the visual search strategy displayed by the cyclists and the presence of other cyclists at the intersection are important factors in predicting the probability of red-light running behavior.

1. Introduction

Using bicycle as a transport mode is healthy, economical, and environmentally friendly. In Europe, for 8% of people bicycles are the most common mode of daily transport (European Commission, 2014). Nevertheless, cyclists still represent one of the road user categories with the highest risk of injuries and fatalities (European Road Safety Observatory, 2015). From 2004 to 2013, cyclists' fatalities decreased by 32%, but from 2010 this tendency has stagnated, with less than a 1% year-to-year reduction. Furthermore, 31% of these fatalities happen at junctions (European Road Safety Observatory, 2015). In 2014, in Italy, there were 18.055 bicycle crashes recorded, and 273 fatalities (Automobile Club d'Italia - Istat, 2014). The mortality index (deaths per 100 crashes) for cyclists is 1,42 which is more than double compared to car users (ISTAT Italian National Institute of Statistics, 2015).

From 2011 to 2015, the city of Bologna registered an increase in cyclist flow of 42%, as well as an enlargement of 16.50 km of the cycling road infrastructure (Rupi, 2015). However, in the period from 2012 to 2014 bicycle crashes increased as well (from 201 to 237). 47.7% of the 237 crashes happened at intersections (Comune di Bologna, 2015). Such high prevalence of crashes at intersection underscores the relevance of studying potentially dangerous behaviors at intersections.

Accident analysis reveals that violation of traffic rules plays a key role in fatal crashes involving cyclists. Red-light violation is one typical violation behavior among cyclists (Pai and Jou, 2014; Wu et al., 2012). Specifically, the rate of red-light violations among cyclists has been measured in different countries and cultures, varying from the 6.9% rate in Melbourne (Johnson et al., 2011) to 87.5% in Dublin (Lawson et al., 2013). Several studies have shown an association between cyclist crash involvement and red-light violations (Johnson et al., 2008; Retting et al., 1999). Cyclists' violations at intersections (e.g. bicyclists ride through at signalized intersections during the red phase) are estimated to account for the 8.8% of total bicyclists' crashes among North Carolina municipalities (University of North Carolina - Highway Safety Research Center, 2014). Assessing which are the most frequent behavioral and demographical characteristics of red-light running cyclists and which is their behavior at signalized intersection can help craft better policies and develop appropriate interventions to prompt cyclists to respect the red-light signal and, possibly, reduce the amount of traffic crashes due to them.

To analyze cyclists' behavior at intersections, in relation to their demographical characteristics, we need to mention that red-light violations may differ and cannot be included in one category. Based on previous studies (Wu et al., 2012; Johnson et al., 2008; Yang et al., 2006) that investigated pedestrian and bicycle road-crossing behavior, Pai and Jou (2014) classified bicyclists red-light crossing behavior into three types: the (1) risk-taking behavior, that is, ignoring the red-light

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and travelling through the junction without stopping (but may slow down); the (2) opportunistic behavior, that is, initially stopping at red-lights but being too impatient to wait for red-lights to turn green and subsequently crossing the junction by seeking gaps among crossing traffic; and the (3) law-obeying behavior, that is, stopping to obey the red-light. While the classification presented by Pai and Jou (2014) is pertinent and relevant it may be argued that it entails inferences or judgements about the cause of the behavior, leading to biased ratings. Thus, the classification is kept in the present study, but names have been changed using a strictly objective description of each behavior: so (1) risk-taking behavior has been renamed as *not stopping at red-light;* (2) opportunistic behavior has been renamed as *violating red-light after an initial stop;* (3) law-obeying behavior has been renamed as *stopping for the whole duration of the red-light*. In particular, distinguishing between not stopping at red-light violations and violating red-light after an initial stop is of utmost importance in order to understand the different levels of risk entailed by different behaviors. Since the violating red-light after an initial stop category involves a stop at the intersection and a violation of the red-light after an evaluation of the situation and eventually the identification of relatively “safe gaps” in the traffic flow, it is considered less dangerous compared to not stopping at red-light (Johnson et al., 2008). Indeed, not stopping at red-light behavior refers to crossing the intersection without stopping and, therefore, leaving less time to identify risks and take necessary maneuvers to avoid potential crashes.

Gender differences in red-light behavior has been broadly investigated in previous studies. General findings indicate that males are more prone to violate the red traffic signal. This was confirmed in the Australian population, both from observational studies (Johnson et al., 2011, 2008), and self-reported measures (Johnson et al., 2013), as in Europe (Richardson and Caulfield, 2015) and China (Wu et al., 2012; Huan and Yang, 2015). Males have been previously found to be more likely to commit not stopping at red-light violations (Pai and Jou, 2014; Wu et al., 2012). The relation between age and red-light infringements has been investigated as well. Johnson et al. (2013) found that, in Australia, young cyclists are the age class that commits more violations (43.9%), followed by middle-age (38.5%) and elderly cyclists (29.9%). Moreover, in a study by Wu et al. (2012) in China, was found that young (under 30 years old) and middle-aged (between 30 and 50) cyclists were 7.63 and 7.92 times respectively more probable to skip a red-light in comparison with old cyclists (older than 50). Furthermore, young cyclists have been found to be more likely to commit not stopping at red-light violations (Pai and Jou, 2014; Wu et al., 2012).

It is not clear if red-light violations are associated with other violations. Pai and Jou (2014) found unhelmeted cyclists to be more prone to skip red-lights whereas cyclists carrying passengers were less prone to violate red-lights. de Waard et al. (2015), in an observational study, found a changing tendency from calling to operating phone screens while bicycling. They also reported that cyclists texting used to cycle further from curbs and used to gaze with less frequency at intersections when generally using a phone. A previous study (de Waard et al., 2010) found that cyclists tended to engage in risk and speed compensation behavior when using the phone and cycling (e.g., by reducing the speed). de Waard et al. (2010) found no speed differences in cyclists that were listening to music, probably meaning that such cyclists did not consider it a mentally demanding task. Nevertheless, other studies suggest otherwise. Kircher et al. (2015) found that cyclists listening to music slightly increased their speed in a real traffic track. Moreover, a study conducted on drivers (Hughes et al., 2013) also found that participants listening to music showed increased peripheral task detection time and reduced driving performance, even if they did not report any increase in subjective mental workload.

To better understand the risk level entailed by cyclists that display different red-light behavior, it can be interesting to investigate their visual search strategies before the crossing phase, exploring if cyclists undertake some kind of risk-evaluation before taking the decision to cross the red-light or not. In relation to smartphone use while cycling, de Waard et al. (2015) found that when at an intersection, cyclist's operating their phone made less head movements to the right than cyclists who were just cycling. In a study on car drivers and cyclists’ interaction at bicycle crossing (Summala et al., 1996) was found that the drivers turning right scanned the right leg of the intersection less frequently and later than those turning left, increasing the probability to overlook a cyclist coming from the right. Visual search strategy, assessed in terms of head movement of the cyclist at the intersection, is really an important variable to be considered if there is an interest in assessing different safety level of cyclists’ behavior at the intersection.

Several authors have delved into psychological and social determinants (e. g., social influence) of red-light violations of different road users. Cyclists are vulnerable road users as well as pedestrians and, since the literature on the effect of social influence on red-light behaviors of cyclists is still scarce, it can be useful to examine some studies on pedestrians to emphasize the main determinants highlighted so far. For example, Rosenbloom (2009) argued that people would feel higher commitment in respecting social norms when they are grouped, thus complying more with the law, whereas, when alone, people are less concerned with the social criticism and will violate the law more easily. In his study, Rosenbloom (2009) observed pedestrians’ red-light crossing and indicated that, the presence of other pedestrians waiting at the crosswalk upon a pedestrian’s arrival, as well as the arrival of other pedestrians to the crosswalk, decreased the likelihood of crossing on a red-light. Also, van der Meel (2013) suggested that pedestrians tend to wait for the red-light more often when there are other pedestrians waiting.

