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Master Thesis [Urban, Port and Transport Economics]

Road design and red-light violations of bicycle lane users in the Netherlands.

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Abstract

Safety and keeping order are one of the main tasks policymakers have in municipalities. These tasks can refer to the crime level, city aesthetics, cleanliness, and traffic behavior. Bicyclists and moped drivers have a reputation of having risky driving behavior which they put themselves as well as others in danger as a cause of their actions. One of the reasons an individual could exercise risky behavior is the traffic circumstances it is situated in. Ignoring a red-light is a common violation made by bicyclists and moped drivers which deteriorates the traffic safety. This paper investigates the risk behavior of bicyclists and moped riders and their relationship with the features of an intersection. Risk behavior is measured by the decision of committing a red-light violation.

Limited researches investigated the relationship between risk-taking behavior of bicyclists and moped drivers and infrastructural road designs. The available literature suggested that there is a relationship between both factors. Previous literature also investigated the behavior of bicyclists and moped drivers in relation to physical and environmental factors. They acknowledged that factors as age, gender and weather conditions have an association with risk-taking behavior.

Data is collected through observation. Four intersections are investigated with each distinguishable by the number of car lanes and the inclusion of a mid-section. The results show that 23,4 percent of the vehicles committed a red-light violation. To determine whether road designs have a significant relationship with red-light violation a regression analysis is conducted. The generated logit model suggested a significant positive effect of mid-section on red-light violations. An interaction effect with crossing an additional lane and mid-section had a significant negative effect. Furthermore, males were positively associated with red-light violations.

Altogether, we can conclude that this research provides evince that road designs influence the behavior of bicyclists and moped drivers. Policymakers should consider how they design future intersections. Based on our results, we suggest that the inclusion of a mid-

section is associated with riskier behaviour. Future research could elaborate even further on infrastructural factors influencing the risk behavior of bicyclists and moped drivers.

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1. Introduction

One of the most important points in the political agendas of cities is to keep their inhabitants and their visitors safe and giving them a safe feeling while being in the city. Safety consists of many aspects such as crime level, city ambiance, cleanliness and traffic behavior. This research will focus on the traffic behavior in the city of Rotterdam and in particular on bicyclists and moped drivers. The number of registered mopeds in the Netherlands is increasing as well as the number of bicyclists (CBS, 2018). Taking into account recent developments of bicycle and moped sharing in the city of Rotterdam, mopeds are becoming more present in the city landscape. These trends are also visible in the number of crashes; moped drivers are relatively dominant in their presence in accidents as a cause of their behavior mostly (SWOV, 2017a). Similarly, bicyclists have a dominant involvement as well in accidents (SWOV, 2017b). It is not a coincidence that both bicycles and mopeds are dominant in accidents in the Netherlands as they often share the bicycle lane in the Netherlands.

Bicyclist and moped drivers are vulnerable for injuries as they are barely protected against possible collisions. People do have the choice to equip themselves with helmets or other protective equipment but are hesitant to wear any protection for various reasons such as comfort, visual appearance and the belief they do not need any protection (Finnoff, Laskowski, Altman & Diehl, 2001). In 2017 63 percent of seriously injured traffic victims were bicyclists (Hendriks, 2018). Furthermore, reports show that the risk of getting seriously injured is the highest for moped drivers (SWOV, 2018).

Statistics from BRON (2019) show that accidents, approximately 20.000 yearly, are consistent over the last three years on intersections. However, the number of injuries and fatalities is increasing on intersections, and the bicyclists make up more than half of these fatalities. Accidents often happen when one party is not following the rules correctly or their driving behavior. Bicyclists and moped drivers are known for their risky driving behavior and violate traffic rules often during travel (De Groot-Mesken, Vissers & Duivenvoorden, 2015).

To research the behavior of bicyclists and moped drivers we will conduct research on bicycle lane users and their behavior on intersections. This research will try to find whether there are possible factors influencing individuals to commit a red-light violation on intersections with a traffic light. These factors can be traffic circumstances and personal behavior (Hendriks, 2018). This research will specifically focus on the existing intersection features and the influence of it on the behavior of the drivers. By concentrating the attention on the design of the intersections, it is possible to determine whether possible design factors are influencing the decision of bicycle lane users to take risks during travel. The research question is as follows:

Do intersection features influence bicycle lane users to take more risks during travel?

A regression analysis is conducted to answer the research question. Risk is measured by the decision of an individual to commit a red-light violation. A logit regression is run to determine whether there is a significant influence of intersection features on the decision of committing a red-light violation. Using camera footage, we can observe the individuals and the environment to capture red-light violators and to create several variables to add to the logit model.

This research is structured into four segments. First of all, previous literature will be discussed to get an understanding of theories relevant to the subject and to substantiate the hypothesis. Secondly, the steps of collecting the data and the methods used to test the research question is explained. Thirdly, the results of the regression analysis are discussed. Lastly, a conclusion is drawn of the results and reflected, while the limitations of this research are discussed, and recommendations are made for policymakers and further research.

2. Literature

This chapter reviews previous literature related to the subjects of this research. With the findings of earlier researches, we can determine what drives the behavior of bicyclists and moped drivers. First, the general theories of the decision-making process and driving behavior are discussed. Second, we investigate whether previous literature found a relationship between traffic environment and driving behavior. Third, the influence of personal characteristics is discussed as there might be differences in behavior between several individual determinants such as age, gender, and mode of transport. Last, environmental circumstances, such as weather and time, are reviewed on their involvement with driving behavior. By taking these steps and reviewing the relevant literature, we can reflect the results and methods used in this research with previous works.

2.1. Risk-taking in traffic

2.1.1. The decision-making process and the theory of planned behavior

Previous economic literature suggested that the decision-making process is a function to maximize utility. Von Neumann and Morgenstern (1944) were one of the pioneers with the creation of the expected utility theory (EUT) to understand the decision-making process under risk. The EUT determines the expected utility as a function of probabilities of certain outcomes, risks and preferences. From all possible decisions an individual has, it should choose a decision yielding the highest expected utility when it is a rational human being.

Kahnemann and Tversky (1979) developed the prospect theory (PT) as a response to the expected utility theory. The PT incorporated the effects of loss aversion. People weigh a loss of χ euros more than a gain of the same χ euros. Kahnemann and Tversky acknowledged that behavior changed when people are faced with a decision possibly leading to larger losses or a decision leading to larger gains. Risk-seeking behavior is observed with decisions leading to potential losses and risk-averse behavior with decisions leading to potential gains.

The EUT and the PT base the decision-making process more on economic incentives as they are often applied to economic cases and are based on previous economic theories. However, the decisions of the individuals in this research are largely not based on economic incentives, but rather by other factors like convenience, preference, and risk. Putting these theories in the context of this research we can hypothesize that ignoring the red-light is convenient as it allows you to maintain the same pace. Also, it might be preferred by some individuals as it shortens the travel time. The risk someone has to take when ignoring the red-light is that they might cause a collision or receive a fine when they get caught by the authorities. Thus, the decision-making process of either obeying or ignoring the red-light is bound by the attitude and characteristics of a certain individual.

French, West, Elander and Wilding (1993) applied the decision-making process of individuals in car traffic. By using a survey from individuals involved in road accidents they assessed how their decision-making was related to the accident. The results indicated that decision-making is correlated with accident rates. Subjects who were classified as making decisions thorough were significantly less involved in traffic accidents. On the other hand, hesitant and intuitive style of making decisions were significantly more involved in traffic accidents.

Ajzen (1991) developed the theory of planned behavior (TPB) to predict the intention of the behavior of an individual. According to the TPB there are three determinants influencing the intention of performing a certain behavior. Firstly, personal attitude towards executing a specific behavior is mentioned. Secondly, the subjective norm is mentioned and refers to the social pressure an individual has to deal with by executing a certain behavior. Thirdly, the perceived behavioral control is explained as the level of control an individual believes it has and is based on knowledge, resources and experience. Parker, Lajunen and Stradling (1998) applied the TPB in their research on predicting driving behavior. With the use of a survey they investigated aggressive driving behavior on the basics of the three components of the TPB. Their results show that attitude and perceived behavioral control are good predictors of aggressive driving behavior.

Ajzen (1991) argues that by gaining experience in certain behaviors, habits can be formed which could be either positive or negative depending on the type of habit. In case of such an occurrence the other two determinants of TPB are irrelevant in an individual's behavior. Bamberg, Ajzen and Schmidt (2003) argued in their research that over time repeated behavioral actions strengthen habitual behavior. De Pelsmacker and Janssens (2007) discovered in their research that habits are developed on violating traffic rules more by personal motivations rather than social norms on their intentions which is consistent with statements made by Ajzen (1991). Applying this matter in the case of this research, it is possible that violating traffic rules as bicyclists or moped drivers could turn into a habit when these behavioral actions recur often. Similar to Parker, Lajunen and Stradling (1998) the findings of De Pelsmacker and Janssens (2007) show that the social norms are less important in driving behavior and are more centered towards personal attitude and beliefs.

Furthermore, making decisions is bound to time limitations in most cases. It is important to acknowledge that the decision to commit a red-light violation is made in a short amount of time. There is no time to make thorough and logical arguments to decide whether or not to violate the rules. Svenson and Maule (1993) suggest that the judgment of making a decision with a time constraint can be influenced negatively. The available information can be interpreted differently (e.g. one may put more emphasis on a less important aspect than on a more important aspect). As bicyclists and moped drivers deal with a certain time pressure it is feasible that they focus on other factors more heavily than others (e.g. one may concentrate on whether cars are approaching the intersection rather than look at the traffic in front of it in case of crossing the road and loses sight what happens ahead of them).

2.1.2. Behavior in traffic of bicyclists and moped drivers

Van der Horst, de Goede, De Hair-Buijssen and Methorst (2014) observed in their research the behavior of bicycle lane users. By recording the bicycle lane, they were able to identify behavior of all users of the bicycle lane in two locations in two different cities in the Netherlands. From the footage the authors noticed that moped drivers were taking more risks as they were more overtaking traffic ahead of them by using the other side of the bicycle lane. Furthermore, they saw that most incidents that occurred on footage pedestrians were involved and a few incidents involved only bicycle lane users. They did notice that the narrower the bicycle lane is the more incidents occur.

Falco, Piccirelli, Girardi, Dal Corso and Nicola (2013) investigated the behavior of adolescent moped drivers with little to none driving experience in Italy. Their results indicate that the youngest, 14 to 15-year-old drivers, subjects of the sample have an emotional and risk-seeking driving behavior. They argue that this group is influential and overestimate their driving abilities. Therefore, it is more likely that they drive careless which makes them vulnerable for negative incidents in the future.

By the use of a survey Steg and van Brussel (2009) tried to discover why young moped drivers are involved in a substantial number of accidents in the case of the Netherlands. From their results it became apparent that moped drivers can be classified as a risk group in traffic as half of their sample were involved in an accident during the past year. Furthermore, the majority regularly committed speeding violations. Following the TPB, when the subjective norm and attitude were positive towards speeding, they were more likely to drive faster. They mentioned that the perceived behavioral control did not predict speeding in contrast to Parker, Lajunen and Stradling (1998).

Feenstra, Ruiter, Schepers, Peter and Kok (2011) researched the behavior of adolescent bicyclists. With the use of a survey they tried to measure the risk behavior of students from a secondary school. The results of their tests show that the risky behavior of adolescents is not performed often. This is contrary to research of Steg and Van Brussel (2009) where the younger moped drivers are classified as a risk group and younger bicyclists did not show strong evidence of risky behavior according to Feenstra, Ruiter, Schepers, Peter and Kok (2011).

2.1.3. Traffic behavior towards red traffic lights

Konecni, Ebbeson and Konecni (1976) investigated the response of car drivers when the traffic light turned yellow at an intersection. Their research found evidence that speed and distance to the traffic light matters whether individuals stop when the traffic light turns yellow. Interestingly, they found that especially young males were more likely to commit a red-light violation. They suggest that this group takes more risk during travel as they speed more compared to the other gender and age groups.

Pai and Jou (2014) researched the behavior of bicyclists facing a red-light in Taiwan. With the use of cameras on particular intersections they were able to observe behavior of each individual. Their results show that scholars are significantly showing riskier behavior than others. Furthermore, during peak hours bicyclists were found to be more prone to cycle through red-light. Also, the authors argue that location influences red-light violations. For instance, in less urbanized areas bicyclists tend to be more prone to ignore the red-light.

