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Changes in speed behavior due to acquired road familiarity.

A comparison between Italy and Norway

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Abstract:

Studying driving behaviour changes over time could lead to better undestand some matters related to highway safety, management and design. For example, it is not clear in which way the presence of recreational users in traffic flow can influence capacity of roads. First step in understanding this relation should be the study of differences between regular and recreational users. In order to appreciate those discrepancies it is important to study the process which leads a recreational user of a given road to become a regular driver of that road. Two road experimentations in Italy and Norway were made in order to inquire speed variations over time among a sample of users. Speed was measured by using GPS technology in both experiments. Data of each experimentation were processed and after, a comparison between the two experiments was made. Italian and Norwegian drivers were divided into risk categories and road sections were divided into visibility classes with the aim of identifying main variables influencing speed changes over time. Firstly, speed trends over time were shown for both experiments and after, an ANOVA analysis was implemented with the aim of understanding in which way visibility and risk attitude can influence speed variations. Italian drivers showed an habituation effect: speed increased over test days even if in different ways according to different risk categories. Instead, Norwegian drivers did not show the same effect: speed remained almost the same over test days for all drivers. Visibility was found as a good predictor of speed, while risk attitude based on self-reported speeding attitude was found as a good predictor of speed only for Norwegian drivers. Finally, a detailed comparison between the two experimentations and a possible explanation of highlighted differences were presented.

Keywords:

1. HABITUATION
2. RECREATIONAL USERS
3. SPEED CHOICE
4. DRIVING BEHAVIOUR

PREFACE

This report is written as a part of my master's thesis in transportation at NTNU in the Spring of 2014.

The topic is changes in speed behaviour due to acquired road familiarity. This topic was chosen because I worked on similar topics in my Italian Bachelor's thesis and data from an experiment were available. I found it interesting and useful in order to get into the world of research and development.

The topic is related to the research conducted by Pasquale Colonna, which concerns relations between habituation effect and traffic safety. However, the work presented in this thesis is performed by myself. I am very grateful to my main supervisor Eirin Ryeng for her precious advices, her availability and her support.

SUMMARY

Study of traffic safety related problems concerns a lot of topics and some of them are not related only to engineering. In order to analyze accident causes it is important to comprehend the influence of human factors, as stated in most papers found in recent literature.

I analyzed three areas related to human factors: risk perception, driving behaviour and speed choice. These topics are related with one another: speed choice depends on risk perception and it is involved in some driving behaviours. Instead, literature is poor of works about influence of memory on driving behaviour, even if in some applications it is important to know driving habituation related factors.

Road users could be divided in: regular users (mainly commuters) and recreational users (people who have no confidence with the route). For example, differences between them are considered in a formula used for calculating capacity and level of service of a given road (HCM 2000). In this formula, there is a coefficient which assumes different values according to the expected percentage of recreational user in traffic flow. However, in literature, it is not possible to find accurate studies about dividing drivers into recreational and regular users and about the influence of these differences on driving behaviour. In order to understand those matters, the first step consists in analyzing process which leads a recreational user to become a regular one: drivers' learning process must be understood.

Hypothesis is that learning process brings users to a condition of habituation and, ways in which risk perception and speed choice are influenced by habituation have to be inquired. Reaching the habituation condition is related, in psychology, to the number of repetitions of the same stimulus. After being exposed to same stimulus, people tend to decrease response to that stimulus over time. Trying to apply these concepts to drivers, a user who usually drive on a given road in the same conditions, should decrease response to external stimulus over time. In this case, decreased response could be connected to a lowered target level of risk and an increasing of speed over time.

In order to inquire about this phenomenon, a road experimentation involving a sample of 19 users was made in Italy, by collecting speed measurements employing GPS

technology. Driving tests were repeated according to this schedule: first four tests four days in a row, fifth test after nine days from the first and the last test after twenty-six days from the first. Drivers were divided into risk categories (risky, prudent, variable) according to distance of their measured speed from mean speed. Furthermore, according to stopping sight distance diagrams, it was possible to divide road sections into visibility categories. Therefore, speed data were processed by considering three diverse drivers categories: risky (speed higher than the mean speed in at least five days out of six), prudent (speed lower than the mean speed in at least five days out of six), variable (speed varying around the means speed); four different visibility conditions: low (0 – 100 m), medium-low (100 – 200 m), medium (200 – 400 m), high (400 – 600 m); six different test days (day 1, day 2, day 3, day 4, day 5, day 6). Results of Italian experimentation are explained as follows: speed linearly increases in going from low visibility sections to higher visibility sections for all drivers; speed increases over the first four days and after tends to remain almost the same. Therefore, a learning process could be noted in the speed increasing over time. However, dividing drivers into risk categories allows us to appreciate two different trends: risky users tend to maintain their speed on the same level after fourth day; prudent users, instead, decrease their speed in fifth day (after five days without driving on that road). Hence, it seems that prudent users lose part of their acquired familiarity and part of the habituation effect by decreasing again speed. Risky users, instead, seem to maintain acquired familiarity even if there was a gap of five days between fourth and fifth test day. It could be suggested that a short memory effect and its efficient transformation in long term memory can be noted for risky users. Instead, it could be stated that prudent users need another test in order to reach the conversion of short term memory in long term memory. Furthermore, in long term, it seems that prudent users' behaviour asymptotically tend to that one of risky users.

The same experimentation was made on a sample of 10 users in Norway. Classification, analysis and data elaboration are the same of the Italian experimentation. However, a difference is the diverse employed GPS instrumentation: in the Norwegian experiment it has got a minor accuracy. Another difference is related to the route chosen for the experimentation: Norwegian route is more winding and characterized by a lower average visibility than the Italian one. Results of the Norwegian experimentation are explained as follows: speed increases in going from low visibility sections to higher visibility sections for all drivers; speed does not increase over time. It could be said that in the Norwegian experimentation it is not possible to appreciate the habituation effect but, actually, there are a lot of confounding factors which makes the comparison difficult.

First confounding factor is related to employed instrumentation: uncertainty connected to measures could be too much high and so it could be not possible to appreciate speed changes over days. Second factor is route-related: the very winding Norwegian route could have limited drivers' speed choice. Third factor is weather-related: the very variable Norwegian weather had a not negligible influence on speed choice, probably preventing habituation development. In fact, in order to reach the habituation, it is necessary that stimulus is always the same over time. Last noticed factor is culture-related: Italian drivers seem to show a higher speeding attitude than the Norwegian ones, even if comparison is difficult because of differences between the two roads. All these highlighted factors, mixed together, have a great influence on trying to make a comparison between the two experiments because it is not easy to understand the influence of each factor by itself.

Therefore, in order to observe habituation to drive effect, experiments should be repeated by employing same instruments and comparable road, weather and traffic conditions. However, Norwegian experiment (as it can be seen also in ANOVA analyses) gives a proof that there is a strict connection between speed and visibility. Hence, employed analysis method could be used also for future works.

Finally, some models were proposed by using risk classes based on self-reported speeding attitude visibility classes and time as speed predictors. Basically, results show that other variables have to be added in order to get more reliable models. This goal will be a challenge for future works.

CONTENTS

1. INTRODUCTION

The most important aim of road traffic safety studies is to reduce the number of road accidents, which are one of the most frequent causes of death all over the world. In order to achieve this goal, it is necessary to understand the actual causes of accidents, which are numerous and varied.

A traffic accident is «*an unexpected event on a road, involving at least one user of the same road and producing a significant negative impact on users and/or on society*».[1]

The unexpected event consists in a mismatch between expectations and reality and can not be foreseen by the road user; as a matter of fact, if it was, the driver would rather avoid it. If the driver is not able to react to it in the right way and immediately, by adopting his behavior to the current rules, then the accident will happen.

Whenever we drive on the road, we automatically accept a certain amount of risk of being involved in an accident. The risk could be quantified as follows:

$$R = P\ x\ I \tag{1}$$

In this formula:

p is the probability that the negative event happens,

I is the intensity of the consequences that the event could cause.

The unity of measurement of risk is money, or rather, the cost of the damage provoked by the accident multiplied by its probability. Therefore we must consider also this cost in the total travel cost, sum of monetary travel cost and the risk related costs:

$$C_u(v) = c_u(v) + P(v)\ x\ I_u(v) \tag{2}$$

In this formula:

C_u(v) is the total travel cost,

c_u(v) is the monetary travel cost,

P(v) x I_u(v) is the risk related cost, where P is the probability and I is the intensity,

[1] Colonna, P., Berloco, N. (2011) "External and internal risk of the user in road safety and the necessity for a control process." *XXIV PIARC world road congress, Mexico City (Mexico)*

v is the value of speed.

Each term of this formula depends on speed (v) and it is related to a single kilometre of the route. Users who do not care about accident risk choose their speed trying to reduce $c_{u,}$ while users who take it into account choose their speed trying to reduce total costs C_u. Risk related costs increase with speed, so people who care about it reduce their speed, but this reduction necessarily entails an increase of travel time and travel total costs. Hence, speed choice is highly related to risk perception and it depends on many subjective features.

Nevertheless, if we want to analyse risk with the aim of reducing it, it is not possible to consider only the eq. 1. In fact, we might even focus our attention on probability and consequences by trying to evaluate the number of accidents and their intensity in a period of time, but this strategy would not take into account the influence of human behaviour. Instead, given that risk perception and speed choice are strongly related to human behaviour and that the possibility of an accident depends on the mismatches between reality and personal expectations, it is impossible to consider traffic safety matters without considering human behaviour. In fact, Yang and Zhang[2] affirm that «*to prevent and reduce traffic accidents, the research are mostly centered around automobile safety design, road traffic facilities and environment improvement, intelligent transport systems, road traffic safety evaluation, accident forecasting, road traffic safety laws and regulations, and especially the human factors which contribute to road traffic accidents*.»

At first sight it could seem that accidents are homogeneously distributed among the population, but actually in the same driving conditions (including type of car, weather and road conditions, speed limits) some people have more chances to get involved in accidents than others, because of some factors influencing their driving behaviour. Driving behaviour could be influenced by:

- personal data (age, gender, walk of life);
- driving experience (years of driving experience, kilometres driven yearly);
- driver's psychology (elaboration of traffic input, ability to adapt to road and weather conditions, confidence in the car and on the road);

[2] Yang, J., Zhang, D. (2009) "Driver risk perception and road traffic accident." *Logistics: pp. 4060-4066*.

- health condition (general diseases, sleep sicknesses, fatigue).

  Each variable could operate individually or mixed with others and can contribute to determine the driver's behavior.

  In this field of research, a lot of work has been done but there are still a lot of features to investigate. For instance, there are still few studies about differences in the driving behaviour of regular and non-regular users, even if this difference could be important in some practical and theoretical applications.

  In fact, if a user does not know the street he is going along, his behaviour will surely be different from that of a regular user and, for example, the non-regular user will decrease his speed in order to maintain his safety level. This means that risk perception is different between the two categories of users, mainly because, other conditions being equal, the non-regular driver values road conditions at the moment. Furthermore, there are some applications like evaluation of highways' traffic flow, in which it is suggested to know composition of traffic flow in order to better estimate it.

  In this case too, in order to go into the merits of the question of differences between regular and non-regular users, it is important to understand the reason why there are these differences by analyzing the problem from the human point of view. Therefore, first of all it is necessary to understand how a recreational road user, which is a synonymous of non-regular road user, becomes a regular user of that road, and this means that we have to look into the user's learning process.

  The main aim of this work is to understand that learning process and to comprehend how driver's behaviour changes over time after newly acquired knowledge of the road. In order to obtain this kind of information I used data from an Italian experimentation and afterwards, after data processing, I validated conclusions using data from another experimentation made in Norway. In order to look into changes in driving behaviour, speed measurements have been used as the main parameter representing driver's behaviour and its changes over time.

  This work is organized by considering expectations of the task document attached at the end of the thesis (cf. Attachment I) and it is divided into six parts, of which this one is the first. The second part is devoted to a deeper analysis of all the matters discussed in this introduction. In fact, all those features are connected with one another and in order to take in traffic safety issues first it is important to study risk perception, factors influencing driving behavior and speed choice. In the second part some of the recent publications about these topics are collected. The third part illustrates the experiment on the Italian road, while the fourth part contains the Norwegian one. In the fifth part there are some considerations about the results of the two experiments and a comparison between them. Finally, in the sixth part there are the conclusions and proposals for future work.

2. STATE OF THE ART

2.1 Introduction

In the state of the art I analyzed topics reported in the introduction, focusing attention on the recent literature dealing with traffic safety. Literature was searched by using NTNU library databases. In particular, I used the ASCE (American Society of Civil Engineering) and Science Direct databases, by typing the following key words: “risk perception”, “driving behaviour”, “speed choice”, “learning” and “drivers”, “memory” and “drivers”, “habituation” and “drivers”.

State of the art is divided into six parts:

- driver’s risk perception, with an explanation of the homeostasis theory, a description of its impact on driver’s behaviour and a summary of recent literature about this topic;
- driving behaviour, with an analysis of the main factors influencing it and a summary of recent literature about this topic;
- speed choice, with an overview of the main factors influencing it and a summary of recent literature about this topic;
- main problems concerning speed choice (maintained speed versus speed limits, driver’s preferred speed versus planner’s design speed, speeding as a cause of accident) and a summary of recent literature about this topic;
- differences between commuters and recreational users, with an explanation of the impact of these differences on practical issues of transportation engineering and a summary of recent literature about this topic;
- learning process, with a short explanation of this process, a description of inner workings of short-term memory and long-term memory and a possible application to driver’s behaviour.

2.2 Driver’s risk perception

In the introduction it was shown that risk perception is a very subjective feature. In fact, according to the eq. 2, by choosing speed drivers accept a certain amount of risk and this means that they are ready to pay an equivalent amount of money. The point is that this quantity varies a lot in the driver population, so it is necessary to find a way to study the problem from the human point of view.

2.2.1 Risk Homeostasis Theory and its interpretation

One of the most popular theories that studied driving risk perception is the Risk Homeostasis Theory (HRT) developed by Wilde (1982)[3]. Wilde stated that humans optimize their level of risk according to four utility factors: the expected benefits of risky behaviour (ex.: gaining time by speeding), the expected costs of risky behaviour (ex.: speeding fines), the expected benefits of safe behaviour (ex.: insurance discounts for accident-free periods), the expected costs of safe behaviour (ex.: time loss).

The level of risk that provides the greatest gain is the target level of risk, and the theory predicts that people will compare their target level of risk to the perceived risk and adjust their behaviour until the two are equal.

It is possible to explain this theory by considering three different risks and two different spheres of influence[1]: the safety budget (bS) which concerns the inner perception, the real risk (rR) which concerns the outer sphere and the perceived risk (pR) which belongs to both spheres, inner and outer.

- Safety budget (bS) is the target level of risk that user chooses in order to maximize travel benefits and it is the maximum level of risk that he is ready to accept. In other words, it is the maximum amount of money that he is disposed to pay for its traffic safety. Safety budget is an inner value of each user and it does not vary in a short period of time. Therefore it is possible to consider bS as the independent variable of the process.
- Perceived risk (pR) is the amount of risk perceived by the user and it depends on his experience, skills and on road traffic conditions.

[3] Wilde, G. (1982) "The theory of risk homeostasis: implications for safety and health." *Risk Analysis vol. 2, Issue 4, pages 209-225, December 2002.*

- Real risk (rR) is the amount of risk that user must engage in a real driving dangerous situation.

In each sphere of influence it's possible to determine two different consequent risks, as follows.

- Inner risk (iR):

$$iR = pR - bS \tag{3}$$

  The inner risk is the difference between perceived risk and safety budget. It consists in the equilibrium between a driver's perception and his unconscious reality. When a driver is on the road, he continuously compares the perceived risk with the target safety budget and, if perceived risk is greater than the budget, then user tends to change his driving behaviour in order to bring back the perceived risk to a value minor or equal to the safety budget. This homeostatic process gives the name to the theory. In fact, it is possible to maintain a long-term stability (the safety budget value) by through short-term fluctuations. The inner risk determines the driver's behaviour in the medium and long term and it depends on the past experience of the driver in similar surrounding conditions and on his current psycho-physical conditions.

- External risk (eR):

$$eR = rR - pR \tag{4}$$

The external risk is the difference between real risk and perceived risk. It consists in the equilibrium between a driver's perception and the reality, and when this equilibrium exists, reality is the same as perception and eR is equal to 0. Instead, when this difference is more than 0, user must face a finite risk in a very short time. If this difference is great and manifests itself suddenly it is more difficult for the driver to avoid the accident.

The total risk is the sum of the inner risk and the external one:

$$R = eR + iR \tag{5}$$

If we put into the eq. 5 the eq. 3 and eq. 4 it could seem that total risk is completely independent of perceived risk. Hence, this could mean that traffic safety studies must focus their attention only on real unexpected risks and on studying development of subject's budget of safety. Actually, it is wrong to sum up two values that concerns two different individual spheres of influence, so inner perceived risk must be distinguished from the outer one.

According to this theory, accidents could not happen because of the dynamic equilibriums above reported. In fact, if a driver must face a finite external risk he could change his behaviour in order to bring back perceived risk below the safety budget. The problem is that often drivers do not estimate in the correct way their perceived risk, so, if the subjective pR is lower than the right one, than keeping it below the safety budget will not be sufficient to avoid the accident. This is the reason why homeostatic equilibriums exist but they are not sufficient to avoid accidents that occur anyway.

However, it must be said that Wilde's theory met a lot of criticism as can be seen for example in McKenna[4]. In fact, he states that the use of target level of risk incorporates contradictory positions and that Wilde can, in principle, «*accommodate any result for any safety measure. If the conventional safety measure fails then this is seen as consistent with his view that safety measures are ineffective and if the conventional safety measure is effective then this can be attacked on methodological grounds or it can be argued that a change in target level of risk has occurred*». Furthermore, Wilde it is attacked because no independent measure of the target level is offered.

Anyway, even if the theory has the weak point in the fact that it cannot be invalidated, it has an important role in focusing the attention on risk compensation, which was very often demonstrated (cf. e.g. paragraph 2.3.2).

2.2.2 Impact of risk perception on driver's behaviour

According to risk homeostasis theory users constantly check their behaviour in order to maintain the same safety budget. Therefore there is a continuous comparison with external conditions, of which some are foreseeable and some others are not predictable

[4] McKenna, F., P. (1990) "In defense of conventional Safety Measures: A Reply to G. J. S. Wilde" *Journal of Occupational Accidents 11, 171-181.*

(e.g. road conditions for non-regular user). The problem is that when safety measures are introduced, the added sense of protection could bring drivers to engage in riskier behaviour to optimize the cost/benefits equilibrium and the overall risk remains basically the same in spite of the safety measures.

It is interesting to understand how homeostatic equilibriums modify driving behaviour. The external equilibrium causes in the user an immediate reaction, in fact when real risk increases then external perceived risk suddenly increases too. Therefore, it is possible to compare this phenomenon with a dazzling effect. Instead, if real risk decreases, the driver submits reality to a trial period before adjusting perceived risk and it is possible to compare this different phenomenon with the dark effect. However changes in risk perception have a direct impact on the driver, who consequently modifies his behaviour, for example increasing or decreasing his speed.

Behaviour skills assume an important role of mediation between risk perception and driving behaviour in different ways. Perceptual skills help driver to maintain the perceived risk minor or equal to the safety budget, operation skills help user to drive car and to make correct manoeuvres, decision-making is important in order to guarantee the internal equilibrium and it depends on operation skills.

2.2.3 Recent literature about risk perception

In this paragraph two experiments concerning the matter of risk perception will be described.

Yang and Zhang in 2009 (cf. reference number 2) tried to verify risk homeostasis theory using data from an experiment carried out on 116 drivers. They selected regular drivers of some sections of road in the province of Guizhou in China and after they divided users in two groups (accident group and non-accident group) according to the number of accident in which they were involved in that roads. The accident group drivers had more than 1 accident during the previous 5 years while the non-accident group drivers had no accidents. The proponents of the experiment recorded the wrong actions of the drivers driving on the sections of accident roads, both in visible traffic conditions and in latent dangerous traffic conditions. The results of the experiment showed that judgment and operation ability in a complex traffic environment of the non-accident group drivers are better than those of the accident group drivers and that there are remarkable differences between accident and non-accident group drivers about wrong operations, especially for latent dangerous traffic conditions. Demonstrating that accident group is worse than the other group in understanding latent dangerous traffic conditions is a proof that risk is perceived in different ways from different people. Furthermore, as expected, people who have a worse risk perception are more frequently involved in accidents.

Tang and Guo in 2008[5] proposed a safety evaluation model which consisted in dividing drivers in accident group and non-accident group taking into account dynamic eyeshot, dark adaption and hearing, which are features related to risk perception. A sample of 500 drivers was submitted to visual and auditory tests. This is an example of visual test in which it was recorded the time taken by the testee to identify the lights lightened stochastically on different zones of a dynamic screen. This test simulates the identification of visual inputs while driving at different speed.

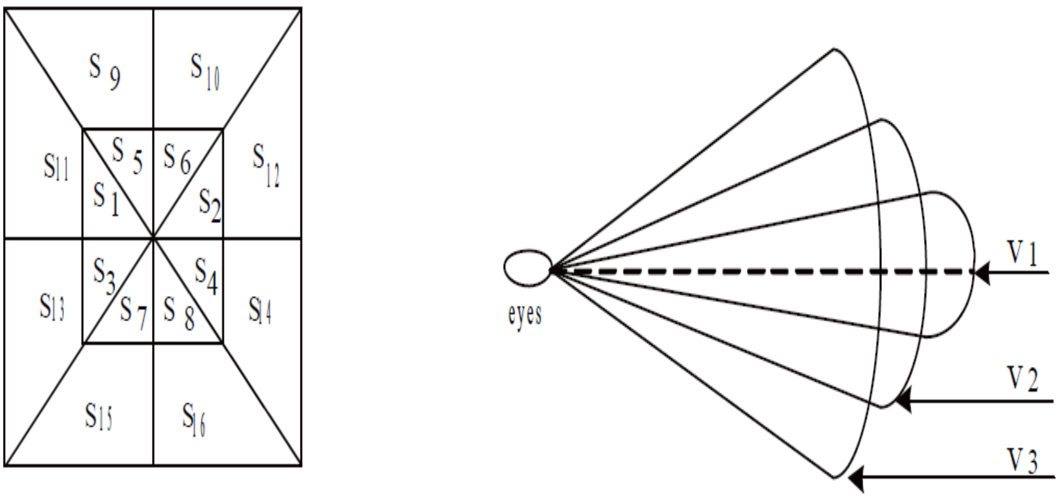

Fig. 2.1 – Testing screen for dynamic eyeshot and relation between speed and eyeshot
Li, P., Wang, D., Sun, F., Wang, C. (2011)[6]

After that, drivers were divided into different groups by Markov distance according to test scores. Finally, this classification was verified by using the accident statistic data

[5] Tang, Y., Guo, Z. (2009) "Driver Safety Evaluation Model Based on Discriminatory Analysis." *Logistics: pp. 2021-2027.*

(considering drivers without any traffic disobedience as the non-accident group, and the others as the accident group). Results showed the validity of dividing drivers into accident group (high accident propensity) and non-accident group (low accident propensity) by considering visual and auditory inputs. This experiment demonstrates again the strong relationship between risk perception and traffic safety.

2.3 Factors influencing driving behaviour

Firstly, in order to analyze key factors influencing driving behaviour it is necessary to identify them. In fact, Li et al.[6] affirm that «*there are various factors affecting driving behavior and each factor has different levels to be discussed in detail, which makes it very difficult to analyze how each factor affects driving behavior*.»

Factors influencing driving behaviour, according to these authors, could be divided into three categories:

- Driver factors, which could also be divided into static characteristics (gender, experience, skills, age, reaction capacity, tendency and others) and driving state (fatigue or drunk driving, using a mobile phone while driving etc.)
- Vehicle factors, which could also be divided into models (vehicle size), performance (deceleration capability, brake performance and turning radius) and running qualities (speed).
- Road traffic environmental factors, including road environment factors (road geometry factors like radius of the plane curve, linear parameters of road longitudinal sections like longitudinal grade, road surface conditions, friction coefficient, road width, length of sight distance) and traffic environment factors (traffic volume, transverse interference and roadside grade).

Hence, a summary of recent literature about these topics follows.

[6] Li, P., Wang, D., Sun, F., Wang, C. (2011) "Study on How to Identify the Key Factors Influencing Driving Behavior." *ICCTP 2011: pp. 2422-2429.*

2.3.1 Driver factors

The effect of age on driving behaviour was analyzed for example by Stamatiadis and Deacon[7]. They said that safest drivers are middle-aged people, while the less safe are the old one. Furthermore they identified a sort of "generational effect" because nowadays, old people are safer than in the past, while young people have a more risky behaviour. On the other hand, Curry[8] demonstrated that in respect to all the accidents caused by an error of the driver, young people made errors in 79.3 % of the total cases.

Experience is a kind of knowledge that people can get from everyday practice, which can make a novice an expert, and it is a widely studied factor in literature. Yu et al.[9] stated that «*behavioral data showed that experienced driver and novice had different driving behavior patterns, and there existed a close relation between driving behavior pattern and driving performance*». Furthermore, Ge et al.[10] planned an experiment in order to prove that, while driving, experienced people react better than others to external inputs. Experiment participants drove in a driving simulator and they were submitted to mental arithmetic task. During tests, experiment members recorded physiological signal like heart-rate variability, heart and breathe rate. The results showed that the secondary task disturbed the performance of the primary task, it added extra mental workload to drivers, so that their driving performance was reduced. Nevertheless, reaction of novices was slower than that of experts, so the conclusion is that experts drive better than novices in dual tasks. This experiment is also interesting from the point of view of the reaction time, because it was found that it varies a lot in the driving population.

Driving skills obviously influence driving behaviour, but the interesting point is the self-perception of driving skills. This problem was analyzed by Gosselin and Gagnon[11],

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[7] Stamatiadis, N., Deacon, J. (1994) "Trends in highway safety: effects of an aging population on accident propensity." *Accident Anal. and Prev., Vol. 27, n. 4, Elsevier Science Ltd.*

[8] Curry, A., Hafetz, J., Kallan, M., Winston, F., Durbin, D. (2010). "Prevalence of teen drivers errors leading to serious motorvehicle crashes." *Accid. Anal. and Prev., Elsevier Science Ltd.*

[9] Yu, L., Sun, X., Ge, Y. (2009) "The Application of Hidden Markov Model in Classifying Novice and Experienced Drivers by Driving Behavioral Features." *International Conference on Transportation Engineering 2009: pp. 3160-3165.*

[10] Ge, Y., Xu, X., Li, J., Lu, X., Zhang, K. (2007) "The Effect of Secondary Task on Driving Performance, Physiological Indices, and Mental Workload: A Study Based on Simulated Driving." *International Conference on Transportation Engineering 2007: pp. 491-496.*

[11] Gosselin, D., Gagnon, S., Stinchcombe, A., Joanisse, M. (2009) "Comparative optimism among drivers: an intergenerational portrait." *Accid. Anal. and Prev., Vol. 28, n. 2, Elsevier Science Ltd.*

who propose the concept of "*comparative optimism*" in the driver population. In fact, according to the authors, there is a general tendency to overrate one's own skills, especially in comparison with older people.

Speeding, fatigue, risky or drunk driving, using a mobile phone while driving are all behavioural factors that increase the probability of getting involved in an accident. However, in comparison with the static one, those factors are related to a conscious risk acceptation by drivers.

2.3.2 Vehicle factors

Vehicle factors could influence a lot driving behaviour, especially when they give to the driver a safer perception of the reality.

In fact, Munich taxi study[12] is an interesting example supporting this statement. In Munich (Germany) part of a group of taxicabs was equipped with anti-lock brakes (ABS), while the remaining had conventional brake systems. In other respects, the two types of cars were identical. Anti-lock braking system (ABS) is an automobile safety system which allows the wheels on a motor vehicle to maintain tractive contact with the road surface according to driver inputs while braking, preventing the wheels from locking up (ceasing rotation) and avoiding uncontrolled skidding[13]. The two different types of taxi were observed during a period of 3 years. After this period the crash rates were a little higher for the cabs with ABS and the accelerometers placed in taxi showed that cabs with ABS did more sudden braking than the others. These results could be explained from the point of view of the risk homeostasis theory. In fact ABS-equipped cabs took more risks in order to maximize their utility, assuming that ABS would have safeguarded them and this means that ABS did not modify their target level of risk.

This is an evidence that cars with better performance and equipped with safety systems could modify driving behaviour.

2.3.3 Road traffic environmental factors

[12] Wilde, G. (1994) "Remedy by engineering?" *Psyc.queensu.ca. Retrieved 2010-12-07.*

[13] Various authors. "Anti-lock Braking System." *Wikipedia, the Free Encyclopedia.*

The influence of road traffic environmental factors could be inquired by examining a model proposed by Chakroborty et al.[14]. Authors stated that humans constantly perceive their driving scenario and react accordingly. Drivers' actions in a given scenario are motivated by two factors: drivers' concern for safety and drivers' urge to reach the destination as soon as possible. Furthermore they said that «*it is felt that these two factors together with the existing traffic rules largely determine the perception-reaction mechanism of every driver in all driving scenarios*». They developed a comprehensive microscopic model of driver behaviour that aims to predict the actions of a driver in a variety of driving scenario, considering:

- Free flow conditions, wherein the only features that affect the driver's behaviour are road edges, curves, lane markings and other static obstacles.
- Car-following situations, wherein drivers are forced to follow another vehicle at speeds lower than the desired one and drivers can choose the stable condition (maintaining a safe distance) or the closing-in and overtaking.
- Passing situations, which assume behavioural importance when the driver has to move into the opposing lane.
- Presence of on-coming vehicle on narrow two-way roads, which brings drivers to move toward their respective road edges.

The main hypothesis of the theory was that each obstacle (both roadway and traffic features) poses a threat to the safety of the test driver and it is assumed that it emanates a positive potential field which repels the driver. Shape and strength of the potential field depends on the property of the obstacle and the potential at any point on the road is the sum of the potential at that point due to all the obstacles present in the driving environment. Hence, it was assumed that an inverse relation exists between the *sustainable speed* at that point (speed that makes the driver comfortable given the scenario) and the potential at that point (resistance posed to the motion of the vehicle).
After setting the hypothesis authors formulated their model and the potential field functions. There are two types of response model:

[14] Chakraborty, P., Agrawal, S., and Vasishtha, K. (2004) "Microscopic modeling of driver behavior in uninterrupted traffic flow." *J. Transp. Eng., 1304, 438–451.*

- Steering response model (SRM), which predicts the choice of steering angles in a given situation. The SRM aims at predicting lateral positions of vehicle on the road over time. Criterion used to predict location of vehicle in the next cross-section is that drivers will choose the point which is accessible and offers the least potential among all accessible points.
- Acceleration response model (ARM), which predicts the acceleration/deceleration rates over time in different situations. Criterion used to calculate this rate is based on the rate of change of potential and the difference between sustainable speed and the actual speed.

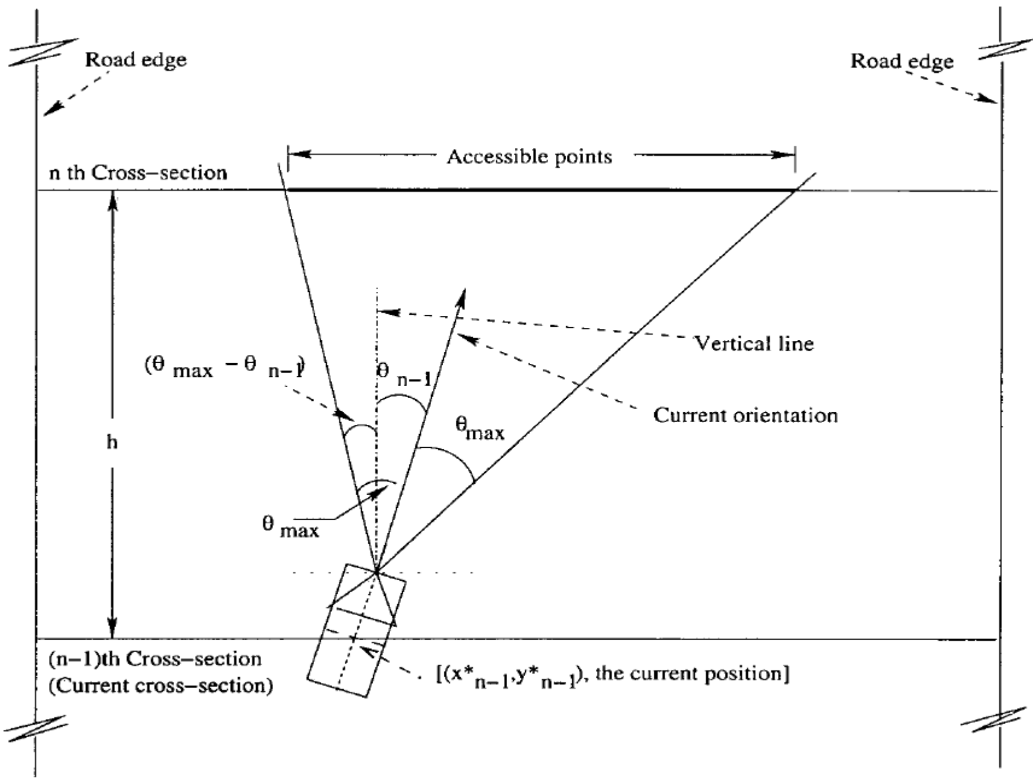

Fig. 2.2 – Schematic explaining procedure to obtain set of accessible points
Chakraborty, P., Agrawal, S., and Vasishtha, K. (2004)[14]

After modeling, driver behaviour was simulated in all the four driving scenarios above reported. It was assumed that the behaviour of a driver can be completely described by specifying the lateral positioning of the vehicle over time and speed of the vehicle over time. The results showed that the proposed model predicts the behaviour along expected lines in all the driving scenarios.

2.4 Speed choice

The behaviour of a driver can be identified using some useful indicators such as speed and lateral positioning of the vehicle. In particular speed and the way in which it is chosen are strictly related with driving behaviour and risk perception. In fact, often, the first reaction to a sudden perceived risk is to brake, while speed increases (even if more slowly) when the driver feels safe again with the external conditions according to the risk perception theory above discussed. Therefore, speed choice is a subjective matter due to its relationship with risk perception, so it is important to study factors influencing speed choice.

2.4.1 Factors influencing speed choice

Firstly, in order to analyze speed choice, it is important to understand that choice depends on a lot of degrees of freedom while driving and that some of them are fixed. Therefore it is necessary to discriminate the free flow speed, which is the desired speed of drivers in low volume conditions and in absence of traffic control devices, from the real speed chosen on a given street. In fact, the real speed chosen is determined by a lot of factors, as explained further below. These factors are:

- Vehicle related, because generally drivers hold relatively high speed if the vehicle performs well;
- Road related, because road influences speed choice through its width, lateral clearance, number of lanes, geometric design, surface and traffic conditions;
- Environment related, because weather and visibility have a great impact on speed: speed chosen in sunny days is notably different from the one in foggy and rainy days;
- Speed limits, even if their influence could be more or less relevant according to the specific situation.

How these factors influence speed choice depends on subjective features. In fact the last factor, but probably the most important, is the human factor. Indeed drivers can be divided into different groups based on their individual personalities and people who belong to different groups have diverse ways to relate to those limitations. This phenomenon depends again on risk perception: people choose their speed, which is a behavioural indicator, according to their target level of risk. In fact, if a user thinks that speeding benefits are more than the expected costs (for example speed fines), he will go faster than the speed limit. This mechanism could be employed for all the factors above reported.

Instead, free flow speed, which is the desired speed in low volume conditions and in absence of traffic control devices, could be connected with human behaviour without taking into account some of the factors above reported: speed limit and road traffic. In fact, in case of low traffic, the presence of other vehicles is not taken into account in the speed choice process; whereas, in case of absence of traffic control devices, expected risk of speeding fines is not taken into account in the same process.

2.4.2 Recent literature about factors influencing speed choice

In the previous paragraph, I made a list of the main factors influencing speed choice. Some conclusions about the influence of each factor could be taken from the study made by Du et al.[15], who chose to use a self-reported behaviour survey. 435 random selected Chinese drivers filled out a questionnaire with their personal details, performance of the vehicles, desired and real speed under the speed limit. These data were used to analyze the distribution of desired speeds, the relationship between the real speed and speed limits, the affection towards desired speed from each factor and the affection from traffic flow characteristics.

Results of distribution of desired speeds showed that most drivers are aware of the importance to follow the traffic rules, that the proportion of women approving speeding is very low compared to male drivers, that young drivers don’t understand the danger of speeding at all and tend to drive above speed limits and finally that drivers of small cars

[15] Du, X., Lu, J., Tan, D., Wu, G. (2010) “Research on Desired Speed under Speed Limit on Ordinary Highway.” *ICCTP 2010: pp. 453-465.*

have the highest proportion against over-speed compared to large car drivers. These sentences are summarized in the fig. 2.3.