For what concerns cyclists, Wu et al. (2012), studying differences on the red-light behavior between electric bike riders and cyclists, found that the smaller the group size of cyclists waiting at the intersection, the less people waiting at the stop line, and the more other riders crossing against the red-light, the more likely a rider would run a red-light. In other words, the number of cyclists crossing illegally was positively associated with the probability of infringing the red-light, that is, the more cyclists skipped the red-light, the more probable it was for other cyclists to infringe it (Wu et al., 2012). Johnson et al. (2011) found that the presence of other road users, both cyclists and drivers, travelling in the same direction had a deterrent effect on cyclists’ red-light infringements. Similarly, in an older study (Bureau Goudappel Coffeng, 1985), has been found that the presence of other cyclists was associated with a reduced probability of infringement by the observed cyclist. This phenomenon could be explained according to the social validation principle of social influence, which states that people tend to consider the appropriateness and correctness of their behavior in a given situation taking into consideration similar people’s behavior (Cialdini and Griskevicius, 2010). This formulation derives from classic literature findings in Social Psychology, stating that individuals decide on appropriate behavior for themselves in a given situation by searching for information as to how similar others have behaved or are behaving in that situation (Asch, 1956; Darley and Latane, 1970).

Social influence is related to group pressure, and thus it could have a relationship with the size of the group. Findings from literature regarding the effect of group size on group pressure are discordant: whereas some authors (Bureau Goudappel Coffeng, 1985) found group pressure on red-light running behavior to increase with larger group size, van der Meel (2013) did not find statistically significant results regarding the relation between group sizes and violating the red-light.

The present study aims at exploring the relationship between red-light violations and behavioral and demographical characteristics of a sample of Italian cyclists. The results of this research will contribute in better defining how the mentioned variables play a role in the widespread phenomenon of red-light running among cyclists.

Table 1
Characteristics of selected observational sites.

Observation Site	Intersection legs	Bicycle Infrastructure	Bicycle Traffic Light	Cyclists' Field of View	Motorized Vehicles Traffic Volume	Waiting time (min–max)
Site 1. San Donato	4	Segregated Bike Track	Yes	~161°	Very High	42– 95 s.
Site 2. Bassi/Indipendenza	3	Not present	No	~111°	Medium/High	40 s
Site 3. Riva Reno/Marconi	4	Painted Bike Lane	Yes	~103°	High	60–85 s
Site 4. Sabotino	4	Segregated Bike Track	Yes	~180°	High	46– 95 s

NOTE: Cyclists' field of view has been calculated approximately using an on-screen protractor and satellite pictures of the intersections.

2. Method

2.1. Procedures

In this cross-sectional study, we adopted an eye-observational methodology to investigate differences in cyclists' behavior at intersections, in relation to traffic light violations, smartphone use, scanning behavior and cyclists' demographical characteristics.

Our observations took place in the urban area of the city of Bologna, Italy. Firstly, we identified a pool of intersections based on two main criteria: a) a reported high volume of bicycle traffic; b) most common type of cycling infrastructure in the Municipality of Bologna. Then, according to previous research (Yang et al., 2006; Du et al., 2013), we selected the observation sites satisfying the following requirements: the presence of pedestrian crossing; enough distance between observation sites so the same cyclists were unlikely to be observed twice; and less likelihood of interfering with observed behavior. Table 1 lists the main characteristics of the selected intersections.

Five observers, who had previous experiences in observational studies, were selected for the present study. Before the actual observations, the observers were trained together to: maximize the inter-rater agreement on specifications of different behaviors, improve observational techniques to collect more behavioral data at once, and guarantee data quality control. Observers were instructed to register specific cyclists' behaviors but where not informed about the hypothesis of the study, allowing to avoid risk of bias. Once the training phase was completed, two observers were randomly selected, to measure the inter-rater reliability. The observers were asked to go in one of the four observation sites and to assess the same cyclists at the same time, during a 1-h session. Inter-rater agreement was excellent for gender (Cohen's Kappa = 1.000) and cyclists' group size (Cohen's Kappa = 1.000). The agreement was very good for red-light behavior (Cohen's Kappa = 0.951), and for age (Cohen's Kappa = 0.848). For the actual observation phase, two observers at time were randomly assigned to different sites and peak times, changing both the observational periods and sites every time. Table 2 summarizes the work observation plan for the four selected intersections and the number of cyclists observed in each site.

The observational survey was made between the 5th of April 2016 and the 29th of April 2016, during peak hours and weekdays. Considering the daily variance of traffic characteristics, we randomly selected the days, setting 1.30 h intervals for each observation made. The time of day included two peak times (from 8 to 9.30 a.m., and from 5.30 to 7 p.m.), during which traffic flow was previously investigated (Rupi, 2015). Furthermore, the observations generally tend to replicate the cyclists' commuters flow, considering cyclists' commuters both workers and university students. Consistent with this, we chose April to get started with the observation also because the cyclists' flow appears to be higher during spring (Thomas et al., 2013). Before starting with the observation, the two researchers had to specify the site and infrastructure characteristics (i.e., number of intersections legs; type of cyclists' infrastructure present). The cyclist field of view has been approximately calculated using an on-screen protractor and satellite pictures. Only the cyclists who approached the intersection during the red-light phase were coded, since we are only interested to observe the red-light behavior (Wu et al., 2012).

Table 2
Observation Plan and percentages of observed cyclists.

Site	Time of the day	Hours of Observations	Number of cyclists (%)
Site 1	Morning (2) and Evening (1)	4.5 h	210 (15.2%)
Site 2	Morning (1) and Evening (2)	4.5 h	365 (26.4%)
Site 3	Morning (1) and Evening (2)	4.5 h	331 (24.0%)
Site 4	Morning (2) and Evening (2)	6 h	475 (34.4%)

Note: Morning comprises from 8:30 to 9:00 a.m.; Evening comprises from 17:00 to 18:30 p.m. The number between parenthesis after Morning and Evening corresponds to the number of observations per each time of the day.

2.2. Measures

We collected the data through a Web App built via Qualtrics software, running through a smartphone. Fig. 1 shows a screenshot of the smartphone app. We tested the instrument at an intersection that fulfilled the inclusion criteria. The app was configured in a way to automatically register the data just collected and immediately refresh the page for a new observation. Specifically, the variables contained in each survey are reported below. The App was designed in a way that one survey contained the data regarding one cyclist.

Each observer was called to register the following variables.

2.2.1. Observation site

The observers had to select the respective site in which the observation took place (1 = San Donato; 2 = Bassi/Indipendenza; 3 = Riva di Reno/Marconi; 4 = Sabotino). To provide detailed information regarding the selected intersections, bird's eye view (BEV) pictures of each observation site, and pictures representing the point of view (POV) of the observers are included below. In BEV pictures a green shape represents the approximate field of view (FOV) of the cyclists. Fig. 2 portraits the intersection at Porta San Donato. It is a quite crowded intersection that connects the east San Donato neighborhood to the historical University Area and city center. It has a high volume of motorized traffic and cyclists' dedicated infrastructure are present (i.e., segregated bike track and cyclists traffic light).