Research from Fietsersbond (2015) found that more than a quarter of the bicyclists commits a red-light violation during travel. They suggest that when a bicyclist belief that there is no danger in crossing the road a big percentage of bicyclists will drive through a red-light. From their sample bicyclists younger than 20 years 35 percent commits a red-light violation. This is in accordance with findings of Falco, Piccirelli, Girardi, Dal Corso and Nicola (2013) and Steg and van Brussel (2009) who argue that the younger participants are taking more risks than other age groups.

2.2. Intersection features

2.2.1. Design

Wang, Xu, Tremont and Yang (2012) found that the traffic environment has a strong relationship with violations made by bicyclists and moped riders. They found that the traffic environment (e.g. segregated bicycle lane and signalized road) had more effect than personal characteristics and the transport mode. Similarly, Hamdar, Mahmassani and Chen (2008) that intersection features accommodate aggressive driving behavior. They found that car drivers show aggressive behavior to cross the intersection when a road has more lanes.

Schleinitz, Petzoldt, Kröling, Gehlert and Mach (2019) found in their research that the red-light violations by bicyclists occur more often at certain crossroad designs. T-intersections had experienced significantly more red-light violations than an intersection with four arms. This suggests differences in risk behavior of cyclists at different infrastructure designs. Schepers en Voorham (2010) investigated the bicyclists' accidents on several types of intersections. They found that bicyclists are less involved in accidents when the cross distance is larger compared to a smaller distance an individual had to cover. When bicyclists had cross three lanes or more lanes, they show a more conservative behavior instead of crossing two lanes as the research suggests. The following hypothesis is formulated:

H1: Crossing an additional car lane has a negative effect on the possibility of crossing through a red-light.

In figure 1 a mid-section[1] is pictured. A mid-section is a small bicycle lane situated between car lanes of two driving directions. In Rotterdam the mid-section is a common occurrence on several crosses. The purpose of a mid-section is that bicyclists could cross the road safer when it is busy and makes the cross less complex (SWOV, 2010). It is possible that when the traffic light turns green and it is busy on the bicycle lane the traffic flow is slow. Because of this slow movement of traffic, it is possible that the traffic light for cars could turn green whilst crossing the road. A mid-section acts as a place for travelers to stop safely on the road and wait when the continuation of crossing the road is safe. The inclusion mid-section also lowers the complexity of a cross, because a traveler only has to pay attention to traffic coming from one direction instead of paying attention to two driving directions.

Schepers en Voorham (2010) found that that the inclusion of a mid-section did not have a significant connection with the number of accidents at crossing facilities. They mention that a mid-section contributes to the safety of the bicyclists as they can rest there when it is busy. Other research supports the assumption that the inclusion of a mid-section on a cross is safer for individuals as the number of crashes is significantly lower than a cross without a mid-section (Schepers, Kroeze, Sweers & Wüst, 2011). However, the inclusion of mid-sections could have effects on the risk behavior of travelers as it creates a haven for travelers if they think that crossing a single car lane is safe to cross. With the presence of a mid-section they can safely stop halfway the cross and wait until the car lane from the is safe to cross according

[1] The Dutch term is "middengeleider" or "middeneiland".

to their own beliefs. More risks could be taken to cross the road illegally and create dangerous situations for themselves and others. The following hypothesis is formulated:

H2: The inclusion of a mid-section has a positive effect on the possibility of a red-light violation.

Figure 1: Mid-section situated between the car lanes.

2.2.2. Traffic congestion and flow

Hennessy and Wiesenthal (1999) researched the relationship between driver aggression and traffic congestion. The results show that the behavior of drivers differed between the level of congestion. The respondents show a more aggressive approach when traffic congestion is at a high level. Similarly, Hamdar, Mahmassani and Chen (2008) found the same results. In their research to investigate aggressive driving behavior they tested whether waiting queues has an influence. They found that long queues and waiting times led to a more aggressive driving approach.

Vandenbulcke et al. (2009) researched the risk of crashing as bicyclists in relation to environmental factors. In their results they found that higher volumes of cyclists on the road lead to lesser risks of crashing. Lower volumes of cyclists lead to higher risks of crashing. This is caused by higher speeds and riskier behavior of cyclists when they are not hindered during travel. Guo, Li, Wu and Xu (2018) found an opposing result in their research of bicyclists, e-bicyclists and e-scooters red-light violations. They acknowledged that bicycle traffic volume increased the probability of ignoring a red-light. However, they do mention that vehicle volume (includes car and all other vehicles) decreased the probability of ignoring a red-light.

2.3. Driver-specific characteristics

2.3.1. Personal features and determinants

Wachtel and Lewiston (1994) researched what factors determined bicycle-motor collisions on intersections in the United States. The results show that older bicyclists are more likely to be involved in a collision in comparison to younger bicyclists as they might have slower reactions to anticipate dangerous situations. Furthermore, gender did not influence the risk of getting involved in a collision and therefore there is no difference in risk-taking between the two genders.

Research from Johnson, Charlton, Oxley and Newstead (2013) investigated personal characteristics influencing the decision of bicyclists to commit a red-light violation. They did find that gender has a significant role on red-light violations. Male bicyclists took more risks than females. This is contrary to the findings of Wachtel and Lewiston (1994). However, their measurement of risk is different and could explain their difference. Furthermore Johnson et al. (2013) found differences between age groups. Younger drivers were more likely to take the risk of ignoring the red-light in comparison with older drivers. Pai and Jou (2014) also discovered that younger bicyclists ignored the red-light more often.

Brandau, Daghofer, Hofmann and Spitzer (2011) researched young moped drivers and their behavior on the roads in the case of Austria. Their research suggests that gender does not have a significant relation with risky behavior. They suggest that personality has a significant influence on risk-taking behavior. The authors suggest that moped drivers are divided into four personality groups in which two personality groups (a group with a low level of openness and a group with a high level of impulsivity and risk-taking) show riskier behavior and are therefore more likely to obtain injuries while driving than the other two groups (a group with a low level of risk-taking behavior and a group with a high level of extraversion).

Wang, Xu, Tremont and Yang (2012) researched moped drivers' behavior in China. With the use of camera footage, they were able to observe the violation behavior of moped drivers. They specifically investigated what factors determine that moped drivers decide to violate traffic rules. Their results suggest that gender has a significant effect on violation behavior. Male moped drivers were significantly associated with a higher chance of a violation. Additionally, they found that age influenced violation behavior. Younger age was also associated with a higher chance of a violation.

2.3.2. Ownership of vehicle and transport mode

Deliverers are known for their risky driving behavior and are relatively often involved in traffic accidents. One of the reasons for their risky driving behavior is that they are not liable for any damage done to the vehicle they use, but instead their employer is responsible for any damage done in case of a collision. Recent data show that food deliverers damage the vehicle six times more than owners of a private moped (Veilig Verkeer Nederland, 2019).

Chung, Song and Yoon (2019) investigated motorcyclist crashes of food deliverers and couriers in South Korea. The majority of motorcyclists on the road are deliverers and couriers. They argued that these types of drivers violate the traffic laws more often due to work pressure. They were more likely to be involved in crashes and to obtain severe injuries.

The concept of vehicle sharing is relatively new in the vehicle market. Several years ago, some cities in the Netherlands were introduced with a couple of companies offering bicycle sharing to the public. Shortly after, moped sharing was introduced. Both sharing vehicles became rapidly popular as it is convenient and is cheaper. Usage of these vehicles are often paid per minute and do not require a big instant investment in a personal bicycle or moped. Nowadays, the sharing vehicles are part of the traffic landscape in the major cities of the Netherlands. After extensive searching there is no existing literature available on the risk behavior of users of sharing bicycles and sharing mopeds for violating traffic rules or aggressive behavior.

We can theorize the possible behavior of individuals using a sharing system. The main implication of a sharing vehicle is ownership. The traveler is not the owner of the vehicle, but the company owning the sharing system. The companies lend their vehicles to their consumers. Klauer et al. (2011) found in their research that car ownership has a significant influence on risk behavior. Personal owned vehicles showed higher levels of crash risks relative to non-personal owned vehicles. This could be explained by the fact that they show responsibility as they do not personally own the concerned vehicle. Applying this concept to that of the sharing systems, individuals should saw less risky behavior than individuals using personally owned vehicles. This effect could be enhanced by the fact that in case of any damage of the sharing vehicle they still will be reliable for the suffered costs if they are at fault (Felyx, 2019; Swapfiets, 2019).

Moral hazard can appear as a result of the ownership of the concerned vehicle. This theory implies that there is a negative behavioral change when risk is shifted to another party. Applying this concept in the case of ownership of vehicles, a behavioral change could occur between different ownership types. For vehicles used to perform a job, the vehicle is (usually) owned by the concerned company. The employees are mainly judged by their speed of performing their job by the employer. To get recognition or better rewards the employer might take extra risks to perform their job better and faster. Besides that, if any damage appears on the vehicle caused by the employer, the employer does not bear the risk of making costs. Thus, it is likely that moral hazard appears in for this case as they are not accountable for any financial damage. However, for sharing systems and rentals the moral hazard problem will not appear. In case of any damage to the concerned vehicle, the traveler is accountable for the financial costs.

For personal owned vehicles moral hazard could appear but is not likely. For personal owned vehicles the bicyclist or moped driver is accountable for all damage, maintenance and other costs it incurs, but also reaps the benefits from owning a vehicle. Thus, risks are carried by the driver itself and moral hazard would not appear. However, people have the option to insure their vehicles. However, it is uncommon that people insure their bicycles. For mopeds it is common to insure their vehicle as it is usually a big financial investment. In the case of mopeds moral hazard could appear.

2.4. Environmental circumstances

2.4.1. Weather conditions

Moped drivers and bicyclists are affected by weather conditions as they are more vulnerable to heavier weather conditions than cars. When it rains, it is misty or windy the driving experience changes and people are forced to change their driving behavior to continue their travel safely. Bijleveld and Churchill (2009) acknowledge the fact that bicyclists and moped drivers are weather sensitive. They argue that unpleasant weather conditions considerably influence the traffic volume of bicycles and mopeds negatively and that crash rates are higher for bicyclists and moped drivers.

Van den Bossche, Wets and Brijs (2004) researched the relationship of weather conditions with traffic safety. Their results suggest that weather conditions have a significant effect on traffic safety. For instance, they found that accidents were relatively less when it is raining. This is the result of conservative driving behavior during heavy rain. Hogema (1996) did also acknowledge that driving behavior significantly differed between rain and dry weather; in the rain people tend to adjust their driving behavior to a more conservative style. Van den Bossche, Wets and Brijs (2004) found similar results during days when it stormed, snowed and thundered. Furthermore, they found that during sunny days more accidents happened than normal. This might be caused by less concentrated and aware drivers due to the pleasant weather conditions.

2.4.2. Time

Åkerstedt, Kecklund and Hörte (2001) researched the influence of time on the risk of car drivers getting involved in an accident. There was a clear difference found between time. During night times the risk of getting involved in an accident is higher than during other time periods. This could be explained by less attentiveness, tiredness of the driver and better traffic flow at night times. Furthermore, they observed that the risk is less during morning peak hours. This might be caused due to traffic congestion and better visibility during daylight. These results are supported by the findings from Doherty, Andrey and MacGregor (1998). They investigated the effect of time on the risk young drivers take. The results show higher rates of risks during night times and weekends.

Dozza (2017) investigated the crash risk of bicyclists in the case of Sweden. The influence of time was tested; daytime versus nighttime and weekdays versus weekends. The results indicate higher crash risks are present during nighttime rather than daytime. Also, weekends show higher risks than weekdays. Similar to the research of Åkerstedt, Kecklund and Hörte (2001), this effect could be explained by smoother traffic flow.

Kim, Takeyama and Nitz (1995) found that Monday mornings and Friday evenings moped drivers show riskier behavior. Their research was located near a university campus which could explain their results. Monday mornings are typically the start of a new week while Friday evenings are the end of the educational week. It is reasonable to assume that people have to attend classes on time and might come in a hurry if they leave too late on Monday mornings. The Friday evenings students travel back home or elsewhere (e.g. celebrate the weekend in the bar) and might, therefore, be less attentive. Pai and Jou (2014) found similar effects on students that use bicycles. Peak hours had a significant relationship with a red-light violation.