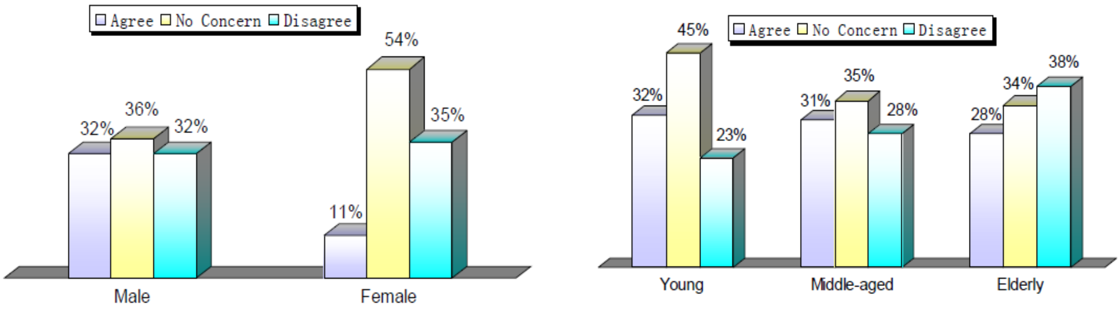

Fig. 2.3a – Attitude of drivers in different gender and ages towards speeding
(Agree = Drivers who agree with speeding, Disagree = Drivers who don't agree with speeding, No concern = Drivers who don't care about speeding)

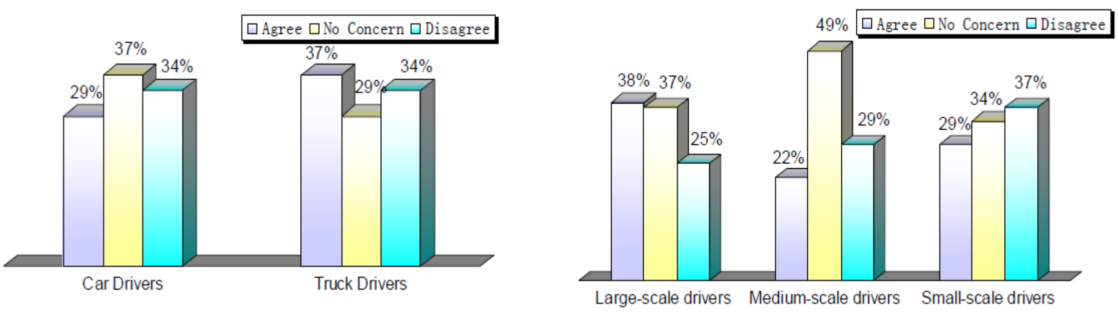

Fig. 2.3b – Attitude of drivers in different motorcycle types towards speeding
(Agree = Drivers who agree with speeding, Disagree = Drivers who don't agree with speeding, No concern = Drivers who don't care about speeding)

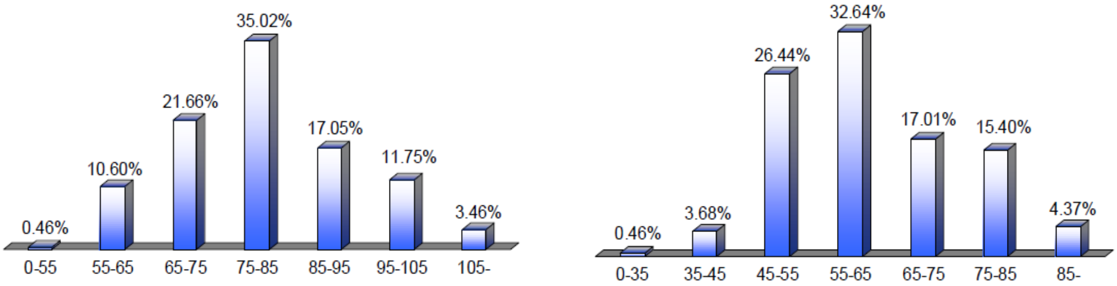

Fig. 2.3c – Distribution of drivers' desired speed on 80 km/h speed limit roads and on 60 km/h speed limit roads
Du, X., Lu, J., Tan, D., Wu, G. (2010)[15]

Results of the same study about the relationship between real speed, desired speed and speed limits showed that over 50 % of drivers desire a speed lower than the speed limit. On the other hand the average level of desired speed is always higher than that of real speed, even under different speed limits. In most cases the desired speed is higher than the speed limit, but sometimes it is inferior and this is due not only to the personalities, skills, reason of travel but also to performance conditions of vehicles. Hence, it can be seen that drivers choose the speed based on the speed limit, as well as according to the road and the weather conditions and the car performances.

Speed limit (km/h)	Desired speed(km/h)			Normal speed(km/h)		
	Distribution range	Mean	Std.Deviation	Distribution range	Mean	Std.Deviation
80	50-180	81.25	14.78	40-120	75.22	11.56
60	30-140	63.31	14.00	30-120	57.21	10.87
40	10-120	46.52	15.52	10-90	40.82	10.54

Fig. 2.4 – Distribution of drivers' desired speed and normal speed under different speed limits Du, X., Lu, J., Tan, D., Wu, G. (2010)[15]

According to the analysis of desired speed and other influential factors, authors come to the following conclusions: the larger is the car, the lower is the desired speed. Car drivers' desired speed is higher than truck drivers' one. Moreover, the older is the driver and the longer is the driving age, the lower is the desired speed. Under low speed limits the age of driving has more impact on desired speed and drivers with good skills can rationally determine the desired speed. Instead, in higher speed limit roads, drivers consider as safe speeds higher than speed limit, due to better road facilities and traffic conditions. Figure 2.5 summarizes the overall impact of the various factors, showing for each factor the percentage of users that perceive that factor as influencing speed.

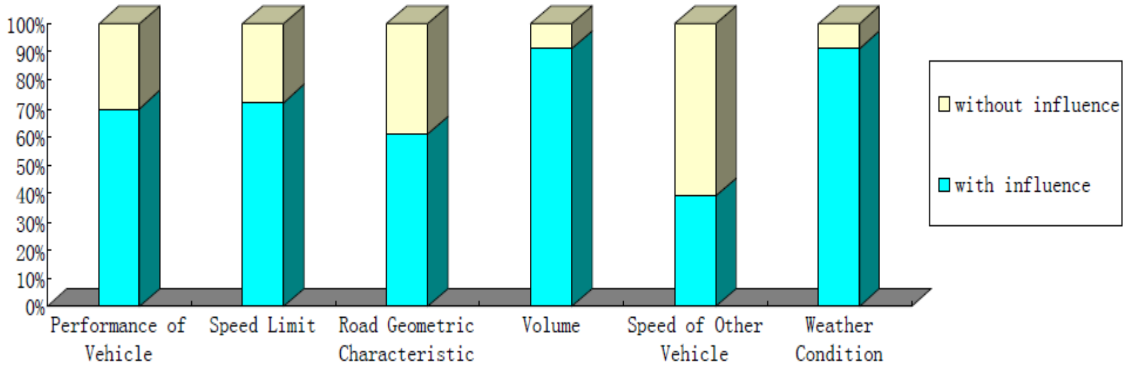

Fig. 2.5 – Distribution of factors influencing drivers' speed choice
Du, X., Lu, J., Tan, D., Wu, G. (2010)[15]

Finally authors proposed a simple formula to estimate the ratio of desired speed to speed limit, which is called *desired f*:

$$f_{desired} = a_1 * S + a_2 * A + a_3 * DA + a_4 * rainy + a_4 * Q + k \tag{6}$$

(S = sex, A = age, DA = years of driving experience, rainy = desired rainy speed, Q = traffic volume)

Coefficient of this formula could be established by using regression models.

Furthermore, another experiment based on stated preference survey was conducted by Ryeng,[16] in order to inquire the importance of some factors on speed choice: influence of speed of other drivers, police enforcements and stricter sanctions. Results show that: «The most influential factor appears to be the speed of other drivers, confirming […] that social pressure is a fundamental determinant for personal speed choices. Also increasing levels of police enforcements are found to reduce speeds, while stricter sanctions were found to only marginally affect a driver's choice of speed». Therefore, the only use of high enforcement levels and strict sanctions as a countermeasure against speeding could be not sufficient to avoid this phenomenon.

[16] Ryeng, E. (2012) "The effect of sanctions and police enforcement on drivers' choice of speed." *Accid. Anal. and Prev., Vol. 45, Elsevier Science Ltd.*

2.5 Problems concerning speed choice

2.5.1 Relationship between observed speed and speed limits

In the previous paragraph it was stated that speed limits are one of the factors influencing driving behaviour. The experiment analyzed was based on self-reported behaviour. Instead, in order to better understand the relationship between real speed and speed limits it should be better to consider experiments focused on observed speed.

The reason for the introduction of speed limits is found in the following sentence: «*Setting speed limit is a common strategy for enhancing safety by controlling driver's speed. Not all drivers are able to judge their vehicles correctly and to anticipate roadway conditions. Inexperienced drivers and young drivers tend to underestimate or misjudge the effects of speed on crash probability*»[17].

In order to obtain a valuation of the relationship between observed speed and speed limit, we can refer to the above quoted work made by Xu et al. Three study sites were set in the proximity of speed limit signs on a four lane-divided Chinese highway. They were used to collect speed and traffic volume data as shown in figure 2.6.

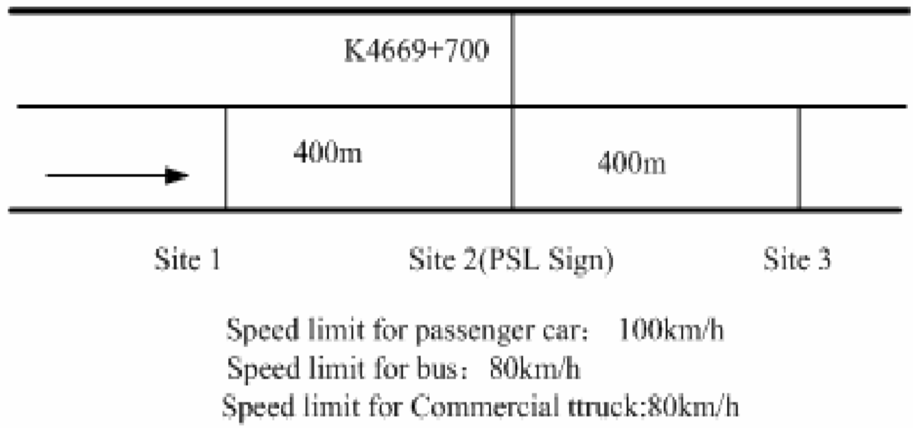

Fig. 2.6 – Location of three study sites and speed limits
Xu, T., Sun, X., He, Y., Xie, C. (2009)[17]

[17] Xu, T., Sun, X., He, Y., Xie, C. (2009) "Actual Speed Distribution vs. Speed Limit on Bo Sai Highway of Xinjiang Province in China." *International Conference on Transportation Engineering 2009: pp. 1068-1073.*

Results of the study could be summarized as follows. For passenger cars, 85 % spot speed at site 1 and site 2 both exceeds 100 km/h. When approaching **a** speed limit sign, it seems that behaviour changes: about 78 % of the passengers travelled below 100 km/h. Hence, the conclusion is that passenger car drivers often ignore speed limits and warning signs, basing their choice on their knowledge and on their risk perception.

2.5.2 Relationship between desired speed and planner's design speed

Engineers plan roads taking into account a design speed, which is a «*selected speed used to determine the various geometric design features of a roadway*»[18] according to the most recent definition given into AASHTO green book. It can be seen as the maximum safe speed that can be maintained over a specified section of highway when conditions are favorable as expected in the design step, but actually meeting a minimum design speed is not enough to ensure a safe roadway. Indeed, according to the American Federal Highway Administration: «*Recently, the concept of design consistency has been used instead of minimum design speeds. This attempts to connect driver's expectations about the roadway with the roadway design. It uses driver behavior models to predict vehicle speeds on highway segments, and compares the predicted speed on adjacent segments. Significant reductions in speed from one segment to the next are flagged as locations where drivers may end up driving too fast for road conditions*»[19].

Hence, the importance of driving behaviour was recognized also in the field of road planning. Therefore, the modern aim of road planners is design consistency, which is the conformance of the geometric features of a road with drivers' expectations[20]. Design is consistent if «*successive elements are coordinated in a way to produce harmonized driver behavior without surprising events*»[21].

In order to evaluate design consistency, one of the most efficient and quantified approach is the *operating speed approach*. According to this method, the value of the

[18] American Association of State Highway and Transportation Officials (AASHTO) (2004) "Policy on Geometric Design of Highways and Streets."
[19] Federal Highway Administration (2000) "Evaluation of Design Consistency Methods for Two-Lane Rural Highways, Executive Summary."
[20] Nicholson, A. (1998) "Superelevation, side friction, and roadway consistency." *J. Transp. Eng. 124(5), 411–418.*
[21] Gibreel, G. M., Easa, S. M., Hassan, Y., El-Dimeery, I. A. (1999) "State of the art of highway geometric design consistency." *J. Transp.Eng. 125(4) 305–313*.

speed differential between two successive elements of a road and the difference between the operating speed and design speed values are the two parameters that, if low, could demonstrate design consistency. Operating speed is defined by AASHTO as the «*speed at which drivers are observed operating their vehicles during free-flow conditions*». If design is consistent, drivers' operating speed is similar to the design speed, and then we obtain the situation of a "*self-explaining road*". It could be also calculated the 85^{th} percentile operating speed, which could be another important predictor of drivers' desired speed. In fact, often, 85^{th} percentile operating speed on a road could be used to set speed limits on that road.

2.5.3 Problems concerning speeding behaviour

Speeding has been recognized around the world as a major cause of road accidents and fatalities. In order to consider the importance of speeding in such events, it is possible to evaluate the Power model[22], a system based on six equations that connect changes in traffic speeds with changes in road crashes at various levels of injury severity.

- Number of fatal accidents: $$Y_1 = \left(\frac{V_1}{V_0}\right)^4 * Y_0 \quad (7.1)$$
- Number of deaths: $$Z_1 = \left(\frac{V_1}{V_0}\right)^4 * Y_0 + \left(\frac{V_1}{V_0}\right)^8 * (Z_0 - Y_0) \quad (7.2)$$
- Number of fatal accidents with serious injuries:
$$Y_1 = \left(\frac{V_1}{V_0}\right)^3 * Y_0 \quad (7.3)$$
- Number of fatal accidents or accidents with injuries:
$$Z_1 = \left(\frac{V_1}{V_0}\right)^3 * Y_0 + \left(\frac{V_1}{V_0}\right)^6 * (Z_0 - Y_0) \quad (7.4)$$
- Total number of accidents with injuries:
$$Y_1 = \left(\frac{V_1}{V_0}\right)^2 * Y_0 \quad (7.5)$$
- Total number of injuries: $$Z_1 = \left(\frac{V_1}{V_0}\right)^4 * Y_0 + \left(\frac{V_1}{V_0}\right)^8 * (Z_0 - Y_0) \quad (7.6)$$

[22] Nilsson, G. (2004). "Traffic safety dimensions and the Power Model to describe the effect of speed on safety." *Bulletin 221. Lund Institute of Technology, Department of Technology and Society, Traffic Engineering Lund.*

In all these equations V is average speed, Y are accidents, Z are injuries or deaths. (subscript 0 indicates observations made before changes in average speed, while subscript 1 indicates observations made after those changes). According to this model, the importance of speeding in accidents and injuries could be understood through an example. It could be taken into account a road on which there are: 100 km/h of traffic average speed, 50 annual accidents with injuries and 70 annual injured people. If average speed decreases to 90 km/h, then annual accidents with injuries are reduced to 40.5 and injured people are reduced to 53.6. However, there is an evident flaw in this model: accident numbers depend only on relative change in speed and not also on initial speed. Instead, it is clear that, for example, a 25 % reduction in speed will not be the same when speed changes from 150 km/h to 100 km/h as it will when speed changes from 60 km/h to 40 km/h. Elvik[23] tried to solve this gap with a re-parametrisation of the Power Model by fitting exponential functions to data points and he logically found that «*the effect on accidents of a given relative change in speed is largest when initial speed is highest*».

Apart from different interpretations of power model, it gives an immediate idea of the importance of speeding in accident related matters. In the Australian state of Queensland, for example, speeding was considered to be a major contributing factor in 14 % of all fatal crashes and it is commonly referred as one of the Fatal Four factor in Australia[24].

Nevertheless, speeding is also one of the most socially acceptable deviant driving behaviours, especially in some countries. Roadside surveys conducted in UK, for example, revealed that drivers stopped by police for speeding did not see their speeding as potentially harmful or as a criminal behaviour and did not feel guilty despite of fines or warnings[25]. Speeding is not regarded as a severe offence by the average driver neither

[23] Elvik, R. (2013) "A re-parameterisation of the Power Model of the relationship between the speed of traffic and the number of accidents and accident victims" *Accident Analysis and Prevention 50, 854-860.*

[24] Queensland Transport (2000). "Road Traffic Crashes in Queensland – 1999." *Brisbane: Queensland Department of Transport.*

[25] Corbett, C., Simon, F. (1992) "Unlawful driving behavior: A criminological perspective." *Contractor Report 310, Transport Research Laboratory, Crowthorne.*

in the Nordic countries[26] and drivers usually consider speeding acceptable[27]. Furthermore, another instance supporting this thesis is given by Mehmood for the Al Ain (UAE) case[28]. In fact he stated that «the culture of speeding is so deeply rooted that a speeding violation is commonly perceived as a normal offense» even if speeding contributed to a remarkable number of sever road crashes in Al Ain.

Because of all these facts it is important to explore the determinants of the speeding behaviour. Mehmood studied this problem by searching a relationship between self-reported speeding behaviour and the drivers' attitudes and beliefs, with the help of questionnaires based on the *Theory of planned behavior*. According to this theory, behavioural intentions have been found to be a strong predictor of subsequent behaviour. He found that the largest contribution to the prediction of reported speeding was provided by the following sentences: "Probability of being caught for speeding is low due to limited police patrol", "Ineffective mechanism for collecting speed fines encourages drivers to speed", "Drivers learn to drive fast by observing their parents/friends/relatives or others", "The lack of understanding of drivers about the consequences of speeding contributes to their speeding behavior". Instead, the constructs related to the amount of the speeding fine, speed cameras, type of vehicles, and offering incentives showed no significant contribution to predicting speeding behavior. Another significant factor is that age and annual mileage driven were recognized as significant contributors in the influence of drivers' attitudes and beliefs (speeding decreases with age and with more mileage). Furthermore, Tay et al.[29], after a similar study based on planned behavior, found this result: «*it appears that personality, attitudes and social norms play a significant role in self-reported speeding. In contrast, enforcement deterrence appears to play a minor role and perceived crash risks seem to have little or no effect on self-reported speeding*».

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[26] Aberg, L. (1997) "The role of perceived risk of detection." *Traffic and transport psychology: Theory and application, T. Rothengatter and E. Carbonell, eds., Elsevier, Oxford, U.K.*

[27] Elvik, R., (2010) "Why some road safety problems are more difficult to solve than others." *Accident Analysis and Prevention 42, 1089–1096.*

[28] Mehmood, A. (2009) "Determinants of Speeding Behavior of Drivers in Al Ain (United Arab Emirates)." *J. Transp. Eng., 135(10), 721–729.*

[29] Tay, R., Watson, B., Hart, S. (2002) "Personal and Social Influences of Speeding." *Traffic and Transportation Studies (2002): pp. 1140-1147.*

2.6 Differences between regular and non-regular users

In the introduction I stated that there are some behavioural differences between regular and non-regular users and that those differences could be important in some applications even if this problem is not frequently studied in literature. In the following paragraphs I will try to give some definitions and to describe related matters and recent literature about this topic.

2.6.1 Definitions and related matters

A regular user of a given road is a driver who is familiar with that road, due to the high frequency of travelling on it. Generally regular users are commuters who drive on a road to go to work and come back home.

A non-regular user of a given road is a driver who uses that route only occasionally. Generally non-regular users are people who drive on a road for reasons other than work purposes. Indeed they could be also named recreational user.

The reason why it is important to study these differences is that a different level of familiarity with the road between the two categories has an important impact on driving behaviour. It can be suggested that risk perception is generally different between the two categories of users mainly because, other conditions being equal, the non-regular driver values road conditions at the moment while the regular one already has knowledge of them. It is understood that road conditions that could be acquired with experience are geometric features and surface conditions; while, for example, traffic conditions must be evaluated at the moment by both categories.

Risk perception and speed choice are strongly connected as it was said in previous chapters. Therefore, different risk perception is often related to different speed choice: it could be proposed that people who feel more confident with a given road tend to go faster than the less confident ones. This mechanism is due to the fact that regular users judge risk with a lower margin of error, mainly because they presume to know exactly a component of the total risk and so, their behaviour could change according to this different perception.

Apart from behavioural consequences that these differences could lead to, it is important to notice that there are some practical issues with which this problem is considered. The most important is the formula suggested by the American HCM authors in order to evaluate traffic flow, in the chapter devoted to road level of service.

In fact, in order to guarantee an adequate functionality to an infrastructure, it is necessary to consider a suitable level of service, which is a measure of the circulation quality. Due to the many variables of the problem, the HCM (Highway Capacity Manual) authors suppose that level of service depends only on two variables: travel speed and traffic flow. In particular, in the HCM 2000[30], traffic flow is calculated using the following formula:

$$\mathrm{Vp} = \frac{\mathrm{V}}{\mathrm{PHF} * \mathrm{N} * f_{HV} * f_p} \tag{8}$$

where:

v_p = 15-min passenger-car equivalent flow rate (pc/h/ln),

V = hourly volume (veh/h),

PHF = peak-hour factor,

N = number of lanes,

fHV = heavy-vehicle adjustment factor,

f_p = driver population factor.

This formula is used to calculate freeways and highways traffic flow. The introduction of the f_p factor since the 1985 HCM edition allows us to consider, for the first time since the first HCM edition, that traffic flow is composed of different categories of users from the point of view of their familiarity with the road. For the f_p factor, HCM 2000 suggests the value 1 in case of traffic flow mainly composed of regular users and values from 0.75 to 0.95 in case of traffic composed of a mix of regular and recreational users. This means that, other conditions being equal, a decreasing of f_p to the minimum of 0.75 brings to a 33 % increasing in estimated traffic flow, compared with the flow calculated using f_p equals to 1. Therefore, the presence of a recreational component in the traffic flow leads up to a remarkable worsening of the road level of service.

[30] Highway Capacity Manual (2000) *Transportation Research Board.*

However, in spite of the importance given to this feature in the HCM, there are only few studies in literature concerning behaviour differences between the two categories. Therefore, in case of flow composed also of recreational users, it is not possible to decide which f_p value to choose in the range of 0.75-0.95.

2.6.2 Practical differences between the two categories – some recent literature

There are some studies in literature which suggest suitable values for the f_p coefficient by using different strategies.

Sharma in 1985[31] suggested to choose f_p classifying roads according to the main category of users employing them, considering two essential parameters: reason for travelling and travel length. The study was conducted on some Canadian highways. Roads classification and fp values are summarized in the following table.

Identified road categories	**Related traffic categories**	**fp suggested values**
Roads driven by commuters in a urban context	Urban commuters	**1,00**
Roads driven by commuters in a regional context	Regional commuters	**0,95**
Roads driven by commuters and other people for other reasons in a regional context	Regional recreational/ commuters	**0,90**
Roads driven in an interregional context	Interregional	**0,85**
Roads driven for long distance travels	Long distance	**0,85**
Roads driven for long distance travels due to touristic reasons	Long distance/recreational	**0,80**
Roads driven mainly for touristic reasons	Highly recreational	**0,75**

Tab. 2.1 – fp values suggested by Sharma (1985)[31]

[31] Sharma, S., (1987) "Driver population factor in new Highway Capacity Manual." *Journal of Transportation Engineering, Vol. 113.*

Furthermore in 2007 in the USA, Heaslip, Louisell and Collura[32] studied the decreasing of capacity in presence of short term work zone on two American freeways. HCM suggests an empirical formula to calculate that reduction. Instead, an experiment based on observations was made in the above mentioned study. Data collected from observations were compared with the simulation made using the HCM formula. The authors proposed to fill the gap between simulated data and the collected ones, by using some factors inferable from behaviour video monitoring (familiarity, adaptability, aggressiveness, accommodation). A correction of the fp factor was suggested mixing these four factors, according to Table 2. Therefore authors have offered f_p values to introduce into the HCM formula in case of work zone.

Familiarity	**Adaptability**	**Aggressiveness**	**Accomodation**	**f_p**
High	High	Medium	High	**1.375**
Medium	Medium	Medium	Medium	**0.9**
Low	Low	Low	Low	**0.64**

Tab. 2.2 – f_p values suggested by Heaslip, Louisell and Collura[32] in case of short term work zone

Instead a study made by Al-Kaisy and Hall (2001)[33] considered the road capacity decreasing in case of freeway lane long term closing. The freeway under examination is in Canada and it is located in a touristic zone. Traffic was controlled during all the time of lane closing and differences were found between morning flow peak (mainly caused by commuters) and the afternoon flow peak (flow with a recreational component). Some differences between morning weekdays flow peak and morning non-working days flow peak were found as well.

The authors have divided the observed capacity values of flow composed of a mix of recreational and regular users, by observed capacity values of flow composed only by

[32] Heaslip K., Louisell C., Collura J. (2007) "Driver population adjustment factors for the Highway Capacity Manual work zone capacity equation." *Transportation Research Board.*

[33] Al-Kaisy, A., Hall, F. (2001) "Examination of the effect of driver population at freeway long-term reconstruction zones." *Transportation Research Board.*

commuters, and after that they calculated the average of the quotient achieved for all the days of observation. Obtained results are shown in Table 2.3.

Analysis type	fp
Difference between morning peak and afternoon peak	**0.93**
Difference between weekdays and non-working days	**0.82-0.85**

Tab. 2.3 – fp values suggested by al-Kaisy and Hall[33] in case of long term work zone

After analyzing those works, it could be said that the role of familiarity is analyzed only from the point of view of the f_p coefficient value determination. Furthermore, also this determination is affected by some problems as the lack of a general method to evaluate that coefficient. Moreover, experiment based evaluation of the f_p coefficient is only related to a specific condition (like work zones). Therefore, in order to evaluate f_p in the mean conditions, it is necessary to study the phenomenon trying to understand the learning mechanisms that lead a recreational user to become a regular one and it is essential to plan some experiments with the aim of the observation of that phenomenon. Using this strategy it should be possible to assess the influence of this feature on the flow traffic forecasting and on traffic safety itself.

2.6.3 Theoretical differences between the two categories – some recent literature

There are some studies in literature concerning the differences between regular and non-regular users from a theoretical point of view. It could be said "theoretical" because until now I analyzed only the practical matter of determination of f_p coefficient. Instead, the problem could be seen from a psychological perspective, considering the role of familiarity in driving tasks.

Role of familiarity was studied for example by Yanko and Spalek[34]. They planned a high-fidelity driving simulator based experiment in order to investigate whether familiarity with the route will affect driving performance. The experiment consisted in forcing 20 test drivers to follow a pace car through a route that they had either previously been made familiar with or not. In fact, test drivers were randomly assigned to the familiar group or the unfamiliar group. Participants assigned to the familiar group drove on the simulated route 1 a total of four times to become familiar with the route. Other participants drove instead the four tests on four different simulated roads (2 – 5). Furthermore, the pace car drove at a constant speed of approximately 72 km/h and participants were instructed to follow the car at a reasonable distance that they felt comfortable with. During test sessions, pace car was programmed to brake at a 20 randomly selected locations and 5 out of 20 women standing on the side of the road were programmed to walk toward the road randomly when the participant was 50 m away. There were made six types of measurement: interval of time between the braking of the pace car and the instant of depression of the brake pedal by participants, interval of time between the onset of the woman's movement and the initial depression of an in-car button devoted to this task, headway distance, lateral position and speed (the last three measurements were continuous). Although headway distance was different between the two groups, with familiar drivers following significantly closer to the pace car, results were difficult to interpret because role of familiarity was affected by the influence of heading distance itself. This is the reason why the experiment was repeated fixing one of the variables: pace car selected speed in order to keep the same heading distance throughout all the driving tests. Reaction time needed to brake was considered as a parameter measuring "Central Response", while reaction time needed to notice lateral obstacles was considered as a parameter measuring "Peripheral Response". A summarizing diagram reporting average reaction times and showing the differences between the two familiarity groups is reported below.

[34] Yanko, M. R., Spalek, T. M. (2013) *"Route familiarity breeds inattention: a driving simulator study." Accid. Anal. and Prev. 2013, Vol. 57.*

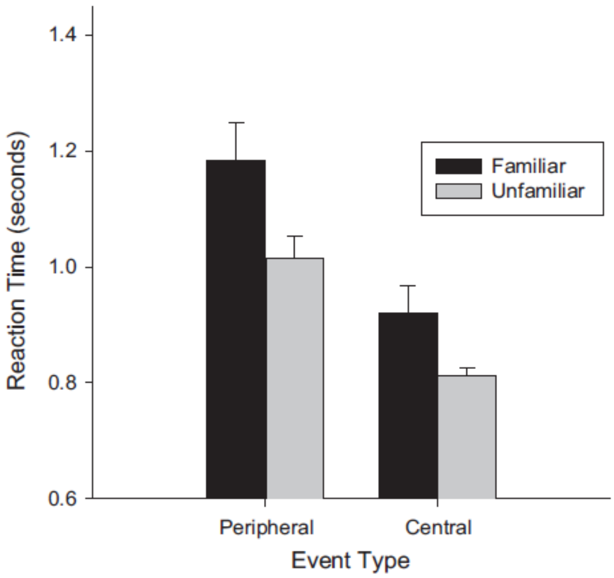

Fig. 2.7 - Reaction times in response to peripheral and centrally occurring emergency events as a function of route familiarity.
Yanko, M. R., Spalek, T. M. (2013)[34]

Results could be commented as follows: route familiarity seems to result in drivers being less able to respond to hazardous events. This result could be compared with a similar study made by Martens and Fox (2007)[35] that showed that route familiarity can lead to inattentional blindness, probably because familiarity could increase the incidence of mind wandering. In order to justify this hypothesis, a third experiment was conducted by Yanko and Spalek. In the third experiment, participants were instructed to maintain a speed of 72 km/h with the aim of keep them focused on the driving task, thereby reducing the incidence of mind wandering. The results showed that, contrary to experiment 2, familiar and unfamiliar drivers did not differ on either the central response or peripheral response measure. This result strongly suggests that responses were due to increased mind wandering along familiar routes.

Explanation of this sentences and a more detailed study of the problem will be in the next chapter devoted to the analysis of the learning process and psychological implications involved in it.

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[35] Martens, M. H., Fox, M.R.J., (2007) "Do familiarity and expectations change perception? Drivers' glances and response to changes." *Transportation Research Part F: TrafficPsychology and Behaviour 10, 476–492.*

2.7 Drivers' learning process

In the previous chapters the importance of driving behaviour studies was highlighted. This field of research probably strays from classic civil engineering issues, because it has a lot of aspects in common with psychological studies. Indeed, in order to understand how a non-regular user becomes a regular one, it is important to study the problem from a psychological point of view by analyzing the learning process. After that, this knowledge could also be applied to driving behaviour.

2.7.1 Learning process and habituation

According to a psychological definition, «*Learning is a goal-directed act. Learning is acquiring new, or modifying and reinforcing, existing knowledge, behaviors, skills, values, or preferences and may involve synthesizing different types of information. […] It does not happen all at once, but builds upon and is shaped by what we already know. To that end, learning may be viewed as a process, rather than a collection of factual and procedural knowledge. Learning produces changes in the organism and the changes produced are relatively permanent*»[36]. This sentence well summarizes all the outstanding topics concerning the learning process. It is important to notice that in modern psychology learning is recognized as a process that changes behaviour as a result of experience. Instead, in the past, it was seen only as the final product of the process.

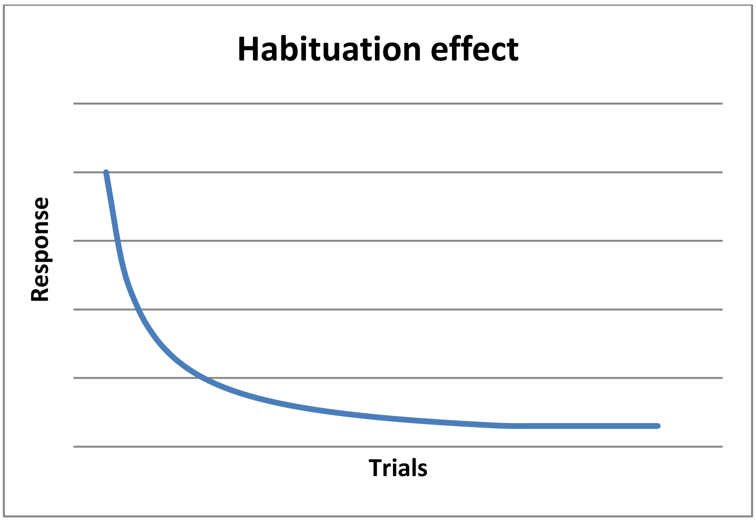
Two important features of learning are that it may occur consciously or without conscious awareness and that it could happen as a result of habituation or classical conditioning. Learning could be also divided into different types like the associative, the non-associative and the observational learning.

Habituation is a form of adaptive behaviour (neuroplasticity) and it is an example of non-associative learning in which behavioural response probability slow decreases with repetition stimulus. If a human perceives that a particular stimulus is not harmful for him, and that stimulus is repeated over time, then he gets used with it showing

[36] Schacter D. L., Gilbert D. T., Wegner, D. M. (2009, 2011) Psychology, 2nd edition. *Worth Publishers. p. 264.*

habituation and reducing subsequent responses. Furthermore, it was noted that an increase in the frequency of stimulus presentation will increase the rate of habituation and that continued exposure to the stimulus after the habituated response shows no further decrement or increment. Habituation processes are adaptive, allowing animals to adjust their behaviours to changes in the surrounding world. In fact, for humans, an initial defensive response to a new stimulus is important to protect themselves from dangerous situations.

There are a lot of theories that try to explain this phenomenon. For example, the Groves and Thompson Dual Process theory of habituation[37] states that there are two interacting processes in the central nervous system: the habituation process and a sensitization process. Both of these processes have an importance in processing inputs and in building behavioural outputs. The tendency to respond to a stimulus depends on which of those processes prevails on the other and it increases with the prevailing of the sensitization process. From a biological point of view those two processes are possible because dual process theory states the existence of two different neural pathways.



[37] Groves, P. M., Thompson, R. F. (1970) "Habituation: A dual-process theory." *Psychological Review, Vol 77(5), Sep 1970, 419-450.*

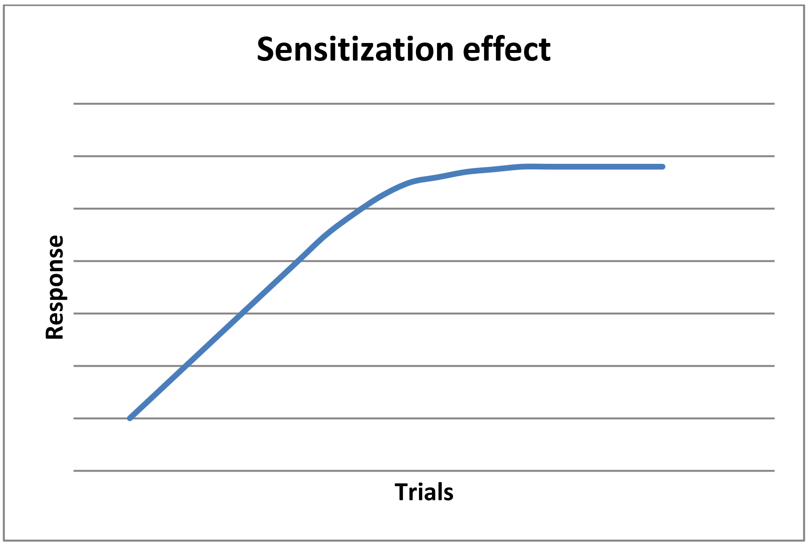


Fig. 2.8a,b – Trends of habituation effect and sensitization effect

After a lot of trials and if habituation effect is active, response becomes constant over time. However, in this phase, if a person approaches a different new stimulus, then the process of habituation restarts, in order to reach habituation also for this other stimulus. This phenomenon is called dishabituation.

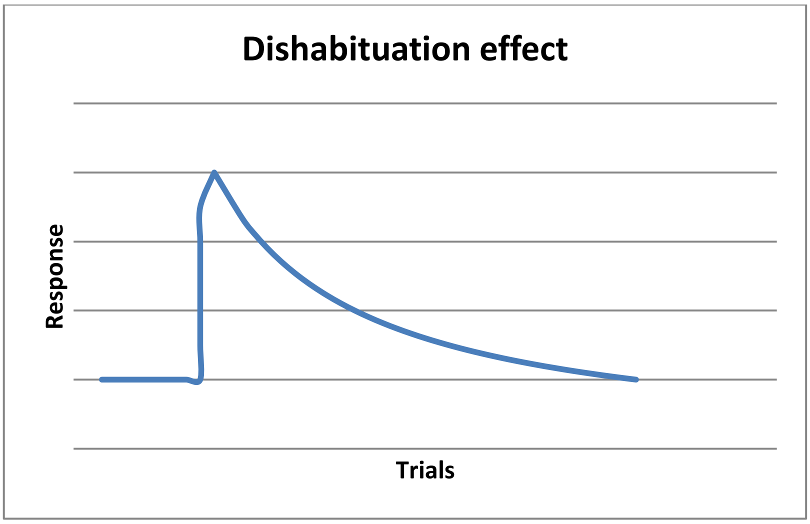


Fig. 2.9 – Trend of dishabituation effect

2.7.2 Short-term and long-term habituation

Moreover, there are two types of habituation: the long-term habituation and the short-term one. One way of demonstrating the difference in them is to conduct a relatively brief series of trials and then check for recovery from habituation. Recovery usually occurs fairly quickly and completely. When, however, a longer series of trials is given, there is a less recovery, and habituation is maintained over a longer time period[38]. There is another way of demonstrate this sentence presenting the stimulus to be habituated at two different interstimulus intervals (ISI) to two different groups of animals: the short ISI group and the long ISI group. When these two different groups are tested after a certain period of time passed by the initial habituation session, the long ISI group might show less recovery from habituation than the short ISI group. Therefore it could be possible that these two types of habituation are related to the difference between short-term memory and long-term memory in humans.