Fig. 3 shows the Bassi/Indipendenza intersection. This site is the most central point of the City of Bologna, closely connected to the main square. While being in a "limited traffic zone" (access is prohibited to non-resident private cars), the intersection presents a quite high traffic

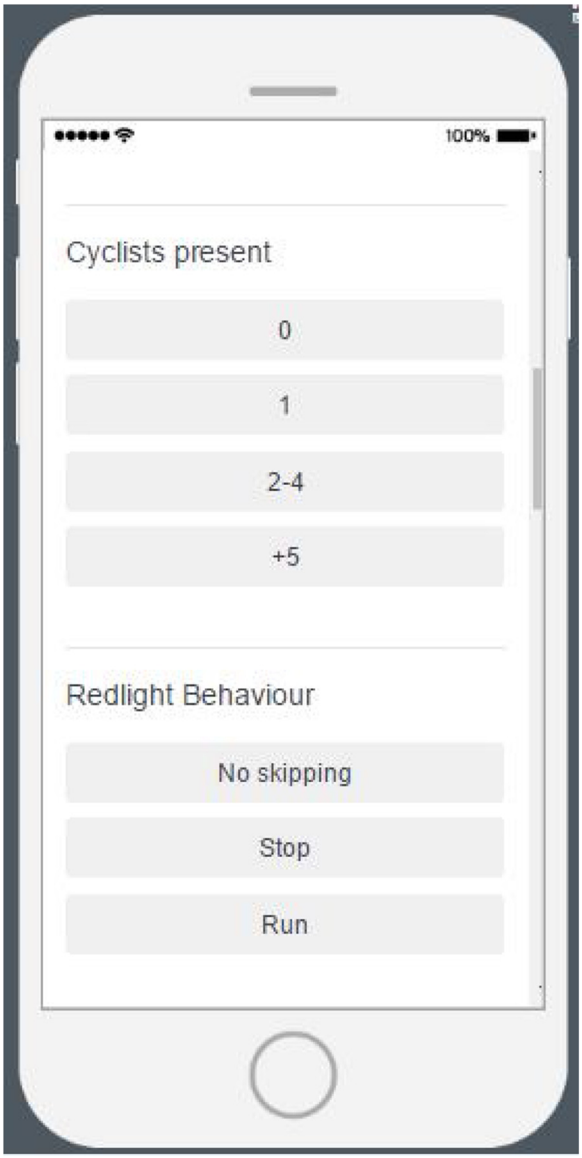

Fig. 1. A screenshot of the smartphone app preview.

volume of buses, taxis, powered two-wheelers, pedestrians and cyclists. No infrastructures dedicated to cyclists are present on site.

Fig. 4 illustrates the Riva Reno/Marconi intersection. It is one of the major intersections connecting the east and west side of the city center. As the above described observation site, it is situated in a "limited traffic zone", though it presents even higher motorized traffic volume, especially goods vehicles, due to the presence of many shops and commercial activities in the area. A painted bicycle lane and a cyclists' traffic light are present.

Fig. 5 shows the intersection of Via Sabotino and Viale Giovanni Vicini. It is a very crowded intersection, especially during peak hours, connecting the neighborhood of Saragozza to the city center. It presents a high volume of motorized vehicles traffic and cyclists' dedicated infrastructure are present (i.e., segregated bike track and cyclists' traffic light).

2.2.2. Red-light waiting time

The observers were asked to register the duration of the red-light in seconds per each observation site, twice during their observation session. First before beginning the observation and second, after finishing it. In most of the selected sites, besides site number 2 (Bassi/Indipendenza) in which the red-light duration time was fixed, observers registered highly variable waiting times. This variability is due to the fact that the majority of traffic lights in the city of Bologna are regulated according to the motor vehicle traffic flow. The traffic flow is detected through inductive loops embedded in the road surface. Due to this traffic light regulation system, it was not possible to determine the exact red-light waiting time for each cyclist observed.

2.2.3. Red-light behavior

In order to get a deeper insight on how the cyclists behave when approaching red-lights, we adopted a similar classification to the one used in the study by Pai and Jou (2014), addressing three types of behavior at traffic light: (1) not stopping at red-light; (2) violating red-light after an initial stop; and (3) stopping for the whole duration of the red-light. Observers were asked to assess "How the cyclists behaved at the intersection?" With a multiple-choice question (0 = The cyclist complied with the red-light signal; 1 = The cyclist initially stopped at red-light but then crossed the intersection before the green light; 2 = The cyclist run straight through the red-light).

2.2.4. Gender

Observers had to register the gender of each observed cyclists reporting it through the mobile application (1 = Male; 2 = Female).

Fig. 2. BEV and observers' POV pictures of site 1.

Fig. 3. BEV and observers' POV pictures of site 2.

Fig. 4. BEV and observers' POV pictures of site 3.

Fig. 5. BEV and observers' POV pictures of site 4.

2.2.5. Age

Age was assessed through an estimation of the observers, which had to register a value that corresponded to one of the three age categories (1 = 0–30 years old; 2 = 31–50 years old; 3 = 50+ years old).

2.2.6. Use of mobile phone

This variable was addressing if the cyclists were engaged in mobile phones related activities when approaching at the intersections. It was assessed through a multiple-choice question: Was the cyclists engaged in a mobile phone related activity? (0 = No; 1 = Yes, s/he was looking at the screen; 2 = Yes, s/he was making/answering a phone call with handheld phone; 3 = Yes, s/he was using headphones). Those options are not mutually exclusives, but we decided to assess this variable only accounting for the most distracting smartphone related activity (de Waard et al., 2015).

2.2.7. Visual search strategies

Since it was not possible to record cyclists eye movement due to the eye-observational methodology used in the present study, we decided to assess the cyclists scanning behavior through observing cyclists head movement when approaching at the intersection (0 = No head movement; 1 = Head turning in one direction; 2 = Head turning in both directions), as done for cyclists and drivers in previous studies (de Waard et al., 2015; Summala et al., 1996).

2.2.8. Group size

As previously done differently in other studies (Wu et al., 2012), we were also interested in assessing if the presence of other cyclists waiting at the intersection, and specifically the cyclists' group size, could influence cyclists' red-light compliance. The variable was assessed through a multiple-choice question: "how many other cyclists were already waiting at the red-light when the cyclists arrived?" (0 = no cyclists; 1 = one cyclist; 2 = from two to four cyclists; 3 = five or more cyclists).

2.3. Statistical analysis

We used SPSS version 23 to carry out the chi-squared statistical analyses. We performed a chi-squared test to examine the relationship between gender, age, distracted cycling and visual search strategies with different type of red-light behavior.

To understand what the role of the variables considered in this study is, in predicting the on-set of different red-light behaviors, we adopted a classification tree methodology. A classification tree classifies observations by recursively partitioning the predictor space and the resultant model can be expressed as a hierarchical tree structure (Elmitiny et al., 2010). Classification trees helps better identify groups, discover relationships between them and predict future events thus supporting decision making processes and risk factor analysis. Due to its non-parametric nature and easy interpretation, decision trees have received wide popularity in a variety of fields, and have been used in plenty of studies (Elmitiny et al., 2010; Pitombo et al., 2011; Rengarasu et al., 2009; Wang et al., 2009; Yan et al., 2010).

In our study, we use classification trees to analyze cyclists' red-light behaviors and highlight homogeneous patterns (Elmitiny et al., 2010) which can be useful for explain and predict cyclists' behavior when approaching the traffic light during a red phase. In a classification tree, the target variable (i.e., not stopping at red-light; violating red-light after an initial stop; stopping for the whole duration of the red-light) is also called root node and contains the entire sample (Fig. 6).

Through a recursive partitioning process, the analysis aims at finding the best "suitable" factor which offers the best partition (e.g., visual search strategy), thus splitting the node into two offspring nodes (Fig. 7).

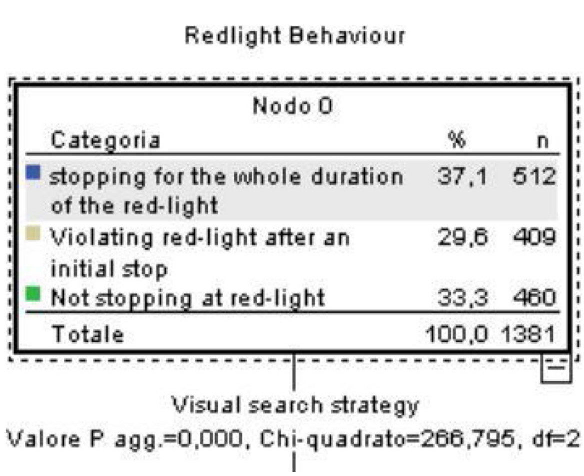

Fig. 6. Root node of the classification tree.

By following a set of decision rules applied sequentially, the classification tree ends by itself when no other partitions are significantly associated with the node (i.e., terminal node) such as node 4 shown in Fig. 8.