3. Data and Methodology

3.1. Data collection

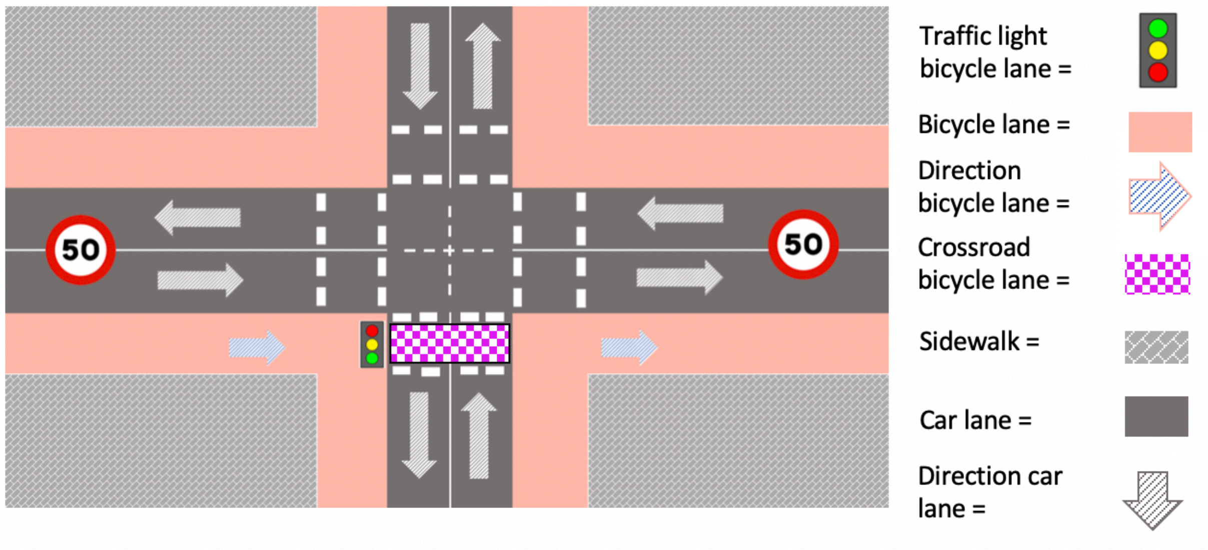
The Dutch intersections can be divided into several types depending on several determinants. Those determinants are speed limit on the intersection, urbanized area (bebouwde kom) or not, crossroad or roundabout, three or four branches, bicycle facilities and type of regulation (Jansen, 2004). This research will solely focus on crossroad intersections. In table 1 the characteristics of the intersections that will be examined are displayed.

Table 1: Intersection features that will be researched.

Features	
Urbanized area	Yes
Speed limit	50 km/h
Branches	4
Bicycle facilities	Separate bicycle lane (mopeds of a maximum speed of 25 km/h allowed)
Regulation	Traffic light

Besides the intersection features, the cross of the intersections itself should have the same features. First of all, the bicycle lane has to be a one-way lane for the simple reason that it is hard to observe the subjects when they pass each other at the same time, which possibly results in imprecise observations. Secondly, during the passage on the crossroad the subjects should pass car lanes coming from both directions due to a higher risk factor coming along for the subjects. This causes that the subjects have to take into account, in deciding to commit a red-light violation, that traffic can collide from left or right, from the perspective of bicyclists or moped riders, into them when they illegally cross the intersection. Furthermore, most crossroads at intersections are designed with traffic coming from both ways and thus creates a more representable picture of the city of Rotterdam related to the topic of this research. Figure 2 depicts a simplified visualization of the intersections used in this research.

Figure 2: Visualization of features of the intersections.[2]



Data is hand-collected by observing moped drivers on various crosses across the municipality of Rotterdam. The crosses are chosen based on certain individual features these crosses possess. First of all, the number of car lanes an individual has to cross to reach the opposite of the bicycle lane. Two intersections have two car lanes and the other two intersections have three car lanes. Secondly, the inclusion of a mid-section on the bicycle lane is considered. Likewise, two intersections will feature a mid-section, while two will not. Thirdly, all intersections have to be in a similar traffic environment[3], apart from the number of car lanes and inclusion of a mid-section, as each other to have better comparability. Thus, among the intersections there are similarities when it comes to the number of car lanes and the inclusion of a mid-section while dealing with a similar environment. Table 2 shows the features each intersection has and its location in the city of Rotterdam.

[2] The visualization of the intersection in figure 2 is not a representation of the actual intersections used in this research. Actual intersections differ in the designs of car lanes and bicycle lanes.

[3] Under a similar traffic environment is understood in this paper the features mentioned in table 1 as well as no presence of railways across the intersection to accommodate the train, metro or tram. Furthermore, the rules and conditions of all intersections should be similar to make sure that there is no other influences possible outside of the ones that are observed. For instance, there should not be any road works present or that road workers manage the traffic at the intersection.

Table 2: Features and the location of the crosses at the intersection.

Intersection[4]	Mid-section	Number of lanes	Intersection location
1	No	2	Westblaak & Hartmanstraat
2	No	3	Blaak & Posthoornstraat
3	Yes	2	Prins Hendrikkade & Van der Takstraat
4	Yes	3	Rochussenstraat & Mathenesserlaan

The way of retrieving data is by filming the bicyclist manually on the intersection. Two people were needed in the process of making reliable results from the recordings. Person 1 has a role to signal when the traffic light turns red-light. Person 2 has a role to film the subjects and person 1 from the opposite of the road where the subjects have to cross. This way it is possible to identify whether the response of the subjects facing a red-light if person 1 signals a red-light. When the traffic light turns green person 1 will hold its bag with the right hand to signal that individuals cross the road are passing through legally (figure 3). When the traffic light turns red person 1 will hold its bag with the left hand to signal that individuals crossing the road are committing a red-light violation (figure 4). When the traffic light is orange person 1 holds the bag with both hands to signal person 2 that the traffic light turns red in a few seconds. Figures 5,7, 9 and 11 shows the plot of all intersections and the positions of person 1 and person 2 on the site. Figures 6, 8, 10, 12 shows the point of view from the camera footage of the intersections.

Figure 3: Person 1 signals green light.

Figure 4: Person 1 signals red-light.

[4] For the remainder of this paper the intersections are named as their respective number given in table 2.

Figure 5: Plot of intersection 1 with the positions of person 1 and person 2.

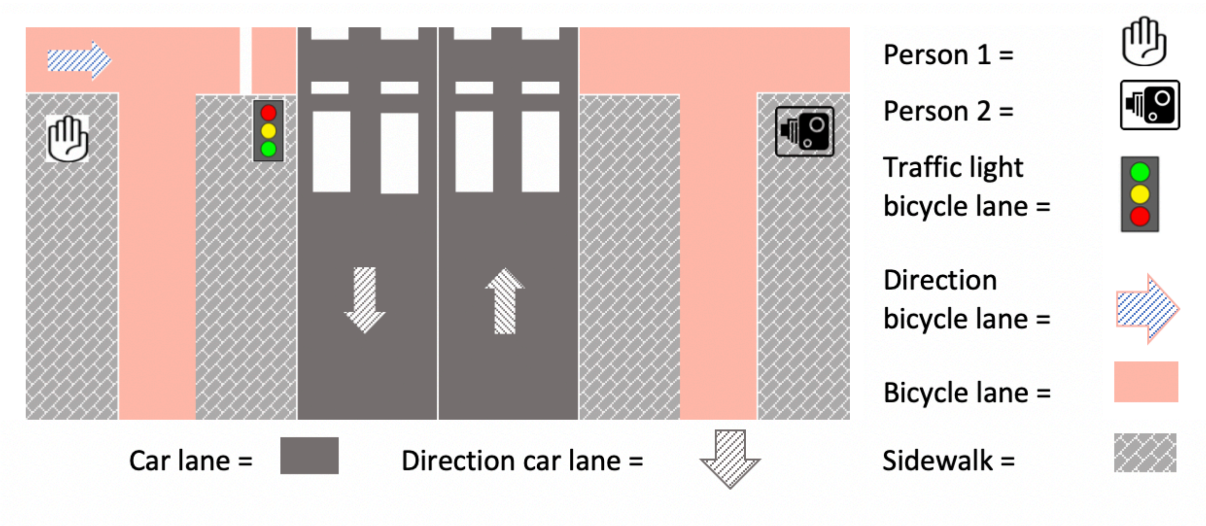


Figure 6: Point of view from intersection 1.

Figure 7: Plot of intersection 2 with the positions of person 1 and person 2.

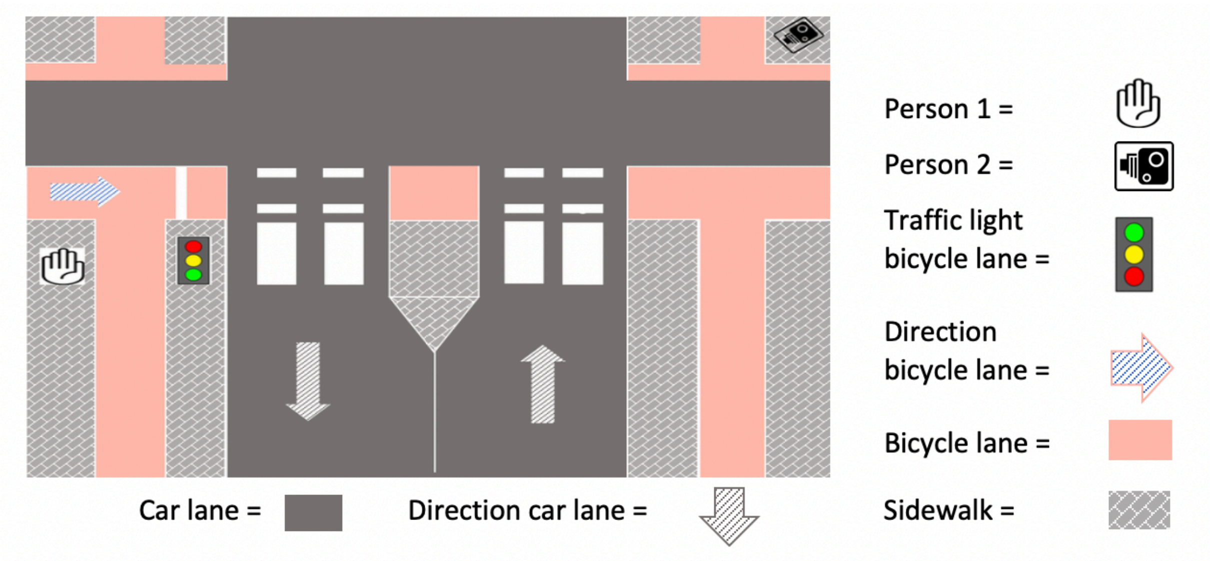


Figure 8: Point of view from intersection 2.

Figure 9: Plot of intersection 3 with the positions of person 1 and person 2.

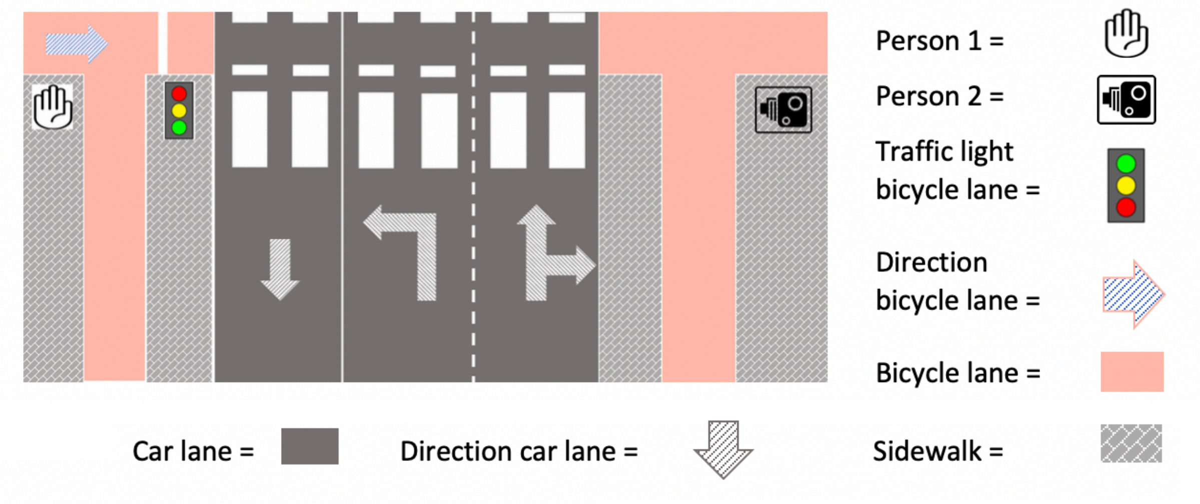


Figure 10: Point of view from intersection 3.