The question is if there are two different neural processes which are responsible of these two types of habituation. Kandel[39] indicates that the answer to this question could be both yes and no. In fact, in both short term memory and long-term habituation, it could be noted a reduction in neural response, but synaptic activity is depressed for longer time periods in long-term than in short-term habituation. Kandel concluded that there may be some changes in the presynaptic terminal of the sensory neuron that result from the extended habituation training, contributing to longer-lasting effect of habituation.

These statements are supported by some experiments, like for example the experiment conducted by Leaton[40], who submitted rats to loud high pitched tone in order to measure their response over time after different types of trials. He initially submitted rats to a stimulus with 24 hours ISI for 30 days and he noticed response decrement over time, which seems to have an asymptote after several stimulus presentations. After this long-term decrements had reached asymptote, 300 stimulus with 1 second ISI produced further response decrements, but these decrements recovered completely within 24

[38] Sarkar , A. (2003) Fundamentals of Animals Behaviour, *Discovery Publishing House.*

[39] Kandel E. R. (1979) Behavioural Biology of Aplysia: Contribution to the Comparative Study of Opisthobranch Molluscs. *W.H.Freeman & Co Ltd*

[40] Leaton, R. N. (1976) "Long-term retention of the habituation of lick suppression and startle response produced by a single auditory stimulus." *J Exp Psychol Anim Behav Process. 1976 Jul;2(3):248-59.*

hours, responsiveness returning to the previously established long-term asymptote. Results of the experiment are summarized in Fig. 2.10, in which the left panel shows trial by trial responsiveness with 24 hours ISI, the center panel shows responsiveness with a 1-sec ISI plotted over blocks of 30 trials and the right panel shows responsiveness for the 3 trials that followed the 300-trials session.

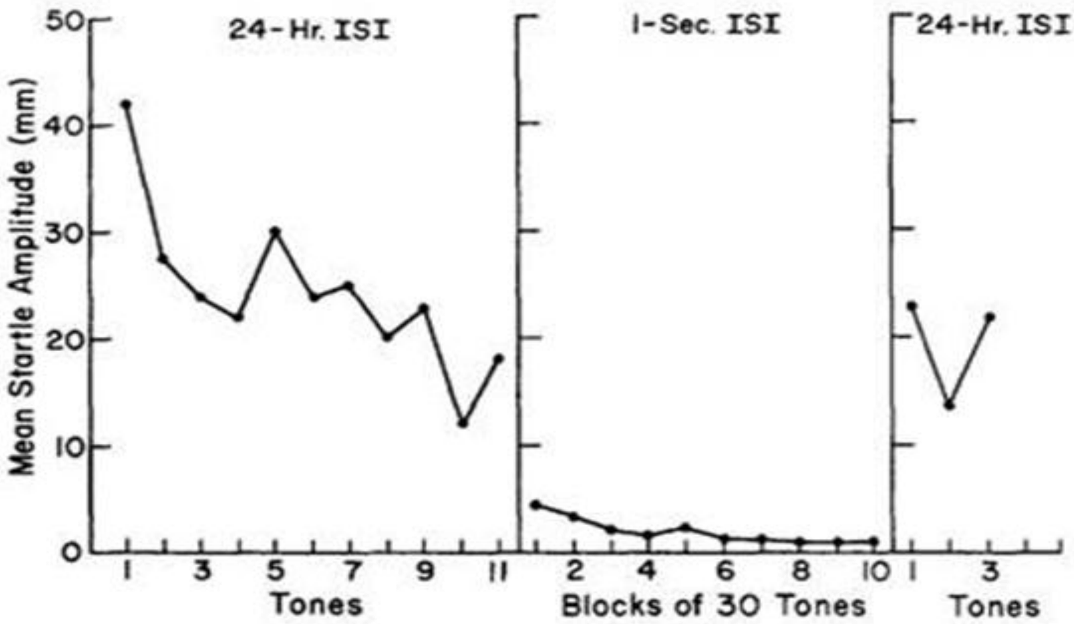


Fig. 2.10 – Results of responsiveness according to Leaton's experiment[40]

In light of the experiment, the author stated that: «*unreinforced stimulus presentations can produce both relatively permanent response decrements and apparently independent short-term decrements. The data also suggest that long-term retention may be more generally characteristic of habituation than is usually assumed*». This finding is crucial in understanding long-term and short-term responses and it could help to comprehend how to apply learning process theories to drivers.

2.7.3 Application to drivers

Learning process and habituation have a remarkable impact on drivers' behaviour. In fact, as a human task, also driving could be submitted to the same rules explained in the previous paragraphs. Learning process in drivers is a complex matter. Apart from analyzing the process that occur when a novice becomes an experienced driver, it could be interesting to analyze the formation process of speed choice and the habituation process, which concern the aims of this work.

Therefore, it is possible to view learning process from the point of view of the speed choice, which is related to the risk perception: «*different individual driver has different standard to the formation of "safe" speed, and so the expected speed is also different*»[41]. It is understood that the word "safe" does not mean the real road traffic safety speed, but the desired speed from an individual point of view. According to Zhifu[42] the process of formation can be divided into 4 stages: initially identification, adjustment, confirmation, and maintenance. It is a continuous cycle process, as shown in fig. 2.11.

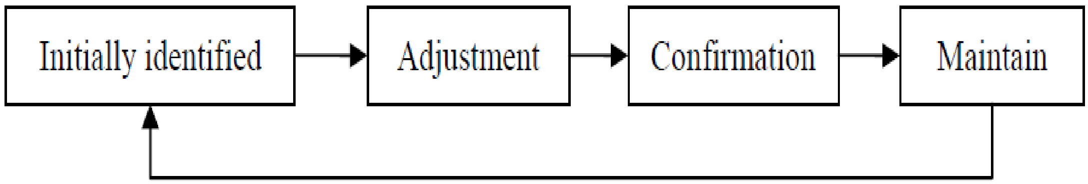


Fig. 2.11 – The formation process of expected speed
Zhifu, J. (2004)[42]

In the first phase the driver obtains traffic information by observing, analyzing and then judging it. In the adjustment phase the correction ability plays the most important role by submitting reality to a trial period in which it is possible to understand if the initially identified perception was correct. The confirmation phase occurs if adjustment phase was positive. The last step of the chain is the maintaining phase, in which knowledge is already acquired. It is a cycle process because if driver is put into a different scenario, then the process starts again. The point is that this process is different for each driver because it depends on attitude, skills, experience, risk perception and a lot of other subjective matters.

[41] Hu, C., Sun, X., Liu, S. (2009) "A Study on Speeding Driving Based on Expected Speed". *ICCTP 2009: pp. 1-6.*
[42] Zhifu, J. (2004) Traffic psychology. *Beijing: China People Public and Security University Press.*

The formation process is almost the same for every type of task in driving and the final condition is always the habituation. Repeatedly engaging a task, in fact «often results in a gradual transition from initial needing to consciously control one's actions, to a state where our actions are governed by more automatic processes»[43]. Automatic processes occur without conscious awareness and do not interfere with separate processes that require attentional resources[44]. These sentences are congruent to the habituation process. Therefore, the normal condition while driving is the habituation, which is also the low fatigue and low energy consumption state and so it is a more natural state. In fact, according to the habituation effect diagram, (fig. 2.8a, par. 2.7.1) the end phase of highly-repeated trials leads up to minimum response. Whenever the driver has to face **a** new stimulus which represents a change in the normal situation, then the attention phase occurs. This is a sensitization phase in which response increases with more trials. (fig. 2.8b, par. 2.7.1) As a result, the driver makes operations in order to react to the different situations and to avoid dangerous consequences such as road accidents. The greater the difference between expectation and reality, the greater will be the level of risk that the driver has to face. This other phase is congruent to the dishabituation effect (fig. 2.9, par. 2.7.1) which tends again to the condition of habituation after a certain period of time (if there are no other stimuli).

A state of mind related with habituation is mind wandering. Mind wandering occurs when the thought process that engages the mind is about topics that are unrelated with the tasks. The problem of mind wandering is that other tasks that require mind reaction, like the encoding of sensory information from the external environment, could be impaired. If executive attention is necessary to respond to a hazard, familiar drivers should perform worse than unfamiliar drivers due to their inclination to mind wandering. These statements are supported by the results of the experiment conducted by Yanko and Spalek. Therefore, familiarity with a given route could be also viewed as a factor affecting driver reaction time, which becomes slower in familiar drivers.

[43] Schneider, W., Shiffrin. R. M. (1977) "Controlled and automatic human information processing: 1. Detection, search, and attention. " *Psychological Review, 84, pp1-66.*

[44] Posner, M. I., Snyder, C. R. R. (1975) "Attention and cognitive control" *In Robert L. Solso (ed.), Information Processing and Cognition: The Loyola Symposium. Lawrence Erlbaum*

Another possible interpretation of this phenomenon is possible with the help of MART (Malleable Attentional Resources theory). MART states that task performance is assumed to vary as a function of mental workload, and so performance is optimal at an intermediate level of either mental workload or arousal. Applying this other theory to the driving behaviour, it is possible to notice that «*during mental underload situations, there is shrinkage of the attentional resource capacity to accommodate the reduction in task demands*»[45].

All these topics above discussed are useful for the understanding of both the Italian and the Norwegian experiments that will be shown in chapter 3 and chapter 4.

[45] Young, M., Stanton, N. (2002) "Malleable attentional resources theory: a new explanation for the effects of mental underload on performance." *Human Factors 44(3), 365–375.*

3. ITALIAN EXPERIMENTATION

3.1 Experiment description

3.1.1 Aims of the experiment

In order to analyze driving behaviour of a sample of users on an existing road, an experiment was conducted by using GPS technology. The chosen road is located in the territory of the municipality of Cassano delle Murge (Bari, Puglia, Italy), near the Mercadante Forest.

One of the main aims of the experiment is to find information about traffic risk perception, and to understand how this perception changes over time. In fact risk perception is a subjective variable, which depends not only on personal features and external inputs, but also on other factors like confidence in a given track. Considering that risk perception has an influence on speed choice, we decided to measure speed selected by users.

The sample of users was composed of twenty persons, whose gender, age and driving experience was completely known. We had precise enough data for nineteen out of twenty users (who are identified with the names from U001 to U019 from now on).

3.1.2 Layout description

Roads interested by GPS survey were named:

- Stretch of road 1, part of the country road S.P. 18, whose length is around 3 km,
- Stretch of road 2, part of the country road S.P. 31, whose length is around 4 km.

The first stretch of road has a nearly regular planimetry, instead it has an elevation profile characterized by steep slopes, gradient changes and counterslopes.

Instead the first part of the second stretch of road has a regular planimetry, including long straight roads spaced out with large radius curves and some intersections with less important roads. The latter end of the second stretch is characterized by two consecutive small radius curves. Definitively stretch 2 has got six straight roads and seven curves, three to the right and four to the left.

According to the Italian Functional Road Classification, these roads are categorized like "Local roads" due to several reasons: the subordinate role in the territory, the limited provided mobility (access to local areas) and the shortness of travel done by users of the roads under examination.
During the survey campaign we observed a low traffic volume and traffic composed of a few cars, heavy vehicles, tractors, bicycles and pedestrians. However, we have not a precise evaluation of the Average Annual Daily Traffic (AADT) for these roads.
Fixed speed limit is 70 km/h on both stretches.

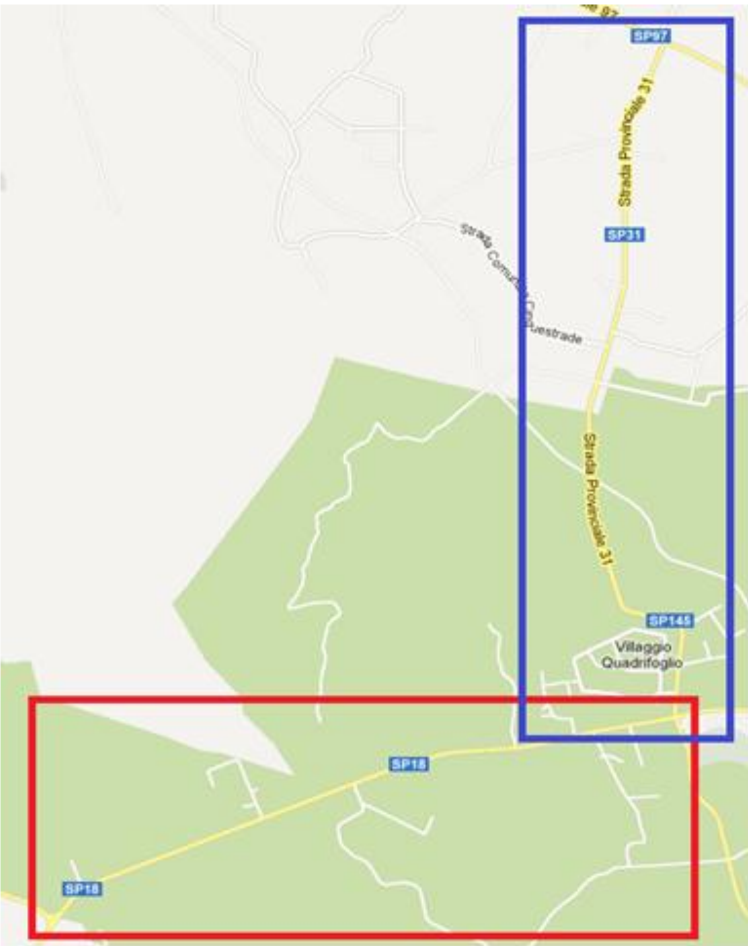


Fig. 3.3a (left): Localization of the two stretches of road (stretch 1 in red and stretch 2 in blue)

Fig. 3.1b (right): Orthophoto of the stretch 2 with items' identification (T = straight road, C = curve)

3.1.3 Employed instruments

In order to survey data we used the Differential Positioning GPS technology (Dynamic Method) that allows to orientate any point with respect to a fixed one, by calculating the baseline vector for the two points. That vector can be transformed into three parts with each part being directed along three perpendicular coordinate axes, with the aim of obtaining three-dimensional information. This way we were able to measure distance along every coordinate with an accuracy of a few millionth parts of the distance. That accuracy is better than the one derivable from the same measurement made with other standard geodetic surveys.

Two receivers were necessary to achieve the GPS Differential Positioning. Each of them was put into the baseline’s extremities and they worked during all the survey campaign. Thanks to this technology it was not necessary that the two receivers were always visible with one another.

The first receiver, the fixed one, was a TPS 1200 Master Leica antenna, composed of an adjustable height tripod and a GPS antenna on the tripod top. Once the tool was assembled, it was necessary to align the instrument with a survey point (a point which has highly accurate GPS coordinates) by using a viewfinder. Furthermore, in order to obtain an almost perfect horizontal system, it was necessary to adjust the bull’s eye level by using the dedicated screws. Finally we measured the height of the antenna above ground.

The second receiver, the movable one, was composed by a Rover antenna and a recorder. The antenna was placed on the car in order to guarantee visibility and functionality. The recorder, connected to a car battery, was located inside the car and it had the task to register the antenna position with respect to the fixed point (baseline) on a USB pen drive.

Fig. 3.2a (on the upper left): Master antenna above the survey point. Fig. 3.2b (on the right): Rover antenna on the car top. Fig. 3.2c (on the lower left): Rover receiver inside the car

3.2 Data collecting

3.2.1 Survey campaign

Users were recruited into Civil and Environmental Engineering classes of Politecnico of Bari. Users are between 22 and 27 years old, with a mean age of 25.32 (Std. Deviation = 2.85). Within the sample, 79 % are male drivers (15 out of 19) and 21 % are female drivers (4 out of 19).

After users had answered to a preliminary questionnaire concerning their driving behaviour (cf. Attachment II), then all of them made the driving test. Driving tests consisted in travelling along a route composed of the above mentioned two stretches of road in this order:

- Stretch 2, from the starting point (Start) to the intersection with stretch 1 – way there
- Stretch 1, from the intersection with stretch 2 to the end point (End) – way there
- Stretch 1, from the end point to the intersection with stretch 2 – way back
- Stretch 2, from the intersection with stretch 1 to the starting point again – way back

The total trip length is about 14 kilometers, from the Start to the Start again.

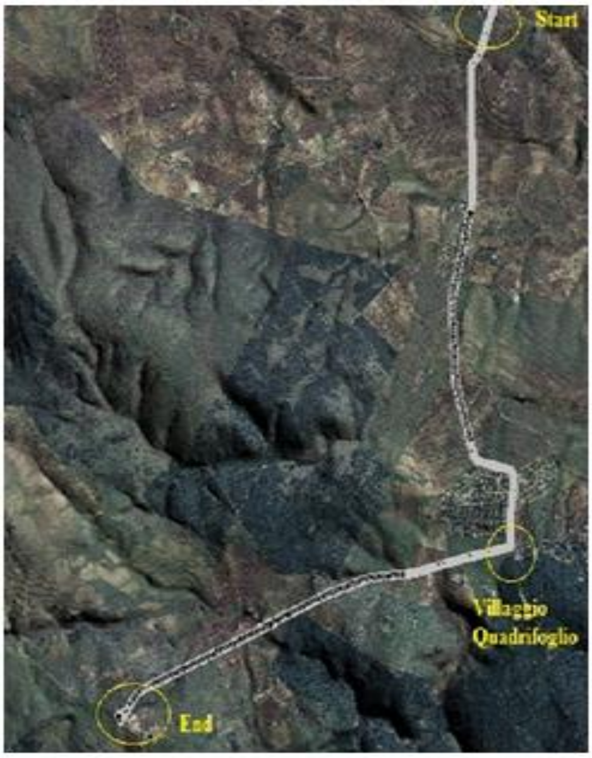


Fig. 3.3 – Road tests' route orthophoto

(In the previous picture Villaggio Quadrifoglio = Intersection between stretch 1 and stretch 2)

We said to every user that he was free to choose his speed according to his wishes. In this sense low traffic volume helped users to feel free to choose speed without any kind of conditioning. Furthermore, for the same reason, we chose to make tests only with good weather conditions and we asked users to drive their own cars.

In order to notice speed choice changing over time we collected data following this chronological schedule:

D1	D2	D3	D4						D5																	D6
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27

Tab. 3.1: Driving tests' chronological schedule for each user

Users had to repeat the same test six times, at the beginning four days in a row (test day 1 – D1, test day 2 – D2, test day 3 – D3, test day 4 – D4) and after these days they had to wait for the 10th day from the first one (test day 5 – D5) and finally for the 27th day from the first one (test day 6 – D6).
All driving tests were made between 28th March 2012 and 13th November 2012.

3.2.2 Obtained data

In order to collect data we used the software released by the company producing the GPS antenna: Leica Geo Office Combined. This software solves the GPS fundamental equation by using 3-point triangulation considering visible satellites, fixed antenna and Rover antenna. Thanks to this system, during the test, we obtained the exact positioning of each point by repeating measurement every second.
Given the fact that we achieved Cartesian coordinates, it is possible to calculate distances, planimetric elements and punctual speed, because we also knew travel time measures of every stretch of roads.
A diagram was drawn by putting punctual speed on the Y axis and space on the X axis for each user and each test.

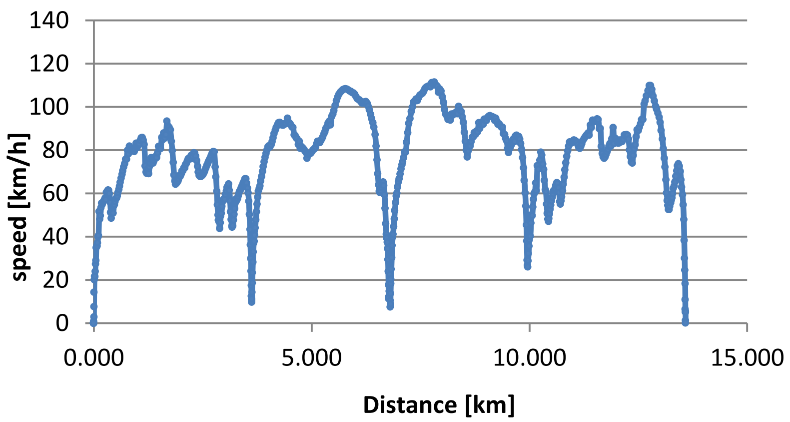


Fig. 3.4 – An example of a speed/distance diagram

3.3 Data processing

3.3.1 Data classification

We decided to analyze speed data set by road section type. We split road sections into subsets based on stopping sight distance calculated using the software Civil Design 8. The classification was made by stopping sight distance because it is a synthetic criterion that can be used to better identify driving behaviour, independently from the planimetric element in which the road section is located and from the driving direction.

We calculated stopping sight distance for 76 road sections of the stretch 1 and for 61 road sections of the stretch 2 and then we identified four road section categories:

- Low stopping sight distance road section "LS" (< 100 meters);
- Medium-low stopping sight distance road section "MLS" (100 – 200 meters);
- Medium stopping sight distance road section "MS" (200 – 400 meters);
- High stopping sight distance road section "HS" (400 – 600 meters).

After calculating the stopping sight distance for each road section, we obtained stopping sight distance diagrams for each stretch of road and for each driving direction.

Fig. 3.5a – Stopping sight distance diagram for stretch of road 1 (way there)

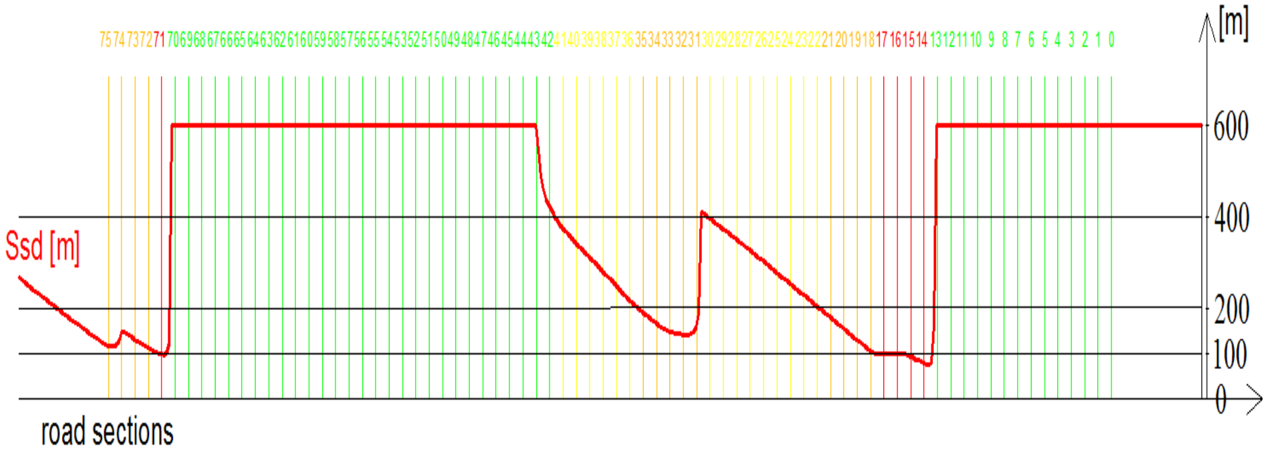


Fig. 3.5b – Stopping sight distance diagram for stretch of road 1 (way back)

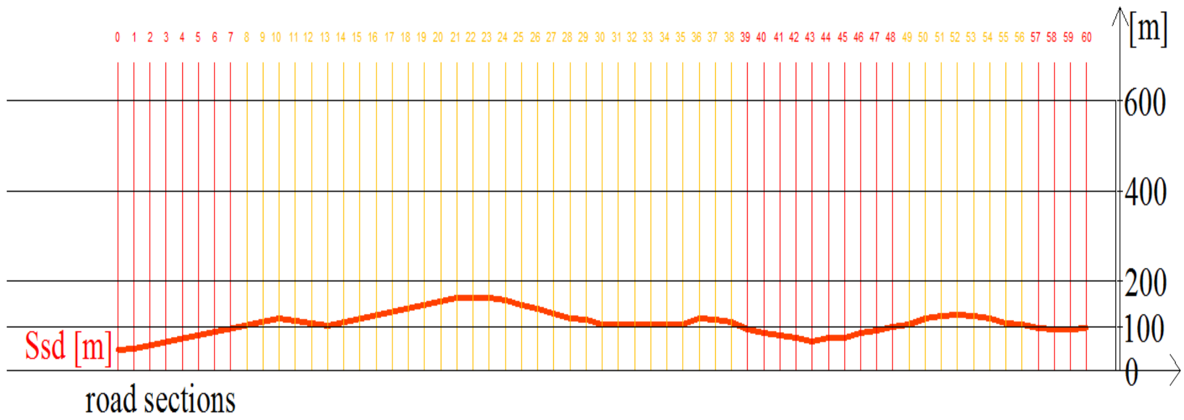


Fig. 3.5c – Stopping sight distance diagram for stretch of road 2 (way there)

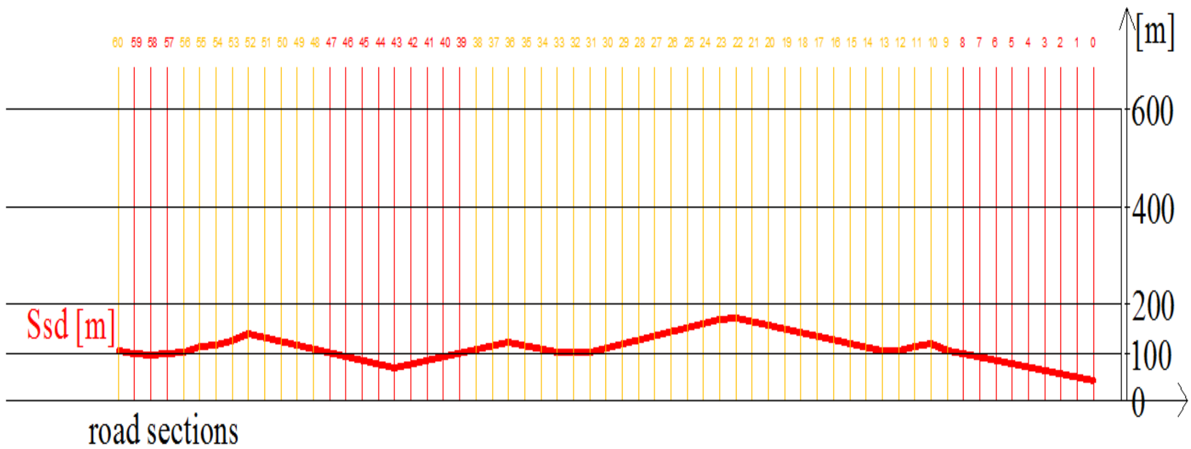


Fig. 3.5d – Stopping sight distance diagram for stretch of road 2 (way back)

It is possible to define the right category for each road section simply by reading these diagrams. In order to identify each section category we used the following color legend:

LS MLS MS HS

After classifying data, we obtained 53 LS, 110 MLS, 38 MS and 73 HS road sections.

3.3.2 Users classification

After data classification, we split users in three groups according to their risk inclination:

- Risky users;
- Prudent users;
- Users with variable behaviour (Variable).

In order to classify users, we calculated average speed of the 19 users for each section of every section category and for each test day. Here is an example of this calculation.

SPEED VALUES - DAY 1

		LOW STOPPING SIGHT DISTANCE ROAD SECTIONS											
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)		
	section	9	10	11	14	15	71	2	3	42	6	7	39
	U01	53	69	53	54	51	55	52	60	67	55	50	56
	U02	60	63	65	57	53	64	51	63	70	67	64	66
	U03	62	52	68	69	58	70	60	70	52	68	70	59
USERS	U04	54	62	55	67	60	53	60	51	54	67	66	61
	U05	59	52	68	67	55	58	66	67	59	51	55	57
	U06	56	52	70	50	63	68	63	50	60	64	52	70
	U07	65	63	61	54	51	62	63	53	66	66	70	68

U08	62	61	58	57	58	55	51	52	58	61	51	67
U09	63	64	50	65	52	52	60	67	64	51	55	58
U10	65	65	55	69	63	52	53	52	65	55	66	51
U11	50	70	50	50	52	62	54	67	65	65	67	70
U12	67	52	52	51	70	55	65	69	66	69	50	64
U13	54	59	53	69	70	50	51	59	59	64	60	55
U14	62	51	52	63	67	53	54	69	58	69	60	64
U15	63	64	53	62	68	62	53	64	53	50	51	52
U16	63	53	58	67	68	65	56	61	53	52	57	59
U17	63	50	59	55	68	70	63	54	62	70	65	62
U18	57	59	51	51	61	65	69	55	51	52	70	67
U19	51	56	59	57	54	69	65	54	55	65	67	56
section-related average speed	59.4	58.8	57.4	59.7	60.1	60	58.4	59.8	59.8	61.1	60.3	61.2

Fig. 3.6 – An example of average speed calculation (test day 1, low stopping sight distance road sections)

Calculation made in the example had to be repeated for every test day and for every section category.

After this calculation, we computed for each section and for each test day the difference of each user speed values from the average speed, as shown below in the example.

DIFFERENCE FROM AVERAGE SPEED VALUES - DAY 1

	LOW STOPPING SIGHT DISTANCE ROAD SECTIONS											
	stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)		
section	9	10	11	14	15	71	2	3	42	6	7	39

	U01	-9.84	2	-8.79	0.58	6.74	4.79	5.68	0.95	-0.58	3.63	-9	0.37
	U02	-2.84	-2	4.21	2.58	-5.26	-1.21	5.68	5.95	-7.58	1.63	-1	3.37
	U03	-3.84	6	-8.79	-5.42	-5.26	6.79	-9.32	-6.05	-1.58	7.63	-9	3.37
	U04	1.16	0	9.21	-8.42	-6.26	0.79	-3.32	-6.05	1.42	-5.37	10	7.37
	U05	-5.84	-7	8.21	-4.42	0.74	-7.21	-5.32	-0.05	2.42	-9.37	0	-1.63
	U06	9.16	6	-6.79	0.58	4.74	5.79	10.7	2.95	-7.58	6.63	6	-4.63
	U07	8.16	-2	9.21	2.58	5.74	5.79	8.68	-10.1	2.42	6.63	5	3.37
	U08	-0.84	-7	-8.79	-2.42	-8.26	-3.21	9.68	-4.05	-7.58	1.63	-6	8.37
	U09	-5.84	6	9.21	-6.42	-5.26	2.79	-0.32	-5.05	11.4	0.63	1	-2.63
USERS	U10	2.16	-9	-7.79	4.58	4.74	1.79	-3.32	0.95	11.4	2.63	7	-5.63
	U11	-0.84	-8	-10.8	2.58	6.74	-10.2	-5.32	5.95	-4.58	-5.37	0	1.37
	U12	8.16	0	1.21	-8.42	2.74	-5.21	-4.32	-6.05	-5.58	-9.37	-2	4.37
	U13	-4.84	10	-5.79	7.58	-4.26	0.79	-4.32	7.95	1.42	-2.37	7	-4.63
	U14	3.16	-3	5.21	7.58	-9.26	2.79	5.68	2.95	-4.58	-2.37	1	1.37
	U15	1.16	11	9.21	6.58	-1.26	-1.21	-9.32	-1.05	3.42	-0.37	2	0.37
	U16	1.16	3	4.21	-5.42	9.74	1.79	-5.32	3.95	5.42	-8.37	-2	-8.63
	U17	-2.84	-4	-8.79	-0.42	0.74	-10.2	7.68	-5.05	-4.58	1.63	5	-3.63
	U18	2.16	-9	3.21	2.58	9.74	0.79	0.68	5.95	8.42	3.63	-8	-3.63
	U19	1.16	7	3.21	3.58	-7.26	3.79	-4.32	5.95	-3.58	6.63	-7	1.37
	maximum difference (absolute value)	9.84	11	10.8	8.42	9.74	10.2	10.7	10.1	11.4	9.37	10	8.63

Fig. 3.7 – An example of difference from average speed values calculation (test day 1, low stopping sight distance road sections)

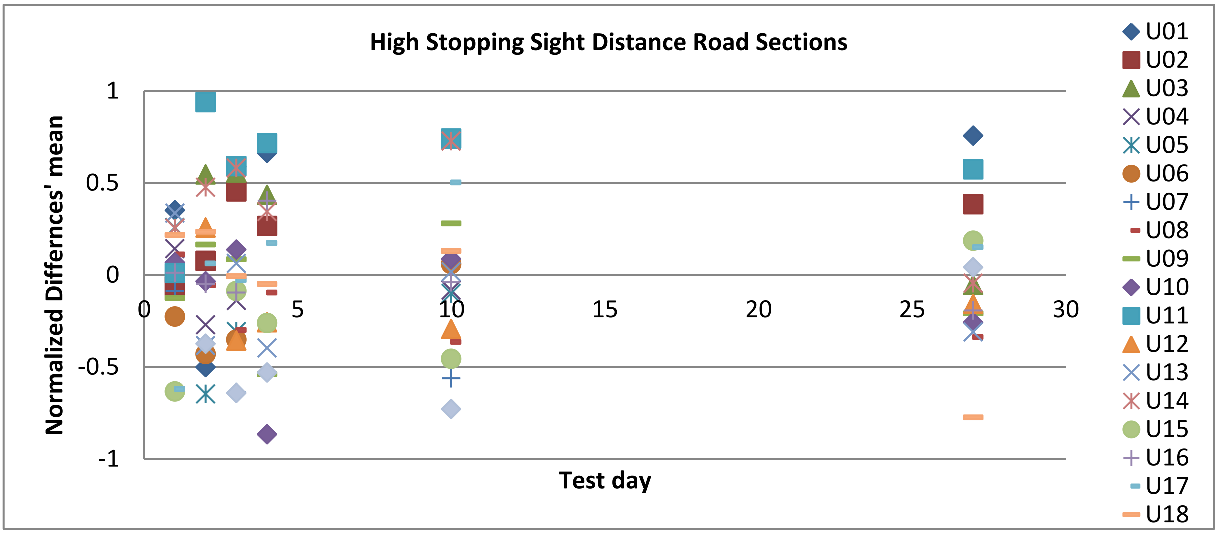
After this, for each section of every category and for each test day, we calculated the normalized to unity difference from the average speed, by dividing each difference in the above mentioned table by the section-related maximum difference (absolute value). Finally, we computed for every user the mean of the normalized differences, for each section category and for each test day, as shown in the example below.