In the present study, the classification tree analysis was carried out using SPSS version 23, and it was based on the CHAID growing method algorithm. It is a statistical multi-way tree algorithm, which explores data quickly and efficiently, building segments and profiles with respect to the desired outcome (Baizyldayeva et al., 2013). The CHAID algorithm only accepts nominal or ordinal categorical predictors, as in our case. In the tree growing, predictors generate candidate splits at each internal node of the tree so that a suitable criterion needs to be defined to choose the best splits of the objects. The algorithm works through three sequential phases: merging, splitting and stopping (Baizyldayeva et al., 2013). The segmentation methodology is characterized by: (1) the partitioning criterion to define the optimality function when choosing the best partition of the objects into homogeneous subgroups; (2) the stopping rule to arrest the growing procedure to build up the tree; and (3) the assignment rule to identify a class as label of each terminal nodes. If a variable, that was initially included in the analysis, it is not displayed in the decision tree nodes split, means that the algorithm wasn't able to find pure enough nodes using that variable. The tree is drawn by repeatedly using these three steps on each node starting from the root node. One classification tree model was developed for the cyclists red-light running decisions.

3. Results

We registered 1381 cyclists approaching the traffic light during the red phase, of which 704 (51.0%) were male and 673 (48.7%) were female. Five observations (0.3%) count as missing. This suggests that the sample distribution by gender is fairly uniform. The sample can be considered representative of the Italian and European cyclists population in terms of gender distribution due to its accordance with data provided by the Eurobarometer 422a report (European Commission, 2014). Relatively to the age, we recorded 504 (36.5%) participants as 30 years old or younger, 561 (40.6%) were coded as being within 31 and 50 years old, and 315 (22.5%) were registered as older than 50. The age distribution of our sample slightly differs from data provided by the European Commission (2014) regarding cyclists age distribution in Europe and in Italy.

Regarding the type of red-light behavior, 512 (37.2%) cyclists did comply with the red-light and waited until it switched to green, 409 (29.6%) violated the red-light after an initial stop, and 460 (33.3%) didn't stop at red-light. Table 3 displays the frequencies of different red-light behaviors observed in each site.

Results of the chi-squared test performed to examine the relationship between gender and type of red-light behavior showed an association between these two variables $\chi 2$ $(2) = 41.65$, $p < 0.001$. Bonferroni comparison showed that males were more likely to not stop at red-light ($p < 0.05$), whereas females were more prone to stop for the whole duration of the red-light ($p < 0.05$) or violate red-light after an initial stop ($p < 0.05$).

The chi-squared test performed to assess the relationship between age of the cyclists and type of red-light behavior showed an association between the two variables $\chi 2$ $(4) = 12.05$, $p < 0.05$. Bonferroni comparison showed that cyclists aged from 31 to 50 years old were more likely to not stopping at red-light ($p < 0.05$) than violating red-light after an initial stop or than stopping for the whole duration of the red-light ($p < 0.05$). Older cyclists, aged more than 50 years old, are considerably more prone to stop for the whole duration of the red-light ($p < 0.05$) than not stopping at red-light.

Regarding smartphone use, we recoded this variable in two separated variables, due to the small number of observations, for the values calling and looking at the screen. First, when accounting for headphone

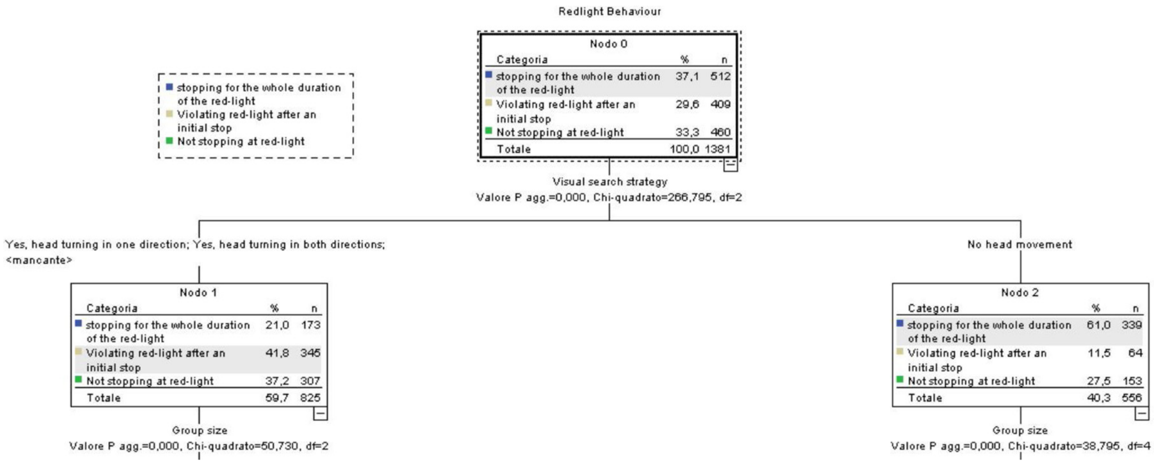

Fig. 7. First partition of the classification tree.

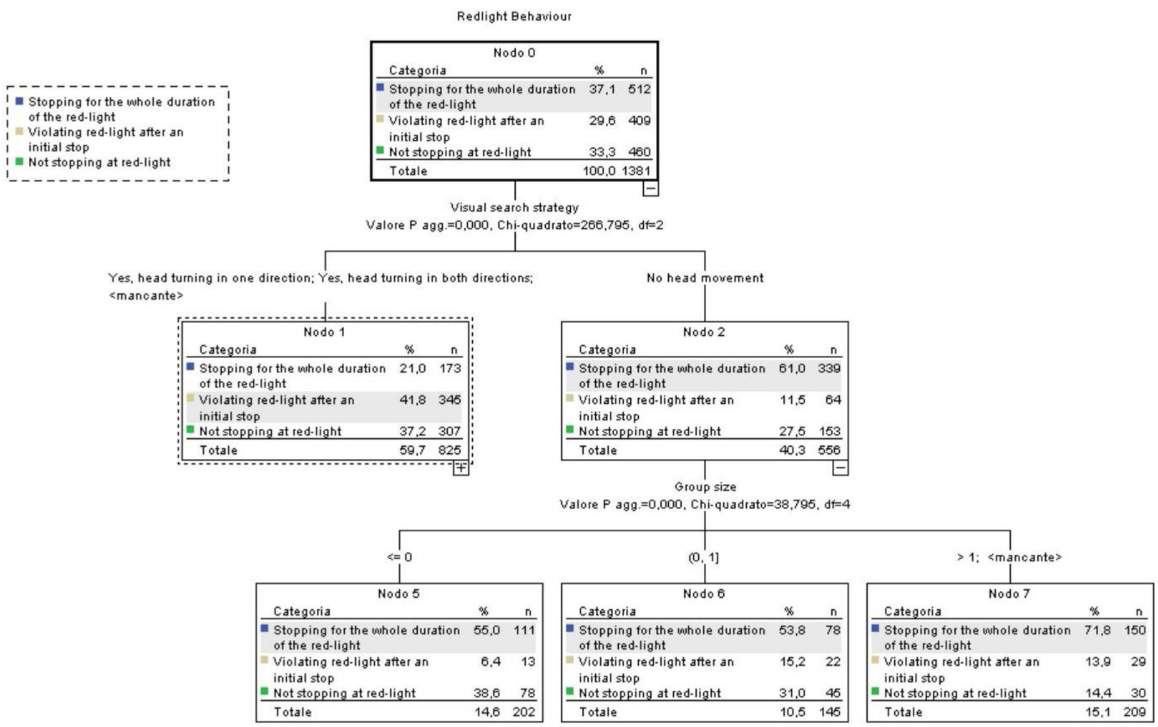

Fig. 8. Second partition of the classification tree and first terminal nodes.

Table 3
Frequencies of red-light behaviors by each observation site.