Figure 11: Plot of intersection 4 with the positions of person 1 and person 2.

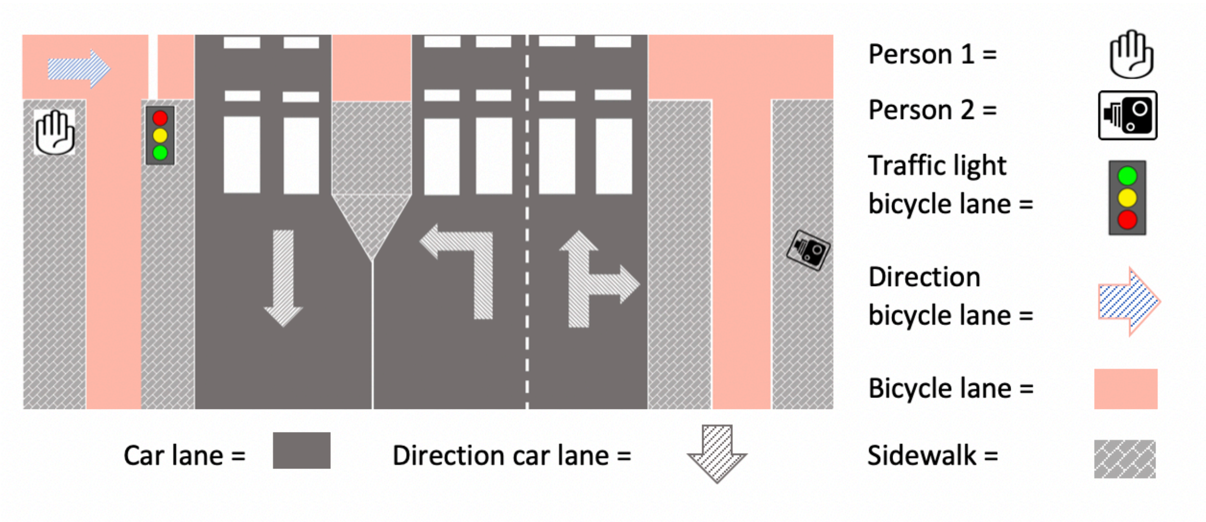


Figure 12: Point of view from intersection 4.

In total each intersection is observed on six different occasions based on the time and date. Every intersection is observed on three different time periods (i.e. morning, afternoon and evening) on two different parts of the week (i.e. weekday and weekend). An intersection will not be observed twice on the same day, but on different dates to get a better understanding of the behavior of individuals in different circumstances.

3.2. Variables

Table 3 shows the variables related to driver-specific characteristics. The category *MOPED* takes the value of 0 if the concerned vehicle is a bicycle and the value of 1 if the vehicle is a moped. This variable only accepts mopeds that possess a blue license plate[5] and not mopeds that possess a yellow license plate[6]. For all intersections it is prohibited that mopeds with a yellow license plate drive on the bicycle lane. However, on several occasions mopeds with a yellow license plate drove on the bicycle lane and are therefore not classified in this variable. A similar situation is noticeable for the category bicycle as there are electric bicycles that possess a yellow license plate. These electric bicycles are treated similarly like mopeds with a yellow license plate and are therefore prohibited to drive on the concerned bicycle lanes. Furthermore, other vehicle types such as mobility scooters, steps and other vehicles are not included in the variable *MOPED*.

[5] Mopeds with a blue license plate have a speed limit of 25 km/h and do not have a helmet obligation for driver and all passengers.

[6] Mopeds/bicycles with a yellow license plate have a speed limit of 45 km/h and have a helmet obligation for driver and all passengers.

Table 3: List of driver specific characteristics and the applied measurement system.

Variable	Type	Explanation	Measurement
RED_LIGHT_VIOLATION	Binary	This is the dependent variable of this research and is to determine whether an individual ignores the red-light or not.	As this is a binary variable there are only two possible outcomes; if one does not ignore the red-light (0) and if one does ignore the red-light (1).
MALE	Binary	The supposed gender of the observed individuals.	For this research we assume two genders; female (0) and male (1).
MOPED	Categorical	The mode of transport used by the observed individual.	Two possible outcomes; bicycle (0) and moped (1).
OWNERSHIP	Categorical	The supposed ownership of the vehicle an individual used.	Type of ownership is categorized in groups; personal ownership (0), sharing/rent service (1), and work (2).
TRAVEL_COMPANION	Binary	The subject is accompanied by an acquaintance during travel.	From the camera footage it has to be notable that the subjects have an interaction or travel next to each other when unnecessary or illogical. Two possibilities: no (0) or yes (1)
2ND_PASSENGER	Binary	The subject has a passenger seated either in front or at the back.	From the camera footage it has to be notable that another person is seated in the same vehicle as to the driver itself. Two possibilities: no (0) or yes (1)

The variable type of *OWNERSHIP* has three categories and is based on certain characteristics of the vehicle and the driver. For the category personal ownership, it is assumed that the vehicle is unmodified for business or marketing purposes and is in the original condition as is meant for personal consumers. For the category rent service/sharing service the vehicles are often noticeable by their branding of the vehicles with the use of bright colors and visible logos on several spots on the vehicle itself. For the category work the vehicles and (occasionally) the drivers are noticeable by the branding on the vehicle and the clothing of the driver. Often the individuals in this category are food deliverers, but also couriers of postal services were observed. See figures 13 and 14 for an example of respectively a sharing/rent vehicle and work-related vehicle.

Figure 13: The type of branding of vehicle suggest rent/sharing vehicle.

Figure 14: Branding of the vehicle and the driver's clothing suggests work-related vehicle.

It is important to address that for the category sharing service/rent service in case of any damage, vandalism or theft of the vehicle the individual self is responsible and is liable for any insurance invoices belonging with one of the mentioned circumstances (Felyx, 2019; Nederlandse Spoorwegen, 2019; Swapfiets, 2019). In the case of sharing mopeds, the costs of any damage are higher than that of sharing bicycles and could be of influence of driving behavior. For the category work, the drivers are not liable for any damage or theft as they are employees, but the employer is responsible for any costs attached to damage or theft. However, there are certain food ordering companies, such as Deliveroo, where their employers are considered as self-employed as they determine when and where they work. These employers are covered for any injuries caused during work practices but have to manage their own vehicle insurance, if they deem necessary[7], as they have to use their own vehicle and are therefore responsible for any damage to their vehicle or to involving parties in case of a collision (Deliveroo, 2019; Wolthuizen, 2017). Obviously for the category personal ownership all damage or insurances are for the owner.

Table 4 displays the variables related to the features of an intersection and table 5 displays other control variables. As mentioned in table 4 *TRAFFIC_VOLUME* is based on the level of traffic an intersection experience. The level of traffic is determined by the number of passers-by in a time frame of thirty minutes. By comparing this number among the various time frames, it is possible to determine which intersections dealt with the most traffic volume and whether traffic volume has a relationship with behavior as found in previous research (Vandenbulcke et al., 2009; Guo, Li, Wu and Xu, 2018).

[7] In food ordering companies where employers are treated as self-employed, they have the choice to use a vehicle of their liking. For the ones that use a bicycle, it is by law not necessary to have a vehicle insurance while it is necessary to have a vehicle insurance for mopeds if one prefers to use a moped for working practices.

Table 4: List of intersection features and the applied measurement system.

Variable	Type	Explanation	Measurement
MID_SECTION	Binary	The section between the car lanes where there is a bicycle lane.	Two possible outcomes; Mid-section is not present in the crossroad (0) and mid-section is present in the crossroad (1).
ADDITIONAL_LANE	Binary	The number of car lanes one has to pass to cross the road.	Two possible outcomes; two lanes to cross (0) and three lanes to cross (1)
TRAFFIC_VOLUME	Continuous	The average number of traffic passing the intersection in one minute.	Number of traffic that crossed the intersection cross relative to the observation time in minutes.
RED_LIGHT_IN%	Continuous	The percentage of time the traffic light is red during the observation.	The total time the traffic light is red relative to the observation time in. minutes.

Table 5: List of other variables and the applied measurement system.

Variable	Type	Explanation	Measurement
RUSH_HOUR	Binary	Whether the observation took place during rush hour.	Two possible outcomes; no (0) if not during rush and yes (1) if during rush hour.
WEEKEND	Binary	The part of the week in which the observation was executed.	Two possible outcomes; weekday (0), and weekend (1).
PART_OF_DAY	Categorical	The part of the day in which the observation was executed.	Three possible outcomes; morning (0), afternoon (1), and evening (2).
DARK	Binary	The brightness of the sky	Two possible outcomes; light (0) and dark (1).
WEATHER_CONDITION	Categorical	The weather condition in which an individual has to travel.	Three possible outcomes dry (0), cloudy (1) and misty (2)
TEMPERATURE	Continuous	The temperature in degrees Celsius during time of observation.	The temperature in degrees Celsius reported on buienradar.nl during the time of observation.

3.3. Descriptive statistics

In total 3031 vehicles have passed the intersection cross from more than 12 hours of footage. On average four vehicles per minute have passed the intersection cross[8]. From table 6 we can see that the weekday mornings (morning rush hour) experienced the most traffic while the mornings at the weekend experienced the least volume of traffic from all time periods. The difference in traffic crowds in the morning and evening on weekdays is substantially higher than during weekends on the same part of the day. However, in the afternoon the number of vehicles that crossed the intersection barely differs from weekdays and weekends. This can be explained due to the fact the commuters are active in traffic during morning and evening weekdays which are the rush hours.

Furthermore, it is noticeable that intersection 2 dealt with the least amount of traffic in comparison with the other intersections. Intersection 1 dealt with the most traffic volume. From table 6 it appears that the morning rush hours were the busiest times on the intersections and the least busy on morning weekends. To put context into these statements; on average 7,31 vehicles per minute passed the intersection cross on morning rush hours and an average of 1,61 vehicles per minute passed the intersection cross on mornings in the weekend (see appendix: table 1). The intersections dealt with 4,01 vehicles per minute on average. The busiest observation moment was at intersection 4 in the morning rush hour with an average of 10,40 vehicles per minute. The least busy observation moment was at intersection 2 and intersection 3 on a morning in the weekend with both having an average of 1 vehicle per minute.

Table 6: Number of people that crossed the intersection.

	PART_OF_DAY and *WEEKEND*						**Total**
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	218	93	151	174	229	80	***945***
Intersection 2	137	31	64	57	125	51	***465***
Intersection 3	192	31	139	91	292	137	***882***
Intersection 4	352	45	68	84	106	84	***739***
Total	***899***	***200***	***422***	***406***	***752***	***352***	***3031***

[8] For detailed statistics of the traffic per minute each observation period refer to appendix: table 1.

From table 7 we see 1512 individuals that passed the intersection faced a red-light during their travel across all intersections. This means approximately 50 percent of the people who passed the intersection cross has faced a red-light (see appendix: table 2). For intersection 2 the number of subjects is now 127 which translates to 27,3 percent of the vehicles that passed the intersection cross faced a red-light. From the vehicles that crossed Intersection 4, 72,1 percent faced a red-light. For intersection 1 and intersection 3 the percentages of people that face a red-light crossing the intersection are respectively 41,5 percent and 52,2 percent. Over the whole sample the average lies at 49,9 percent. Thus, intersection 1 and intersection 3 closely resembles the average of the sample.

Table 7: Number of subjects that faced a red-light.