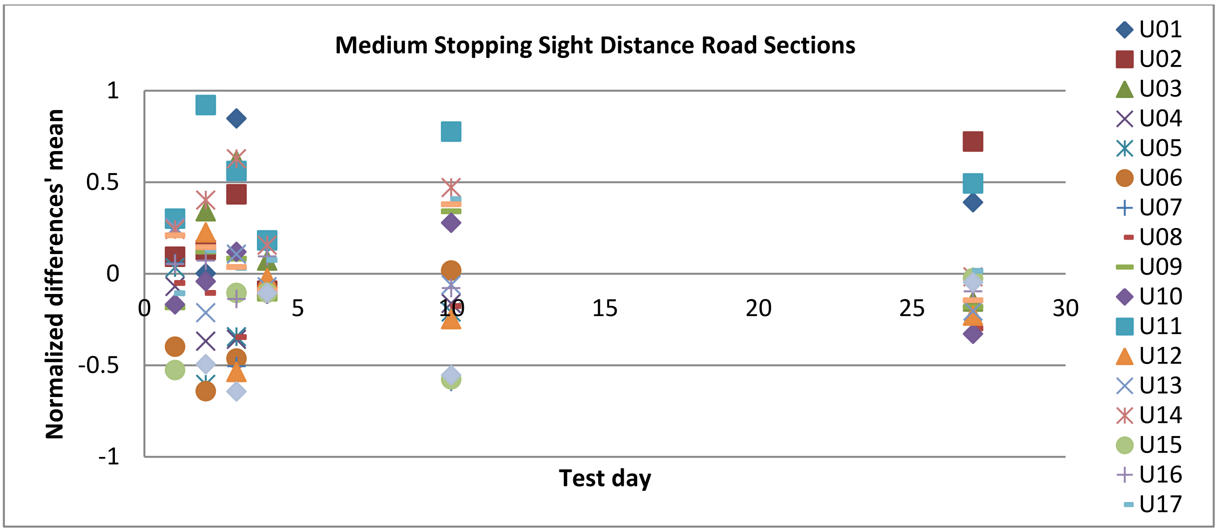
NORMALIZED TO UNITY DIFFERENCES FROM AVERAGE SPEED VALUES - DAY 1

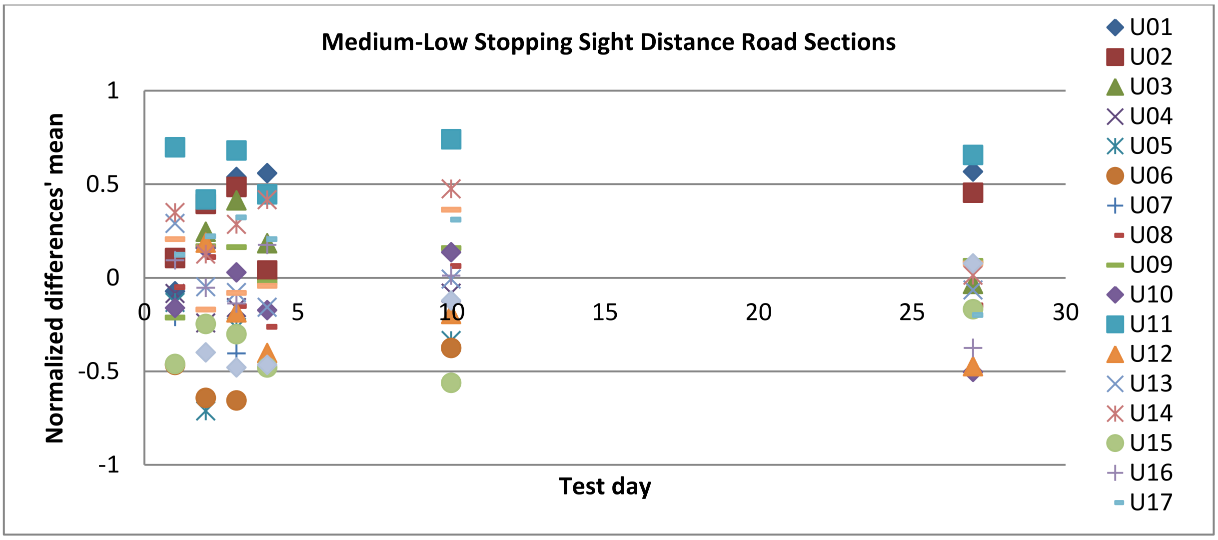
		LOW STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			Mean of the normalized differences
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	-1	0.18	-0.81	0.07	0.69	0.47	0.53	0.09	-0.05	0.39	-0.9	0.04	-0.0248
	U02	-0.29	-0.18	0.39	0.31	-0.54	-0.12	0.53	0.59	-0.66	0.17	-0.1	0.39	0.0409
	U03	-0.39	0.55	-0.81	-0.64	-0.54	0.66	-0.87	-0.6	-0.14	0.81	-0.9	0.39	-0.2072
	U04	0.12	0	0.85	-1	-0.64	0.08	-0.31	-0.6	0.12	-0.57	1	0.85	-0.0085
	U05	-0.59	-0.64	0.76	-0.53	0.08	-0.71	-0.5	-0.01	0.21	-1	0	-0.19	-0.2587
	U06	0.93	0.55	-0.63	0.07	0.49	0.57	1	0.29	-0.66	0.71	0.6	-0.54	0.2808
	U07	0.83	-0.18	0.85	0.31	0.59	0.57	0.81	-1	0.21	0.71	0.5	0.39	0.3822
	U08	-0.09	-0.64	-0.81	-0.29	-0.85	-0.31	0.91	-0.4	-0.66	0.17	-0.6	0.97	-0.2170
	U09	-0.59	0.55	0.85	-0.76	-0.54	0.27	-0.03	-0.5	1	0.07	0.1	-0.3	0.0088
	U10	0.22	-0.82	-0.72	0.54	0.49	0.18	-0.31	0.09	1	0.28	0.7	-0.65	0.0831
	U11	-0.09	-0.73	-1	0.31	0.69	-1	-0.5	0.59	-0.4	-0.57	0	0.16	-0.2113
	U12	0.83	0	0.11	-1	0.28	-0.51	-0.4	-0.6	-0.49	-1	-0.2	0.51	-0.2064
	U13	-0.49	0.91	-0.54	0.9	-0.44	0.08	-0.4	0.79	0.12	-0.25	0.7	-0.54	0.0701
	U14	0.32	-0.27	0.48	0.9	-0.95	0.27	0.53	0.29	-0.4	-0.25	0.1	0.16	0.0986
	U15	0.12	1	0.85	0.78	-0.13	-0.12	-0.87	-0.1	0.3	-0.04	0.2	0.04	0.1692
	U16	0.12	0.27	0.39	-0.64	1	0.18	-0.5	0.39	0.47	-0.89	-0.2	-1	-0.0343
	U17	-0.29	-0.36	-0.81	-0.05	0.08	-1	0.72	-0.5	-0.4	0.17	0.5	-0.42	-0.1977
	U18	0.22	-0.82	0.3	0.31	1	0.08	0.06	0.59	0.74	0.39	-0.8	-0.42	0.1368
	U19	0.12	0.64	0.3	0.43	-0.75	0.37	-0.4	0.59	-0.31	0.71	-0.7	0.16	0.0952

Fig. 3.8 – An example of calculation of users' mean of normalized differences (day test 1, low stopping sight distance road sections)

Afterwards it was possible to draw diagrams for each section category, putting normalized differences' mean values computed for each user on the y-axis (values achieved on the far right column in figures 3.8) and test day on the x-axis.


High Stopping Sight Distance Road Sections
Normalized Differnces' mean
1
0.5
0
-0.5
-1
0
5
10
15
20
25
30
Test day
U01
U02
U03
U04
U05
U06
U07
U08
U09
U10
U11
U12
U13
U14
U15
U16
U17
U18


Medium Stopping Sight Distance Road Sections
Normalized differences' mean
1
0.5
0
-0.5
-1
0
5
10
15
20
25
30
Test day
U01
U02
U03
U04
U05
U06
U07
U08
U09
U10
U11
U12
U13
U14
U15
U16
U17


Medium-Low Stopping Sight Distance Road Sections
Normalized differences' mean
1
0.5
0
-0.5
-1
0
5
10
15
20
25
30
Test day
U01
U02
U03
U04
U05
U06
U07
U08
U09
U10
U11
U12
U13
U14
U15
U16
U17

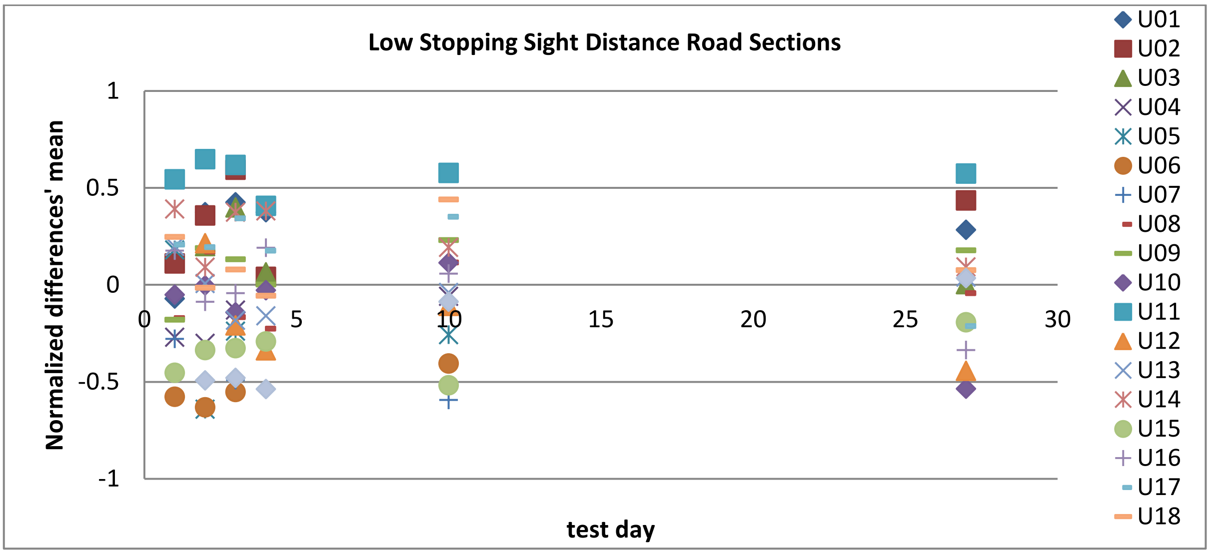


Fig. 3.9a, b, c, d – Normalized mean of the differences/test day diagrams for each section category

We defined users' categories reading these diagrams by using the following rules:

- Risky users, if their normalized mean of the differences were positive (speeds higher than the mean) in at least five out of the six test days;
- Prudent users, if their normalized mean of the differences were negative (speeds lower than the mean) in at least five out of the six test days;
- Variable users, if it was not possible to identify an unambiguous behaviour during all the test days, because of many fluctuations around the zero value.

At the end of this procedure, we obtained number of users for each section category and each risk category.

SECTION CATEGORY	NUMBER OF RISKY USERS	NUMBER OF PRUDENT USERS	NUMBER OF VARIABLE USERS
LS	8	8	3
MLS	7	8	4
MS	6	8	5
HS	6	8	5

Tab. 3.2 –Summarizing table of the categories

3.3.3 Data elaboration

After data classification, we calculated average speed for each section category and for each test day, separating data into the three risk categories, as shown in the example below.

AVERAGE SPEED - RISKY USERS

		TEST DAY 1												
		HIGH STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	56	62	70	63	51	64	64	53	68	57	54	50	
	U02	66	63	57	64	66	64	59	54	59	62	62	51	
	U03	51	64	62	58	67	70	63	57	53	50	58	54	
	U11	63	50	68	56	59	58	52	51	58	55	57	62	
	U14	60	52	70	64	53	59	58	50	70	67	53	51	
	U17	51	67	57	50	56	61	55	66	63	60	59	63	HS - risky users' average speed – day 1
	section average speed	57.8	59.7	64	59.2	58.7	62.7	58.5	55.2	61.8	58.5	57.2	55.2	59.03

		TEST DAY 2												
		HIGH STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	58	51	68	56	62	51	51	65	67	65	58	53	
	U02	69	59	59	57	58	53	70	56	62	68	60	69	
	U03	55	51	56	57	55	59	70	53	50	52	65	69	
	U11	51	60	58	51	70	55	52	59	60	56	58	56	
	U14	53	64	54	57	67	67	54	61	51	53	58	59	
	U17	55	63	64	63	55	63	68	68	66	53	52	69	HS - risky users average speed – day 2
	section average speed	56.8	58	59.8	56.8	61.2	58	60.8	60.3	59.3	57.8	58.5	62.5	59.17

		TEST DAY 3												
		HIGH STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	57	57	63	66	67	64	58	56	52	52	68	58	
	U02	56	51	51	57	64	54	68	68	64	55	61	65	
	U03	60	52	60	66	66	60	50	65	59	64	59	68	
	U11	52	54	53	58	50	56	50	57	67	51	56	65	
	U14	61	54	62	60	62	53	62	56	58	68	57	65	
	U17	53	68	68	56	55	50	62	53	55	52	64	66	HS - risky users average speed – day 3
	section average speed	56.5	56	59.5	60.5	60.7	56.2	58.3	59.2	59.2	57	60.8	64.5	59.03

		TEST DAY 4												
		HIGH STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	57	53	51	58	53	61	50	59	55	64	55	56	
	U02	67	53	57	52	53	53	54	54	58	55	56	59	
	U03	55	52	62	54	63	60	70	70	62	61	69	70	
	U11	65	63	65	51	67	52	66	67	58	69	62	54	
	U14	62	64	61	58	66	58	70	66	61	61	67	64	
	U17	57	58	50	54	53	69	52	61	66	66	64	57	HS - risky users average speed – day 4
	section average speed	60.5	57.2	57.7	54.5	59.2	58.8	60.3	62.8	60	62.7	62.2	60	59.65

		TEST DAY 5												
		HIGH STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	70	52	51	54	56	54	58	67	53	66	51	63	
	U02	52	69	65	53	50	69	53	70	59	62	50	52	
	U03	61	53	60	65	66	59	54	58	70	65	52	70	
	U11	70	65	67	62	64	67	62	61	56	51	69	56	
	U14	70	61	67	59	58	50	60	61	53	67	53	63	
	U17	63	52	56	70	68	54	59	57	69	64	53	70	HS - risky users average speed – day 5
	section average speed	64.3	58.7	61	60.5	60.3	58.8	57.7	62.3	60	62.5	54.7	62.3	60.26

		TEST DAY 6												
		HIGH STOPPING SIGHT DISTANCE ROAD SECTIONS												
		stretch 1 (way there)			stretch 1 (way back)			stretch 2 (way there)			stretch 2 (way back)			
	section	9	10	11	14	15	71	2	3	42	6	7	39	
USERS	U01	64	60	58	62	50	52	61	54	63	64	63	63	
	U02	68	52	63	64	63	51	52	67	53	60	63	52	
	U03	68	68	56	64	68	60	59	64	58	58	69	56	
	U11	61	55	58	54	69	60	56	60	67	55	64	65	
	U14	62	55	65	59	64	64	62	57	50	68	51	53	
	U17	62	52	53	57	58	58	51	54	54	50	59	57	HS - risky users average speed – day 6
	section average speed	64.2	57	58.8	60	62	57.5	56.8	59.3	57.5	59.2	61.5	57.7	59.29

Fig. 3.10a, b, c, d, e, f – An example of calculation of average speed in each test day (high stopping sight distance – risky users)

Calculation made in the example had to be repeated for every section category and for every risk category.

After this calculation it was possible to draw average speed/day test diagrams for each section category, considering three different data sets for the three risk categories and vice versa.

On the next page there are the four diagrams obtained by splitting data into section categories, and after the three ones obtained by splitting data into risk categories.

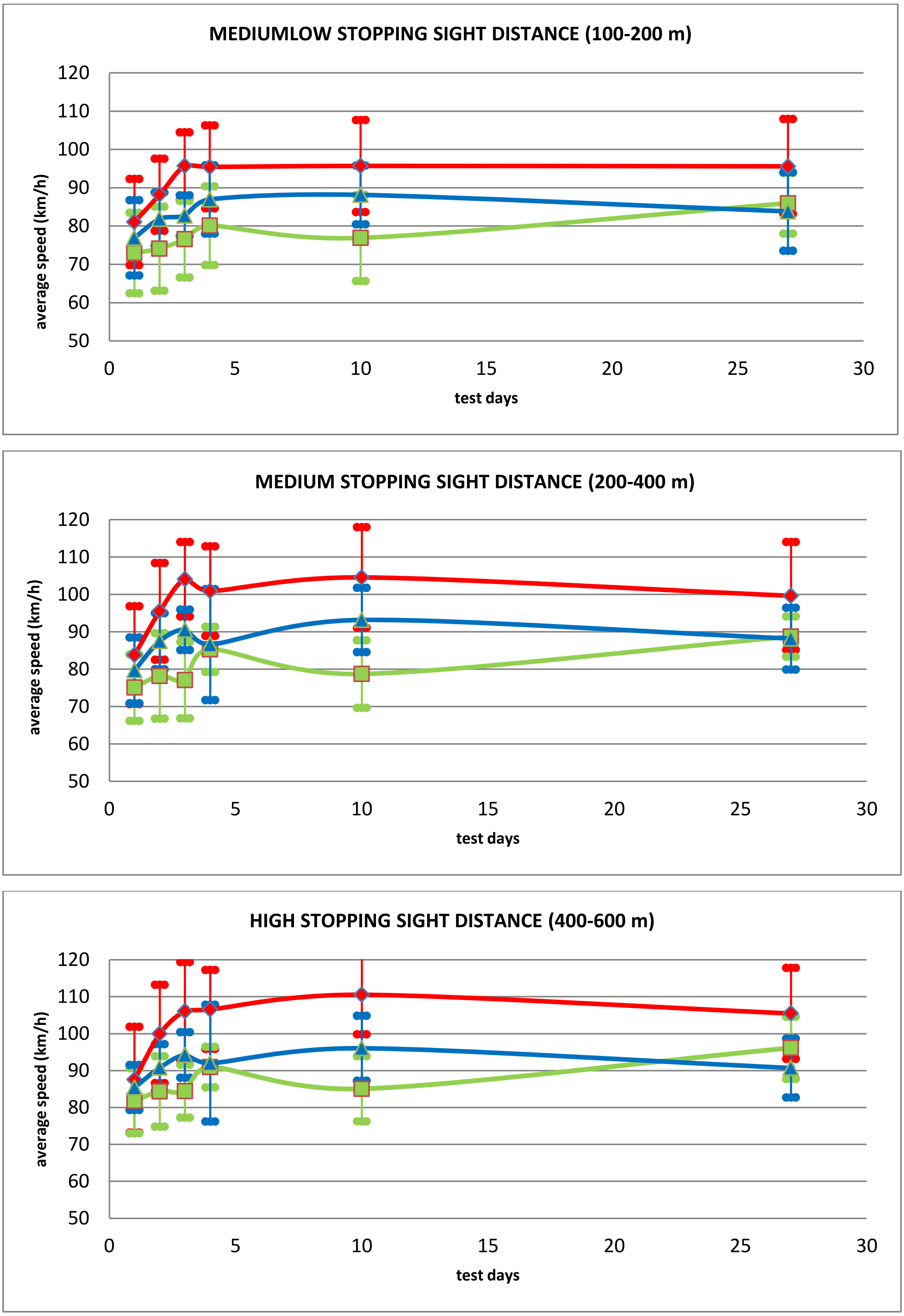


Fig. 3.11a, b, c, d – Average speed-test day diagrams, differentiated by section category

COLOR LEGEND:

risky users variable users prudent users

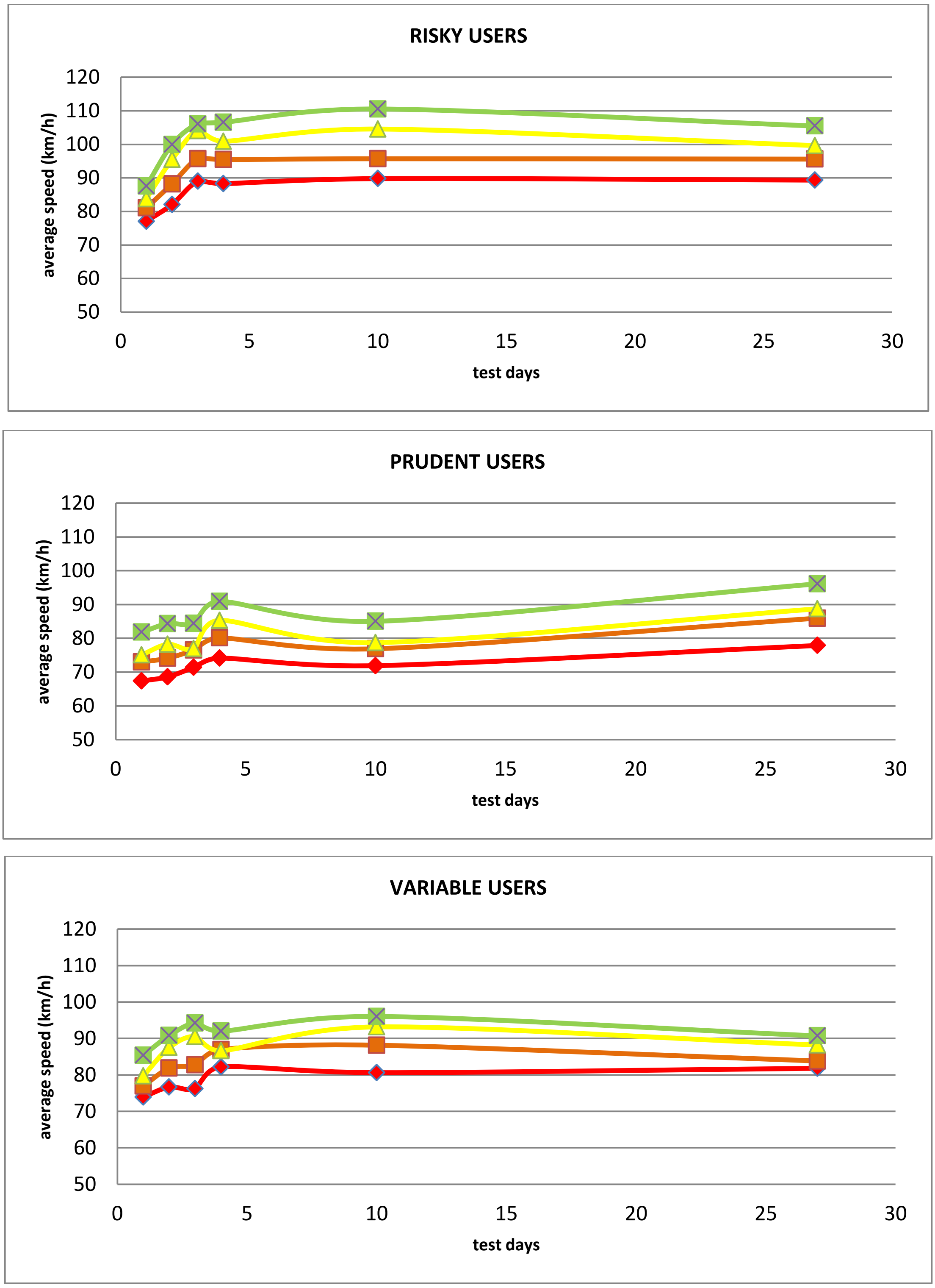


Fig. 3.12a, b, c – Average speed/test day diagrams, differentiated by risk category

COLOR LEGEND:

LS MLS MS HS

After calculating average speed, we computed speed standard deviation considering all users together (without differentiating them for risk category), for each test day and each section category.

After this calculation it was possible to draw speed standard deviation/test day diagrams for each section category. We put the four curves on one diagram, which is given below.

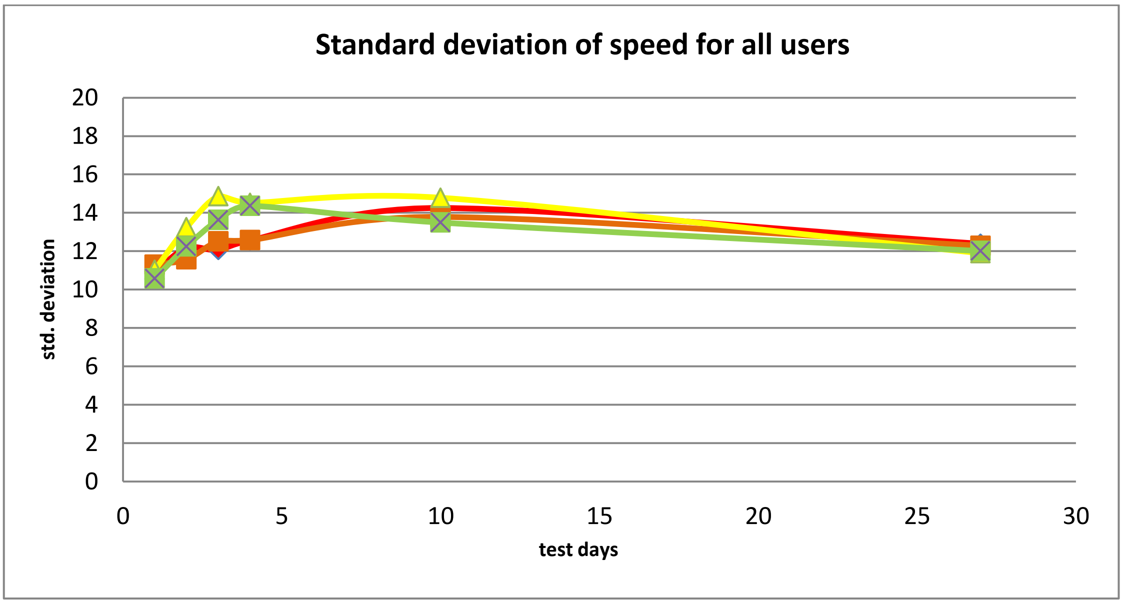


Fig. 3.13– Speed standard deviation/test day diagram

COLOR LEGEND:

LS MLS MS HS

For the first four test days, we noticed that average speed-test day diagrams had an almost straight trend. For this reason we calculated gradient of that line for prudent users and for the risky ones.

From now on, in other diagrams and in the comparison chapter (cf. chapter 5), I will consider only prudent and risky users, because variable users could be seen better as people that can't be classified by risk, due to their changing behaviour over time, than as a specific risk category by itself. In fact, when I divided drivers into risk categories, I stated that it was not possible to identify an unambiguous behaviour during all the test days for variable users, because of many fluctuations of speed around mean value.

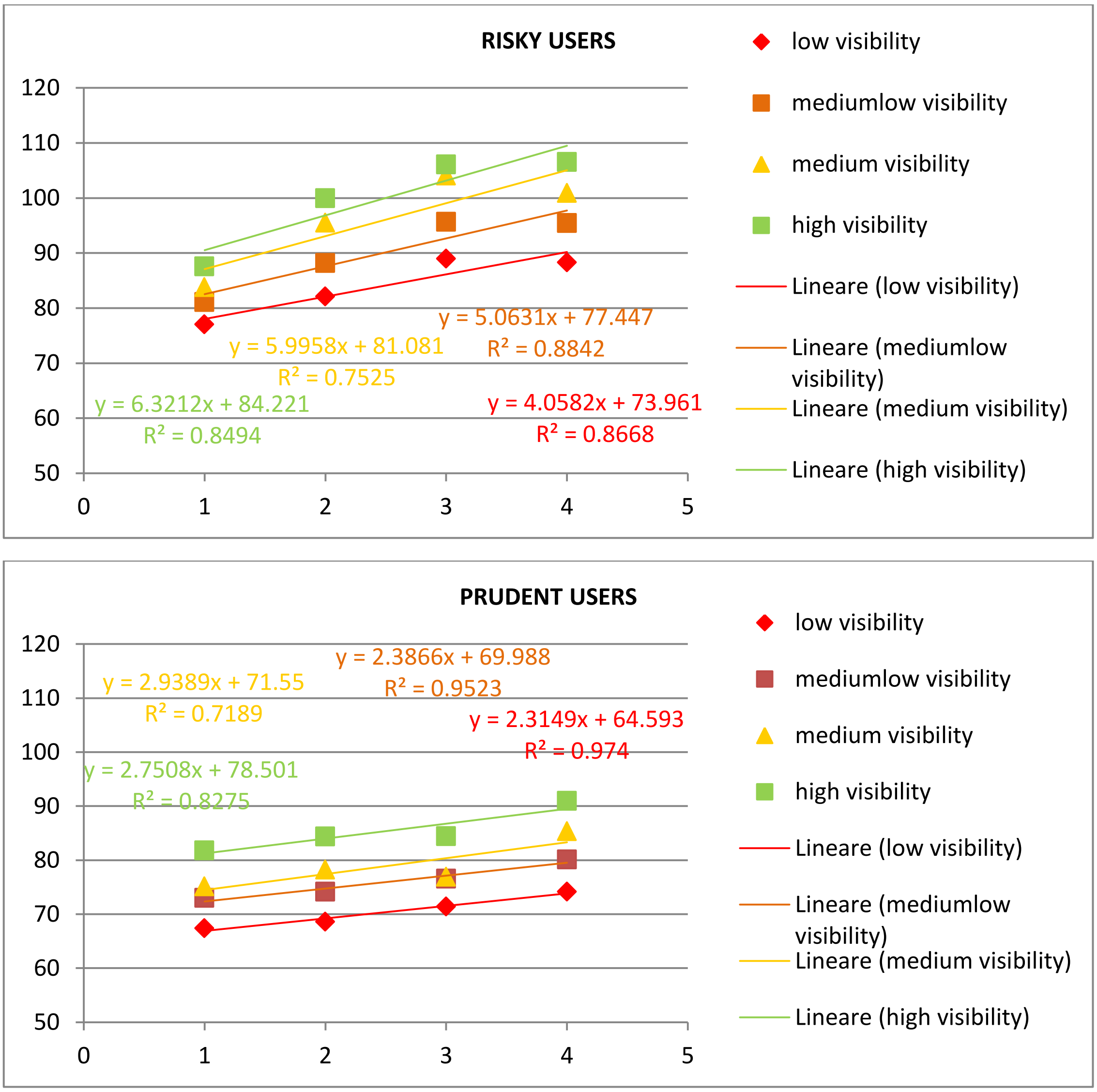
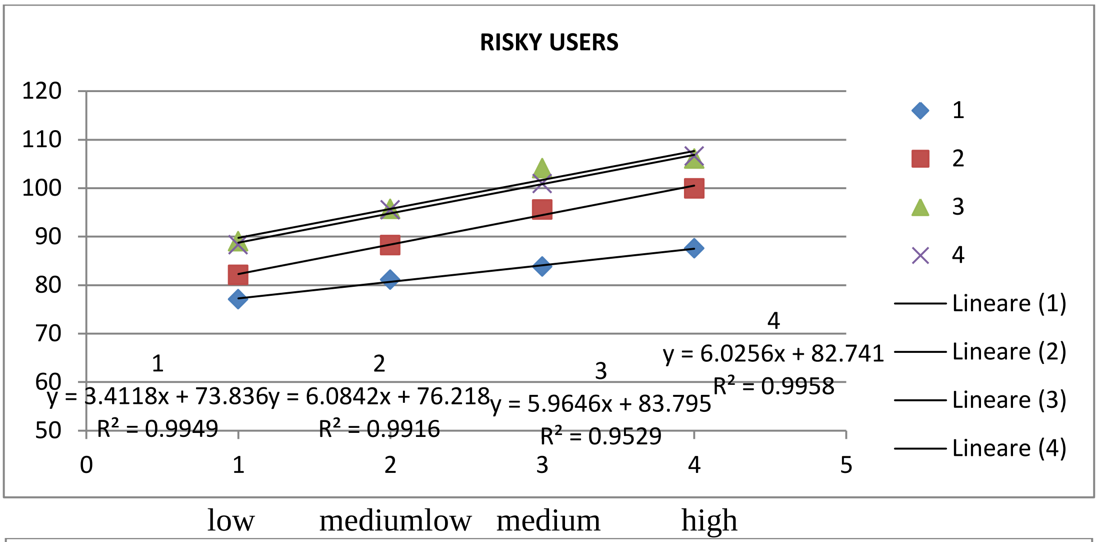


Fig. 3.14a, b – Linear speed trends for each visibility class in the first four days (average speed/first four test days diagrams)

	STOPPING SIGHT DISTANCE CLASS			
	LOW	MEDIUM-LOW	MEDIUM	HIGH
RISKY USERS	4.06	5.06	6.00	6.32
PRUDENT USERS	2.31	2.39	2.94	2.75

Tab. 3.3 – gradient values a=△v/△t, related to the fictitious line derivable from the average speed/first four test days diagram, for each risk class and each visibility class

Furthermore, in order to clarify the relation between visibility classes, speed and risk classes, we drew a diagram (with speed on the y-axis and visibility class on the x-axis) by using speed data in the first four days.



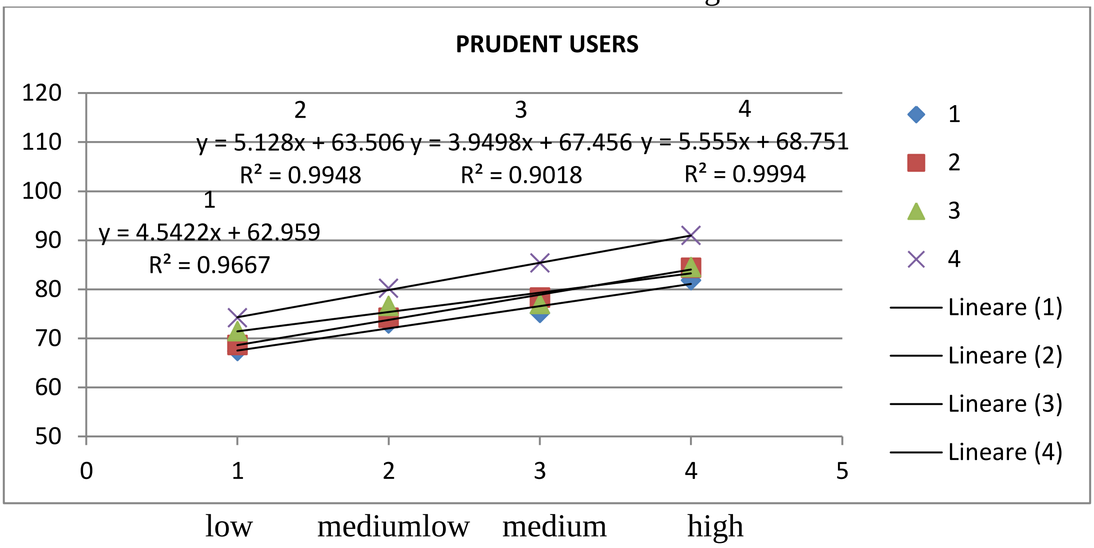
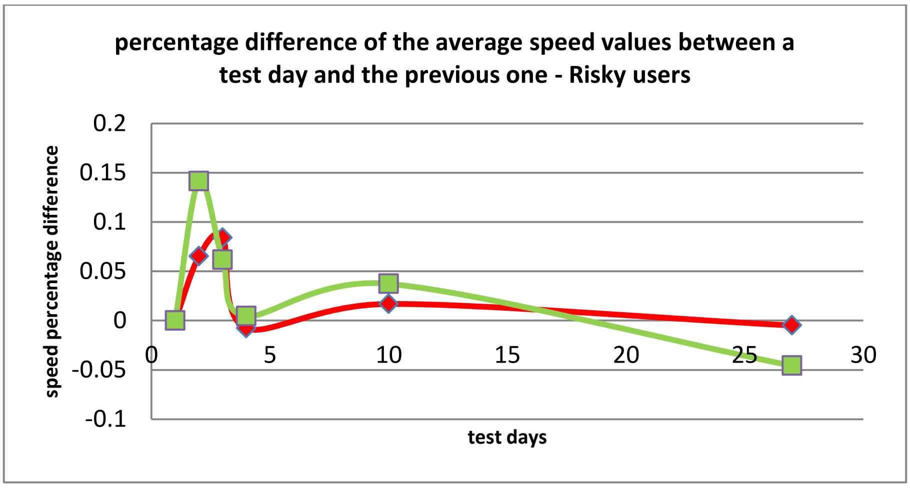


Fig. 3.15a, b – Linear speed trends for each day in the first four days (average speed/visibility class diagrams)

	DAY			
	1	**2**	**3**	**4**
RISKY USERS	3.41	6.08	5.96	6.03
PRUDENT USERS	4.54	5.13	3.95	5.56

Tab. 3.4 – gradient values, related to the fictitious line derivable from the average speed/visibility class diagram, for each risk class and each visibility class

In the end, we computed the percentage difference of the average speed between a test day and the previous one. Percentage difference of speed-test day diagrams for prudent users and for the risky ones, considering the extreme categories of stopping sight distance (low and high) are given below.



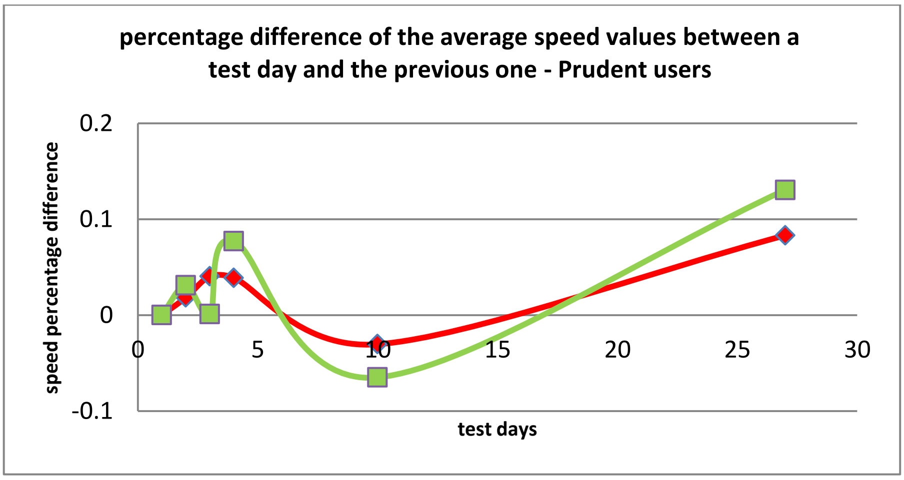
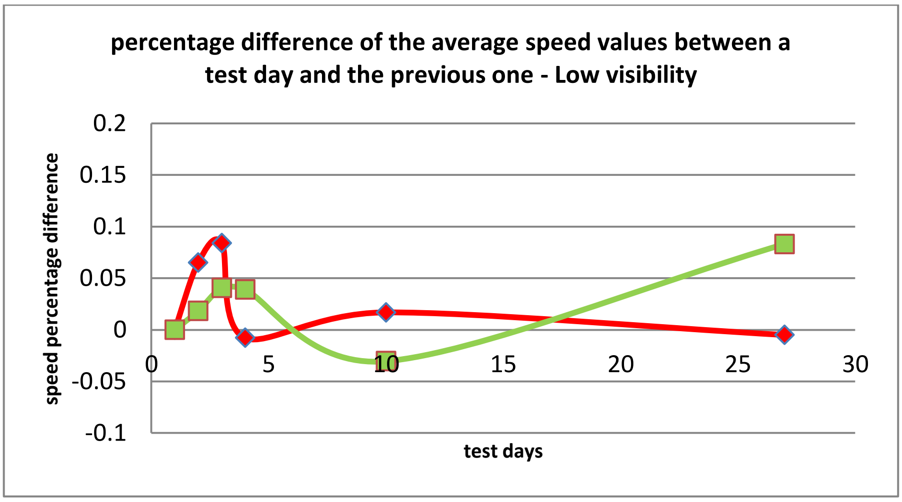


Fig. 3.16 – Speed percentage difference/test day diagrams, differentiated by risk category

COLOR LEGEND:

LS HS



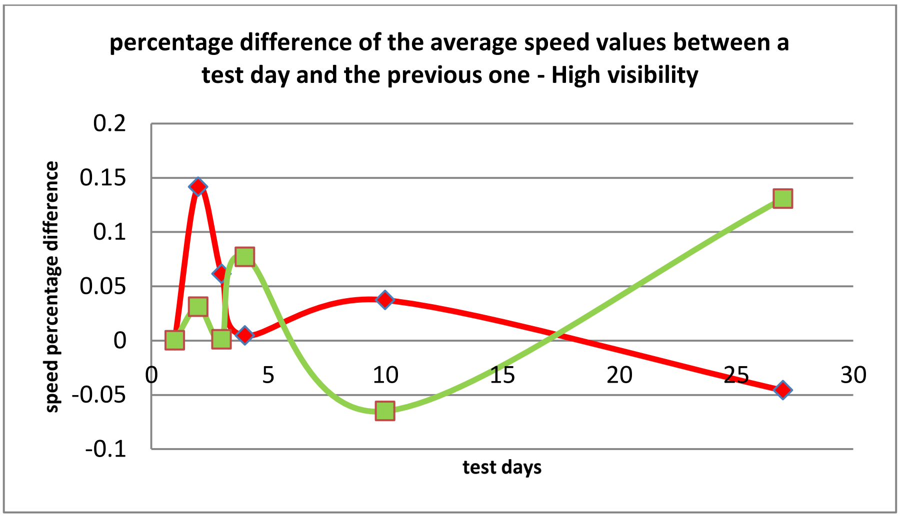


Fig. 3.17 – Speed percentage difference/test day diagrams, differentiated by section category

COLOR LEGEND:

Risky users Prudent users

3.4 Discussion

Analyzing speed diagrams, it is possible to notice a nearly uniform speed trend during the six test days, in particular for prudent users and the risky ones.