	Red-light Behavior					
	Stopping for the whole duration of the red-light		Violating red-light after an initial stop		not stopping at red-light	
Observation sites	n	%	n	%	n	%
1. San Donato	150	71.4%	35	16.7%	25	11.9%
2. Bassi/ Indipendenza	79	21.6%	45	12.3%	241	66.0%
3. Riva Reno/ Marconi	158	47.7%	102	30.8%	71	21.5%
4. Sabotino	125	26.3%	227	47.8%	123	25.9%

use, the chi-squared analysis showed no association between headphone users and different red-light behavior $\chi2$ (2) = 0.99, p > 0.05, while the analysis showed an association between smartphone use (either calling or operating the screen) and the red-light behavior $\chi2$ (2) = 9.47, p < 0.01. Bonferroni comparison showed that cyclists using smartphone for either calling or operating the screen were more prone to stop for the whole duration of the red-light.

Furthermore, the chi-squared analysis showed an association between visual search strategies and the cyclists' red-light behavior $\chi2$ (4) = 257.81, p > 0.001. Bonferroni comparison showed that cyclists who stop for the whole duration of the red-light will be more likely to make no head movement when in the proximity of the intersection, looking only at the green light, while cyclists that decided to violate the red-light after an initial stop will be more likely to look at one side or both, when in the proximity of the intersection.

Table 4
Frequencies and χ^2 values of demographic characteristics and cycling behavior by Red-light violations (N = 1381).

	Red-light Behavior						
	Stopping for the whole duration of the red-light		Violating red-light after an initial stop		Not stopping at red-light		
	n	%	*n*	%	*n*	%	χ^2
1. Gender							$41{,}65^{***}$
Male	227_a	32.2%	186_a	26.4%	291_b	41.3%	
Female	284_a	42.2%	221_a	32.8%	168_b	25%	
2. Age							$12{,}05^{*}$
1–30	199_a	39.5%	141_a	28.0%	164_a	32.5%	
31–50	180_a	32.1%	$174_{a,b}$	31.0%	207_b	36.9%	
> 50	132_a	41.9%	$94_{a,b}$	29.8%	89_b	28.3%	
3. Use of headphones							0.91
No	434_a	37.5%	338_a	29.2%	384_a	33.2%	
Yes	77_a	35.0%	71_a	32.3%	72_a	32.7%	
4. Use of smartphone							9.47^{**}
No	486_a	36.4%	402_b	30.1%	$446_{a,b}$	33.4%	
Yes	25_a	59.5%	7_b	16.7%	$10_{a,b}$	23.8%	
6. Visual search strategies							$257{,}81^{***}$
No	339_a	61.0%	64_b	11.5%	153_c	27.5%	
1 side	137_a	20.2%	287_b	42.3%	254_c	37.5%	
2 sides	31_a	23.7%	55_b	42.0%	$45_{a,b}$	34.4%	
5. Group size							99.73^{***}
0	160_a	30.3%	121_a	22.9%	247_b	46.8%	
1	116_a	34.8%	110_a	33.0%	107_a	32.1%	
2–4	182_a	42.3%	149_a	34.7%	99_b	23.0%	
5+	53_a	62.4%	27_a	31.8%	5_b	5.9%	

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

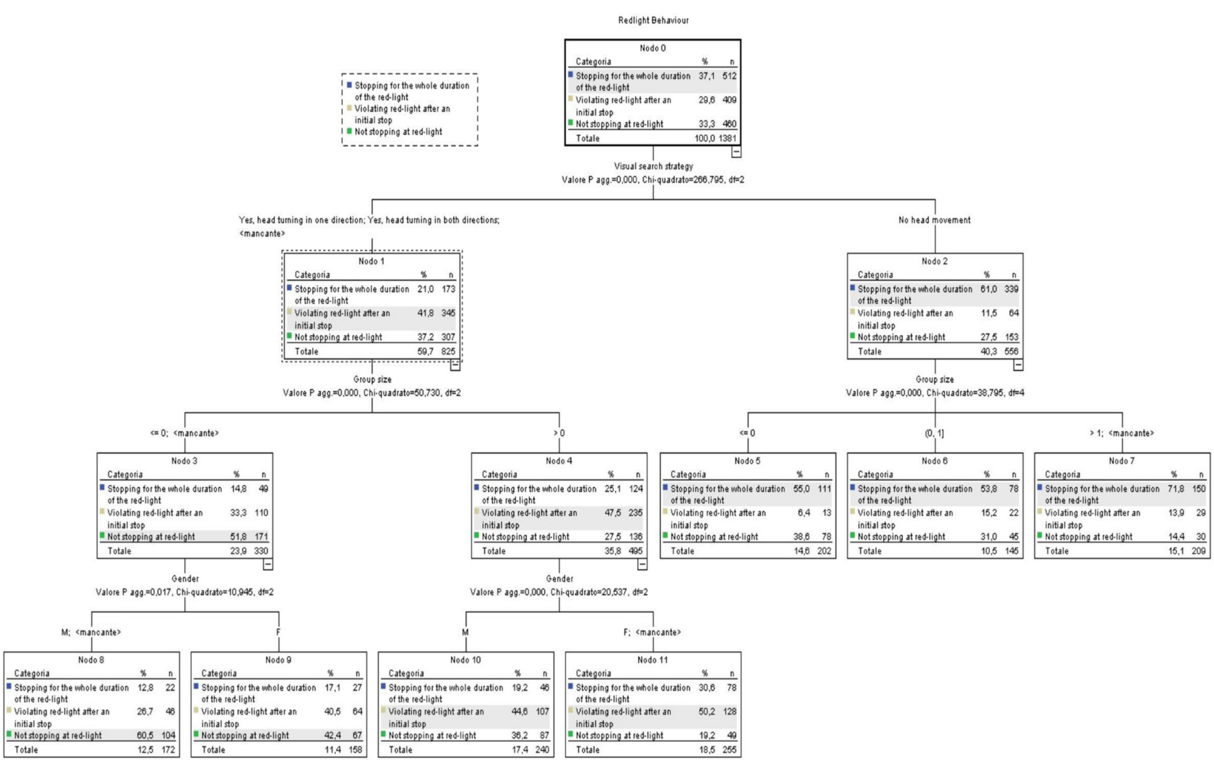

Fig. 9. Classification tree diagram for the red-light violating and law obeying behavior decision model.

Table 4 displays the frequency and the χ^2 values for all the variables by the red-light behavior.

Fig. 9 illustrates the classification tree diagram for the cyclists' red-light behaviors model, which includes seven terminal nodes. Node 0 is composed by a 37.1% of cyclists that stopped for the whole duration of the red-light, a 29,6% of cyclists that violated the red-light after an initial stop and a 33,3% of cyclists that didn't stop at red-light. The first best split is obtained using the variable "Visual search strategy". If the cyclist turns the head in one or two directions, displaying a visual search strategy, the tree categorizes it as node 1, with a 21% chance to stop for the whole duration of the red-light, a 41,8% chance to violate the red-light after an initial stop and 37,2% chance to not stopping at the red-light. If the cyclists make no head turning in the proximity of the intersection, the tree categorizes it as node 2, meaning that the cyclists have 61% chance to stop for the whole duration of the red-light, a 11,5% chance to violate the red-light after an initial stop and 27,5% chance to not stopping at the red-light. Both node 1 and 2 are not considered pure enough and need further splitting. The splitting goes on until all the terminal nodes reach the desired purity. For clarity reason a wider picture of the Classification Tree model is included in Appendix A.

The classification rules generated by the model to predict the cyclists' red-light behavior are the following:

If the cyclists do not display a visual search strategy and there are no cyclists present at the intersection (node 5), s/he will be more likely to stop for the whole duration of the red-light, with a 55% chance. Similarly, if cyclists' do not display a visual search strategy and there is none or one cyclist present at the intersection (node 6) cyclists will be more likely to stop for the whole duration of the red-light (53.9%). The probability of stopping for the whole duration of the red-light rises to 71,8% when there are more than one cyclists present at the intersection (node 7).