	PART_OF_DAY* and *WEEKEND						***Total***
	Morning		**Afternoon**		**Evening**		
	Weekday	**Weekend**	**Weekday**	**Weekend**	**Weekday**	**Weekend**	
Intersection 1	84	39	67	72	94	35	***392***
Intersection 2	51	8	14	17	25	12	***127***
Intersection 3	127	9	62	53	139	70	***460***
Intersection 4	238	36	47	62	83	67	***533***
Total	***500***	***92***	***190***	***204***	***341***	***185***	***1512***

However, the difference between intersection 2 and intersection 4 with the average sample value for vehicles facing a red-light is considered substantial. This suggests that the traffic light acts differently on each intersection cross. This seems the case when looking at the percentage of time the traffic light is turned red seen in table 8[9]. For all intersections the red-light time percentage and the vehicles facing a red-light percentage are similar to each other. This means that on average intersection 2 the traffic light spends most of the time green while intersection 4 spends most of the time red. For intersection 1 the traffic light is on average slightly more often green than red and for intersection 3 the traffic light is slightly more often red than green.

[9] Refer to appendix: table 3 for a detailed overview of the time the traffic light is red during each observation.

Table 8: Percentage of people facing a red-light relative to the number of people that crossed the intersection (blue bar) and the percentage of time the traffic light is red relative to the observation time (orange bar).

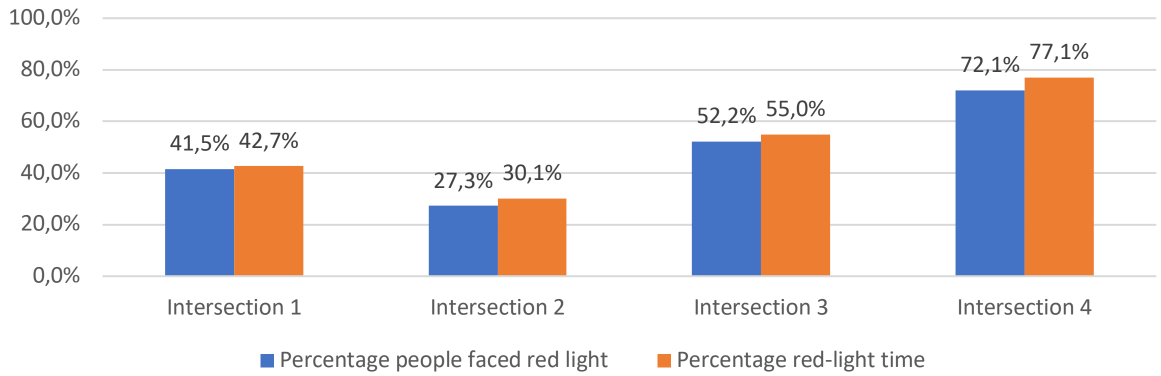


Table 9 and 10 gives an insight into determinants that distinguishes subjects based on their vehicle and the ownership of the vehicle. Approximately 90 percent of the sample consisted of subjects that used bicycles as transport mode. Mopeds were used as transport mode for 9,2 percent of the subjects while less than one percent of the subjects chose an alternative transport mode. For 1312 subjects, personal vehicle ownership is assumed which translates to approximately 87 percent of the sample. Sharing and rental vehicles and company-owned vehicles consist for respectively 9,8 percent and 3,4 percent of the sample.

Table 9: Transport mode and ownership of vehicle.

	OWNERSHIP			
	Personal	Sharing/Rent	Work	***Total***
Bicycle	1203	115	42	***1360***
Moped	101	31	7	***139***
Other	8	2	3	***13***
Total	***1312***	***148***	***52***	***1512***

Table 10: Transport mode and ownership of vehicles in percentage of total traffic facing a red-light; 1512 subjects.

	OWNERSHIP			
	Personal	Sharing/Rent	Work	***Total***
Bicycle	79,6%	7,6%	2,8%	***89,9%***
Moped	6,7%	2,1%	0,5%	***9,2%***
Other	0,5%	0,1%	0,2%	***0,9%***
Total	***86,8%***	***9,8%***	***3,4%***	***100,0%***

From the bicyclists it is assumed that 88,5 percent is owned personally (see appendix: table 5). For moped drivers it is assumed that 72,7 percent personally own the vehicle. Relatively spoken rental mopeds are more dominant within the group of moped drivers in comparison with the share of rental bicycles within the group of bicyclists. This is not unexpected given the recent development in moped sharing in Rotterdam and the higher costs of personally owning and maintaining a moped compared to a bicycle. The presence of work-owned vehicles has the lowest representation for both bicyclists as moped drivers with respectively 3,1 percent and 5 percent.

3.4. Methods

A regression analysis will be executed to measure the probability of committing a red-light violation. As the dependent variable is binary, a logit model is generated. Before starting a regression analysis, data has to be modified to appropriately begin modeling a logit model.

As earlier mentioned 1512 vehicles faced a red-light during the observation period. A total of thirteen vehicles were observed that were neither a bicycle nor a moped. From those thirteen vehicles nine were yellow licensed mopeds, two electric steps, one skateboard and one mobility scooter. This research will restrict the vehicles into two groups, namely bicycle or moped. The yellow licensed mopeds are not included in the variable *MOPED* as they are treated differently as blue licensed mopeds in terms of traffic and safety rules. Therefore, these vehicles are removed from the sample.

Furthermore, it is important to note that not all of these individuals had the opportunity to decide to ignore the red-light. Some people were hindered by other subjects in front of them waiting in line before the traffic light. In figure 15 only the three subjects situated in front of the traffic light are able to commit a red-light violation, while everyone behind them are not in the position to commit a red-light violation as they are hindered by the front three. Therefore, the individuals that were hindered were removed from the database. Table 11 shows that the sample size consists of 1081 unique subjects. Comparing table 7 and 11 with each other almost half of the subjects on weekday mornings and over 100 subjects of weekday evenings are removed from the sample. This is an unsurprising outcome as at these times the rush hour takes place and naturally more traffic passes along the bicycle lane which creates queues in front of the traffic light when it is turned red.

Figure 15: Individuals hindered at the traffic light.

Table 11: Number of subjects that faced a red-light and were able to commit a red-light violation.

	PART_OF_DAY* and *WEEKEND						**Total**
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	66	39	56	59	58	29	***307***
Intersection 2	48	8	14	16	24	12	***122***
Intersection 3	67	9	49	47	78	57	***307***
Intersection 4	94	35	38	54	70	54	***345***
Total	***275***	***91***	***157***	***176***	***230***	***152***	***1081***

After the modifications a regression analysis is conducted. The logit regression is used in this research to test the hypotheses. The outcome of the logit regression is the logarithm of the odds (log odds). For any value of the log odds, the probability value will be between 0 and 1 when converting log odds to probability. An Ordinary Least Squares (OLS) regression does not fit values between 0 and 1. This could lead to out-of-bounds estimations; a logit or probit model is more appropriate for this research. A logit and probit regression differ slightly in terms of their estimations of the same model. The preference to use logit is that the interpretation of the model is easier than that of a probit model. The coefficients generated from the logit models should be interpreted in terms of log odds. The higher the value of the log odds outcome, the higher the probability of a red-light violation.

A correlation matrix is created to determine whether there are variables that have a strong relationship with each other. This research has produced primarily binary variables. Therefore, a tetrachoric correlation matrix is generated to determine if high correlation between binary variables exist. The correlation between binary-and-continuous and continuous-and-continuous variables is determined with a Pearson correlation matrix. A correlation value of .75 or higher is chosen as a guideline for a high correlation. In case of a high correlation a Variance Inflation Factor (VIF) test is made to test for multicollinearity. In case of a VIF-value of ten or higher we assume a high correlation and one of the variables should be excluded from the model. Important to mention is that a VIF test is generated after a regression model.

To determine the final model the Bayesian Information Criteria (BIC) values are taken into consideration. The BIC is preferred over the Akaike Information Criteria (AIC) as it penalizes for the number of parameters. Also, the pseudo R^2 is taken into consideration as this value explains the proportion of variance of the dependent variable that is explained by the model. Finally, the model must make sense. Models with a better BIC and pseudo R^2 does not necessarily mean the model is better than others. The relationships must also make sense and not be based purely on statistical outputs. The model selection is based on those three criteria. With the final model the two hypotheses can be tested. The significance level is set at five percent. The sign of the coefficients indicates whether there is a negative or positive effect of the variables on the probability of committing a red-light violation.

4. Results

4.1. Main findings

The results of this research indicate that 253 vehicles ignored the red-light over the whole observation period. This means that 23,4 percent of the sample committed a red-light violation. Tables 12 and 13 show respectively the frequency and relative statistics of the subjects that committed a red-light violation at each observation moment. Intersection 1 experienced the most red-light violations in the morning on a weekday in absolute numbers with a total of 21 subjects. Intersection 1 had absolutely and relatively spoken the least experience with red-light violations in the evening on a weekend when nobody committed a red-light violation. Intersection 2 had relatively the most red-light violators in the morning on a weekend with 62,5 percent of the subjects committing a red-light violation.

Table 12: Number of subjects that committed a red-light violation.

	Part of day and Weekend						Total
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	21	11	11	6	12	0	***61***
Intersection 2	20	5	5	8	6	4	***48***
Intersection 3	17	5	9	11	12	18	***72***
Intersection 4	19	10	6	11	17	9	***72***
Total	***77***	***31***	***31***	***36***	***47***	***31***	**253**

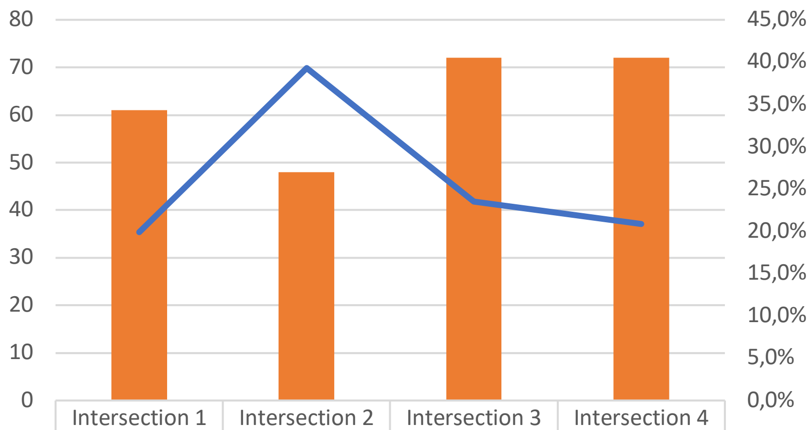
Table 13: The percentage of subjects that committed a red-light violation relative to subjects having the opportunity to commit a red-light violation.

	Part of day and Weekend						Total
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	31,8%	28,2%	19,6%	10,2%	20,7%	0,0%	***19,9***%
Intersection 2	41,7%	62,5%	35,7%	50,0%	25,0%	33,3%	***39,3***%
Intersection 3	25,4%	55,6%	18,4%	23,4%	15,4%	31,6%	***23,5***%
Intersection 4	20,2%	28,6%	15,8%	20,4%	24,3%	16,7%	***20,9***%
Total	***28,0***%	***34,1***%	***19,7***%	***20,5***%	***20,4***%	***20,4***%	**23,4**%

From table 13 it is noticeable that during weekends in the morning and afternoon relatively more red-light violations occurred than during weekdays. Only the evenings showed no percentual difference between weekdays and weekends. However, taking the day as a whole there is no relative difference between weekdays and weekends (see appendix: table 6). The mornings experience absolute and relative more red-light violations than the afternoons and evenings (see appendix: table 7). 29,5 percent of the subjects crossed the intersection during a red traffic light in the mornings, 20,1 percent in the afternoons and 20,4 percent in the evenings. There is a difference of 9,1 percent point between morning and evening, and a percentual difference of 44,6 percent.

Comparing the intersections individually from each other we see that intersection 3 and intersection 4 experienced the most red-light violations in absolute terms; 72 violations. Intersection 2 experienced the least red-light violations in absolute terms; 48 violations. However, relatively intersection 2 experienced the most violations. Compared to the second-highest relative red-light violations, intersection 3, there is a difference of 15,8 percent point and a percentual difference of 67,2 percent.