Although average speed diagrams have similar shape for each risk category, average speeds increase of about 5 km/h by going from curves obtained for lower sight road sections to the curves obtained for the higher ones. Furthermore, average speeds increase of a value between 5 km/h and 20 km/h by going form curves obtained for prudent users to the curves obtained for the risky ones.

In particular, diagrams 3.15a and 3.15b clearly show the increase of speed from low visibility sections to the highest ones. This increasing trend is almost perfectly linear; in fact R^2 values are always greater than 0.9 on each of the first four days. This finding shows that the choice of clustering sections according to visibility is truly appropriate in order to study speed choice. In fact, as shown, visibility has a very direct effect on speed choice, in different ways according to the different risk categories.

In the first four days, for every risk category and for every section category, it is possible to perceive a speed growing tendency. Instead in the 5^{th} test day we can observe the maximum difference between risky users' behaviour and prudent users' behaviour. In fact in the 5^{th} day test, risky users travelled on average at the same speed or faster than the previous test day, whereas prudent users drove slower than the previous test day. On the other hand in the 6^{th} test day difference between opposite behaviour categories is little again. In fact risky users drove on average at the same speed of the two previous test days, whereas prudent users travelled faster (about 10 km/h more for each section category) than the 5^{th} test day.

Tendency of the average speed/test day diagrams could be simplified, to a good approximation, as follows:

- growing linear trend on the first four days and constant trend on the other days for risky users;
- growing linear trend on the first four days (with a smaller slope) and a concave up parabolic trend on the other days for prudent users.

In particular, line drawn for the first four days fits very well speed data, both for risky users and for the prudent ones. In fact R-squared values found for those lines are always greater than 0.7.

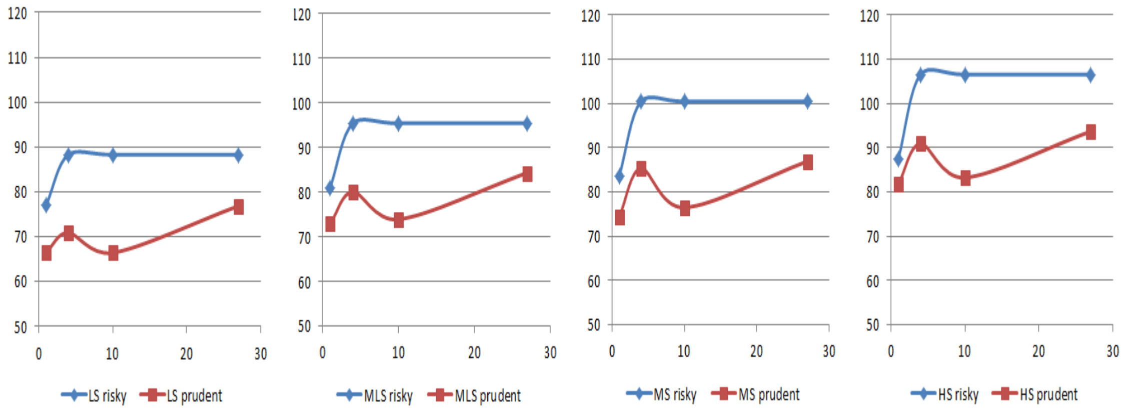


Fig. 3.18 –Speed adaptation trends

Given that in the 6th test day, trends of opposite behaviours converge, the curve of risky users seems to be the asymptote of the curve of prudent users.

We can confirm the above statements by analyzing standard deviation diagrams. In fact we notice lowest standard deviation values on 1st test day, on which it is also possible to perceive similar SD values for each section category. After the first test day, standard deviation starts to increase and it gets the maximum on the 3rd or 4th day for high and medium visibility sections and on the 5th day for medium-low and low visibility sections. In fact in these days there is the maximum variability, as though we could read on average speed diagrams. Finally on the 6th test day, variability decreases again.

3.5 Conclusions

Considering what we have shown up to this point, we can try to draw a conclusion about the evolution over time of the confidence on a given road both for risky users and for the prudent ones.

The speed growing tendency noticed on the first four days reveals that a better confidence on a given road leads up to a speed increasing for all users. This growing tendency is more evident for risky users. In fact, average speed/test day diagrams show higher slopes for the fictitious line that fits the first four test days for risky users. This slope value could represent a type of “short-term learning parameter of efficiency” that is higher for risky users and it can vary a little with changing in stopping sight distance (very similar a-values for the four section categories). This fact should mean that the slope value could represent an index of the inner risk perception, only lightly dependent from the road.

However, more in detail, it is possible to appreciate that in the short term, road differences are understood by risky users more quickly than by the prudent ones. This sentence is evidently proved by looking at the diagrams 3.15a and 3.15b: risky users' speed/visibility slope increases already on the second day, while prudent users' slope clearly increases only on the fourth day.

Instead, we can look into the mix between short-term and long-term learning, by analyzing data of the 5^{th} and the 6^{th} test day. Studying the results, it seems that risky users became soon confident in the road, trusting in their short-term learning. Risky users keep this confidence until the last test day, showing an efficient transformation of short-term learning in long term learning. Instead, it seems that prudent users need to test again the route on the 5^{th} test day. This fact could mean that they have lost part of their confidence and that there was an inefficient transformation from their short term-learning to long-term learning. In fact they become confident in the road only after a long time. All this could be related to the analysis of the $\triangle$v (in respect to the previous day)/test day diagrams. In fact, in those diagrams we could notice different tendencies of the $\triangle$ depending on risk category, especially for high stopping sight distance road sections, in which speed is chosen with the maximum number of degrees of freedom. This fact could mean that $\triangle$v might represent an index of the internalization of the external risk during the process that makes users confident in the road.

It is possible to read these results from a psychological point of view. In fact, according to the habituation theory discussed in paragraphs 2.7.1 and 2.7.2, we could use speed measurements as a response parameter and test days as a trial parameter. After a lot of trials, response decreases due to the habituation effect. If we use speed as a response parameter, than a decreasing in response will correspond to an increasing in speed. Basically, this conclusion is possible because speed increases if the risk perception is lower and a decreasing in response is connectable to a decreasing in risk perception. Therefore, it could be noted an evident habituation effect that leads up to a continuous increasing of speed (decreasing in response) over time. However, there is a remarkable difference between risky users and the prudent ones, because it seems that, after four test days, the habituation process is concluded only for risky users. In fact, after the fourth test day, they show an almost constant speed value over time, even if inputs are not given every day. Instead, a dishabituation effect occurs in prudent users in the fifth test day, probably due to their different risk perception. However, it seems that the habituation effect starts again after the fifth test day, because in the sixth test day speed increases again even if there is a lack of inputs between the fifth and the sixth test days. The most relevant effect connectable to this analysis is that habituation effect is noticeably stronger in risky users than in the prudent ones.

In conclusion, we could notice a short-term and a long-term learning process connectable to the habituation effect. This effect is different, depending on the users' risk inclination. This suggests that the confidence in a road is achieved in different ways depending on risk inclination and that risk perception depends a lot on person's inner variables, as well as external elements.

4. NORWEGIAN EXPERIMENTATION

4.1 Experiment description

4.1.1 Aims of the experiment

In order to verify conclusions obtained by the Italian experiment, another similar experiment was conducted by using GPS technology. The new road under investigation is located in the territory of the municipality of Trondheim (Sør-Trøndelag, Norway), and it connects the city of Trondheim with the small town of Klæbu.

The aims of this experiment are similar to the Italian one. Besides, it will be interesting to see how speed adaption varies according to country of drivers.

The sample of users was composed of ten persons, whose gender, age and driving experience was completely known. We had precise enough data for all ten users (who are identified with the names from U001 to U010 from now on).

4.1.2 Layout description

The road used for the experimentation is the road named Fv885. In particular the stretch of road under investigation is between the roundabout where that road crosses the Bratsbergvegen and the entrance of the Klæbu town. The length of this stretch is of 8.4 kilometers.

The road has a very irregular planimetry and elevation profile. From the planimetric point of view, it is possible to say that it is very winding. In fact it is characterized by several curves, of which some have a small curvature radius. In particular, 6 out of the 44 total curves have a curvature radius minor than 100 meters. From the altimetric point of view, it is characterized by high grade values, especially in the first and central part. Maximum and average grade values are respectively 8.3 per cent and 2 per cent. Instead, between the first and second kilometer and between the third and the fifth kilometer of the stretch, grade is almost everywhere equal to 0.

According to the Norwegian Road Classification, this road is categorized like "county road". In the Italian Functional Road Classification these types of road could be identified as "Secondary Extra-Urban Roads" due to their role in the territory, the characteristics of their traffic flow (short and medium length of travel) and to their function of penetration in local viability.

During the survey campaign we observed a low traffic volume and traffic composed of a few cars, tractors and bicycles. Values of AADT vary from 2400 at the roundabout (starting point) and 1080 at the entrance of Klæbu (ending point). However, on most of the distance it varies between 1400 and 1360.

Fixed speed limit is 70 km/h on most of the distance, except for last sections at the entrance of Klæbu, where it is 50 km/h.

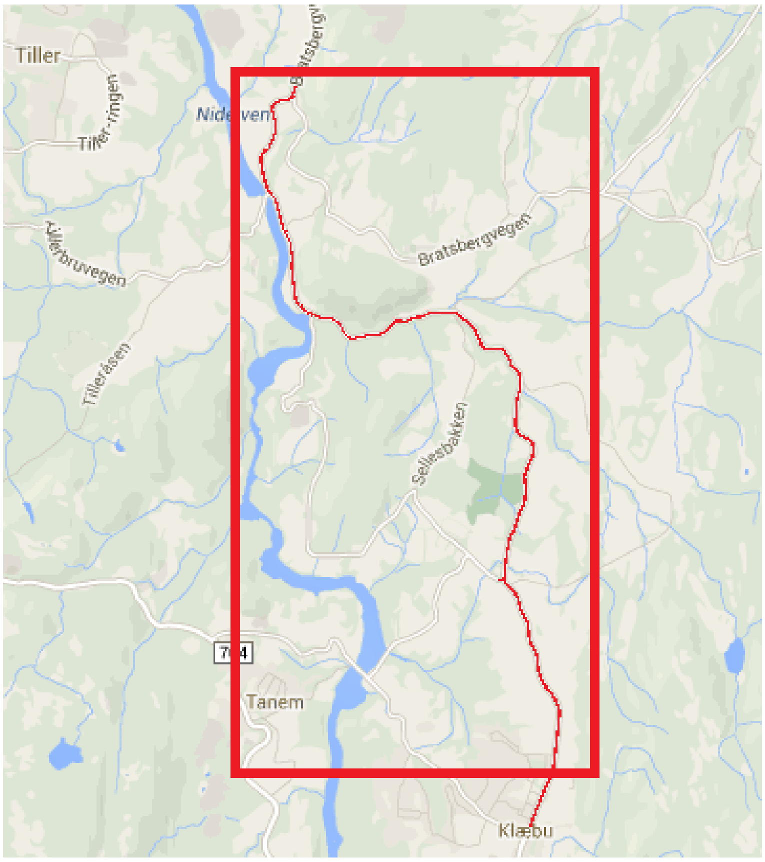


Fig. 4.1-Localization of the stretch of road

4.1.3 Employed instrumentation

In order to survey data we used portable devices *Garmin GPSmap 60CSx*. We have at our disposal six receivers, which were swapped between the ten users during the survey campaign.

GPS receivers can calculate their positions by precisely timing the signals sent by GPS satellites above the Earth. However, GPS measurements yield only a position by using 3-point triangulation with visible satellites, and neither speed nor direction. Nevertheless, the employed GPS units can automatically derive speed and direction values from two or more position measurements. The problem of this automatic calculation is that changes in speed and direction can only be computed with a delay, and that derived direction becomes inaccurate when the distance travelled between two position measurements is near or below the random error of position measurement of the device itself.

In particular, accuracy of the used receivers is typically minor than 10 metres for position measurements and of 0.05 m/s for speed measurements steady state.

4.2 Data collecting

4.2.1 Survey campaign

Users were recruited into Civil Engineering classes of the NTNU university and only one of them is a phD student. Users are between 20 and 30 years old, with a mean age of 23.80 (Std. Deviation = 6.16). Within the sample, 80 % are male drivers (8 out of 10) and 20 % are female drivers (2 out of 10).

After users have answered a preliminary questionnaire (cf. Attachment II) concerning their driving behaviour, then all of them made the driving test. Driving tests consisted in travelling back and forth along the above mentioned route. The total trip length is about 17 kilometres, from the Start to the Start again.

Fig. 4.2 –Road tests' route orthophoto

We said to every user that he was free to choose his speed according to his wishes. In this sense low traffic volume helped users to feel free to choose speed without any kind of conditioning. Furthermore, for the same reason, we chose to make tests only with good weather conditions and we asked users to drive their own cars.

However, we found some difficulties in organizing tests always in days characterized by good weather conditions because of the fixed chronological schedule and the very variable weather conditions of the Norwegian autumn.

In fact, in order to notice speed choice changing over time we collected data following the same chronological schedule used for the Italian experiment.

D1	D2	D3	D4						D5																	D6
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27

Tab. 4.1: Driving tests' chronological schedule for each user

Users had to repeat the same test six times, at the beginning four days in a row (test day 1 – D1, test day 2 – D2, test day 3 – D3, test day 4 – D4) and after these days they had to wait for the 10th day from the first one (test day 5 – D5) and finally for the 27th day from the first one (test day 6 – D6).

All driving tests were made between 7th October 2013 and 18th November 2013.

In order to consider how bad weather conditions could influence speed data, we asked to all the users to report weather conditions during tests. Furthermore, we asked to report also traffic conditions, with the aim of checking if the hypothesis of low traffic volume is followed or not (cf. Attachment III).

4.2.2 Obtained data

In order to collect data we used the software released by the company producing the GPS receiver: Garmin MAPSOURCE. Thanks to this software, it is possible to localize on the map every point recorded by the receiver.

The accuracy of the instrumentation employed for the Norwegian experiment made impossible to use the same technique of punctual speed measurement exploited in the Italian experiment. Therefore, we chose a distance measurement, repeating measures every 50 metres and obtaining average speed data along every section.

Therefore, it was not possible to draw a punctual speed/distance diagram for each test day and each user. Instead, it could be possible to draw an average speed/distance diagram, but we chose another way to process data in order to efficiently compare average speed values of every user.

4.3 Data processing

4.3.1 Preliminary operations

In order to solve the problems discussed in the previous paragraph, it was necessary to do some preliminary operations on collected data.

In fact, given that average speed measures in each section are not comparable with one another, due to poor accuracy of distance measurement, we chose to consider average speed in given road segments equal for each user. Hence, we divided the route into segments and we chose to make this division by considering calculated stopping sight distance.

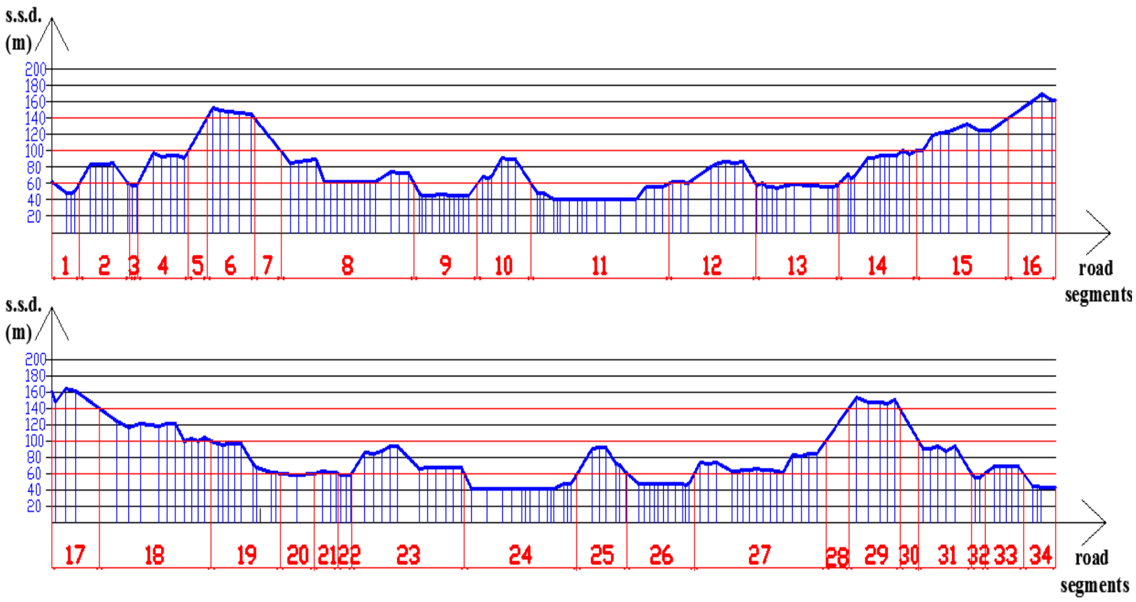


Fig. 4.3-Individuation of road segments using stopping sight distance/distance diagram

First of all we considered four visibility classes: < 60 m, 60-100 m, 100-140 m, > 140 m, and after we defined each segment by identifying its end in the point where visibility class changed, as shown in the above diagram. Therefore, there were identified 34 road segments along which it was possible to compute average speed dividing time taken to drive on that segment by its length.

4.3.2 Data classification

After the preliminary operations, we decided to analyze speed data set by road segment type as we did in the Italian experimentation and according to the same reasons. We split the 34 road segments into subsets based on calculated stopping sight distance, using the same categories already used for the Italian experimentation:

- Low stopping sight distance road section "LS" (< 100 meters);
- Medium-low stopping sight distance road section "MLS" (100 – 200 meters);
- Medium stopping sight distance road section "MS" (200 – 400 meters);

- High stopping sight distance road section “HS” (400 – 600 meters).

After calculating the stopping sight distance for each road section, we obtained stopping sight distance diagrams for the road under investigation.

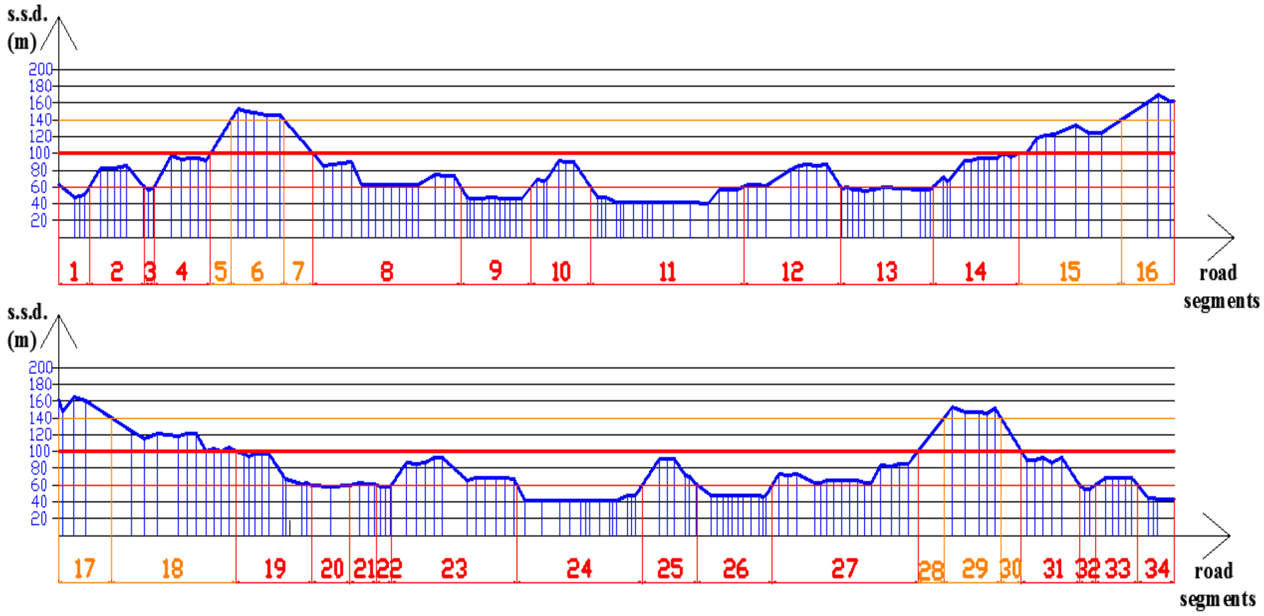


Fig. 4.4 – Stopping sight distance diagrams (way there and way back)
(with a 100 m fixed horizontal line in order to divide low s.s.d. road sections from medium-low s.s.d. road sections)

It is possible to define the right category for each road section simply by reading these diagrams. In order to identify each segment category we used the following color legend:

LS MLS MS HS

After classifying data, we obtained 24 LS, 10 MLS, 0 MS and 0 HS road segments. Another difference between the two experiments is that in Norwegian experiment there are only sections belonging to low and medium-low visibility category.

4.3.3 Users classification

After data classification, we split users in three groups as we did in the Italian experimentation according to their risk inclination:

- Risky users;
- Prudent users;
- Users with variable behaviour (Variable).

In order to classify users, we calculated average speed of the 10 users for each segment of every segment category and for each test day. Here there is an example of this calculation.

		SPEED VALUES - DAY 1					
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS					
		(way there)			(way back)		
	segments	4	8	10	24	27	31
USERS	U01	50	59	55	52	61	56
	U02	64	56	61	60	59	67
	U03	64	51	61	56	58	57
	U04	61	51	56	68	52	63
	U05	53	57	50	57	57	52
	U06	63	51	62	67	52	57
	U07	51	62	68	62	56	60
	U08	68	51	56	59	63	64
	U09	53	61	61	55	66	61
	U10	57	67	64	50	69	59
	segment-related average speed	58.4	56.6	59.4	58.6	59.3	59.6

Fig. 4.5 – An example of average speed calculation (test day 1, low stopping sight distance road segments)

Calculation made in the example had to be repeated for every test day and for every segment category.

After this calculation, we computed for each section and for each test day the difference of each user speed values from the average speed, as shown below in the example.

		SPEED VALUES - DAY 1					
		LOW STOPPING SIGHT DISTANCE ROAD SECTIONS					
		(way there)			(way back)		
	segments	4	8	10	24	27	31
USERS	U01	-8.4	2.4	-4.4	-6.6	1.7	-3.6
	U02	5.6	-0.6	1.6	1.4	-0.3	7.4
	U03	5.6	-5.6	1.6	-2.6	-1.3	-2.6
	U04	2.6	-5.6	-3.4	9.4	-7.3	3.4
	U05	-5.4	0.4	-9.4	-1.6	-2.3	-7.6
	U06	4.6	-5.6	2.6	8.4	-7.3	-2.6
	U07	-7.4	5.4	8.6	3.4	-3.3	0.4
	U08	9.6	-5.6	-3.4	0.4	3.7	4.4
	U09	-5.4	4.4	1.6	-3.6	6.7	1.4
	U10	-1.4	10.4	4.6	-8.6	9.7	-0.6
	maximum difference (absolut value)	9.6	10.4	9.4	9.4	9.7	7.6

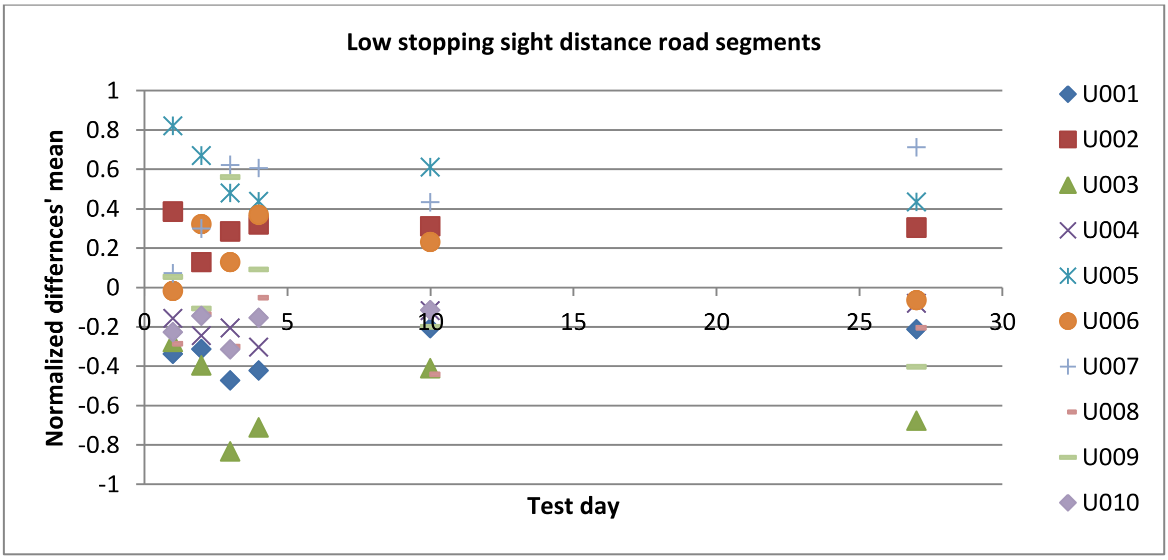
Fig. 4.6 – An example of difference from average speed values calculation (test day 1, low stopping sight distance road segments)

After this, for each segment of every category and for each test day, we calculated the normalized to unity difference from the average speed, by dividing each difference in the above mentioned table by the segment-related maximum difference (absolute value). Finally, we computed for every user the mean of the normalized differences, for each segment category and for each test day, as shown in the example below.

	NORMALIZED TO UNITY DIFFERENCES FROM AVERAGE SPEED VALUES - DAY 1						
	LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						Mean of the normalized differences
	(way there)			(way back)			
segments	4	8	10	24	27	31	
USERS U01	-0.875	0.231	-0.468	-0.702	0.175	-0.474	-0.352
U02	0.583	-0.058	0.170	0.149	-0.031	0.974	0.298
U03	0.583	-0.538	0.170	-0.277	-0.134	-0.342	-0.090
U04	0.271	-0.538	-0.362	1.000	-0.753	0.447	0.011
U05	-0.563	0.038	-1.000	-0.170	-0.237	-1.000	-0.489
U06	0.479	-0.538	0.277	0.894	-0.753	-0.342	0.003
U07	-0.771	0.519	0.915	0.362	-0.340	0.053	0.123
U08	1.000	-0.538	-0.362	0.043	0.381	0.579	0.184
U09	-0.563	0.423	0.170	-0.383	0.691	0.184	0.087
U10	-0.146	1.000	0.489	-0.915	1.000	-0.079	0.225

Fig. 4.7 – An example of calculation of users' mean of normalized differences (day test 1, low stopping sight distance road segments)

Afterwards it was possible to draw diagrams for each segment category, putting normalized differences' mean values of each user on the y-axis and test day on the x-axis.



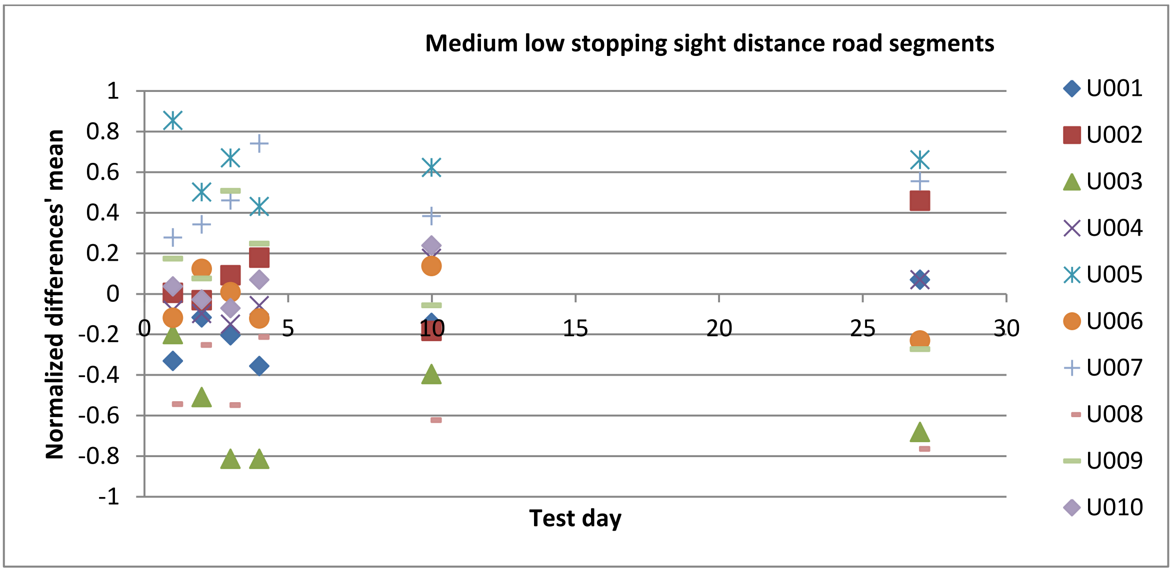


Fig. 4.8a, b – Normalized mean of the differences/test day diagrams for each segment category

We defined users' categories reading these diagrams by using the following rules:

- Risky users, if their normalized mean of the differences were positive (speeds higher than the mean) in at least five out of the six test days;
- Prudent users, if their normalized mean of the differences were negative (speeds lower than the mean) in at least five out of the six test days;
- Variable users, if it was not possible to identify an unambiguous behaviour during all the test days, because of many fluctuations around the zero value.

At the end of this procedure, we obtained number of users for each segment category and each risk category.

SEGMENT CATEGORY	NUMBER OF RISKY USERS	NUMBER OF PRUDENT USERS	NUMBER OF VARIABLE USERS
LS	3	5	2
MLS	3	3	4

Tab. 4.2 –Summarizing table of the categories

4.3.4 Data elaboration

After data classification, we calculated average speed for each segment category and for each test day, separating data into the three risk categories, as shown in the example below.

AVERAGE SPEED - RISKY USERS

		TEST DAY 1						
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						
		(way there)			(way back)			
	segment	4	8	10	24	27	31	
USERS	U02	51	69	56	57	59	55	LS risky users' average speed day 1
	U05	54	58	57	53	65	64	
	U07	54	53	61	59	67	51	
	segment average speed	53.00	60.00	58.00	56.33	63.67	56.67	57.94

		TEST DAY 2						
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						
		(way there)			(way back)			
	segment	4	8	10	24	27	31	
USERS	U02	64	60	50	52	70	51	LS risky users' average speed day 2
	U05	68	62	53	58	69	67	
	U07	64	60	69	54	68	60	
	segment average speed	65.33	60.67	57.33	54.67	69.00	59.33	61.06

		TEST DAY 3						
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						
		(way there)			(way back)			
	segment	4	8	10	24	27	31	
USERS	U02	56	50	61	52	60	68	LS risky users' average speed day 3
	U05	59	66	69	61	70	55	
	U07	70	54	56	70	53	61	
	segment average speed	61.67	56.67	62.00	61.00	61.00	61.33	60.61

		TEST DAY 4						
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						
		(way there)			(way back)			
	segment	4	8	10	24	27	31	LS risky users' average speed day 4
USERS	U02	65	64	64	55	56	54	
	U05	59	61	62	68	59	63	
	U07	59	52	52	69	58	64	
	segment average speed	61.00	59.00	59.33	64.00	57.67	60.33	60.22

		TEST DAY 5						
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						
		(way there)			(way back)			
	segment	4	8	10	24	27	31	LS risky users' average speed day 5
USERS	U02	50	60	54	63	57	69	
	U05	67	61	61	60	67	57	
	U07	59	51	51	64	64	54	
	segment average speed	58.67	57.33	55.33	62.33	62.67	60.00	59.39

		TEST DAY 6						
		LOW STOPPING SIGHT DISTANCE ROAD SEGMENTS						
		(way there)			(way back)			
	segment	4	8	10	24	27	31	LS risky users' average speed day 6
USERS	U02	61	67	55	53	54	70	
	U05	51	59	63	54	59	53	
	U07	67	57	63	66	65	58	
	segment average speed	59.67	61.00	60.33	57.67	59.33	60.33	59.72

Fig. 4.9a, b, c, d, e, f – An example of calculation of average speed in each test day (low stopping sight distance – risky users)

Calculation made in the example had to be repeated for every section category and for every risk category.

After this calculation it was possible to draw average speed/day test diagrams for each section category, considering three different data sets for the three risk categories and vice versa.

The two diagrams obtained by splitting data into segment categories and the three ones obtained by splitting data into risk categories are shown below.