If the cyclists instead display a visual search strategy at the proximity of the intersection, turning their head on one or two sides, and there are no other cyclists present at the intersection, male cyclists will be more likely (60,5%) to not stop at the red-light (node 8) than female cyclists (42,4%; node 9). If there is at least one cyclist present at the intersection instead, the likelihood of not stopping at the red-light for male cyclists lowers (36,2%) while the probability of violating the red-light after an initial stop rises considerably (44,6%; node 10). In the same scenario, female cyclists will be more likely to violate the red-light after an initial stop (69.3%; node 11).

In brief, stopping for the whole duration of the red-light is more likely amongst who displays some kind of visual search strategy and arrives at the intersection when there are one or more cyclists (around 50% of the cases), while not stopping at the red-light is more frequent among who displays a visual search strategy and arrives alone at the intersection (again, around 50% of the cases).

The three variables age, use of smartphone, and use of headphones are not reported in the decision tree because the algorithm was not able to find pure nodes when accounting for those variables.

4. Discussion and conclusions

The added value of our findings is to contribute in explaining how cyclists behave when crossing at signalized intersections, assessing which are their most frequent demographic and behavioral characteristics in relation to the probability to pass a red-light.

The results, showing a higher percentage of males not stopping at red-light, are in accordance with previous findings (Wu et al., 2012; Johnson et al., 2011, 2008; Johnson et al., 2013; Richardson and Caulfield, 2015). We also found that old cyclists aged more than 50 years old, are considerably more prone to stop for the whole duration of the red-light ($p < 0.05$) than not stopping at red-light, as previous study already shown both for older cyclists (Bai et al., 2015) and for adult pedestrian (Dommes et al., 2015).

Results shows how a lower presence of cyclists is associated with a higher probability of the observed cyclist of not stopping at red-light. Furthermore, according to the literature (Wu et al., 2012; Johnson et al., 2011; Rosenbloom, 2009; van der Meel, 2013; Bureau Goudappel Coffeng, 1985), the bigger the number of cyclists at the intersection, the more the percentage of cyclists that stop for the whole duration of the red-light, showing that when cyclists are alone, they tend to put themselves more at risk. This could be due to a lesser concern regarding social criticism, which could intervene when there are more cyclists waiting at the intersection, acting as social deterrents as we know from the theory of social control framework (Hirschi, 1969).

The classification tree analysis gave us more insight regarding the importance of each analyzed variables in predicting red-light violation by cyclists. The growing algorithm classified the visual search strategy as the most important variable in predicting red-light violations, showing that when the cyclists display a visual search strategy at the intersection, the probability that they will violate the red-light highly increases. Even though this result highlights the need of further research in order to understand what the causal relationship between the visual search strategy displayed by the cyclists and the red-light violation decision is, we can give a possible explanation to this phenomenon outlining two scenarios. In the first scenario, cyclists could make an a-priori decision to comply with the traffic light when approaching at the intersection, thus not scanning the surroundings and posing absolute trust in the traffic regulation. At the same time the cyclists could decide, due to different reasons, to violate the red-light and thus begin to scan the surroundings, searching for safe gaps in the oncoming stream of traffic, and making a risk-evaluation to understand if it is actually possible to carry on with his decision. Furthermore, it is possible that bicycle use levels and cyclists experience with the specific intersection play a role in this decision-making process. For example, those who cycle the most and often travel through that specific intersections, could be more used to predict the traffic light phases and traffic gaps, thus behaving in a more riskier way. This study highlights the need to gather more data on cyclists' perceptions and decision-making processes at the intersection, integrating observational studies with surveys and interview.

The presence of other cyclists waiting at the intersection is the second most important discriminant. The greater effect reduction on red-light violation is observed when there is more than one cyclist present at the intersection. As previously mentioned when discussing the results of the chi-squared analysis, one possible explanation could be that the group size affects somehow the willingness to comply with the law through the effect of social influence. In addition, as Rosenbloom (2009) argued, people in group will be concerned about social criticism and thus will have a higher probability to comply with the traffic light. A further support to this explanation can be found in the fact that as the group size increases, the probability that the cyclists will stop for the whole duration of the red-light raises. We can also argue that this result could be due to the physical structure of the intersection: for example, in countries like The Netherlands where there is a prevalence of cycle tracks, 3 cyclists stopped at the red-light are enough to block the crossing path, thus impeding cyclists that arrive later on to violate the red-light. In the city of Bologna, cycle tracks are very scarce and the most prevalent cycling infrastructures are cycle lanes. Cycle lanes does not have any physical barrier to prevent cyclist to abandon them, thus leaving more space to overtake other cyclists. In the selected observation sites, cyclists are able to reach the stop line exiting from the cycle lane, even when there are already many cyclists waiting at the stop line. This is enough to exclude a physical explanation to this phenomenon.

The gender of the cyclists is another important variable in predicting red-light violations. In fact, the terminal nodes show that when the cyclists are males, the probability that they will skip the red-light increases in every situation. There could be a potential role of different risk perceptions among male and female. Gender has an effect that does not seem to manifest itself in a simple or constant way across ages or contexts (Byrnes et al., 1999). The present study contributes in clarifying how gender influences the probability of red-light violation among cyclists.

The classification tree analysis results highlight not only processes that inhibits red-light violations, but processes that could foster red-light violations as well. The present study shows how there is a process that facilitates red-light obeying behavior and inhibits not stopping at the red-light among cyclists who do not display a visual search strategy, and that this process is linked with the presence of other cyclists. To discuss this finding, we could argue that who does not scan the intersection and does not have a pre-determined intention to cross the red-light will probably violate the intersection following other cyclists who violate the red-light. This can be linked to social norms processes or changes is risk perception related to looking at other cyclists' red-light violation behaviors (e.g., cyclists could feel safer in crossing the red-light when they see other cyclists doing it). Instead, who does not scan the intersection and, probably have a pre-determined intention to cross the red-light, this intention is inhibited by the presence of others waiting at the intersection. The pre-determined intention to cross could be determined by the cycling experience and experience of the cyclist with the specific intersection that can lead to habituation effect. For cyclists who display a scanning strategy this process works in the opposite way.

4.1. Limitations and future research

There could be other variables influencing cyclists' red-light behavior, which the present study did not take into account due to constraints or because they diverge from the main objective of the research. Constrains are related to the fact that it was not possible to use camera recordings due to privacy rules in the Municipality. Future studies should foresee to build on present findings and assess other variables that may influence cyclists' red-light behavior. Here, we propose few suggestions. For instance, it may be that the oncoming traffic volume or the traffic speed, influence the cyclists' red-light behavior (Yang et al., 2006; van der Meel, 2013; Harrell, 1991; Yagil, 2000). Moreover, the field of view could also play a relevant role in determining cyclists' visual scanning strategy at intersection. Future studies, using instruments such as gaze trackers, could shed light on such relationship. Additionally, to better understand the effect of social pressure, the present study could be integrated with qualitative data on peoples' attitudes and beliefs concerning traffic light violations and, more in general, obeying the law. The sample of the current study does not include children aged less than 15 years old because of the very low number of observations for this age category. Including them could have showed different trends through the considered age groups. For example, another research (Ben-Moshe, 2003) that examined the road crossing decisions of pedestrian children and adolescents (6, 9 and 13-year-old boys and girls) revealed that participants standing with their peer group on a crosswalk were much laxer regarding risk-taking in crossing the street than the same participants standing alone. Other studies (Christensen and Morrongiello, 1997; Miller and Byrnes, 1997) confirmed those findings, showing the adolescent tendency to take more risks in the presence of their peer group.

Care should be taken when interpreting the findings of the present study because of three main limitations. First, this study is limited by a lack of generalizability to other settings (different regions as well as different countries) or to other conditions (e.g., different weather conditions or during off-peak hours). For instance, the frequency of red-light violations may be different from that of other settings. Second, although we have selected different settings and coded their similarities and differences, we cannot rule out the possibility that potential bias due to confounding variables (e.g., road infrastructure characteristics) exists. Third, is important to mention that in our study we are not taking into account exposure. This is due to the observational design, which is more site based than individual based, not permitting to take data like exposure into account. Future studies could extend these findings, taking into account exposure data, like the individual kilometers travelled per day, or the number of red-lights encountered in the most frequent path travelled by cyclists. Fourth, we acknowledge that camera recordings would have allowed us to gather even more data with a higher accuracy but unfortunately the local municipality did not allow the installation of cameras at intersections due to privacy rules and consequent restrictions. To reduce the workload and increase accuracy of the observers, we did not register more variables, such as the actual red-light waiting time or the intended path of the cyclist considered. Future observational studies can focus on these other variables.