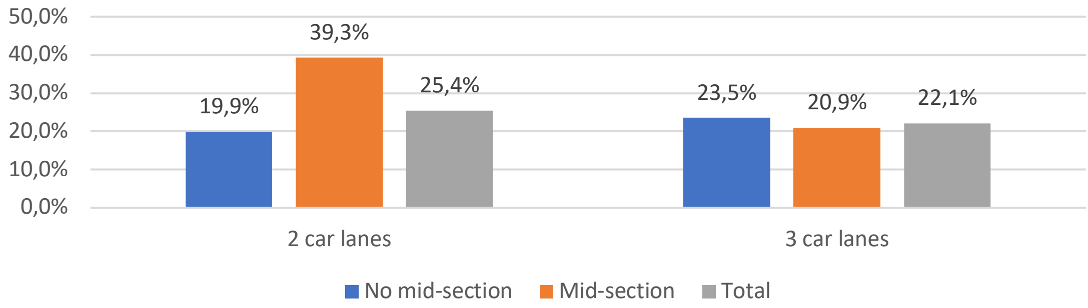
Figure 16: Histogram of the number of subjects that committed a red-light violation and the percentage of subjects that committed a red violation relative to subjects having the opportunity to commit a red-light violation at each intersection.



	Intersection 1	Intersection 2	Intersection 3	Intersection 4
Number of red-light violations	61	48	72	72
Percentage of red-light violations	19,9%	39,3%	23,5%	20,9%

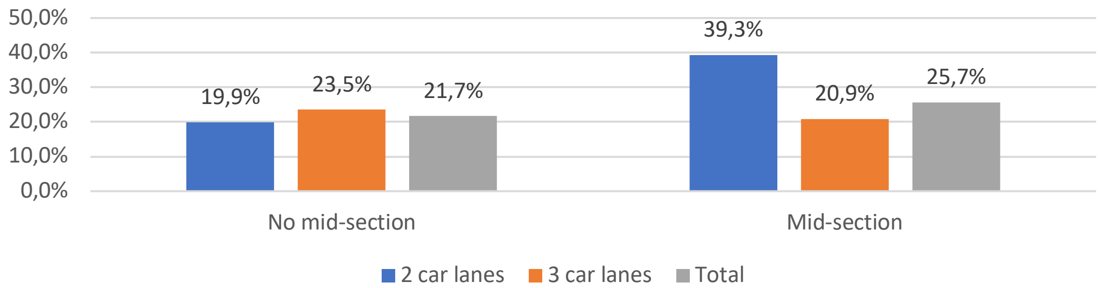
In figure 17 the percentage of red-light violations is visualized in groups with the same number of car lanes. The intersections with two car lanes experienced 109 red-light violations which is 25,4 percent of the subjects. The intersections with three car lanes experienced 144 red-light violations which is 22,1 percent of the subjects. Between the two groups there is a 3,3 percent point difference and a percentual difference of 14,7. These statistics suggest that less risks are taken when an additional car lane has to be crossed.

Figure 17: Percentage of red-light violations from intersections with the same number of car lanes.



In figure 18 the percentage of red-light violations is visualized in groups with the same mid-section situation, either included or excluded. The intersection that did not include a mid-section experienced 133 red-light violations which is 25,7 percent of the subjects. The intersection that did include a mid-section experienced 120 red-light violations which is 21,7 percent of the subjects. Between the two groups there is a 4 percent point difference and a percentual difference of 18,4 percent. These statistics suggests that more risks are taken when a mid-section is included in the cross compared to a cross that does not have a mid-section.

Figure 18: Percentage of red-light violations from intersections with or without a mid-section.



4.2. Statistical analysis

4.2.1. Multicollinearity

Before generating a logistic regression, a test for multicollinearity is conducted for possible highly correlated variables. When the absolute correlation value is equal or above .75, we speak of highly positive or negative correlated variables. It is not necessarily needed to exclude one of the highly correlated variables from the regression model. A VIF test is performed to determine if the high correlation is problematic in the regression model. The VIF test has to be generated after a linear regression model with the same variables used as the final logit model.

The tetrachoric and Pearson correlation values are displayed in appendix table 8 and table 9. All weather-related variables (*WEATHER_CONDITION*, *DARK* and *TEMPERATURE*) indicated high or perfect correlations with each other and other variables. The high correlations of the weather-related variables were not surprising. For instance, the variable *DARK* has a positive perfect correlation with *EVENING* which is logical. The observations were made in a time span of two weeks. During observation the values of *WEATHER_CONDITION* and *TEMPERATURE* were quite similar over the 24 observation periods (see appendix: table 10). Therefore, we cannot measure the effect of weather circumstances on risk behavior correctly. All weather-related variables are excluded from the regression models.

Furthermore, the variable *OWNERSHIP* with the category work has shown a negative perfect correlation with the variables *TRAVEL_COMPANY* and *2nd_PASSENGER*. This is logical as it is quite unusual to travel with a companion or have another passenger on the vehicle for individuals who use a company-owned vehicle to perform their labor. This will slow them down and they will not perform their labor efficiently.

Additionally, *RUSH_HOUR* has a negative perfect correlation with *WEEKEND* and *PART_OF_DAY* for the category afternoon. This makes sense as the *RUSH_HOUR* is only present on weekdays in the mornings or evenings. From the Pearson correlation matrix, we observe a high correlation between the variables *RED_LIGHT_IN%* and *ADDITIONAL_LANE*. If both variables are included in a regression model, a VIF test has to be performed if the relationship is troublesome for the correctness of the regression.

4.2.2. Logit regression

Four models are generated to determine the best model for interpreting the effect of the variables of interest, *ADDITIONAL_LANE* and *MID_SECTION*, on the probability of *RED_LIGHT_VIOLATION*. The model that suits this research best is chosen to test the hypotheses. First, it has to be determined which variables are excluded from the regression model as a perfect correlation is detected between several variables. This is done by running several regressions and argue which one of the perfectly correlated variables fit the model better than the other. This is done by comparing the BIC and R^2 values when one or the other variable is added in the model and by theorizing which variable fits better according to logic and previous literature. Second, we have to select the model that fits this research best according to the criteria we set. Lastly, based on the results of the final regression model we can determine if we either reject or fail to reject the hypotheses.

First, we have to account for the multicollinearity issue discussed in paragraph 4.2.1. After running several regressions, we observed that there is not a substantial difference in BIC and pseudo R^2 values if we include one or the other variables when we use the same models (see appendix table: 11). For the continuation of this research we drop *WEEKEND*, *PART_OF_DAY*, *2nd_PASSENGER* and *TRAVEL_COMPANION* from every model.

The preference of *RUSH_HOUR* over *WEEKEND* and *PART_OF_DAY* is made based on the meaning and explanatory value of the variable. Often travelers during rush hours are in a hurry. Typically, during rush hours travelers have school or work as a destination or departure point. *WEEKEND* and *PART_OF_DAY* fail to do capture this effect whilst rush hour does. Another point of preferring *RUSH_HOUR* is the fact that it accounts for relative traffic volume[10] of the intersection itself. Rush hours are usually the busiest moments in traffic. This dataset

[10] By relative traffic volume we mean that it accounts for the level of traffic an intersection experience itself. Rush hours are typically busier than other parts of the day. Thus, rush hour captures this effect. Traffic volume itself does not account for this, because other intersections deal, in absolute terms, with more traffic than other intersections based on their location and/or nearby facilities.

did see that the intersections had their busiest moments during rush hours (see table 6). So, *RUSH_HOUR* captures the effect of relatively high traffic volume for the intersections. The variables *WEEKEND* and *PART_OF_DAY* capture this effect to some extent, but not as meaningful as rush hour does.

The preference of *OWNERSHIP* over *2^{nd}_PASSENGER* and *TRAVEL_COMPANION* is made because of its explanatory addition to the model. *OWNERSHIP* distinguishes subjects based on vehicle ownership and explains to an extent what the travel purpose is; personal ownership mostly for work and school destinations, sharing/rent service for leisure use or work and school destination, work owned to perform your occupation.

The first generated model, model 1, is created with all variables possible. As mentioned, there is a high correlation between the variables red-light time percentage and car lanes. After performing a VIF test there was no multicollinearity observed. Both variables can exist in the same model. The estimates of model 1 are shown in table 14.

Although there was no multicollinearity detected when adding *RED_LIGHT_IN%* in model 1, it might improve the performance of the regression. Model 2 removes red-light time percentage from the regression of model 1. The estimates of model 2 are shown in table 14. In comparison with model 1 the AIC hardly changed and the pseudo R^2 did decrease in value. Model 1 is provisionally preferred over model 2.

Model 3 removes *RED_LIGHT_IN%* and *TRAFFIC_VOLUME* from the regression of model 1. *TRAFFIC_VOLUME* is removed from the model as it has a correlation with *RUSH_HOUR* of 0.7040. Although it might not exceed the limit we set for a high correlation, it is close to the limit. Removing it from the regression might improve the model. The estimates of model 3 are shown in table 14. The BIC increased and pseudo R^2 decreased in comparison with model 1. However, model 1 is provisionally still the preferred model due to its explanatory value.

Model 4 uses the same variables as model 3 but adds an interaction between *ADDITIONAL_LANE* and *MID_SECTION*. By including an interaction term, it is implied that the effect on the dependent variable by an independent variable is affected by the value of another independent variable. Applying this with *ADDITIONAL_LANE* and *MID_SECTION*, we can determine whether there is a significant effect of the interaction between both variables on *RED_LIGHT_VIOLATION*. The VIF test did not observe a multicollinearity problem when the interaction term is added to the model. The estimates of model 4 are shown in table 14. The interaction term is not included in model 1 as it generated a multicollinearity issue after conducting a VIF-test.

Table 14: Logit regression models.

	Model 1	Model 2	Model 3	Model 4
ADDITIONAL_LANE	.338687	(.3301951)*	(.3882831)*	(.0436372)
MID_SECTION	.4014919*	.184959	.3349855*	.8376327**
*ADDITIONAL_LANE*MID_SECTION*				
- 1*1				(.8173353)**
MOPED	(.0917436)	(.0649753)	(.0520744)	(.0842231)
OWNERSHIP:				
- *OWNERSHIP_RENT*	.2999105	.2481025	.2683827	.3090738
- *OWNERSHIP_WORK*	(.0929937)	(.0624013)	(.0165558)	(.0276025)
MALE	.5231878**	.5389799**	.5511665**	.5311086**
RUSH_HOUR	.4238792	.455083**	.1467239	.1275293
TRAFFIC_VOLUME	(.0674538)	(.846692)		
RED_LIGHT_IN%	(2.376769)**			
CONSTANT	(.4260114)	(1.183404)**	(1.50385)**	(1.663382)**
BIC	1207.519	1207.607	1204.323	1204.145
Pseudo R^2	0.0302	0.0242	0.210	0.0271

*Significant at 1%/5% is **/*.*

Model 4 is selected as the preferred logit regression. The BIC value was lowest in comparison with models 1,2 and 3. Although, there was not much difference among them. Furthermore, the pseudo R^2 is only higher for model 1. Besides these factors, this model gives the best explanatory value of determining the effect of *ADDITIONAL_LANE* and *MID_SECTION* by including an interaction effect.

According to model 4 the coefficient of *ADDITIONAL_LANE* is not significant. Therefore, we cannot interpret this variable. This implies that there is no significant difference in red-light violations based on the car lanes one has to cross. *MID_SECTION* has a significant effect. The coefficient has a positive sign with a value of .837627. This implies that if *MID_SECTION* takes the value of 1 it increases the log odds with .8009206 ceteris paribus.

Moreover, the interaction term *ADDITIONAL_LANE*MID_SECTION* has a significant effect. The coefficient has a negative sign with a value of .8173353. This implies that if *ADDITIONAL_LANE*MID_SECTION* takes the value of 1 the log odds decrease with .8173353 ceteris paribus. The following examples is given to illustrate the effects of *MID_SECTION* and *ADDITIONAL_LANE*MID_SECTION*. Let us assume a random individual that crosses an intersection with *ADDITIONAL_LANE*=0 and *MID_SECTION*=1 keeping all other variables at their base value. The log odds value increases with .837627 ceteris paribus. Now assume another random individual cross an intersection with *ADDITIONAL_LANE*=1 and *MID_SECTION*=1 keeping all other variables at their base value. MID_SECTION increases the log odds value by .8376327 and the interaction term decreases the log odds value by .8173353 ceteris paribus. The results imply that *MID_SECTION* increases the log odds value, but this effect diminishes when *ADDITIONAL_LANE*MID_SECTION* takes the value of 1. Although, the coefficient of *ADDITIONAL_LANE* was not significant, it does have an effect through an interaction and decreases the log odds outcome.