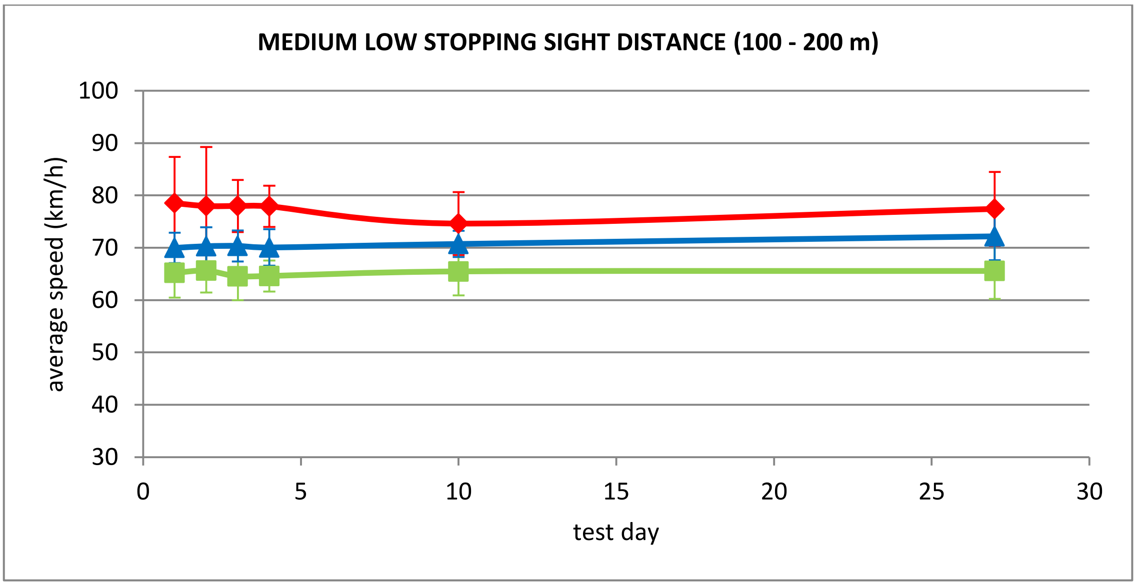


Fig. 4.10a, b – Average speed-test day diagrams, differentiated by segment category

COLOR LEGEND:

risky users variable users prudent users

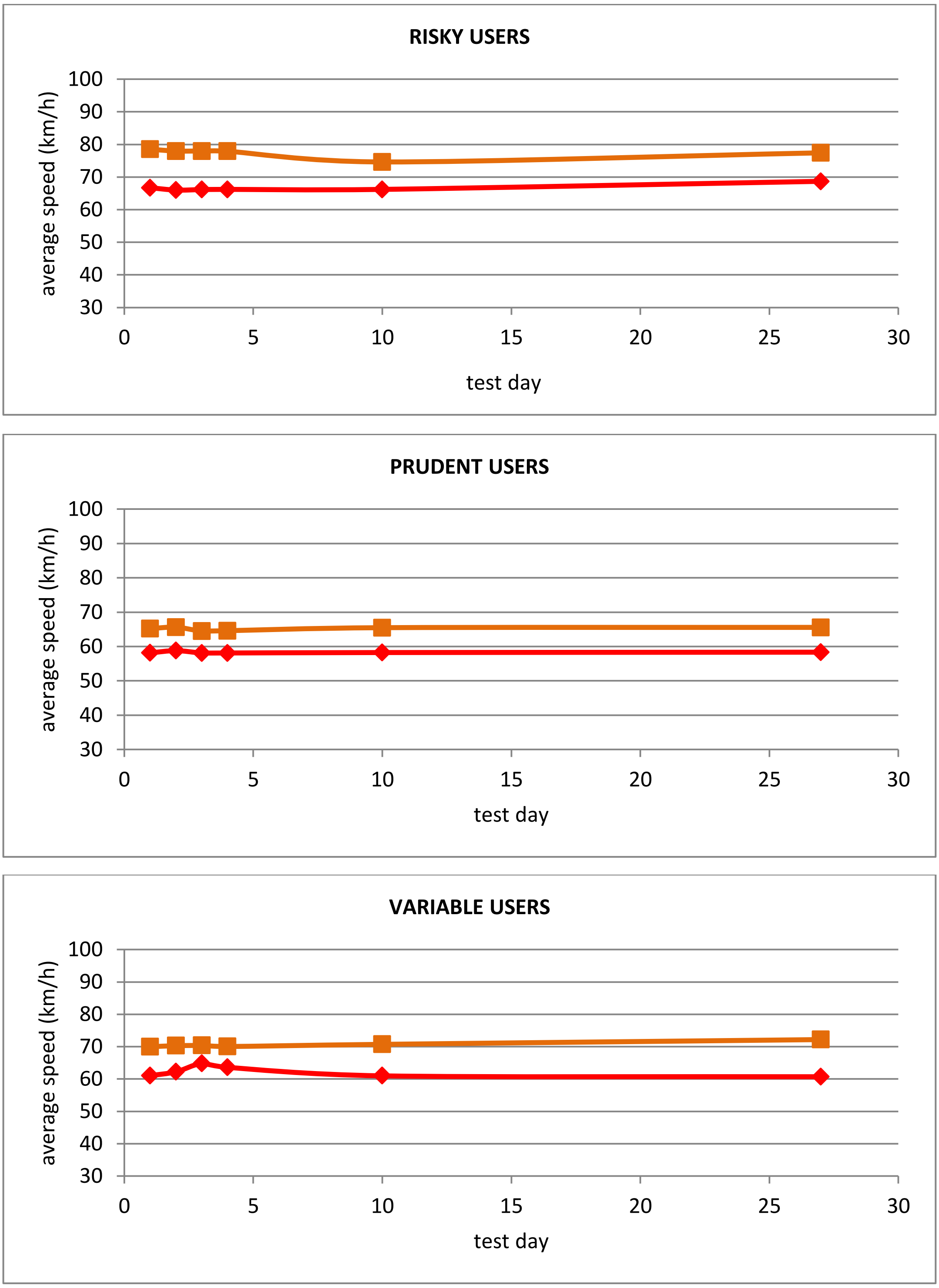


Fig. 4.11a, b, c – Average speed/test day diagrams, differentiated by risk category

COLOR LEGEND:

LS MLS

After calculating average speed, we computed speed standard deviation considering all users together (without differentiating them for risk category), for each test day and each segment category.

After this calculation it was possible to draw speed standard deviation/test day diagrams for each section category. We put the two curves on one diagram, which is given below.

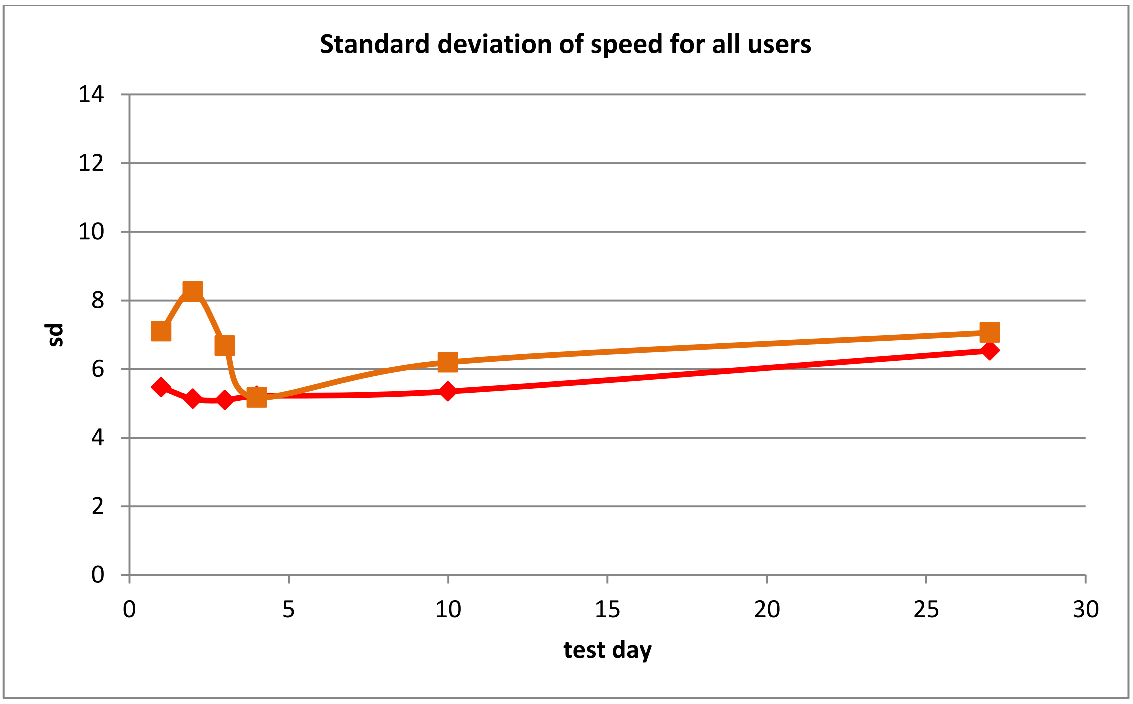
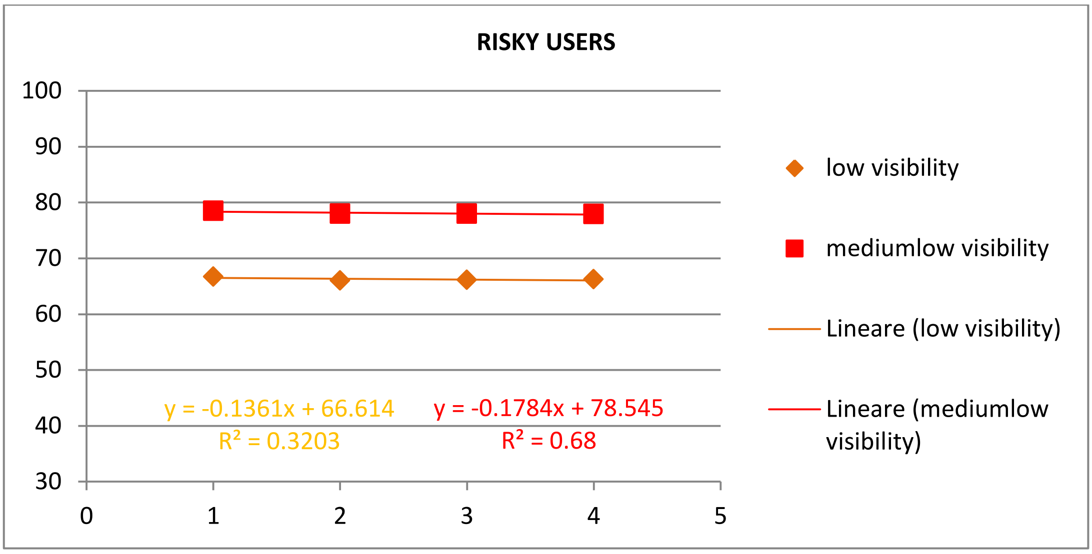


Fig. 4.12– Speed standard deviation/test day diagram

COLOR LEGEND:

LS MLS

In the Norwegian experiment, it is not possible to see a clear increasing linear trend in the first four days. However, we drew the same diagrams made for the Italian experiment with the aim of the comparison between the two different situations. Calculation of gradients in the average speed/test day diagrams is shown below.



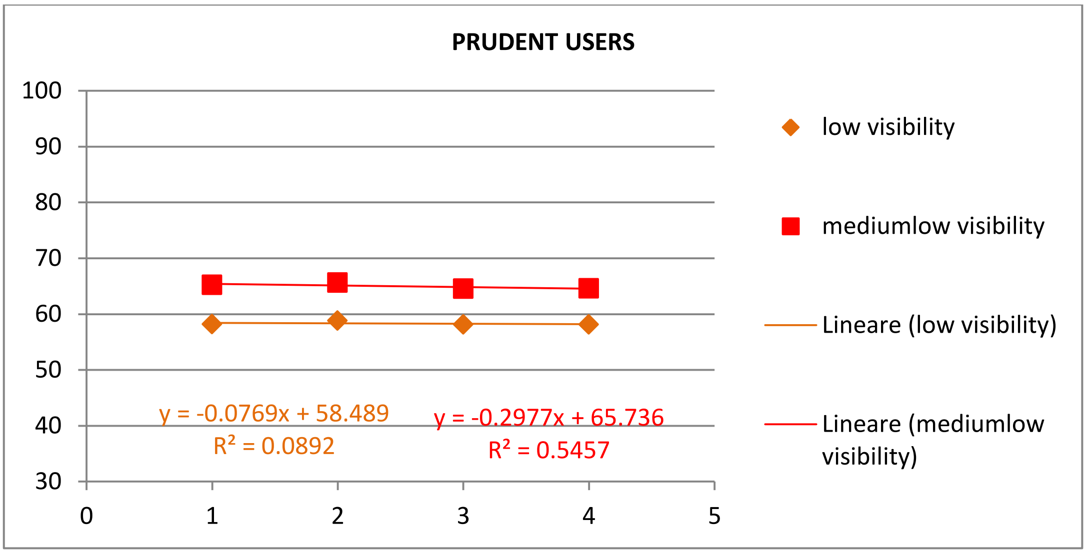
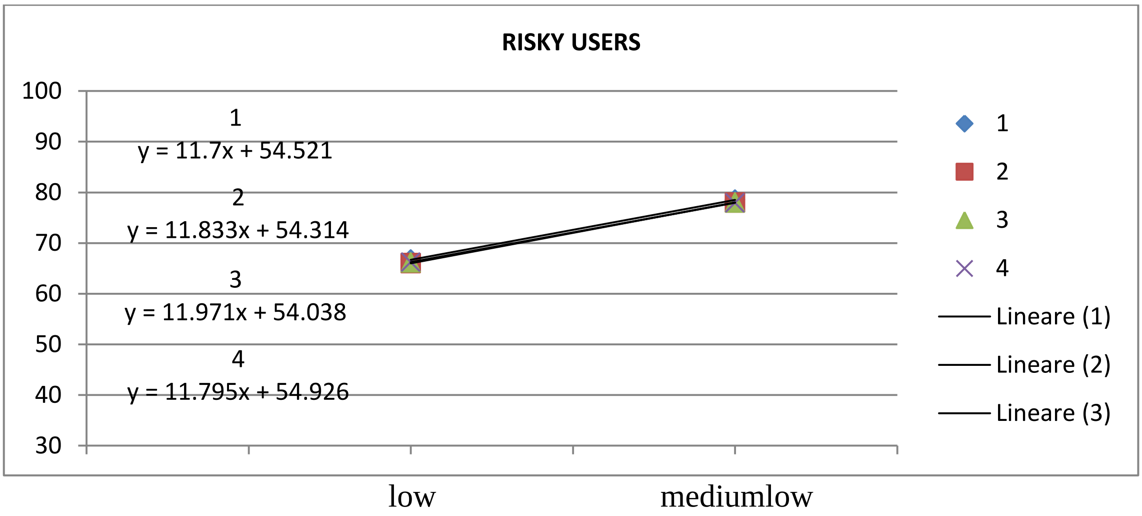


Fig. 4.13a, b – Linear speed trends for each visibility class in the first four days (average speed/first four test days diagrams)

	STOPPING SIGHT DISTANCE CLASS	
	LOW	MEDIUM-LOW
RISKY USERS	- 0.18	- 0.14
PRUDENT USERS	- 0.08	- 0.30

Tab. 4.3 – gradient values a=$\Delta v/\Delta t$, related to the fictitious line derivable from the average speed/first four test days diagram, for each risk class and each visibility class

Furthermore, average speed/visibility class diagrams are shown below. The following gradients values are related to these diagrams.



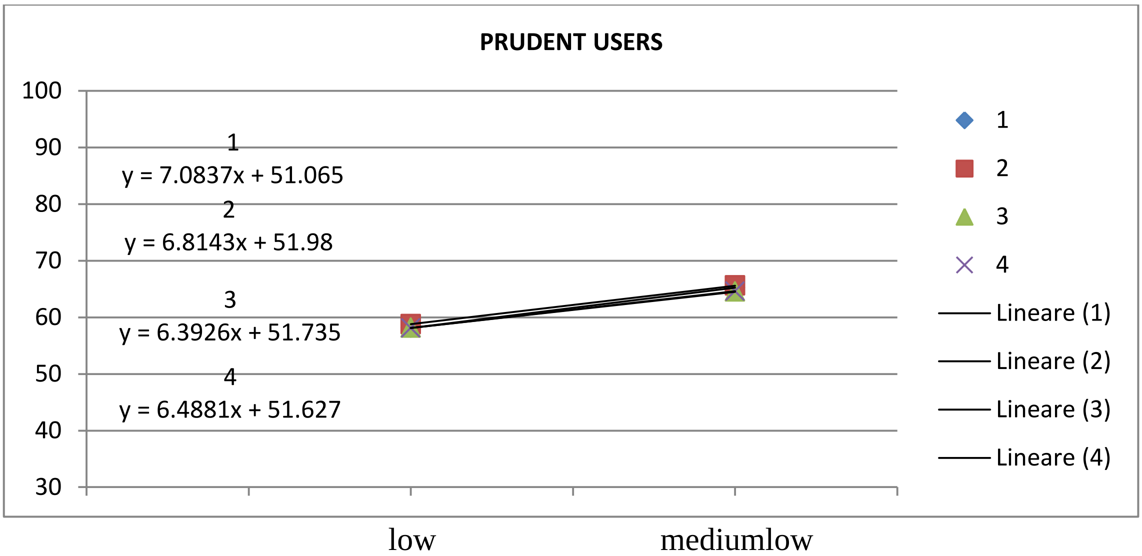


Fig. 4.14a, b – Linear speed trends for each day in the first four days (average speed/visibility class diagrams)

	DAY			
	1	**2**	**3**	**4**
RISKY USERS	11.30	11.83	11.97	11.80
PRUDENT USERS	7.08	6.81	6.39	6.49

Tab. 4.4 – gradient values, related to the fictitious line derivable from the average speed/visibility class diagram, for each risk class and each visibility class

In the end, we computed the percentage difference of the average speed between a test day and the previous one. Percentage difference of speed-test day diagrams for prudent users and for the risky ones, considering the extreme categories of stopping sight distance (low and medium-low in this case) are given below.

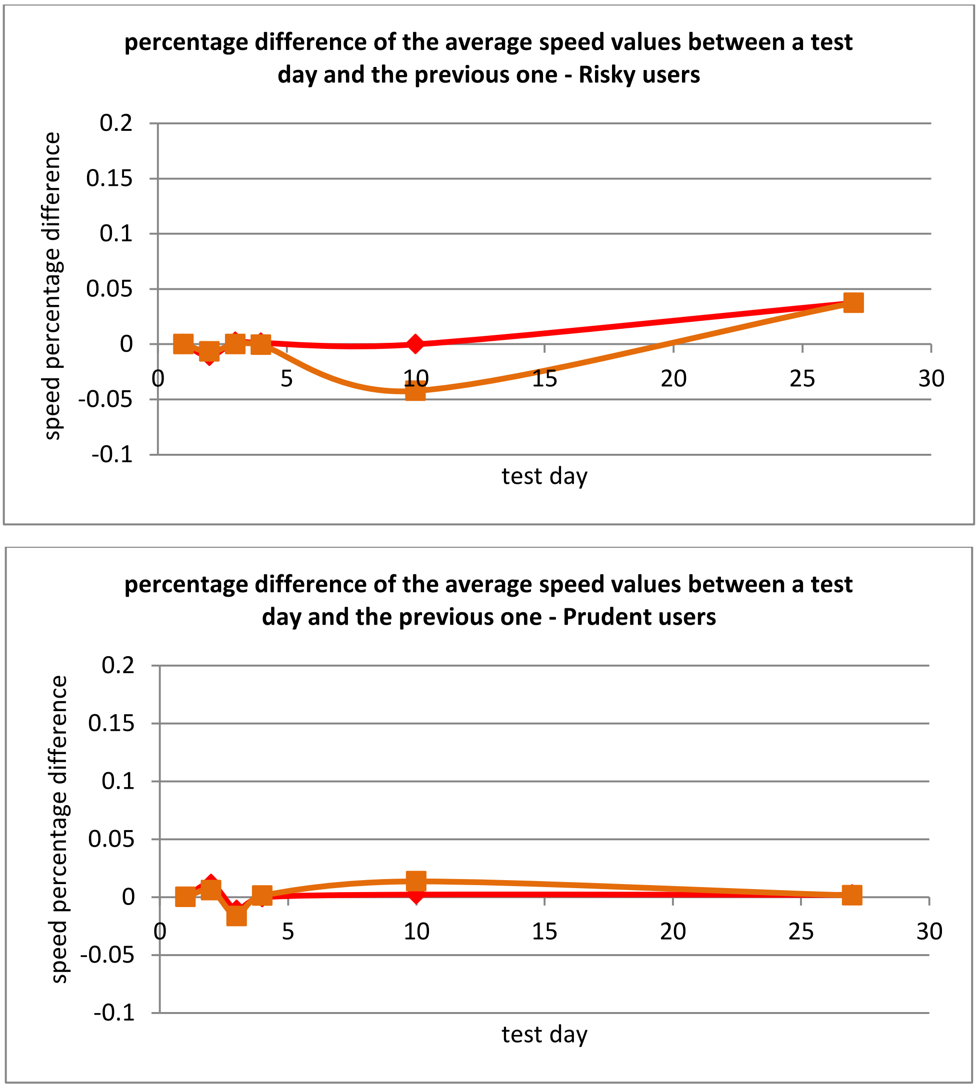
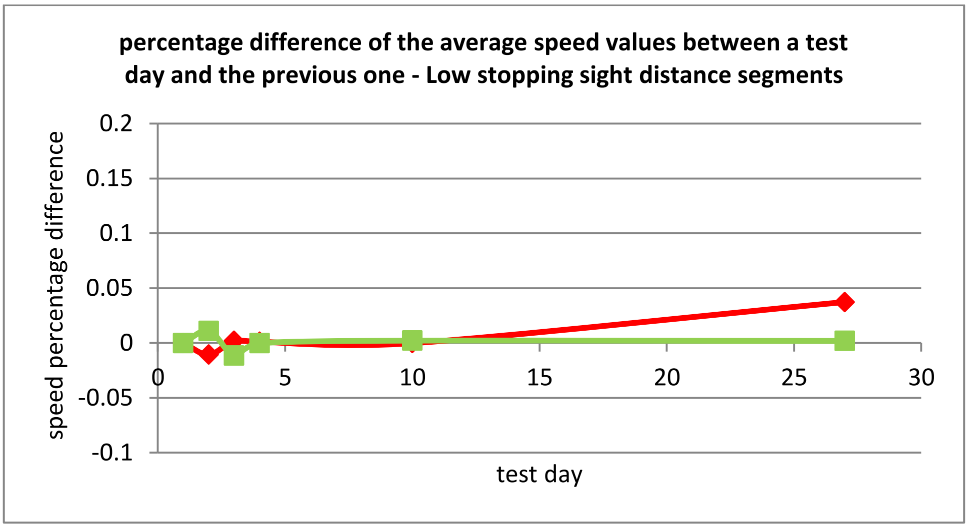


Fig. 4.15 – Speed percentage difference/test day diagrams, differentiated by risk category

COLOR LEGEND:

LS

MLS



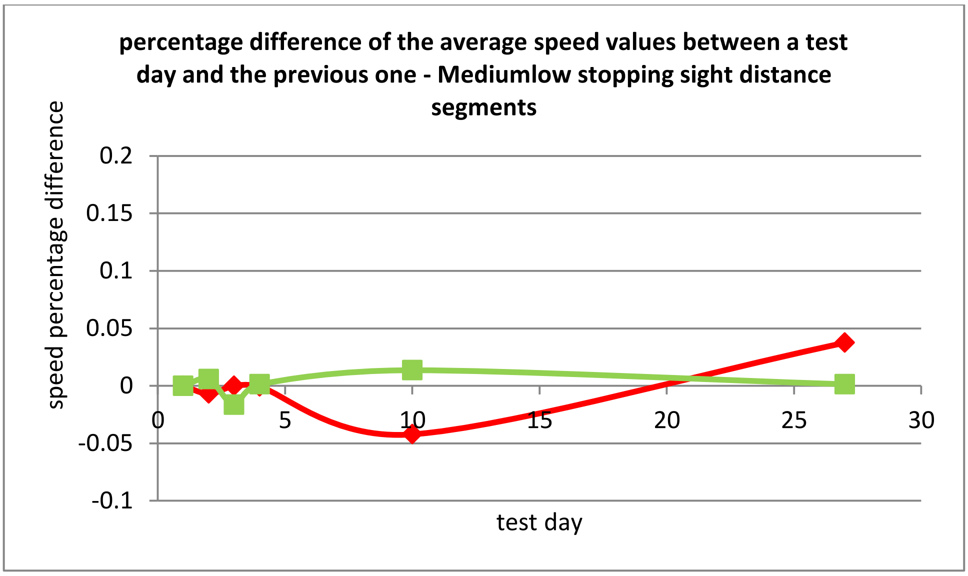


Fig. 4.16 – Speed percentage difference/test day diagrams, differentiated by segment category

COLOR LEGEND:

Risky users

Prudent users

4.4 Discussion

Analyzing speed diagrams, unlike the Italian experiment, it is possible to notice that average speed doesn't vary significantly during the six test days for all risk categories.

Although average speed diagrams have similar shapes for each risk category, average speeds increase between 5 and 10 km/h by going from curves obtained for lower sight road sections to the curves obtained for the higher ones. Furthermore, average speeds increase of about 10 km/h by going form curves obtained for prudent users to the curves obtained for the risky ones.

In particular, diagrams 4.14a and 4.14b clearly show the increase of speed from low visibility sections to the highest ones. In this case, the increasing trend is represented by a line connecting the two speed points, because in this experiment there are only two visibility classes. This finding shows that the choice of clustering sections according to visibility is once again truly appropriate in order to study speed choice. In fact, as shown, visibility has a very direct effect on speed choice, in different ways according to different risk categories.

Therefore, on the first four days, for every risk category and for every section category, it is not possible to perceive a speed growing tendency. The same thing happens on the 5th and 6th test days, wherein speed seems to have approximately the same value of the previous days. The only exceptions are the decrease of speed on the 5th day of risky users in medium-low visibility segments and the increase of speed on the 3rd and 4th days of variable users in low visibility segments. However, we have to take into account that the Norwegian sample is smaller than the Italian one and so each category in which users are divided by risk attitude could be composed of few people. Therefore, the average could be influenced a lot by single variations of each user over time, especially if the category is not so numerous. This is exactly the case of the exception above mentioned: in medium-low visibility segments we have 3 risky users and in the low visibility segments we have only 2 variable drivers. For the same reason, it is uncertain if the light increase of speed from day 5 to day 6 observed for risky users (in both of visibility classes) and for variable users (only for medium-low visibility segments) could be considered or not significant.

Hence, tendency of the average speed/test day diagrams could be simplified, to a good approximation, with a zero-slope linear trend for all the users. Lines drawn in this way fit speed data to a good approximation, even if R-squared values are minor than the ones obtained in the Italian experiment, mainly due to above explained causes.

Equally, the standard deviation of speed diagram shows an almost zero-slope trend, especially for low visibility segments. This fact means that the distribution of speed of all users around the mean doesn't vary over time notably. Instead, on medium low visibility segments, standard deviation of speed seems to be higher in the first three days. However, this could be explained by the fact that medium-low visibility segments are less than the low visibility segments and so they are much affected by missing values due to bad weather and traffic conditions which are frequent on those days.

4.5 Conclusions

In light of what we have shown up to this point, we can try once again to draw a conclusion about the evolution over time of the confidence on a given road both for risky users and for the prudent ones.

The constant tendency of speed noticed over test days reveals that in this case a better confidence on a given road does not lead up to a speed increasing regardless of risk inclination. The only little increase of speed from the 5^{th} to the 6^{th} test day is not significant for the reasons previously discussed.

Equally, even if road differences are clearly understood by all the users, it seems that there is not any kind of improvement over time about this knowledge. This sentence is evidently proved by looking at the diagrams 3.15a and 3.15b: slopes don't increase over time. However, there is a significant difference between risky users and the prudent ones in reacting to changes on the road. In fact, risky users increase much more their speed in medium-low visibility segments than the prudent ones in respect to the low visibility segments, as it could be seen in the same above reported diagrams.

Therefore, it is not possible to draw clear conclusions about habituation in speed behaviour because results seem to show no adaptation both in the short term and in the long term. Even if speed choice is still evidently depending on visibility conditions and risk attitude, we cannot find the same habituation effect found in the Italian experiment.

The main conclusion of these results is that habituation could not occur for every driver, for every road and in general it depends on the variations of the surrounding conditions.

This topic will be well analyzed in the chapter devoted to the comparison between the Italian experimentation and the Norwegian one.

5. COMPARISON BETWEEN ITALIAN AND NORWEGIAN EXPERIMENTATIONS

5.1 Introduction

In this chapter I will analyze the differences between the Italian experimentation and the Norwegian one, by making a comparison between them.
First of all, I will analyze the differences between Italian and Norwegian in regard to driving behaviour, in order to better understand results of both experimentations.
Furthermore, I will make a qualitative comparison by looking at diagrams and data from the two experiments and I will try to draw the first clear conclusions.
Afterwards, I used results from an ANOVA analysis made on the two data sets in order to better understand the differences between them. Two different models will be proposed to fit data from the two different experiments.
Finally, in the last part of the chapter, I will try to explain differences found during the comparison.

5.2 Driving behaviour, culture and risk perception: differences between Italy and Norway

Human factors may be related to risk perception and driving behaviour in different ways depending on a lot of factors. It seems that the way in which such factors influence driving behaviour is different depending on the country. An interesting point of view in this sense is given by Nordfjærn et al.[46], who argued that «*although certain aspects of road traffic is standardized across countries by the Vienna convention, dialects in communication is likely to be important for road traffic safety in different countries and may be a part of different countries specific 'road traffic culture'* ». This means that drivers from different countries may vary their driving behaviour because they are

[46] Nordfjærn, T., Şimşekoğlu, Ö., Rundmo, T. (2014) "Culture related to road traffic safety: A comparison of eight countries using two conceptualizations of culture." *Accident Analysis and Prevention 62, 319-328.*

exposed to different point of views and values, even if road traffic shows similar rules in most of the countries.

There are a lot of recent studies in literature about cultural differences in driving behaviour. Rakauskas et al.[47] stated that drivers in rural areas tend to be more risky than drivers in urban area. Warner et al.[48] argued that Finnish and Swedish drivers reported fewer aggressive violations than drivers from Turkey and Greece on a dedicated questionnaire. Özkan et al.[49] found that drivers from countries in Southern Europe and the Middle East reported more aggressive violations and errors than drivers from Western Europe. However, my aim is to compare drivers' attitudes in Italy and Norway but, unfortunately, there are few studies in literature with regard to this direct comparison.

Nevertheless, a lot of work has been done in these countries in order to find information about risk perception, speeding, driving behaviour. Given that both the Norwegian and the Italian experimentation are focused on speed choice analysis, it could be interesting to find some research data about this topic or similar ones in the two mentioned countries. Elvik[50] studied the effect on safety of lower environmental speed limits in the city of Oslo (Norway) and he presented a before-and-after study of the situation. Speed limits were reduced in Oslo from the former 80 km/h limit to the new 60 km/h limit on three main roads in Oslo between November and March. On the first road (national road 4) the mean speed was reduced from 76.7 to 70.2 km/h, on the second road (ring 3 road) the mean speed was reduced from 76.3 to 69.9 km/h, on the third road (European road 18) the mean speed was reduced from 76.0 km/h to 72.9 km/h. Apart from the direct consequences on safety (in fact there was an overall after-estimate accidents reduction of 28%), it is important to note that Norwegians are helpful to lower their speed in response to speed limits reduction, even if mean speed is slightly higher than the new

[47] Rakauskas, M. E., Ward, J. N., Gerberich, S. G. (2009) "Identification of differences between rural and urban safety cultures." *Accident Analysis and Prevention 41, 931-937.*

[48] Warner, H. W., Özkan, T., Lajunen, T., Tzamalouka, G. (2011) "Cross-cultural comparison of drivers' tendency to commit different aberrant driving behaviours." *Transport. Res. Part F: Traffic Psychol. Behav. 14, 390-399.*

[49] Özkan, T., Lajunen, T., Chliaoutakis, J. E., Parker, D., Summala, H. (2006) "Cross-cultural differences in driving behaviours: a comparison of six countries." *Transport. Res. Part F: Traffic Psychol. Behav. 9. 227-242.*

[50] Elvik, R. (2013) "A before-after study of the effects on safety environmental speed limits in the city of Oslo, Norway" *Safety Science 55, 10-16.*

fixed speed limit. The same Norwegian availability in changing attitudes (even if it is not in the same field of research) is shown also in the study about response to reduction of the blood acohol concentration made by Assum.[51] He found that, after the reduction of legal blood alcohol concentration limit in Norway from 0.5 to 0.2 g/l, the percentage of drivers stating that they will drink no alcohol before driving has increased from 82 to 91 percent. In Italy, De Luca et al.[52] proposed a way to discover particular hazardous "black spots" by identifying discrepancies between operating speeds and design speeds in four different road sections in southern Italy. In this study it's a given that operating speeds implemented by drivers are noticeably higher than design speeds. In the same field of speed choice, Colonna et al.[53] found that standard deviation of the speeds can be considered as an indicator of perceived risk: test drivers tend to modify their behaviour, reducing the SD of speeds, when they increase perceived speed due e.g. due to geometric layout.

Furthermore, in the above quoted study of Nordfjærn et al. about influence of cultural differences on driving behaviour, there is a cross-cultural comparison including Norway. The aim of this study was to examine country differences in road traffic risk perception, attitudes and behaviour in samples from Norway, Russia, India, Sub-Saharian Africa and Near Est countries. The findings showed that: «*Norwegians reported overall safer attitudes towards traffic safety and driver behaviour than the remaining country clusters. […] cultural factors were stronger predictors of driver behaviour. Moreover, risk perception and attitudes solely predicted driver behaviour in the Norwegian and Russia/India clusters*».

In light of the aim of this thesis, the most useful comparison is between Italy and Norway. Gitelman et al.[54], in their proposal to design a global indicator for road safety, made a comparison between all the European countries based on a lot of parameters. In

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[51] Assum, T. (2010) "Reduction of the blood alcohol concentration limit in Norway – Effects on knowledge, behavior and accidents." *Accident Analysis and Prevention 42, 1523-1530.*

[52] De Luca, M., Dell'Acqua, G., Lamberti, R. (2012) "Road safety analysis using operating speeds: case studies in southern Italy." *Procedia – Social and Behavioral Sciences 53, 703-711.*

[53] Colonna, P., Aquilino, A., Berloco, N., Ranieri, V. (2013) "Relationships between Road Geometry, Drivers' Risk Perception and Speed Choice: an Experimental Study" 2013 *Annual meeting of the TRB*

[54] Gitelman, V., Doveh, E., Hakkert, S., (2010) "Designing a composite indicator for road safety" *Safety Science 48, 1212-1224.*

this study, road safety is considered as a pyramid (SUNflower approach[55]) consisting of several layers, from bottom to top: safety measures and programmes, safety performance indicators (intermediate outcomes), numbers of accident fatalities/injuries (the final outcome), social costs of accident fatalities/injuries and an additional "Structure and culture" layer to include the background conditions of the system or the policy context. The safety performance indicators (SPIs) was firstly explored by ETSC (2001)[56] because it was felt that accidents are *«only the tip of the iceberg, because they occur as the "worst case" result of unsafe operational conditions in the road traffic system»*. Those indicators were developed considering the seven problem areas developed by the SafetyNet project[57]: alcohol and drug-use, speeds, protective systems, daytime running lights, vehicles, roads and trauma management. All the parameters considered in the study were provided by national representatives of the European countries, were based on road safety programmes, background papers and follow-up reports and they are shown in the following tables.

Definition of basic indicators for the A-group: characteristics of national safety programmes.

Indicators	Possible values
A1 Safety targets	a. Ambitious b. Available but not ambitious c. Not available
A2 Selection of interventions	a. Sound analysis and diagnosis of road safety problems preceded the programme's development, and evidence-based interventions were selected b. Some analysis was performed, and evidence-based interventions were selected c. Detailed analysis of road safety problems was performed, however, the selection of interventions was arbitrary d. The diagnosis of road safety problems was poor and the selection of interventions was arbitrary
A3 Economic evaluation	a. Detailed economic evaluation preceded the programme's composition b. Some economic evaluation was performed c. Economic evaluation was not performed
A4 Monitoring the programme's performance	a. Systematic monitoring takes place b. A need for monitoring is stated but monitoring reports are not found c. No evidence of monitoring activities
A5 Programme's stakeholders	a. Commitment was stated on the governmental level, and the programme is supervised by a central authority which is empowered to coordinate the activities of all other bodies b. No commitment from the government, however, a central authority was commissioned for the programme's performance c. A number of authorities share the responsibility for the programme's performance d. No authority has a clear responsibility for the programme's performance

[55] Koornstra, M., Lynam, D., Nilsson, G., Noordzij, P., Pettersson, H. E., Wegman, F., Wouters, P. (2002) "SUNflower: a comparative study of the development of road safety in Sweden, the United Kingdom and the Netherlands." SWOW Insitute for Road Safety Research, Leidschendam, the Netherlands.
[56] European Traffic Safety Council (2001) "Transport Safety Performance Indicators", *Brussels*
[57] Hakkert, A. S., Gitelman, V., Vis, M. A. (2007) "Road safety performance indicators: Theory." *Deliverable D3.6 of the EU FP6 Project SafetyNet*.

Definition of basic indicators for the B-group: final outcomes.

Issues considered	Indicators defined[a]
Personal risk	B1 Fatalities per million inhabitants
Traffic risk	B2 Fatalities per million passenger cars
	B3 Fatalities per 10 billion passenger-km travelled
Scope of traffic injury	B4 Injury accidents per fatality[b]
Scope of the problem of vulnerable road users	B5 Share of pedestrian fatalities out of the total fatalities
	B6 Share of bicyclist fatalities out of the total fatalities
	B7 Share of motorcyclist fatalities out of the total fatalities

Definition of basic indicators for the C-group: intermediate outcomes, SPIs.

Safety areas considered	Indicators defined
Alcohol-impaired driving	C1 Share of total for fatalities in drink-driving accidents
Use of protective systems in cars	C2 Daytime wearing rates of seat belts in the front seats (aggregated for driver and front passenger)
	C3 Daytime wearing rates of seat belts in the rear seats
Vehicles: crashworthiness of the passenger car fleet	C4 Average EuroNCAP score of passenger car fleet
	C5 Median age of the passenger car fleet
Vehicle fleet composition	C6 Share of motorcycles in the vehicle fleet
	C7 Share of heavy goods vehicles (HGV) in the vehicle fleet

Fig. 5.1a, b, c – Definition of basic indicators of road traffic safety

Using the results of countries' clustering based on four different analyses, (PCA = Principal Component Analysis, FA = Factorial Analysis, made in three different ways considering diverse factors) five groups of countries with different levels of safety performance were defined as follows:

1 - Countries with the highest level of safety performance: Sweden, Norway, France, Great Britain, Germany.

2 - Countries with a relatively high level of safety performance: Switzerland, the Netherlands, Finland, Denmark, Ireland, Austria, Luxembourg, Malta.

3 - Countries with a medium level of safety performance: Cyprus, Slovenia, Portugal, Belgium, Spain.

4 - Countries with a relatively low level of safety performance: Estonia, Slovakia, Greece, Czech Republic.

5 - Countries with a low level of safety performance: Latvia, Hungary, Poland, Lithuania, Italy.