4.2. Practical implication

Traffic safety organizations should consider implementing campaigns to increase peoples' negative injunctive norm on red-light skipping. This means to better explicit through signs and advertisements that red-light violation is a socially disapproved behavior at a community level. In fact, (Lawrence, 2015) found that injunctive norm messages could be effective in reducing phone-related distracted driving, but only when they focus people's attention on social disapproval of that behavior. Hirschi (1969) assumes that strengthening the ties to conventional social institutions might increase the commitment of individuals to normative behavior. Authorities might be willing to apply this principle by implementing public educational programs for increasing self-control and hence normative and safer behavior.

Additionally, taken into consideration highlighted cyclists pattern behaviors at intersections, several innovative countermeasures, with the potential of reducing red-light skipping, can be foreseen. First, an example of this is the green wave for cyclists, that is a traffic light control plan where the green phase is synchronized between two or more traffic lights (on sequential intersections). This innovative infrastructure should facilitate a continuous traffic flow by reducing the number of stops for red, whereas at the same time discouraging illegal crossing behavior and preventing potentially dangerous conflicts between road users. Moreover, considering the social pressure played by group size, changes in the intersection design, layout and road markings, should be implemented in order to facilitate cyclists' congestion at the intersection. Within this scenario, there could be the opportunity to exploit innovative type of infrastructure that can monitor the number of cyclists waiting at the intersection and adapt the traffic-light plan in order to give them priority and avoid illegal crossings. Finally, the development of new forms of infrastructure-to-vehicle and vehicle-to-cyclist communication can find a fertile ground to grow since they can enhance road users' situation awareness, inform them in case a potential collision is likely to happen and autonomously break the vehicle if the road user does not react in time.

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Appendix A

Classification Tree analysis diagram

See Fig. A1.

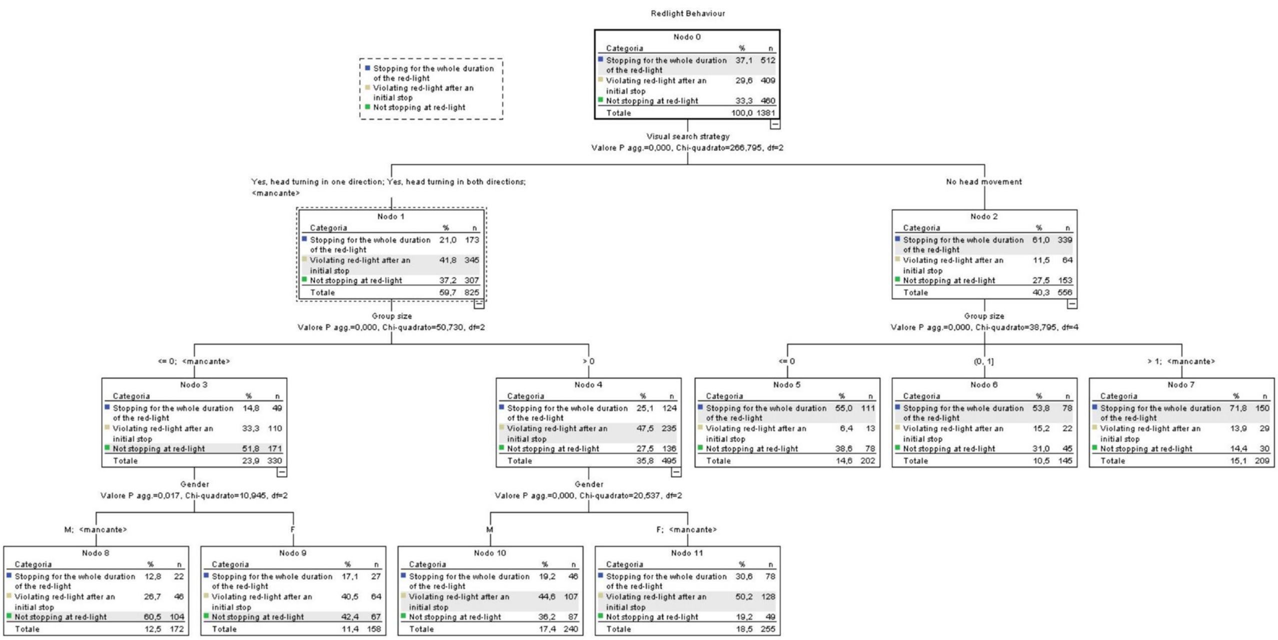

Fig. A1. Classification Tree analysis for all the observed cyclists.

Appendix B

Classification Tree analysis for the sample in each single observation site

See Figs. B1–B4.

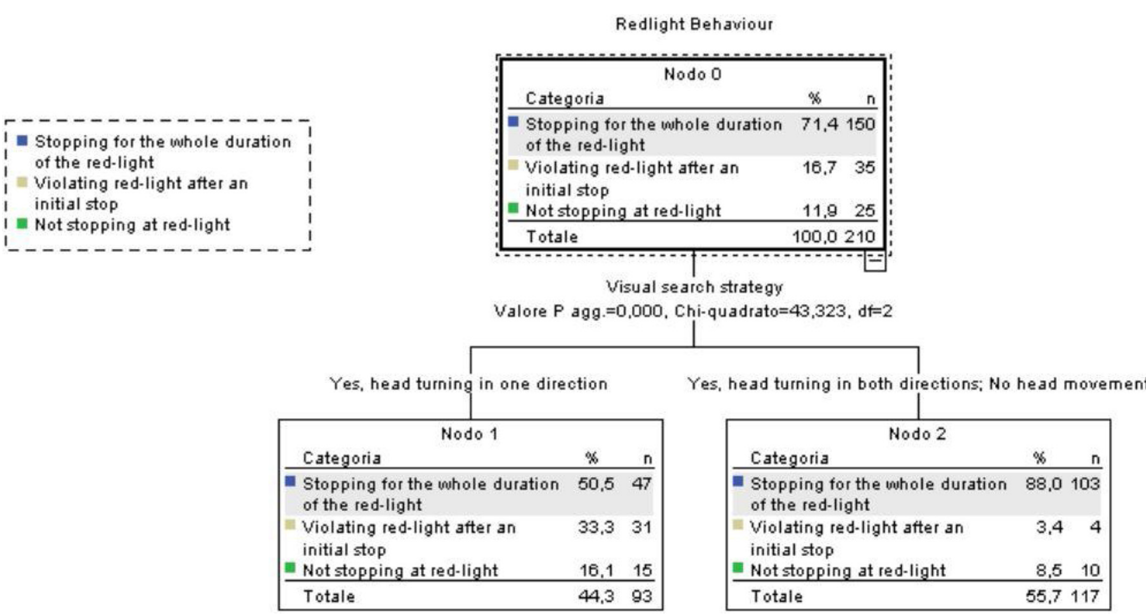

Fig. B1. Classification tree analysis for observation site 1 – San Donato.