Furthermore, *MALE* has a significant effect. The coefficient has a positive sign with a value of .5476764. No significant effect is detected for *MOPED.* This indicates that the use of a bicycle or moped did not significantly differ in terms of risky behavior. Similarly, *OWNERSHIP_RENT* and *OWNERSHIP_WORK* did significantly differ from the reference which is *OWNERSHIP_PERSONAL.* Also, *RUSH_HOUR* was deemed to be not significant.

4.2.2.1. Conclusion hypothesis 1

H1: Crossing an additional car lane has a negative effect on the possibility of crossing through a red-light.

Model 4 rejects hypothesis 1. The coefficient of *ADDITIONAL_LANE* was not significant. However, the interaction term *ADDITIONAL_LANE*MID_SECTION* had a significant negative effect on the probability of a *RED_LIGHT_VIOLATION*. This implies that the interaction between *ADDITIONAL_LANE* and *MID_SECTION* decreases the log odds value compared to an intersection with only *MID_SECTION*.

4.2.2.2. Conclusion hypothesis 2

H2: The inclusion of a mid-section has a positive effect on the possibility of a red-light violation.

Model 4 accepts hypothesis 2. *MID_SECTION* had a significant positive effect. However, the interaction term *ADDITIONAL_LANE*MID_SECTION* had a significant negative effect on the probability of a *RED_LIGHT_VIOLATION*. This does not imply that hypothesis 2 is rejected because the value of *MID_SECTION* is greater than that of *ADDITIONAL_LANE*MID_SECTION*. The interaction term implies that the positive effect of *MID_SECTION* is weakened when it interacts with *ADDITIONAL_LANE*.

5. Conclusion

This research investigated the risk bicycle lane users, bicyclists and moped drivers, make during traveling in the Netherlands. Risk was measured by the choice a traveler makes when facing a red traffic light. Previous literature suggested that the design of the cross could influence behavior of travelers (Wang, Xu, Tremont and Yang, 2012; Schleinitz, Petzoldt, Kröling, Gehlert and Mach, 2019). Data is collected from observing video footage made on four intersections in Rotterdam based on their design features. A regression analysis is conducted to determine whether intersection features influence red-light violations. The conclusion of the results is discussed in the following paragraph. The research question is as follows:

Do intersection features influence bicycle lane users to take more risks during travel?

5.1. Results

Statistics showed that 23,4 percent of the individuals committed a red-light violation if they had the opportunity to do so. This statistic resembles closely the statistic observed from Fietsersbond (2015). Their questionnaire discovered that more than a quarter of the bicyclists commits a red-light violation when traveling. Furthermore, our results suggest that relatively spoken more violations occur on intersection crosses with two car lanes rather than three car lanes. Also, relatively more violations were discovered on intersection crosses with a mid-section rather than without a mid-section.

To test the research question, a regression analysis is executed to determine whether intersection features influence risk behavior. The regression analysis tested if there is a significant relationship of crossing an additional car lane and the inclusion of mid-section with red-light violations. A logit model is estimated. The results suggested that the inclusion of a mid-section did have a significant positive effect on red-light violations. Crossing an additional car lane did not have a significant effect. However, an interaction effect between mid-section and an additional car lane resulted in a significant negative effect. The interaction effect implied that crossing an intersection with a mid-section has a negative influence on red-light violations when it interacts with an additional car lane. Implying that crossing an additional car lane does lower the probability of a red-light violation when it interacts with mid-section. However, this value does not outweigh the effect of mid-section.

Additionally, the regression model found that males had a higher probability of a red-light violation than females. This is consistent with results from previous literature (Johnson, Charlton, Oxley and Newstead, 2013; Wang, Xu, Tremont and Yang, 2012). There was no significant effect shown by moped drivers. This indicates that there is no significant difference found in risk behavior between bicyclists and moped drivers. Also, vehicle ownership was found not to be significant. Based on this research there is no significant difference found in behavior between personal, sharing/rental and company owned vehicles. Additionally, there was no significant effect of rush hours in risk behavior.

Ultimately, we can conclude that intersection features can have an effect on the risk behavior of bicycle lane users. The regression analysis did reject *Hypothesis 1: Crossing an additional car lane has a negative effect on the possibility of crossing through a red-light.* However, it did accept *Hypothesis 2: The inclusion of a mid-section has a positive effect on the possibility of a red-light violation.* Furthermore, an interaction between an additional car lane and mid-section had a significant effect. The interaction between both variables suggested that crossing an additional car lane while dealing with a mid-section diminishes the effect of a mid-section.

5.2. Policy recommendation

This research found that 23,4 percent of the subjects committed a red-light violation. This is a worrying statistic for governmental authorities who want to ensure the safety of their inhabitants. It is important to acknowledge that it is likely that a large part of the sample is familiar with the roads. Over time drivers get more comfortable with crossing a road which they often pass. This could result that they become so comfortable that they are willing to take more risks. Bad habits can be formed and are typically hard to get rid of.

Policymakers should consider tackling this issue as it puts people in danger. It is reasonable to think that bicyclists and moped drivers are less fined for a red-light violation in comparison with cars. This could be caused by the fact that the authorities have several instruments to catch red-light violators for cars. For instance, there is camera surveillance placed on several roads. These cameras are placed in a way to capture red-light violators. The camera will take a picture of the evidence and the authorities can send the owner of the car a fine. Bicycle lanes do not have this type of surveillance as bicycles do not have a license plate. The only way bicycles and mopeds can be fined is if they are caught in action. Policymakers should consider developing a way of effectively catching red-light violators on bicycle lanes. For instance, they might consider to more manpower to catch violators or perhaps considering a license plate for bicycles to identify the owner of the bicycle.

The Dutch traffic laws charge 90 euros and 160 euros for bicycles and mopeds for a red-light violation whilst cars are charged 240 euros for the same violation (Openbaar Ministerie, 2020). There is a difference in the treatment of a violation between these three vehicle types. As mentioned, the authorities mainly turn their attention to violations of car drivers. The height of red-light violation fine by car drivers is also quite high compared to that for bicyclists and moped drivers. It is reasonable to assume that car drivers do not commit a red-light violation as frequently as bicyclists and moped drivers. This assumption is based on literature who found substantially less red-light violators for car drivers than found in this research (Shinar, Bourla & Kaufman, 2004; Yan, Li, Zhang and Hu, 2016). This difference of relative red-light violations could be that the financial risk weighs in the decision-making process. Policymakers could treat all vehicles the same way and raise the fines for bicyclists and moped drivers. This might result in fewer violators.

The regression analysis showed that the inclusion of a mid-section has a significant effect on red-light violations. However, the purpose of the mid-section is to create a safety net to cross the road in two stages when it is busy. This supposedly creates a safer environment for bicyclists and moped drivers. However, the mid-section counters this effect as it could be used as a piece of lane for red-light violators to cross the road in stages. As seen in figure 19 you can see that this individual ignored the red-light and is waiting on the mid-section to proceed to cross the full road when he thinks it is appropriate. This leads to misuse of the mid-section and encourages dangerous behavior. Policymakers have to reconsider if a mid-section does create a safer traffic environment as the results of this research tend to suggest the opposite effect.

Figure 19: Subject pictured ignored red-light and uses the mid-section as a "waiting area".

5.3. Limitations

Literature did observe that age has a significant effect on risky driving behavior by bicyclists and moped riders. Unfortunately, this variable was hard to capture from the footage. Due to the cold weather during filming, the subjects were predominantly wearing winter coats and hats. It was therefore difficult to appropriately group individuals in the right age category as it might cause biased results. Thus, the reason why this variable was not included in the analysis. Furthermore, the variables related to weather were not included in the model. The reason is that the weather conditions and temperature were quite consistent during the period of filming. The filming took place in the last weeks of January during the winter season. This means that there is no comparison with substantially different weather conditions such as the difference between winter temperatures and summer temperatures. We could not test if particular weather circumstances had a significant effect on the probability of committing a red-light violation.

This research was done through observation. The data is gathered by what we see or assume with our own judgment. It fails to capture the psychological aspect of making a choice. We cannot investigate the mind of the subjects and the motivations of their choice by means of observation. Furthermore, we cannot determine the level of familiarity the subject has with crossing a particular intersection. It is highly plausible that a large portion of the subjects is familiar with an intersection. They could create habits concerning their choice of ignoring the red-light as they might know the mechanics of the intersections.

Additionally, the involvement of cars is not taken in this research. The involvement of cars passing the intersection cross might be of influence for the decision to ignore the red-light as previous research showed (Guo, Li, Wu & Xu, 2018). It was not possible to capture the presence of cars from the available resources. However, from the footage we saw that some subjects were observing their surroundings whether they decide to ignore the red-light. They were checking whether a car was approaching the cross to determine whether it was safe enough according to them to ignore the red-light. This is an example of overestimating their perceived control as discussed by Parker, Lajunen and Stradling (1998). By overestimating perceived control, individuals bring themselves as well as others in danger by making risky decisions.

5.4. Future research

This research investigated four types of intersections. Besides the mid-section and number of lanes, all intersections had a similar traffic environment. However, the city of Rotterdam and the Netherlands possess more than just the investigated types of intersections. Therefore, results should be carefully interpreted. Future research could investigate a wider variety of crosses on intersections to determine whether the same or different traffic environments impact the probability of a red-light violation. For instance, it might be interesting to see whether there is a significant difference between three-branch intersections and four-branch intersection in terms of red-light violations as previous suggested that there is a difference (Schleinitz, Petzoldt, Kröling, Gehlert & Mach, 2019).

Additionally, limited research has been done on the effect of ownership on risk behavior. The branch of sharing and rent services are rapidly expanding whilst food delivery services are experiencing growth as well (RTLZ, 2019). There is no existing literature available that did quantitative analysis on driving behavior of shared vehicles or food deliverers. This research gathered data by observing in the morning, afternoon and evening. The evenings were filmed when the rush hour is at its peak; approximately from 17:00 to 17:30. From *OWNERSHIP_WORK* we did not see a significant effect on risk behavior. Almost all of the subjects belonging in this category were food deliverers. However, food delivery restaurants usually meet their peak hours after rush hours when people return home from their work and order food. Food deliverers experience more work pressure and are more active after the rush hour. Future research can capture the effect of food deliverers more accurately by observing later in the evenings as well. They may be willing to take more risks to be faster and earn more money.

Also, it might be of value for policymakers to investigate whether there are geographical differences in risk behavior. It might be so that certain areas in a given municipality experience relatively higher cases of red-light violations. For instance, in an area where there is a school located. People who travel to school by bicycle or moped may have a hurry to be on time. Therefore, it is possible that we see relatively more violations on intersections that bicyclists and moped drivers cross to get to school than other intersections. The same example can be applied for areas with a public transport station or a business park.

Furthermore, future research could investigate what it will take to prevent violations from bicyclists and moped riders. A way of researching this is by use of surveys. For example, a survey can be conducted to determine whether bicyclists and moped drivers adjusted their driving behavior after they received a fine for ignoring the red-light. This way policymakers can review whether their policies concerning this matter are effective and make a change in general traffic safety. The policymakers might want to reevaluate their policies if research indeed shows that driving behavior did not changes after receiving a fine in the current system. As the results of this research found a relatively high number of red-light violators, it might be beneficial for traffic safety to investigate what it will take to decrease risky behavior of bicyclists and moped drivers.

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7. Appendix

Table 1: Average traffic per minute.

	PART_OF_DAY and WEEKEND						Total
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	7,08	2,84	4,62	5,41	7,31	2,49	***4,92***
Intersection 2	4,71	1,00	1,71	1,91	3,87	1,64	***2,43***
Intersection 3	6,58	1,00	4,92	2,75	8,76	4,65	***4,79***
Intersection 4	10,40	1,52	2,11	2,80	3,46	2,60	***3,92***
Total	***7,31***	***1,61***	***3,23***	***3,24***	***5,89***	***2,81***	***4,01***

Table 2: Percentage of people facing a red light relative to the number of people that crossed the intersection.