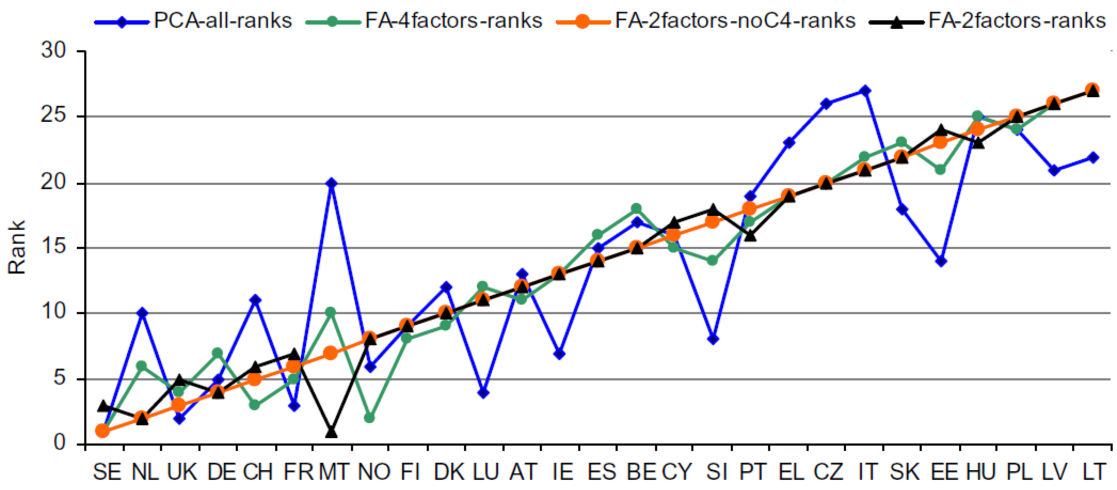


Fig. 5.2 - Final countries' ranks resulting from four analyses

Country	Code	B1	B2	B3	B4	B5	B6	B7	D1	D2	C1	C2	C3	C4	C5	C6	C7	A1	A2	A3	A4	A5
		Fatalities per million inhabitants-2006	Fatalities per million passenger cars-2006	Fatalities per 10 billion pkm-2006	Injury Accidents per fatalities-2006	Pedestrian fatalities as % of total-2006 (%)	Bicyclist fatalities as % of total-2006 (%)	Motorcyclist + moped fatalities as % of total-2006 (%)	Number of passenger cars per 1000 inhabitants, 2006	Population per 1 km^2 of area-2006	Share of drink-driving accidents-2005	Wearing rate-Front seats aggregated-2005	Wearing rate-Rear seats-2005	Average EuroNCAP score-2003	Median age of passenger cars-2003	% Motorcycles in fleet-2006 (%)	% HGV in fleet-2006 (%)	Safety targets	Selection of interventions	Economic evaluation	Monitoring	Stake-holders
Italy	IT	96	162	74	42.0	12.6	4.8	23.8	597	196.3	n/a	71	n/a	n/a	7.9	20.5	8.7	c	d	c	c	d
Norway	NO	52	116	n/a	32.7	14.5	3.3	15.3	445	14.4	n/a	91	83	21	8	9.4	17.0	b	a	a	b	b

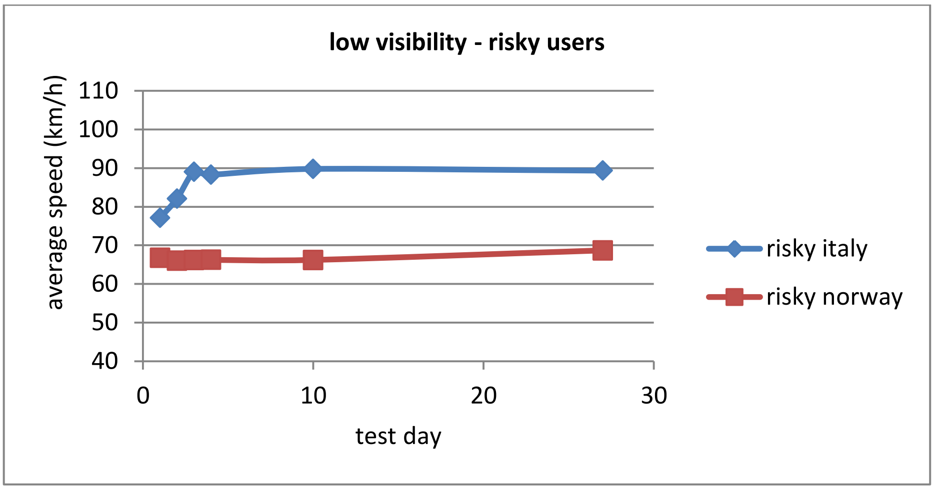
Fig. 5.3 – Basic indicators of road traffic safety – Italy and Norway

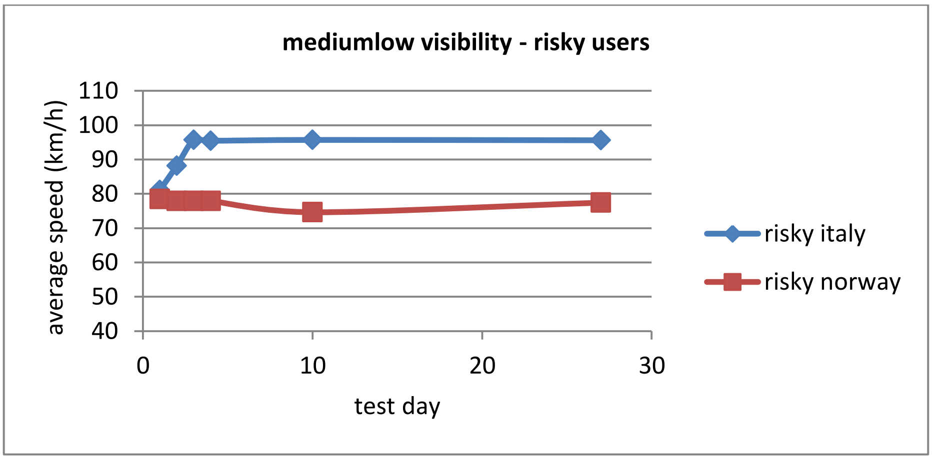
Even if this study does not consider traffic safety from the human point of view in the comparison (perceived risk, speeding, driving behaviour), it give us a portrait of the traffic safety situation in the two countries. Therefore, the conclusion is that explanations and comparison between the two experimentations cannot consider these evident discrepancies between the two countries.

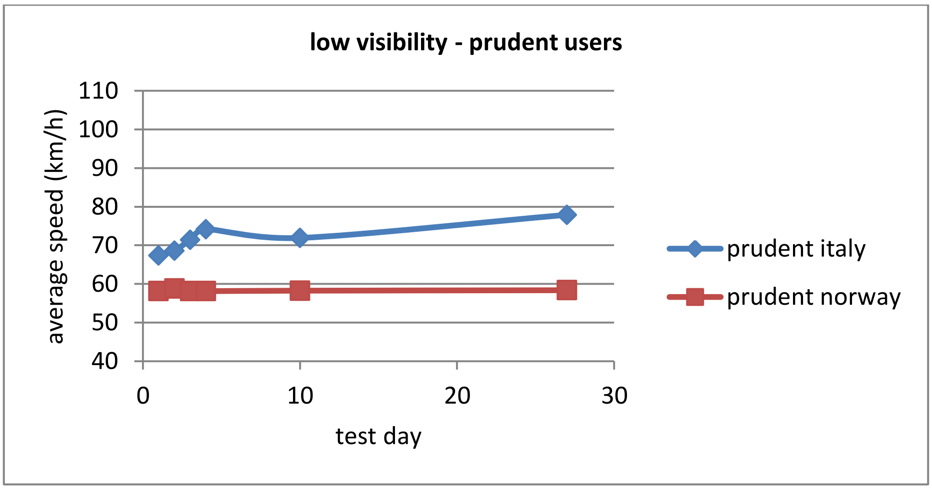
5.3 Experimentations - Qualitative comparison

In order to make a qualitative comparison between the two experiments I will show combined diagrams of average speed with additional operations. It is possible to compare only low and medium-low visibility classes, because in the Norwegian experiment there are no medium and high visibility segments.

Comparison is made only for prudent and for risky users, because variable users could be seen better as people that can't be classified by risk, due to their changing behaviour over time, than as a specific risk category by itself.







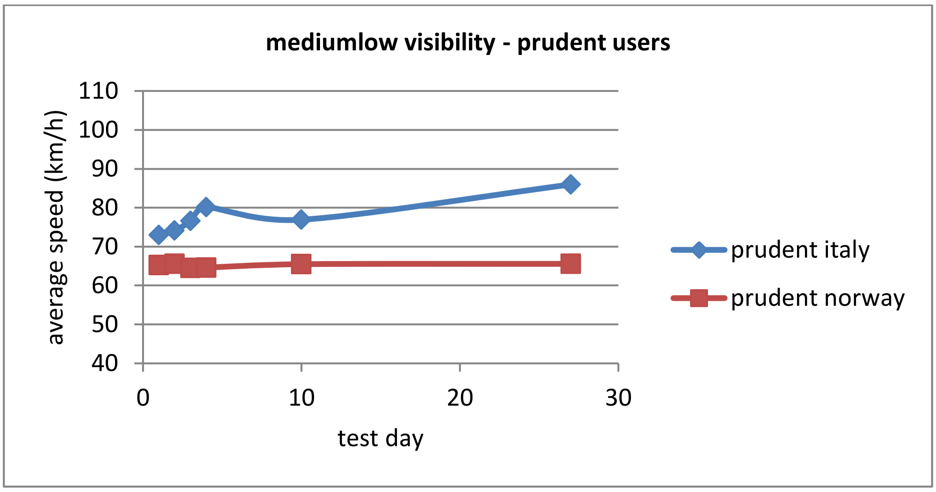
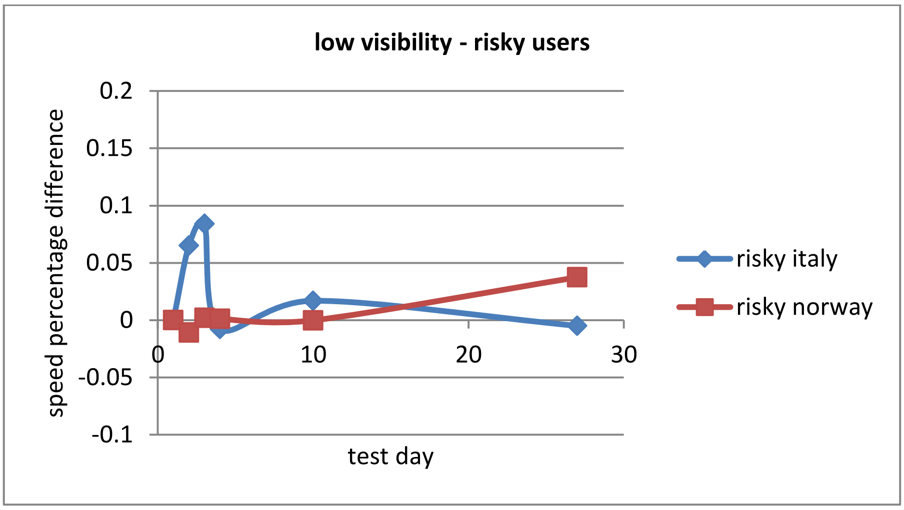


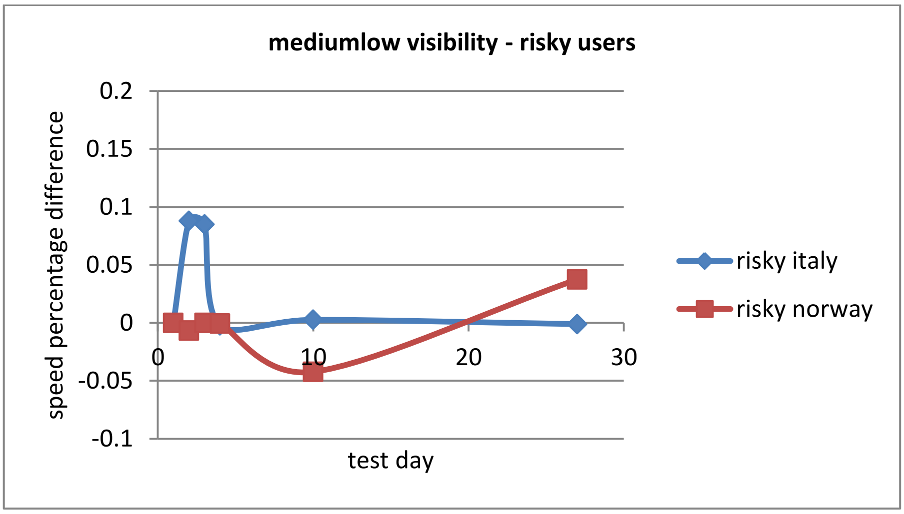
Fig. 5.4a, b, c, d – Comparison between Italy and Norway: Average speed/test day diagrams, differentiated by visibility and risk categories

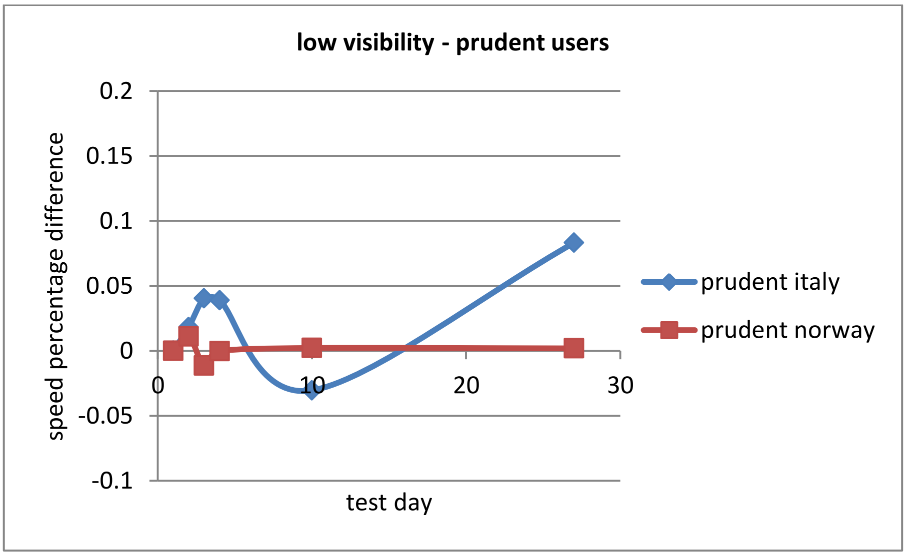
In all diagrams above reported there are the combined speed trends of Italian and Norwegian experiments, divided for visibility and risk categories.

As I have already said, the increase of speed over time is evident in the Italian trends, while this effect is practically absent in the Norwegian trends.

Another important finding is that on average, Italian speeds in comparable visibility conditions are significantly higher (from the 10 km/h to the 20 km/h higher) than the Norwegian speeds. The cause of this remarkable difference could be the discrepancies between the roads themselves. In fact, Norwegian road is more winding than the Italian one and it includes some small-radius curves and so, on average, stopping sight distance is lower on the Norwegian road even if visibility classes are defined in the same way. However, this matter could be more complicated than as it seems. In fact, we must take into account that risk perception could be different for drivers from different countries and that speed choice is related to risk perception as already stated.


low visibility - risky users
speed percentage difference
0.2
0.15
0.1
0.05
0
-0.05
-0.1
0
10
20
30
test day
risky italy
risky norway


mediumlow visibility - risky users
speed percentage difference
0.2
0.15
0.1
0.05
0
-0.05
-0.1
0
10
20
30
test day
risky italy
risky norway


low visibility - prudent users
speed percentage difference
0.2
0.15
0.1
0.05
0
-0.05
-0.1
0
10
20
30
test day
prudent italy
prudent norway

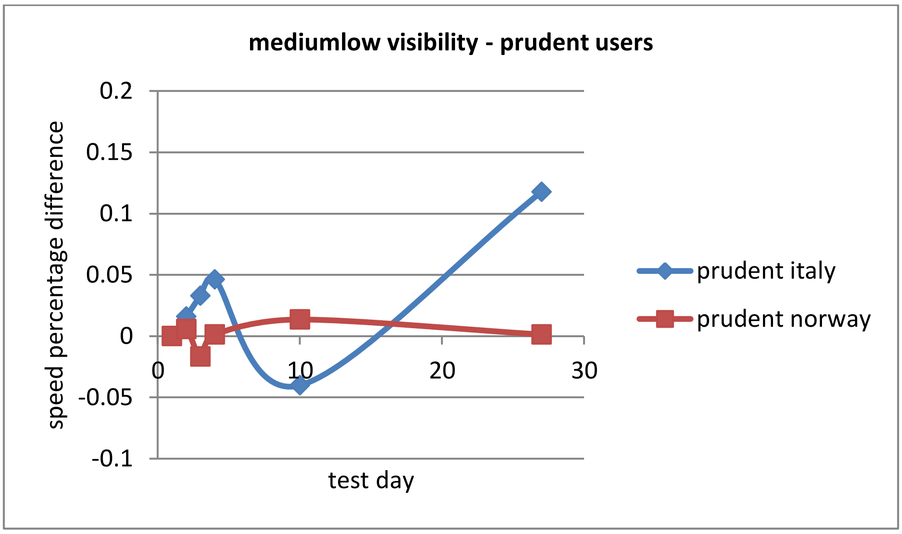
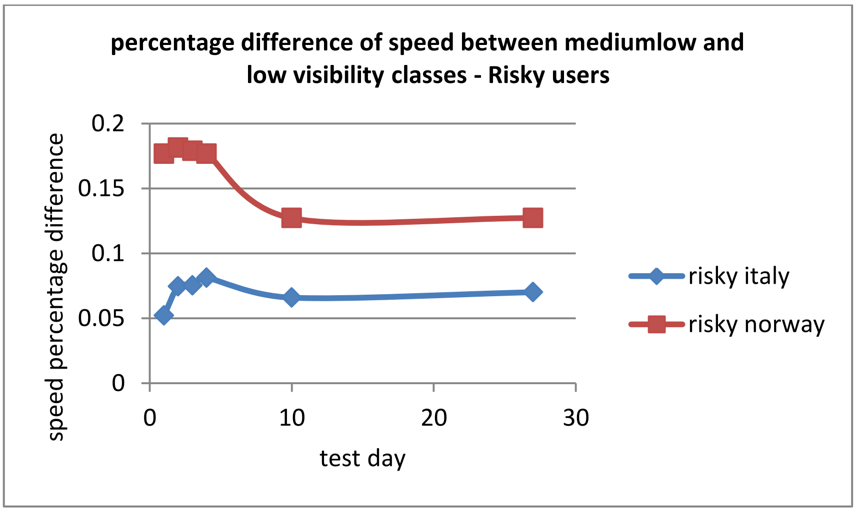


Fig. 5.5a, b, c, d – Comparison between Italy and Norway: speed percentage difference (between one test day and the previous one)/test day diagrams, differentiated by visibility and risk categories

Looking at combined speed percentage difference/test day diagrams is another way to appreciate the same trends. In the Italian speed data there are positive notable values of Δv on the second and on the third day especially for risky users, while prudent users show remarkable positive Δv on the sixth day. Instead, in the Norwegian speed data Δv is almost always near to 0, except for fifth and sixth day of risky users. This difference is not so relevant and anyway it is not so clear if it could represent a start of a light habituation effect or not.



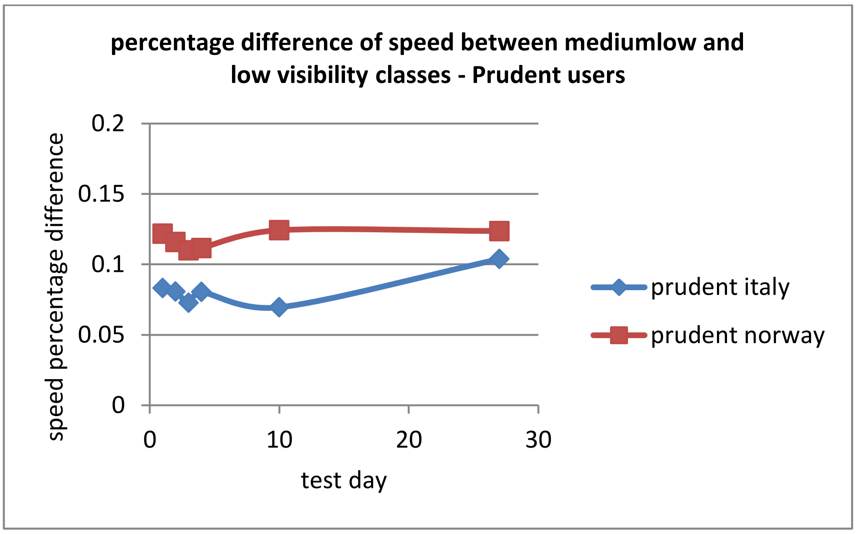


Fig. 5.6a, b – Comparison between Italy and Norway: speed percentage difference (between different visibility classes)/test day diagrams, differentiated by risk categories

The above reported further elaboration allows us to have an overall perception of speed increasing while going from low visibility class to medium-low visibility class in only one diagram.

The most notable effect is that speed always increases in this change of visibility in both the experiments, confirming the already stated effect that visibility has got on speed. In particular, in the Norwegian experiment, this increase of speed is more evident than in the Italian one. This result could be explained by the fact that the road used for the Norwegian experiment is more winding than the Italian one and it is characterized by some small-radius curves. Therefore, on average, stopping sight distances in Norwegian low visibility segments are lower than stopping sight distances in Italian low visibility sections and so, in the shift of visibility to medium-low class, the Norwegian increase of speed is more evident than the Italian one.

It could be also noted that trends of risky users are very similar with highest values on the 2^{nd}, the 3^{rd}, the 4^{th} day and lower values on the 5^{th} and on the 6^{th} day; while trends of prudent users are less comparable.

5.4 Experimentations - Comparison based on ANOVA analysis

5.4.1 ANOVA analysis for the Italian experiment

ANOVA analysis was conducted on the Italian data. The main aims were to find detailed statistical information about those data and to search for a model to fit all the observations to a good approximation.

First of all, a table with basic statistical information (mean and standard deviation) about speed data divided by classes is shown below.

Descriptive statistics (Dependent variable: SPEED)					
RISKCLASS	**SECTIONCLASS**	**DAY**	**Mean**	**Std. Deviation**	**N**
Total	1 = low ssd	day1	72.5908	12.44449	689
		day2	75.8725	14.79265	785
		day3	80.1843	15.07598	848
		day4	83.5814	15.83557	636
		day5	78.7306	16.88693	687
		day6	85.4558	15.97414	625
		Total	79.2100	15.76601	4270
Total	2 = mediumlow ssd	day1	77.0293	12.64639	1320
		day2	81.3236	14.74671	1508
		day3	85.4962	15.42876	1650
		day4	89.8812	15.10465	1210
		day5	83.1732	16.91000	1320
		day6	91.9961	13.83539	1191
		Total	84.5830	15.64561	8199
Total	3 = medium ssd	day1	79.0467	13.73068	418
		day2	86.8676	17.71132	456
		day3	88.6750	19.21304	532
		day4	95.7175	15.61822	342
		day5	85.7711	18.09115	418
		day6	94.6989	16.03042	343
		Total	88.0421	17.82730	2509
Total	4 = high ssd	day1	84.4100	13.64105	803
		day2	92.1310	15.96423	876
		day3	93.7157	17.52308	1021
		day4	100.3122	15.35712	730
		day5	92.0077	16.76140	799
		day6	101.7035	14.41282	675

		Total	93.7120	16.71873	4904
Total	Total	day1	78.1785	13.63258	3230
		day2	83.4522	16.51341	3625
		day3	86.8733	17.10435	4051
		day4	91.8017	16.51642	2918
		day5	84.7528	17.65109	3224
		day6	93.1930	15.76051	2834
		Total	86.1173	17.00739	19882

Tab. 5.1 – Italian exp.: mean, standard deviation and sample size for every speed data subset (cf. Attachment IV for complete descriptive statistics)

I considered only data of risky and prudent users for the reasons already explained in the previous paragraph.

After that, I used the software SPSS (Statistical Package for Social Sciences) in order to find an overall model able to explain speed variations. This analysis was made by using the univariate Generalized Linear Model (GLM) procedure in SPSS. Speed was considered as the desired output (the only dependent variable), while risk class, section class and test day were considered as independent variables. The first model chosen is explained by the following equation:

$$SPEED = \beta_1 + \beta_2 * RISKCLASS + \beta_3 * SECTIONCLASS + \beta_4 * DAY \tag{9}$$

Therefore, first of all, I searched for the influence of main effects on speed, without considering how they interact with one another. Results of this analysis are shown below in two summarizing tables.

In the first table there is information about influence of each factor on the dependent variable with their statistical significance (based on the F-ratio). In fact, values on the last column (Sig.) are probability values. If they are less or equal to the fixed α-value (in our analysis the chosen α significance level is 0.05), then we can reject the hypothesis that variances in the groups are equal. This means that, in example, risky users' speed means and prudent users' speed means are different with a 95 % confidence interval.

Tests of Between-Subjects Effect (Dependent variable: SPEED)					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected model	2083429,683[a]	9	231492.187	1254.430	.000
Intercept	123363154.881	1	123363154.881	668491.000	.000
RISKCLASS	1088196.340	1	1088196.340	5896.813	.000
SECTIONCLASS	600211.647	3	200070.549	1084.160	.000
DAY	352089.199	5	70417.840	381.586	.000
Error	3667173.701	19872	184.540		
Total	153199242.236	19882			
Corrected Total	5750603.384	19881			

a. R squared = .362 (Adjusted R squared = .362)

Tab. 5.2 – Italian exp.: influence of each category on speed forecast (only main effects)

In the second table there are the computed values of β-coefficients with their statistical significance (based on the t-value). In fact, probabilities of significance are calculated for each group of each category. Therefore, in our case, if this value is less or equal to 0.05, then the related β-coefficient is different from 0 with a 95 % confidence interval. In each category, there is a β-value set to zero because other β-coefficients are computed with respect to that value.

Parameter estimates (Dependent variable)						
Parameter	**B**	**Std. deviation error**	**t**	**Sig.**	**Confidence interval 95%**	
					Lower Bound	**Upper Bound**
Constant	91.813	.329	279.080	.000	91.169	92.458
[RISKCLASS=1.00]	15.151	.197	76.791	.000	14.765	15.538
[RISKCLASS=3.00]	0[a]					
[SECTIONCLASS=1.00]	-15.656	.285	-54.988	.000	-16.214	-15.098
[SECTIONCLASS=2.00]	-9.734	.245	-39.675	.000	-10.215	-9.253
[SECTIONCLASS=3.00]	-5.696	.333	-17.081	.000	-6.349	-5.042
[SECTIONCLASS=4.00]	0[a]					
[DAY=1.00]	-13.020	.351	-37.115	.000	-13.707	-12.332
[DAY=2.00]	-7.979	.341	-23.367	.000	-8.648	-7.310
[DAY=3.00]	-3.907	.334	-11.679	.000	-4.562	-3.251
[DAY=4.00]	-1.553	.358	-4.335	.000	-2.255	-.851
[DAY=10.00]	-3.869	.355	-10.893	.000	-4.565	-3.173
[DAY=27.00]	0[a]					

a. This parameter is set to zero because it is redundant.

Tab. 5.3 – Italian exp.: parameter estimates of the model (only main effects)
(Riskclass: 1 = risky, 3 = prudent. Sectionclass: 1 = low, 2 = medium-low, 3 = medium, 4 = high)

The analysis of significance on Table 5.2 and Table 5.3 shows us that each main factor could be associated to speed and that each parameter estimate is significant. However, the R-squared value is of 0.362 and so about two-thirds of the variations are not explained by the considered variables.

In order to improve the model it is possible to consider also interactions between independent variables. Therefore, a full factorial model (considering all the possible combinations between the variables) and a two-ways interaction model (considering only two-ways combinations) were developed.

Due to the very little difference in R-squared values between those two other models (minor than 0.005), I decided to show only results of the two-ways interaction model. The equation of that model is below reported.

$$SPEED = \beta_1 + \beta_2 * RISKCLASS + \beta_3 * SECTIONCLASS + \beta_4 * DAY + \beta_5 * RISKCLASS * SECTIONCLASS + \beta_6 * RISKCLASS * DAY + \beta_7 * SECTIONCLASS * DAY \tag{10}$$

Afterwards, I developed the same analysis for this other model. Results are shown in the following tables.

Tests of Between-Subjects Effect (Dependent variable: SPEED)					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected model	2209420,546[a]	32	69044.392	387.007	.000
Intercept	117603299.605	1	117603299.605	659188.751	.000
RISKCLASS * DAY	912136.727	1	912136.727	5112.699	.000
SECTIONCLASS * DAY	594689.326	3	198229.775	1111.115	.000
RISKCLASS * SECTIONCLASS	319205.870	5	63841.174	357.842	.000
RISKCLASS	7529.655	3	2509.885	14.068	.000
SECTIONCLASS	110023.853	5	22004.771	123.341	.000
DAY	8879.064	15	591.938	3.318	.000
Error	3541182.838	19849	178.406		

Total	153199242.236	19882				
Corrected Total	5750603.384	19881				

a. R squared = .384 (Adjusted R squared = .383)

Tab. 5.4 – Italian exp.: influence of each category on speed forecast (two-ways interaction)

Parameter estimates (Dependent variable)						
Parameter	**B**	**Std. deviation error**	**t**	**Sig.**	**Confidence interval 95%**	
					Lower Bound	**Upper Bound**
Constant	95.131	.638	149.042	.000	93.880	96.382
[RISKCLASS=1.00]	10.821	.623	17.376	.000	9.600	12.042
[RISKCLASS=3.00]	0[a]					
[SECTIONCLASS=1.00]	-15.861	.828	-19.150	.000	-17.485	-14.238
[SECTIONCLASS=2.00]	-9.162	.713	-12.857	.000	-10.559	-7.766
[SECTIONCLASS=3.00]	-8.424	.977	-8.626	.000	-10.338	-6.510
[SECTIONCLASS=4.00]	0[a]					
[DAY=1.00]	-14.601	.797	-18.316	.000	-16.163	-13.038
[DAY=2.00]	-10.668	.787	-13.560	.000	-12.210	-9.126
[DAY=3.00]	-10.443	.759	-13.760	.000	-11.930	-8.955
[DAY=4.00]	-4.317	.839	-5.143	.000	-5.963	-2.672
[DAY=10.00]	-9.047	.787	-11.494	.000	-10.590	-7.505
[DAY=27.00]	0[a]					
[RISKCLASS=1.00] * [SECTIONCLASS=1.00]	-1.593	.573	-2.780	.005	-2.717	-.470
[RISKCLASS=1.00] * [SECTIONCLASS=2.00]	-1.375	.494	-2.782	.005	-2.344	-.406
[RISKCLASS=1.00] * [SECTIONCLASS=3.00]	2.295	.676	3.396	.001	.970	3.619
[RISKCLASS=1.00] * [SECTIONCLASS=4.00]	0[a]					
[RISKCLASS=3.00] * [SECTIONCLASS=1.00]	0[a]					
[RISKCLASS=3.00] * [SECTIONCLASS=2.00]	0[a]					
[RISKCLASS=3.00] * [SECTIONCLASS=3.00]	0[a]					
[RISKCLASS=3.00] * [SECTIONCLASS=4.00]	0[a]					
[RISKCLASS=1.00] * [DAY=1.00]	-2.285	.703	-3.252	.001	-3.663	-.908
[RISKCLASS=1.00] * [DAY=2.00]	4.515	.685	6.591	.000	3.172	5.858
[RISKCLASS=1.00] * [DAY=3.00]	10.223	.671	15.240	.000	8.908	11.537
[RISKCLASS=1.00] * [DAY=4.00]	5.010	.733	6.834	.000	3.573	6.447
[RISKCLASS=1.00] * [DAY=10.00]	10.794	.727	14.854	.000	9.369	12.218
[RISKCLASS=1.00] * [DAY=27.00]	0[a]					
[RISKCLASS=3.00] * [DAY=1.00]	0[a]					
[RISKCLASS=3.00] * [DAY=2.00]	0[a]					
[RISKCLASS=3.00] * [DAY=3.00]	0[a]					

[RISKCLASS=3.00] * [DAY=4.00]	0[a]					
[RISKCLASS=3.00] * [DAY=10.00]	0[a]					
[RISKCLASS=3.00] * [DAY=27.00]	0[a]					
[SECTIONCLASS=1.00] * [DAY=1.00]	4.184	1.020	4.102	.000	2.185	6.183
[SECTIONCLASS=1.00] * [DAY=2.00]	-.152	.993	-.153	.878	-2.099	1.795
[SECTIONCLASS=1.00] * [DAY=3.00]	1.632	.973	1.677	.093	-.275	3.539
[SECTIONCLASS=1.00] * [DAY=4.00]	-.863	1.038	-.831	.406	-2.897	1.171
[SECTIONCLASS=1.00] * [DAY=10.00]	.844	1.034	.816	.414	-1.182	2.870
[SECTIONCLASS=1.00] * [DAY=27.00]	0[a]					
[SECTIONCLASS=2.00] * [DAY=1.00]	2.081	.882	2.360	.018	.353	3.809
[SECTIONCLASS=2.00] * [DAY=2.00]	-1.106	.860	-1.286	.199	-2.791	.580
[SECTIONCLASS=2.00] * [DAY=3.00]	.792	.840	.943	.346	-.854	2.438
[SECTIONCLASS=2.00] * [DAY=4.00]	-.969	.898	-1.079	.280	-2.730	.791
[SECTIONCLASS=2.00] * [DAY=10.00]	-.494	.894	-.553	.580	-2.247	1.258
[SECTIONCLASS=2.00] * [DAY=27.00]	0[a]					
[SECTIONCLASS=3.00] * [DAY=1.00]	2.017	1.202	1.679	.093	-.338	4.373
[SECTIONCLASS=3.00] * [DAY=2.00]	2.013	1.177	1.711	.087	-.294	4.319
[SECTIONCLASS=3.00] * [DAY=3.00]	2.408	1.144	2.105	.035	.166	4.651
[SECTIONCLASS=3.00] * [DAY=4.00]	1.244	1.246	.998	.318	-1.199	3.686
[SECTIONCLASS=3.00] * [DAY=10.00]	1.591	1.219	1.305	.192	-.799	3.980
[SECTIONCLASS=3.00] * [DAY=27.00]	0[a]					
[SECTIONCLASS=4.00] * [DAY=1.00]	0[a]					
[SECTIONCLASS=4.00] * [DAY=2.00]	0[a]					
[SECTIONCLASS=4.00] * [DAY=3.00]	0[a]					
[SECTIONCLASS=4.00] * [DAY=4.00]	0[a]					
[SECTIONCLASS=4.00] * [DAY=10.00]	0[a]					
[SECTIONCLASS=4.00] * [DAY=27.00]	0[a]					

a. This parameter is set to zero because it is redundant.

Tab. 5.5 – Italian exp.: parameter estimates of the model (two-ways interaction)

(Riskclass: 1 = risky, 3 = prudent. Sectionclass: 1 = low, 2 = medium-low, 3 = medium, 4 = high)

The analysis of significance on Table 5.4 and Table 5.5 shows us that each main factor and each two-way interaction between them could be associated to speed. Instead, this time, only some parameter estimates are significant. More in detail, all main effects parameters, all riskclass*day parameters and all riskclass*sectionclass parameters are significant, while only some riskclass*day parameters are significant. However, the R-squared value is of 0.384 and so the model was improved by considering also two-ways interactions. There is a remarkable interaction effect between risk classes and days and between risk classes and section classes.

5.4.2 ANOVA analysis for the Norwegian experiment

ANOVA analysis was conducted on the Norwegian data too. The main aims were to find detailed statistical information about those data and to search for a model to fit all the observations to a good approximation.

First of all, a table with basic statistical information (mean and standard deviation) about speed data divided by classes is shown in the next page.

Descriptive statistics (variable: SPEED)					
RISKCLASS	**SEGMENTCLASS**	**DAY**	**mean**	**standard deviation**	**N**
Total	1 = low	day1	61.11	7.63	179
		day2	61.25	6.83	179
		day3	60.77	6.72	164
		day4	61.04	6.90	163
		day5	60.73	7.14	173
		day6	62.57	8.62	146
		Total	61.21	7.31	1004
Total	2 = mediumlow	day1	71.29	10.18	57
		day2	71.92	12.05	59
		day3	71.60	10.38	57
		day4	70.64	8.42	46
		day5	70.17	9.82	55
		day6	70.98	10.22	50
		Total	71.13	10.24	324
Total	Total	day1	63.57	9.37	236
		day2	63.90	9.58	238
		day3	63.56	9.13	221
		day4	63.15	8.27	209
		day5	63.00	8.83	228
		day6	64.71	9.75	196
		Total	63.63	9.17	1328

Tab. 5.6 – Norwegian exp.: mean, standard deviation and sample size for every speed data subset (cf. Attachment IV for complete descriptive statistics)

The employed working method is the same of the Italian experimentation and so I used the Generalized Linear Model tool in the SPSS software.

Firstly, I chose a model form by considering only main factors. This model is explained by the following equation:

$$SPEED = \beta_1 + \beta_2 * RISKCLASS + \beta_3 * SEGMENTCLASS + \beta_4 * DAY \qquad (11)$$

Results of the model analysis are shown below in two summarizing tables.