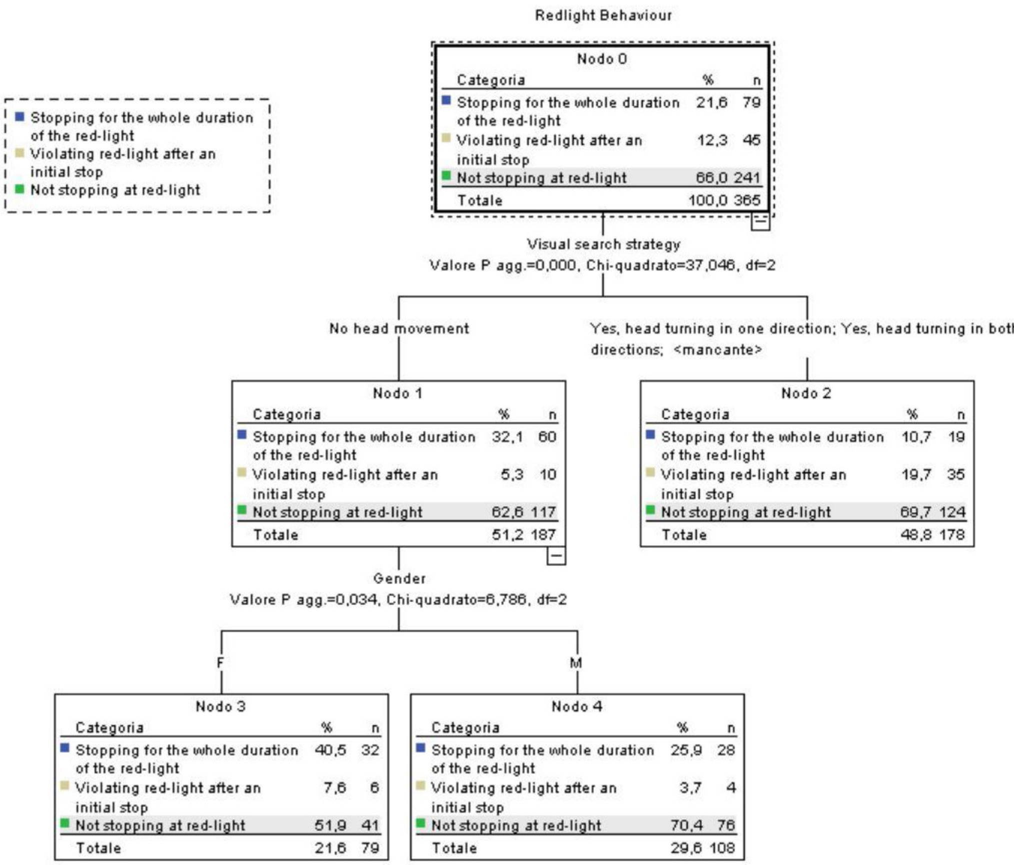

Fig. B2. Classification tree analysis for observation site 2 – Bassi.

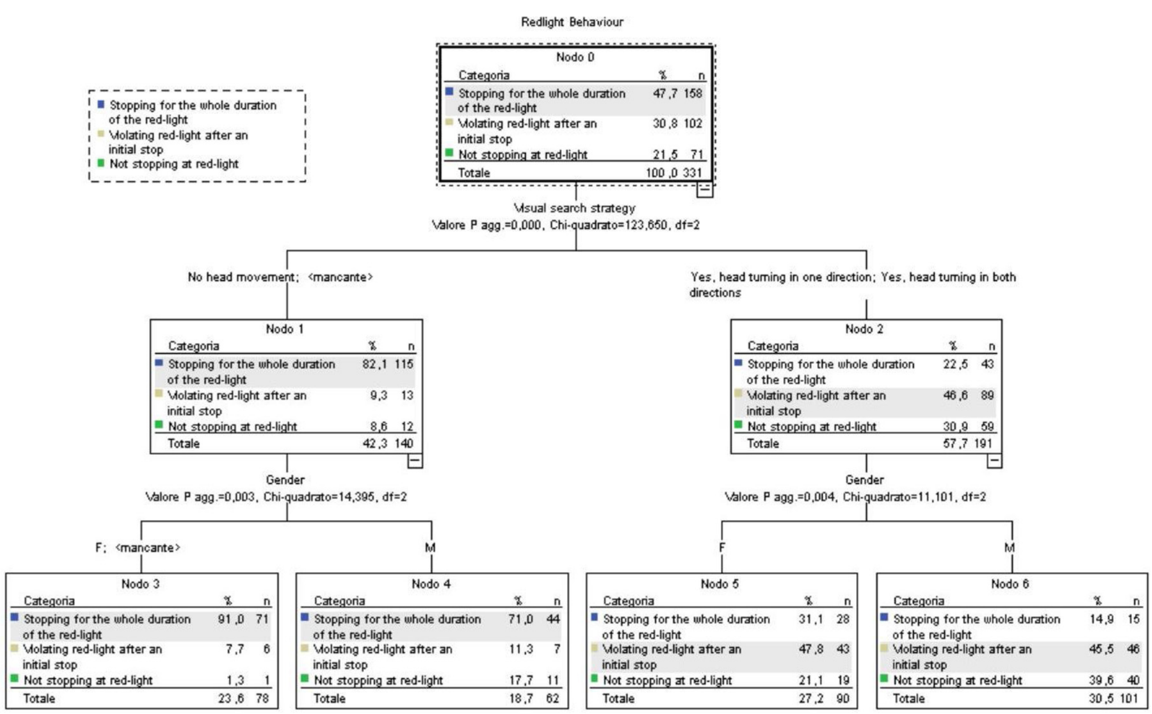

Fig. B3. Classification tree analysis for observation site 3 – Riva Reno.

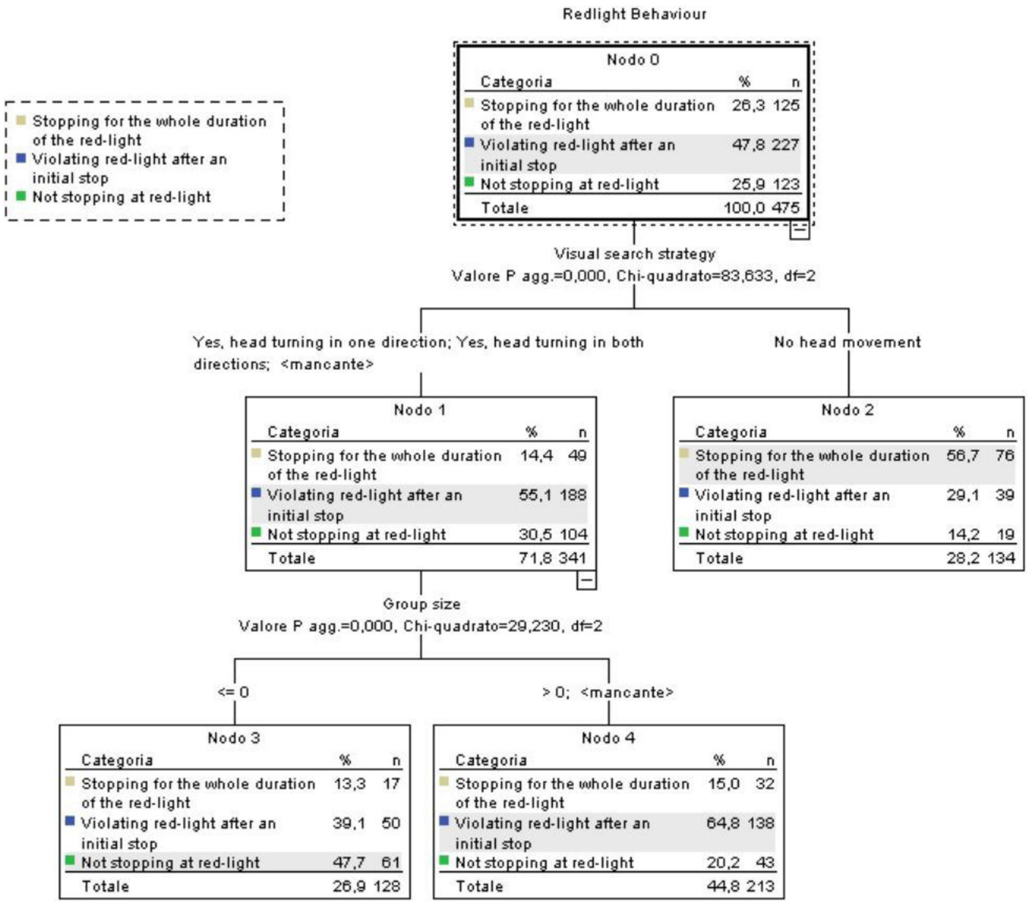

Fig. B4. Classification tree analysis for observation site 4 – Sabotino.

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