	PART_OF_DAY and WEEKEND						Total
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	*38,5%*	*41,9%*	*44,4%*	*41,4%*	*41,0%*	*43,8%*	***41,5%***
Intersection 2	*37,2%*	*25,8%*	*21,9%*	*29,8%*	*20,0%*	*23,5%*	***27,3%***
Intersection 3	*66,1%*	*29,0%*	*44,6%*	*58,2%*	*47,6%*	*51,1%*	***52,2%***
Intersection 4	*67,6%*	*80,0%*	*69,1%*	*73,8%*	*78,3%*	*79,8%*	***72,1%***
Total	***55,6%***	***46,0%***	***45,0%***	***50,2%***	***45,3%***	***52,6%***	***49,9%***

Table 3: Percentage of time the traffic light was red during observation.

	PART_OF_DAY and WEEKEND						Total
	Morning		Afternoon		Evening		
	Weekday	Weekend	Weekday	Weekend	Weekday	Weekend	
Intersection 1	*39,5%*	*36,9%*	*42,6%*	*46,7%*	*41,6%*	*49,1%*	***42,7%***
Intersection 2	*34,4%*	*33,1%*	*24,8%*	*29,5%*	*28,8%*	*31,4%*	***30,1%***
Intersection 3	*63,2%*	*36,5%*	*59,9%*	*57,2%*	*60,5%*	*52,6%*	***55,0%***
Intersection 4	*71,9%*	*81,8%*	*77,8%*	*74,8%*	*81,0%*	*75,7%*	***77,1%***
Total	***52,8%***	***46,5%***	***49,9%***	***52,1%***	***52,8%***	***52,4%***	***51,1%***

Table 4: Descriptive statistics of variables.

	Mean	Standard Deviation	MIN	MAX
RED_LIGHT_VIOLATION	.2340426	.4235949	0	1
MID_SECTION	.4320074	.4955847	0	1
ADDITIONAL_LANE	.6299722	.4830353	0	1
MOPED	.1110083	.3142879	0	1
OWNERSHIP_PERSONAL	.8492137	.3580061	0	1
OWNERSHIP_WORK	.0425532	.2019409	0	1
OWNERSHIP_RENT	.1082331	.3108184	0	1
TRAVEL_COMPANION	.120259	.3254147	0	1
2ND_PASSENGER	.039778	.1955276	0	1
MALE	.544186	.4982756	0	1
DARK	.3533765	.4782396	0	1
WEATHER_COND_DRY	.53284	.4991513	0	1
WEATHER_COND_CLOUDY	.4227567	.4942261	0	1
WEATHER_COND_MISTY	.0444033	.2060848	0	1
TEMPERATURE	4.242368	2.40803	0	9
WEEKEND	.3876041	.4874289	0	1
MORNING	.3385754	.4734442	0	1
AFTERNOON	.3080481	.4619002	0	1
EVENING	.3533765	.4782396	0	1
RUSH_HOUR	.46716	.4991513	0	1
TRAFFIC_VOLUME	5.064995	2.621491	.9867374	10.40394
RED_LIGHT_IN%	.5653056	.1656164	.2475556	.8183869

Table 5: Percentage of subjects with a specific ownership of vehicle relative to total traffic crowd of the concerned vehicle.

	OWNERSHIP			
	Personal	Rent	Work	***Total***
Bicycle	88,5%	8,5%	3,1%	***100,0%***
Moped	72,7%	22,3%	5,0%	***100,0%***
Other	61,5%	15,4%	23,1%	***100,0%***

Table 6: red-light violations per part of week.

	Weekday	Weekend
Red-light violation	155	98
Traffic passed	662	419
Percentage of red-light violations	23,4%	23,4%

Table 7: Red-light violations per time period.

	Morning	Afternoon	Evening
Red-light violation	*108*	*67*	*78*
Traffic passed	*366*	*333*	*382*
Percentage of red-light violations	*29,5%*	*20,1%*	*20,4%*

Table 8: Tetrachoric Matrix for full sample.

	RED_LIGHT_VIOLATION	MID_SECTION	ADDITIONAL_LANE	MOPED	OWNERSHIP_PERSONAL
RED_LIGHT_VIOLATION	1				
MID_SECTION	0.0826	1			
ADDITIONAL_LANE	-0.1190	0.3128	1		
MOPED	0.0235	-0.1750	-0.0337	1	
OWNERSHIP_PERSONAL	-0.0585	0.2514	-0.0797	-0.3204	1
OWNERSHIP_WORK	0.0058	-0.1571	0.2724	0.0987	
OWNERSHIP_RENT	0.0702	-0.2423	-0.0207	0.3416	
TRAVEL_COMPANION	-0.1172	-0.1282	0.0989	-0.2431	0.2756
2ND_PASSENGER	-0.1187	-0.2183	-0.1660	0.6290	-0.1042
MALE	0.1864	-0.0686	-0.0054	0.3573	-0.2569
DARK	-0.0942	-0.0256	0.3206	0.0614	-0.0147
WEATHER_COND_DRY	-0.0881	0.2889	0.5659	0.0977	0.0272
WEATHER_COND_CLOUDY	0.0225	-0.4501	-0.4058	-0.0580	-0.0804
WEATHER_COND_MISTY	0.2449	1	-1	-0.2191	0.2999
WEEKEND	0.0007	-0.0158	0.1317	0.0736	-0.1510
MORNING	0.1813	0.1687	-0.1741	-0.2739	0.0004
AFTERNOON	-0.0973	-0.1504	-0.1499	0.1859	0.0151
EVENING	-0.0942	-0.0256	0.3206	0.0614	-0.0147
RUSH_HOUR	0.0445	0.1088	-0.0536	-0.1859	0.1315

	OWNERSHIP_WORK	OWNERSHIP_RENT	TRAVEL_COMPANION	2ND_PASSENGER	MALE
OWNERSHIP_WORK	1				
OWNERSHIP_RENT		1			
TRAVEL_COMPANION	-1	-0.1718	1		
2ND_PASSENGER	-1	0.2036	-0.1350	1	
MALE	0.6768	0.0674	0.0211	0.0438	1
DARK	0.3508	-0.1731	0.0050	-0.1280	0.0771
WEATHER_COND_DRY	0.2265	-0.1404	0.2298	0.0579	0.0456
WEATHER_COND_CLOUDY	-0.1758	0.1809	-0.1899	-0.0055	-0.0156
WEATHER_COND_MISTY	-1	-0.2191	-0.2425	-1	-0.1267
WEEKEND	0.2359	0.0736	0.2578	0.4145	0.1629
MORNING	-0.4484	0.1637	-0.1952	-0.1417	-0.1564
AFTERNOON	-0.0356	-0.0019	0.1778	0.2450	0.0823
EVENING	0.3508	-0.1731	0.0050	-0.1280	0.0771
RUSH_HOUR	-0.2538	-0.0457	-0.2406	-0.3528	-0.1828

	DARK	WEATHER_COND_DRY	WEATHER_COND_CLOUDY	WEATHER_COND_MISTY	WEEKEND
DARK	1				
WEATHER_COND_DRY	0.6424	1			
WEATHER_COND_CLOUDY	-0.5672		1		
WEATHER_COND_MISTY	-1			1	
WEEKEND	0.0258	0.2825	-0.1743	-1	1
MORNING	-1	-0.5073	0.3246	1	-0.3380
AFTERNOON	-1	-0.1627	0.2607	-1	0.3101
EVENING	1	0.6424	-0.5672	-1	0.0258
RUSH_HOUR	0.3180	-0.0888	-0.0626	1	-1

	MORNING	AFTERNOON	EVENING	RUSH_HOUR
MORNING	1			
AFTERNOON		1		
EVENING			1	
RUSH_HOUR	0.6163	-1	0.3180	1

Table 9: Pearson Matrix for full sample.

	RED_LIGHT_VIOLATION	MID_SECTION	ADDITIONAL_LANE	MOPED	OWNERSHIP_PERSONAL
TRAFFIC_VOLUME	-0.0474	-0.2215	0.0342	-0.0692	0.0633
TEMPERATURE	-0.0757	-0.0501	0.2810	0.1013	-0.0620
RED_LIGHT_IN%	-0.0881	0.4248	0.8350	-0.0561	-0.0041

	OWNERSHIP_WORK	OWNERSHIP_RENT	TRAVEL_COMPANION	MALE	DARK
TRAFFIC_VOLUME	-0.0797	-0.0211	0.0240	-0.1136	0.0026
TEMPERATURE	0.1200	-0.0066	0.1317	0.0578	0.4444
RED_LIGHT_IN%	0.0225	-0.0098	0.0082	-0.0524	0.0969

	WEATHER_COND_DRY	WEATHER_COND_CLOUDY	WEATHER_COND_MISTY	WEEKEND	MORNING
TRAFFIC_VOLUME	0.1173	-0.1063	-0.0293	-0.5819	0.3282
TEMPERATURE	0.7714	-0.6199	-0.3807	0.4158	-0.5976
RED_LIGHT_IN%	0.1736	-0.0549	-0.2881	0.0035	-0.0685

	AFTERNOON	EVENING	RUSH_HOUR	2ND_PASSENGER	TRAFFIC_VOLUME
TRAFFIC_VOLUME	-0.3387	0.0026	0.7040	-0.0673	1
TEMPERATURE	0.1519	0.4444	-0.3812	0.0465	-0.2154
RED_LIGHT_IN%	-0.0301	0.0969	0.0238	-0.0820	0.0308

	TEMPERATURE	RED_LIGHT_IN%
TRAFFIC_VOLUME		
TEMPERATURE	1	
RED_LIGHT_IN%	0.1550	1

Table 10: Measured weather conditions.

	PART_OF_DAY	*WEEKEND*	*WEATHER_CONDITION*	*TEMPERATURE*
Intersection 1	*MORNING*	*WEEKDAY*	*CLOUDY*	*2°*
	AFTERNOON	*WEEKDAY*	*CLOUDY*	*5°*
	EVENING	*WEEKDAY*	*CLOUDY*	*6°*
	MORNING	*WEEKEND*	*CLOUDY*	*2°*
	AFTERNOON	*WEEKEND*	*CLOUDY*	*3°*
	EVENING	*WEEKEND*	*DRY*	*6°*
Intersection 2	*MORNING*	*WEEKDAY*	*CLOUDY*	*2°*
	AFTERNOON	*WEEKDAY*	*CLOUDY*	*2°*
	EVENING	*WEEKDAY*	*DRY*	*6°*
	MORNING	*WEEKEND*	*DRY*	*7°*
	AFTERNOON	*WEEKEND*	*DRY*	*8°*
	EVENING	*WEEKEND*	*DRY*	*6°*
Intersection 3	*MORNING*	*WEEKDAY*	*MISTY*	*0°*
	AFTERNOON	*WEEKDAY*	*CLOUDY*	*7°*
	EVENING	*WEEKDAY*	*DRY*	*6°*
	MORNING	*WEEKEND*	*DRY*	*7°*
	AFTERNOON	*WEEKEND*	*CLOUDY*	*2°*
	EVENING	*WEEKEND*	*DRY*	*6°*
Intersection 4	*MORNING*	*WEEKDAY*	*DRY*	*3°*
	AFTERNOON	*WEEKDAY*	*DRY*	*6°*
	EVENING	*WEEKDAY*	*CLOUDY*	*2°*
	MORNING	*WEEKEND*	*DRY*	*2°*
	AFTERNOON	*WEEKEND*	*DRY*	*7°*
	EVENING	*WEEKEND*	*DRY*	*9°*

Table 11: BIC values and R^2 values (R^2 value shown between parentheses).

	Full model	**Full model minus RED_LIGHT_IN%**	**Full model minus RED_LIGHT_IN% & TRAFFIC VOLUME**	
RUSH_HOUR	*1207.519 (0.0302)*	*1207.607 (0.0242)*	*1204.323 (0.0210)*	**OWNERSHIP**
WEEKEND & PART_OF_DAY	*1210.453 (0.0396)*	*1209.289 (0.0347)*	*1205.788 (0.0317)*	**2^{ND}_PASSENGER & TRAVEL_COMPANION**
RUSH_HOUR	*1206.248 (0.0313)*	*1206.103 (0.0255)*	*1202.323 (0.0227)*	**2^{ND}_PASSENGER & TRAVEL_COMPANION**
WEEKEND & PART_OF_DAY	*1212.519 (0.0379)*	*1211.311 (0.0329)*	*1208.497 (0.0294)*	**OWNERSHIP**