Tests of Between-Subjects Effects (dependent variable: SPEED)					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected model	50635.976[a]	7	7233.711	156.672	.000
Intercept	4281672.114	1	4281672.114	92734.853	.000
RISKCLASS	26251.842	1	26251.842	568.577	.000
SEGMENTCLASS	19286.603	1	19286.603	417.720	.000
DAY	162.730	5	32.546	.705	.620
Error	60945.879	1320	46.171		
Total	5488874.132	1328			
Corrected Total	111581.855	1327			

a. R squared = .454 (Adjusted R squared = .451)

Tab. 5.7 – Italian exp.: influence of each category on speed forecast (only main effects)

Parameter Estimates (dependent variable: SPEED)						
Parameter	**B**	**Std. error**	**t**	**Sig.**	**Confidence interval 95%**	
					Lower bound	**Upper bound**
Constant	67.520	.614	109.971	.000	66.316	68.724
[RISKCLASS=1.00]	9.171	.385	23.845	.000	8.416	9.925
[RISKCLASS=3.00]	0[a]					
[SEGMENTCLASS=1.00]	-8.917	.436	-20.438	.000	-9.773	-8.061
[SEGMENTCLASS=2.00]	0[a]					
[DAY=1.00]	-.686	.657	-1.044	.297	-1.974	.603
[DAY=2.00]	-.538	.655	-.821	.412	-1.824	.748
[DAY=3.00]	-.825	.667	-1.238	.216	-2.134	.483
[DAY=4.00]	-.968	.676	-1.432	.152	-2.294	.358
[DAY=10.00]	-1.130	.662	-1.706	.088	-2.429	.169
[DAY=27.00]	0[a]					

a. This parameter is set to zero because it is redundant

Tab. 5.8 – Norwegian exp.: parameter estimates of the model (only main effects)
(Riskclass: 1 = risky, 3 = prudent. Segmentclass: 1 = low, 2 = medium-low)

The analysis of significance on Table 5.7 and Table 5.8 shows us that all main factors but day factor could be associated to speed and that all parameter estimates but day estimates are significant. However, the R-squared value is of 0.454 and so about half of the variations are not explained by the considered variables.

In order to improve the model it is possible to consider also interactions between independent variables. Therefore, a full factorial model (considering all the possible combinations between the variables) and a two-ways interaction model (considering only two-ways combinations) were developed.

Due to the very little difference in R-squared values between those two other models (minor than 0.005), I decided to show only results of the two-ways interaction model. The equation of that model is below reported.

$$SPEED = \beta_1 + \beta_2 * RISKCLASS + \beta_3 * SEGMENTCLASS + \beta_4 * DAY + \beta_5 * RISKCLASS * SEGMENTCLASS + \beta_6 * RISKCLASS * DAY + \beta_7 * SEGMENTCLASS * DAY \tag{12}$$

Afterwards, I developed the same analysis for this other model. Results are shown in the following tables:

Tests of Between-Subjects Effects (dependent variable: SPEED)					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected model	52147.422[a]	18	2897.079	63.806	.000
Intercept	4257815.591	1	4257815.591	93775.280	.000
RISKCLASS	25008.641	1	25008.641	550.797	.000
SEGMENTCLASS	20075.243	1	20075.243	442.143	.000
DAY	189.883	5	37.977	.836	.524
RISKCLASS * DAY	327.791	5	65.558	1.444	.206
SEGMENTCLASS * DAY	19.556	5	3.911	.086	.994
RISKCLASS * SEGMENTCLASS	1148.673	1	1148.673	25.299	.000
Error	59434.433	1309	45.404		
Total	5488874.132	1328			
Corrected Total	111581.855	1327			

a. R squared = .467 (Adjusted R squared = .460)

Tab. 5.9 – Norwegian exp.: influence of each category on speed forecast (two-ways interaction)

Parameter Estimates (dependent variable: SPEED)						
Parameter	B	Std. Error	t	Sig.	Confidence interval 95%	
					Lower bound	Upper bound
Constant	64.973	1.073	60.572	.000	62.869	67.078
[RISKCLASS=1.00]	14.311	1.173	12.205	.000	12.011	16.612
[RISKCLASS=3.00]	0[a]					
[SEGMENTCLASS=1.00]	-6.550	1.163	-5.630	.000	-8.832	-4.268
[SEGMENTCLASS=2.00]	0[a]					
[DAY=1.00]	.262	1.435	.183	.855	-2.553	3.077
[DAY=2.00]	1.069	1.435	.745	.456	-1.746	3.884
[DAY=3.00]	.115	1.451	.079	.937	-2.732	2.962
[DAY=4.00]	.352	1.496	.236	.814	-2.582	3.287
[DAY=10.00]	.172	1.442	.119	.905	-2.658	3.001
[DAY=27.00]	0[a]					
[RISKCLASS=1.00] * [DAY=1.00]	-1.522	1.333	-1.142	.254	-4.137	1.093
[RISKCLASS=1.00] * [DAY=2.00]	-2.758	1.328	-2.076	.038	-5.364	-.151
[RISKCLASS=1.00] * [DAY=3.00]	-1.515	1.359	-1.115	.265	-4.181	1.150
[RISKCLASS=1.00] * [DAY=4.00]	-2.082	1.368	-1.523	.128	-4.765	.600
[RISKCLASS=1.00] * [DAY=10.00]	-3.263	1.348	-2.421	.016	-5.907	-.619
[RISKCLASS=1.00] * [DAY=27.00]	0[a]					
[RISKCLASS=3.00] * [DAY=1.00]	0[a]					
[RISKCLASS=3.00] * [DAY=2.00]	0[a]					
[RISKCLASS=3.00] * [DAY=3.00]	0[a]					
[RISKCLASS=3.00] * [DAY=4.00]	0[a]					
[RISKCLASS=3.00] * [DAY=10.00]	0[a]					
[RISKCLASS=3.00] * [DAY=27.00]	0[a]					
[SEGMENTCLASS=1.00] * [DAY=1.00]	-.533	1.511	-.353	.724	-3.496	2.431
[SEGMENTCLASS=1.00] * [DAY=2.00]	-.798	1.504	-.531	.596	-3.749	2.152
[SEGMENTCLASS=1.00] * [DAY=3.00]	-.586	1.523	-.384	.701	-3.574	2.403
[SEGMENTCLASS=1.00] * [DAY=4.00]	-.670	1.577	-.425	.671	-3.764	2.424

[SEGMENTCLASS=1.00] * [DAY=10.00]	-.140	1.523	-.092	.927	-3.127	2.847
[SEGMENTCLASS=1.00] * [DAY=27.00]	0[a]					
[SECTIONCLASS=2.00] * [DAY=1.00]	0[a]					
[SEGMENTCLASS=2.00] * [DAY=2.00]	0[a]					
[SEGMENTCLASS=2.00] * [DAY=3.00]	0[a]					
[SEGMENTCLASS=2.00] * [DAY=4.00]	0[a]					
[SEGMENTCLASS=2.00] * [DAY=10.00]	0[a]					
[SEGMENTCLASS=2.00] * [DAY=27.00]	0[a]					
[RISKCLASS=1.00] * [SEGMENTCLASS=1.00]	-4.393	.873	-5.030	.000	-6.106	-2.679
[RISKCLASS=1.00] * [SEGMENTCLASS=2.00]	0[a]					
[RISKCLASS=3.00] * [SEGMENTCLASS=1.00]	0[a]					
[RISKCLASS=3.00] * [SEGMENTCLASS=2.00]	0[a]					

a. This parameter is set to zero because it is redundant

Tab. 5.10 – Norwegian exp.: parameter estimates of the model (two-ways interaction)
(Riskclass: 1 = risky, 3 = prudent. Segmentclass: 1 = low, 2 = medium-low)

The analysis of significance on Table 5.9 and Table 5.10 shows us that all main factors but day factor and only riskclass⁎segmentclass two-way interaction could be associated to speed. Instead, this time, only some parameter estimates are significant. More in detail, all main effects parameters but day parameters and riskclass⁎segmentclass parameters are significant. Almost every riskclass⁎day parameter are significant, while any segmentclass*day parameters are significant. However, the R-squared value is of 0.467 and so the model was improved by considering also two-ways interactions, even if not so much. There is a remarkable interaction effect between risk classes and segment classes.

5.4.3 Comparison between the two ANOVA analyses

In order to make a comparison between the two experiments, main results of the two ANOVA analyses are summarized in the following tables.

	R squared	SIGNIFICANCE OF THE FACTORS					
		main factors			two-ways interactions		
		risk class	visibility class	day	riskclass* visibilityclass	visibilityclass* day	riskclass* day
ITALY	0.385	yes	yes	yes	yes	yes	yes
NORWAY	0.467	yes	yes	no	yes	no	no

Tab. 5.10 – Comparison between the two ANOVA analyses: Significance of the factors and R squared values

Significance of the factors influencing speed and R-squared values are reported in Table 5.10. In the Italian experiment all the main factors and the interactions between them could be associated to speed. Instead, in the Norwegian experiment test day factor and interactions including day factor could be not associated to speed.

R-squared values are similar: more than half of the speed variations could be not explained by the considered factors for both the experiments.

	MAIN FACTORS					
	DAY					
	1	2	3	4	10	27
	-14.601	-10.668	-10.443	-4.317	-9.047	0
ITALY	RISK CLASS		VISIBILITY CLASS			
	RISKY	PRUDENT	LOW	MEDIUMLOW	MEDIUM	HIGH
	10.821	0	-15.861	-9.162	-8.424	0
	CONSTANT	95.131				

TWO-WAYS INTERACTION										
VISIBILITY CLASS*DAY					RISK CLASS*DAY			RISK CLASS*VISIBILITY CLASS		
	LOW	MEDIUMLOW	MEDIUM	HIGH		RISKY	PRUDENT		RISKY	PRUDENT
1	4.184	2.081	2.017	0	**1**	-2.285	0	**LOW**	-1.593	0
2	-0.152	-1.106	2.013	0	**2**	4.515	0	**MEDIUMLOW**	-1.375	0
3	1.632	0.792	2.408	0	**3**	10.223	0	**MEDIUM**	2.295	0
4	-0.863	-0.969	1.244	0	**4**	5.010	0	**HIGH**	0	0
5	0.844	-0.494	1.591	0	**5**	10.794	0			
6	0	0	0	0	**6**	0	0			

Tab. 5.11 – Summarizing tables for Italian coefficients (red = not significant)

NORWAY	MAIN FACTORS					
	DAY					
	1	2	3	4	10	27
	0.262	1.069	0.115	0.352	0.172	0
	RISK CLASS		**VISIBILITY CLASS**			
	RISKY	PRUDENT	LOW	MEDIUMLOW		
	14.311	0	-6.55	0		
	CONSTANT	64.973				

TWO-WAYS INTERACTION								
VISIBILITY CLASS*DAY			**RISK CLASS*DAY**			**RISK CLASS*VISIBILITY CLASS**		
	LOW	**MEDIUMLOW**		**RISKY**	**PRUDENT**		**RISKY**	**PRUDENT**
1	-0.533	0	**1**	-1.522	0	**LOW**	-4.393	0
2	-0.798	0	**2**	-2.758	0	**MEDIUMLOW**	0	0
3	-0.586	0	**3**	-1.515	0			
4	-0.67	0	**4**	-2.082	0			
5	-0.14	0	**5**	-3.263	0			
6	0	0	**6**	0	0			

Tab. 5.12 – Summarizing tables for Norwegian coefficients (red = not significant)

				ITALY	**NORWAY**
MAIN EFFECTS		CONSTANT		95.131	64.973
		RISK CLASS	RISKY	10.821	14.311
			PRUDENT	0.000	0.000
		VISIBILITY	LOW	-15.861	-6.550
			MEDIUMLOW	-9.162	0.000
		DAY	1	-14.601	0.262
			2	-10.668	1.069
			3	-10.443	0.115
			4	-4.317	0.352
			5	-9.047	0.172
			6	0.000	0.000
2-WAYS INTERACTIONS	**RC*VC**	RISKY	LOW	-1.593	-4.393
			MEDIUMLOW	-1.375	0.000

		PRUDENT	LOW	0.000	0.000
			MEDIUMLOW	0.000	0.000
	RC*D	DAY 1	RISKY	-2.285	-1.522
			PRUDENT	0.000	0.000
		DAY 2	RISKY	4.515	-2.758
			PRUDENT	0.000	0.000
		DAY 3	RISKY	10.223	-1.515
			PRUDENT	0.000	0.000
		DAY 4	RISKY	5.010	-2.082
			PRUDENT	0.000	0.000
		DAY 5	RISKY	10.794	-3.263
			PRUDENT	0.000	0.000
		DAY 6	RISKY	0.000	0.000
			PRUDENT	0.000	0.000
	VC*D	DAY 1	LOW	4.184	-0.533
			MEDIUMLOW	2.081	0.000
		DAY 2	LOW	-0.152	-0.798
			MEDIUMLOW	-1.106	0.000
		DAY 3	LOW	1.632	-0.586
			MEDIUMLOW	0.792	0.000
		DAY 4	LOW	-0.863	-0.670
			MEDIUMLOW	-0.969	0.000
		DAY 5	LOW	0.844	-0.140
			MEDIUMLOW	-0.494	0.000
		DAY 6	LOW	0.000	0.000
			MEDIUMLOW	0.000	0.000

Tab. 5.13 –Comparison of coefficients of from the two experiments (red = not significant)

Values and significance of the β-coefficients of the two models are reported in Table 5.11 and Table 5.12. In order to compare the two experiments I had to consider only low and medium-low visibility classes. The comparison between the coefficients is shown in Table 5.13, by considering only equations 10 and 12. Coefficient values are not perfectly comparable with one another due to the lack of two visibility classes in Norwegian experiment, but trends could be discussed the same by looking at them. Discussion about coefficient values will be made in the last paragraph of the chapter.

5.5 Models based on stated speeding – ANOVA comparison

A possible counterargument to modeling tools used in the previous paragraph is that speed was used at the same time as an input and as an output of the problem. In fact, measured speed was used to classify users into risk categories and it was also the final output of the model. Therefore, in this paragraph I propose an alternative method to classify users by considering their answers to a self-reported driving behaviour questionnaire.

The considered question is the following: "Have you ever gone faster than the speed limits?" There were five possible answers: never, sometimes, enough times, a lot of times, very frequently.

	userID	overspeed
ITALY	1	enough times
	2	enough times
	3	enough times
	4	enough times
	5	a lot of times
	6	a lot of times
	7	a lot of times
	8	a lot of times
	9	sometimes
	10	a lot of times
	11	a lot of times
	12	sometimes
	13	very frequently
	14	enough times
	15	a lot of times
	16	enough times
	17	a lot of times
	18	a lot of times
	19	enough times

	userID	overspeed
NORWAY	1	enough times
	2	enough times
	3	sometimes
	4	sometimes
	5	a lot of times
	6	a lot of times
	7	a lot of times
	8	very frequently
	9	a lot of times
	10	sometimes

Tab. 5.14 – Answers given to the question regarding over-speed by Italian and Norwegian drivers

Drivers were divided into two risk categories based on stated speeding: “YES” for drivers who answered enough times or a few times and “NO” for drivers who answered often or very often.

ANOVA analyses were made again considering these two different risk categories.

5.5.1 – ANOVA analysis for the Italian experiment – models based on stated speeding

ANOVA analysis was conducted again on the Italian data with similar aims.

First of all, a table with basic statistical information (mean and standard deviation) about speed data divided by classes is shown below.

Descriptive statistics (Depdendent variable: SPEED)					
STATEDSPEEDING	SECTIONCLASS	DAY	Media	Standard deviation	N
Total	low ssd	day1	72,5908	12,44449	689
		day2	75,8725	14,79265	785
		day3	80,1843	15,07598	848
		day4	83,5814	15,83557	636
		day5	78,7306	16,88693	687
		day6	85,4558	15,97414	625
		Total	79,2100	15,76601	4270
	mediumlow ssd	day1	77,0293	12,64639	1320
		day2	81,3236	14,74671	1508
		day3	85,4962	15,42876	1650
		day4	89,8812	15,10465	1210
		day5	83,1732	16,91000	1320
		day6	91,9961	13,83539	1191
		Total	84,5830	15,64561	8199
	medium ssd	day1	79,0467	13,73068	418
		day2	86,8676	17,71132	456
		day3	88,6750	19,21304	532
		day4	95,7175	15,61822	342
		day5	85,7711	18,09115	418
		day6	94,6989	16,03042	343
		Total	88,0421	17,82730	2509
	high ssd	day1	84,4100	13,64105	803
		day2	92,1310	15,96423	876

		day3	93,7157	17,52308	1021
		day4	100,3122	15,35712	730
		day5	92,0077	16,76140	799
		day6	101,7035	14,41282	675
		Total	93,7120	16,71873	4904
	Total	day1	78,1785	13,63258	3230
		day2	83,4522	16,51341	3625
		day3	86,8733	17,10435	4051
		day4	91,8017	16,51642	2918
		day5	84,7528	17,65109	3224
		day6	93,1930	15,76051	2834
		Total	86,1173	17,00739	19882

Tab. 5.15 – Italian exp.: mean, standard deviation and sample size for every speed data subset (cf. Attachment IV for complete descriptive statistics)

I considered only data of risky and prudent users for the reasons already explained in the previous paragraph.

For the previous explained reasons, I directly used the two-ways interaction model:

$$SPEED = \beta_1 + \beta_2 * STATEDSPEEDING + \beta_3 * SEGMENTCLASS + \beta_4 * DAY + \beta_5 * STATEDSPEEDING * SEGMENTCLASS + \beta_6 * STATEDSPEEDING * DAY + \beta_7 * SEGMENTCLASS * DAY \quad (13)$$

In the first table there is information about influence of each factor on the dependent variable with their statistical significance (based on the F-ratio).

Tests of Between-Subjects Effects (dependent variable: SPEED)					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected model	1088968,863[a]	32	34030,277	144,899	,000
Intercept	117921026,763	1	117921026,763	502101,666	,000
STATEDSPEEDING	33541,680	1	33541,680	142,819	,000
SECTIONCLASS	518631,550	3	172877,183	736,102	,000
DAY	363374,307	5	72674,861	309,446	,000

STATEDSPEEDING * SECTIONCLASS	971,212	3	323,737	1,378	,247
STATEDSPEEDING*DAY	27155,999	5	5431,200	23,126	,000
SECTIONCLASS * DAY	10447,247	15	696,483	2,966	,000
Error	4661634,521	19849	234,855		
Total	153199242,236	19882			
Corrected Total	5750603,384	19881			

a. R-squared = ,189 (corrected R-squared = ,188)

Tab. 5.16 – Italian exp.: influence of each category on speed forecast (two-ways interaction)

In the second table there are the computed values of β coefficients with their statistical significance (based on the t-value).

Parameter estimates (Dependent variable: SPEED)						
Parameter	**B**	**Std. deviation error**	**t**	**Sig.**	**Confidence of interval 95%**	
					Lower bound	**Upper bound**
Intercetta	102,505	,642	159,706	,000	101,247	103,763
[STATEDSPEEDING=1,00]	-2,274	,718	-3,169	,002	-3,681	-,867
[STATEDSPEEDING=2,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=1,00]	-16,626	,887	-18,744	,000	-18,365	-14,888
[SECTIONCLASS=2,00]	-9,837	,765	-12,861	,000	-11,336	-8,338
[SECTIONCLASS=3,00]	-7,347	1,050	-6,997	,000	-9,405	-5,289
[SECTIONCLASS=4,00]	0[a]	.	.	.	.	.
[DAY=1,00]	-15,997	,906	-17,653	,000	-17,774	-14,221
[DAY=2,00]	-8,571	,841	-10,191	,000	-10,219	-6,922
[DAY=3,00]	-4,744	,827	-5,738	,000	-6,364	-3,123
[DAY=4,00]	-1,637	,877	-1,866	,062	-3,356	,082
[DAY=10,00]	-9,245	,907	-10,192	,000	-11,023	-7,467
[DAY=27,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=1,00] * [SECTIONCLASS=1,00]	1,232	,654	1,885	,059	-,049	2,514
[STATEDSPEEDING=1,00] * [SECTIONCLASS=2,00]	,373	,566	,658	,510	-,737	1,482
[STATEDSPEEDING=1,00] * [SECTIONCLASS=3,00]	,904	,774	1,167	,243	-,614	2,421
[STATEDSPEEDING=1,00] * [SECTIONCLASS=4,00]	0[a]	.	.	.	.	.

[STATEDSPEEDING=2,00] * [SECTIONCLASS=1,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [SECTIONCLASS=2,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [SECTIONCLASS=3,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [SECTIONCLASS=4,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=1,00] * [DAY=1,00]	-1,023	,816	-1,253	,210	-2,622	,577
[STATEDSPEEDING=1,00] * [DAY=2,00]	-2,054	,790	-2,599	,009	-3,604	-,505
[STATEDSPEEDING=1,00] * [DAY=3,00]	-5,826	,769	-7,572	,000	-7,334	-4,318
[STATEDSPEEDING=1,00] * [DAY=4,00]	,884	,838	1,055	,291	-,758	2,526
[STATEDSPEEDING=1,00] * [DAY=10,00]	,303	,816	,372	,710	-1,297	1,904
[STATEDSPEEDING=1,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=1,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=2,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=3,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=4,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=10,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=1,00] * [DAY=1,00]	3,979	1,176	3,382	,001	1,673	6,285
[SECTIONCLASS=1,00] * [DAY=2,00]	-,012	1,138	-,011	,992	-2,242	2,218
[SECTIONCLASS=1,00] * [DAY=3,00]	2,482	1,113	2,231	,026	,302	4,663
[SECTIONCLASS=1,00] * [DAY=4,00]	-,595	1,190	-,500	,617	-2,928	1,738
[SECTIONCLASS=1,00] * [DAY=10,00]	2,552	1,178	2,167	,030	,244	4,860
[SECTIONCLASS=1,00] * [DAY=27,00]	0[a]	.	.	.	.	.

[SECTIONCLASS=2,00] * [DAY=1,00]	2,064	1,019	2,025	,043	,067	4,062
[SECTIONCLASS=2,00] * [DAY=2,00]	-1,124	,985	-1,141	,254	-3,054	,807
[SECTIONCLASS=2,00] * [DAY=3,00]	1,178	,961	1,226	,220	-,706	3,061
[SECTIONCLASS=2,00] * [DAY=4,00]	-,780	1,030	-,757	,449	-2,800	1,240
[SECTIONCLASS=2,00] * [DAY=10,00]	,682	1,020	,669	,504	-1,317	2,681
[SECTIONCLASS=2,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=3,00] * [DAY=1,00]	1,409	1,393	1,011	,312	-1,321	4,138
[SECTIONCLASS=3,00] * [DAY=2,00]	1,707	1,349	1,266	,206	-,937	4,351
[SECTIONCLASS=3,00] * [DAY=3,00]	1,858	1,311	1,417	,156	-,712	4,429
[SECTIONCLASS=3,00] * [DAY=4,00]	2,358	1,429	1,650	,099	-,443	5,160
[SECTIONCLASS=3,00] * [DAY=10,00]	,536	1,393	,385	,700	-2,194	3,267
[SECTIONCLASS=3,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=4,00] * [DAY=1,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=4,00] * [DAY=2,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=4,00] * [DAY=3,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=4,00] * [DAY=4,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=4,00] * [DAY=10,00]	0[a]	.	.	.	.	.
[SECTIONCLASS=4,00] * [DAY=27,00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Tab. 5.17 – Italian exp.: parameter estimates of the model two-ways interaction)
(Riskclass: 1 = risky, 3 = prudent. Sectionclass: 1 = low, 2 = medium-low, 3 = medium, 4 = high)

The analysis of significance on Table 5.16 and Table 5.17 shows us that each main factor could be associated to speed and that each parameter estimate related to main factor is significant (except coefficient related to day 4). However, not all the two-ways interactions between factors are significant and most of the interactions-related coefficients are not significant too. (Reducing two-ways interactions only to the significant interactions does not lead to any evident improvement). It is very important to note that the R-squared value is of 0.189 and so chosen variables explain only a quantity minor than a fifth of the total variations.

5.5.2 – ANOVA analysis for the Norwegian experiment – models based on stated speeding

ANOVA analysis was conducted again on the Norwegian data too.

First of all, a table with basic statistical information (mean and standard deviation) about speed data divided by classes is shown below.

Descriptive statistics (dependent variable: SPEED)					
STATEDSPEEDING	**SEGMENTCLASS**	**DAY**	**mean**	**Std. deviation**	**N**
Total	low	day1	61,1082	7,62588	179
		day2	61,2543	6,82626	179
		day3	60,7706	6,71746	164
		day4	61,0384	6,90485	163
		day5	60,7253	7,13845	173
		day6	62,5674	8,61659	146
		Total	61,2140	7,31047	1004
	mediumlow	day1	71,2937	10,18233	57
		day2	71,9170	12,05402	59
		day3	71,5982	10,38016	57
		day4	70,6426	8,42096	46
		day5	70,1669	9,81597	55
		day6	70,9839	10,22363	50
		Total	71,1292	10,24418	324
	Total	day1	63,5683	9,37236	236
		day2	63,8975	9,58348	238
		day3	63,5632	9,13240	221
		day4	63,1522	8,26948	209
		day5	63,0029	8,82726	228
		day6	64,7145	9,74695	196
		Total	63,6331	9,16983	1328

Tab. 5.18 – Norwegian exp.: mean, standard deviation and sample size for every speed data subset (cf. Attachment IV for complete descriptive statistics)

I considered only data of risky and prudent users for the reasons already explained in the previous paragraph.

For the previous explained reasons, I directly used the two-ways interaction model:

$$SPEED = \beta_1 + \beta_2 * STATEDSPEEDING + \beta_3 * SEGMENTCLASS + \beta_4 * DAY + \beta_5 * STATEDSPEEDING * SEGMENTCLASS + \beta_6 * STATEDSPEEDING * DAY + \beta_7 * SEGMENTCLASS * DAY \tag{14}$$

In the first table there is information about influence of each factor on the dependent variable with their statistical significance (based on the F-ratio).

Tests of between-Subjects Effects (dependent variable: SPEED)					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected model	37584,008[a]	18	2088.000	36.936	.000
Intercept	3889923.083	1	3889923.083	68811.587	.000
STATEDSPEEDING	10838.843	1	10838.843	191.736	.000
SEGMENTCLASS	14156.275	1	14156.275	250.420	.000
DAY	213.207	5	42.641	.754	.583
STATEDSPEEDING * DAY	295.976	5	59.195	1.047	.388
SEGMENTCLASS * DAY	98.568	5	19.714	.349	.883
STATEDSPEEDING * SEGMENTCLASS	260.373	1	260.373	4.606	.032
Error	73997.847	1309	56.530		
Total	5488874.132	1328			
Corrected Total	111581.855	1327			

a. R-squared = ,337 (corrected R-squared = ,328)

Tab. 5.19 – Norwegian exp.: influence of each category on speed forecast (two-ways interaction)

In the second table there are the computed values of β coefficients with their statistical significance (based on the t-value).

Parameters estimate (dependent variable: SPEED)						
Parameter	B	Std. Deviation error	t	Sig.	Confidence of interval 95%	
					Lower bound	Upper bound
Intercept	65,485	1,330	49,251	,000	62,876	68,093
[STATEDSPEEDING=1,00]	9,166	1,330	6,889	,000	6,556	11,776
[STATEDSPEEDING=2,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=1,00]	-5,606	1,369	-4,096	,000	-8,291	-2,921
[SEGMENTCLASS=2,00]	0[a]	.	.	.	.	.
[DAY=1,00]	1,212	1,733	,699	,484	-2,188	4,613
[DAY=2,00]	,844	1,734	,487	,627	-2,559	4,246
[DAY=3,00]	,218	1,746	,125	,901	-3,207	3,644
[DAY=4,00]	-,363	1,816	-,200	,842	-3,925	3,199
[DAY=10,00]	,605	1,738	,348	,728	-2,805	4,015
[DAY=27,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=1,00] * [SEGMENTCLASS=1,00]	-2,155	1,004	-2,146	,032	-4,124	-,185
[STATEDSPEEDING=1,00] * [SEGMENTCLASS=2,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [SEGMENTCLASS=1,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [SEGMENTCLASS=2,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=1,00] * [DAY=1,00]	-2,084	1,505	-1,384	,166	-5,037	,869
[STATEDSPEEDING=1,00] * [DAY=2,00]	-,922	1,501	-,615	,539	-3,866	2,022
[STATEDSPEEDING=1,00] * [DAY=3,00]	-,322	1,520	-,212	,832	-3,303	2,658
[STATEDSPEEDING=1,00] * [DAY=4,00]	-,700	1,543	-,454	,650	-3,727	2,326
[STATEDSPEEDING=1,00] * [DAY=10,00]	-2,758	1,504	-1,833	,067	-5,709	,193
[STATEDSPEEDING=1,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=1,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=2,00]	0[a]	.	.	.	.	.

[STATEDSPEEDING=2,00] * [DAY=3,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=4,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=10,00]	0[a]	.	.	.	.	.
[STATEDSPEEDING=2,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=1,00] * [DAY=1,00]	-1,716	1,725	-,995	,320	-5,101	1,668
[SEGMENTCLASS=1,00] * [DAY=2,00]	-1,713	1,718	-,997	,319	-5,083	1,658
[SEGMENTCLASS=1,00] * [DAY=3,00]	-1,936	1,731	-1,118	,264	-5,333	1,461
[SEGMENTCLASS=1,00] * [DAY=4,00]	-,839	1,801	-,466	,641	-4,371	2,694
[SEGMENTCLASS=1,00] * [DAY=10,00]	-1,429	1,730	-,826	,409	-4,823	1,964
[SEGMENTCLASS=1,00] * [DAY=27,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=2,00] * [DAY=1,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=2,00] * [DAY=2,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=2,00] * [DAY=3,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=2,00] * [DAY=4,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=2,00] * [DAY=10,00]	0[a]	.	.	.	.	.
[SEGMENTCLASS=2,00] * [DAY=27,00]	0[a]	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

Tab. 5.20 – Norwegian exp.: parameter estimates of the model two-ways interaction)
(Riskclass: 1 = risky, 3 = prudent. Segmentclass: 1 = low, 2 = medium-low)

The analysis of significance on Table 5.19 and Table 5.20 shows us that main factors except day factor could be associated to speed and that each parameter estimate related to main factor except day coefficients is significant. However, only the stated speeding-segment class interaction between factors is significant and almost all the interactions-related coefficients are not significant too. The R-squared value is of 0.337 and so chosen variables explain about a third of the total variations.

5.5.3 Comparison between the two ANOVA analyses – models based on stated speeding

In order to make a comparison between the two experiments considering stated speeding instead of risk classes based on speed, main results of the two ANOVA analyses are summarized in the following tables.

	R squared	SIGNIFICANCE OF THE FACTORS					
		main factors			two-ways interactions		
		risk class	visibility class	day	riskclass* visibilityclass	visibilityclass* day	riskclass* day
ITALY	0.189	yes	yes	yes	no	yes	yes
NORWAY	0.337	yes	yes	no	yes	no	no

Tab. 5.21 – Comparison between the two ANOVA analyses considering stated speeding: Significance of the factors and R squared values

Significance of the factors influencing speed and R-squared values are reported in Table 5.21. In the Italian experiment all the main factors and the interactions between them except the risk class*visibility class interaction could be associated to speed. Instead, in the Norwegian experiment test day factor and interactions including day factor could be not associated to speed.

R-squared values are low: more than two-thirds half of the speed variations could be not explained by the considered factors for both the experiments after introducing stated speeding. In particular the Italian value is noticeably low.

ITALY	MAIN FACTORS					
	DAY					
	1	2	3	4	10	27
	-15.997	-8.571	-4.744	-1.637	-9.245	0
	RISK CLASS		VISIBILITY CLASS			
	YES	NO	LOW	MEDIUMLOW	MEDIUM	HIGH
	-2.274	0	-16.626	-9.837	-7.347	0
	CONSTANT	102.505				

TWO-WAYS INTERACTION										
VISIBILITY CLASS*DAY					RISK CLASS*DAY			RISK CLASS*VISIBILITY CLASS		
	LOW	MEDIUMLOW	MEDIUM	HIGH		YES	NO		YES	NO
1	3.979	2.064	1.409	0	**1**	-1.023	0	**LOW**	1.232	0
2	-0.012	-1.124	1.707	0	**2**	-2.054	0	**MEDIUMLOW**	0.373	0
3	2.482	1.178	1.858	0	**3**	-5.826	0	**MEDIUM**	0.904	0
4	-0.595	-0.780	2.358	0	**4**	0.884	0	**HIGH**	0	0
5	2.552	0.682	0.536	0	**5**	0.303	0			
6	0	0	0	0	**6**	0	0			

Tab. 5.22 – Summarizing tables for Italian coefficients (red = not significant)

NORWAY	MAIN FACTORS					
	DAY					
	1	2	3	4	10	27
	1.212	0.844	0.218	-0.363	0.605	0
	RISK CLASS		VISIBILITY CLASS			
	YES	NO	LOW	MEDIUMLOW		
	9.166	0	-5.606	0		
	CONSTANT	65.485				

TWO-WAYS INTERACTION								
VISIBILITY CLASS*DAY			RISK CLASS*DAY			RISK CLASS*VISIBILITY CLASS		
	LOW	MEDIUMLOW		YES	NO		YES	NO
1	-1.716	0	**1**	-2.084	0	**LOW**	-2.155	0
2	-1.713	0	**2**	-0.922	0	**MEDIUMLOW**	0	0
3	-1.936	0	**3**	-0.322	0			
4	-0.839	0	**4**	-0.700	0			
5	-1.429	0	**5**	-2.758	0			
6	0	0	**6**	0	0			

Tab. 5.23 – Summarizing tables for Norwegian coefficients (red = not significant)

				ITALY	NORWAY
MAIN EFFECTS		CONSTANT		102.505	65.485
		RISK CLASS	YES	-2.274	9.166
			NO	0.000	0.000
		VISIBILITY	LOW	-16.626	-5.606
			MEDIUMLOW	-9.837	0.000
		DAY	1	-15.997	1.212
			2	-8.571	0.844
			3	-4.744	0.218
			4	-1.637	-0.363
			5	-9.245	0.605
			6	0.000	0.000
2-WAYS INTERACTIONS	**RC*VC**	YES	LOW	1.232	-2.155
			MEDIUMLOW	0.373	0.000
		NO	LOW	0.000	0.000
			MEDIUMLOW	0.000	0.000
	RC*D	DAY 1	YES	-1.023	-2.084
			NO	0.000	0.000
		DAY 2	YES	-2.054	-0.922
			NO	0.000	0.000
		DAY 3	YES	-5.826	-0.322
			NO	0.000	0.000
		DAY 4	YES	0.884	-0.700
			NO	0.000	0.000
		DAY 5	YES	0.303	-2.758
			NO	0.000	0.000
		DAY 6	YES	0.000	0.000
			NO	0.000	0.000
	VC*D	DAY 1	LOW	3.979	-1.716
			MEDIUMLOW	2.064	0.000
		DAY 2	LOW	-0.012	-1.713
			MEDIUMLOW	-1.124	0.000
		DAY 3	LOW	2.482	-1.936
			MEDIUMLOW	1.178	0.000
		DAY 4	LOW	-0.595	-0.839
			MEDIUMLOW	-0.780	0.000
		DAY 5	LOW	2.552	-1.429
			MEDIUMLOW	0.682	0.000
		DAY 6	LOW	0.000	0.000

			MEDIUMLOW	0.000	0.000

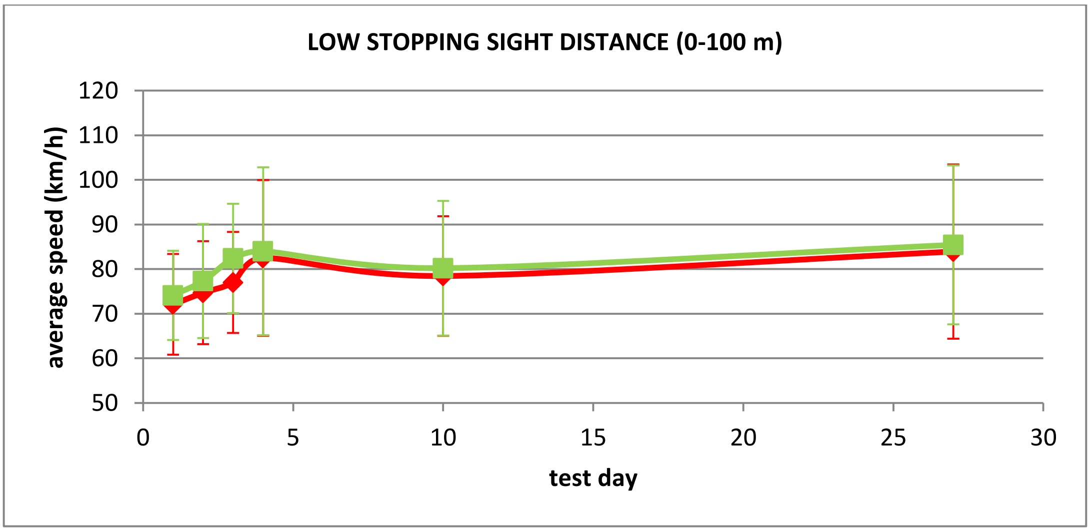
Tab. 5.24 – Comparison of coefficients of from the two experiments (red = not significant)

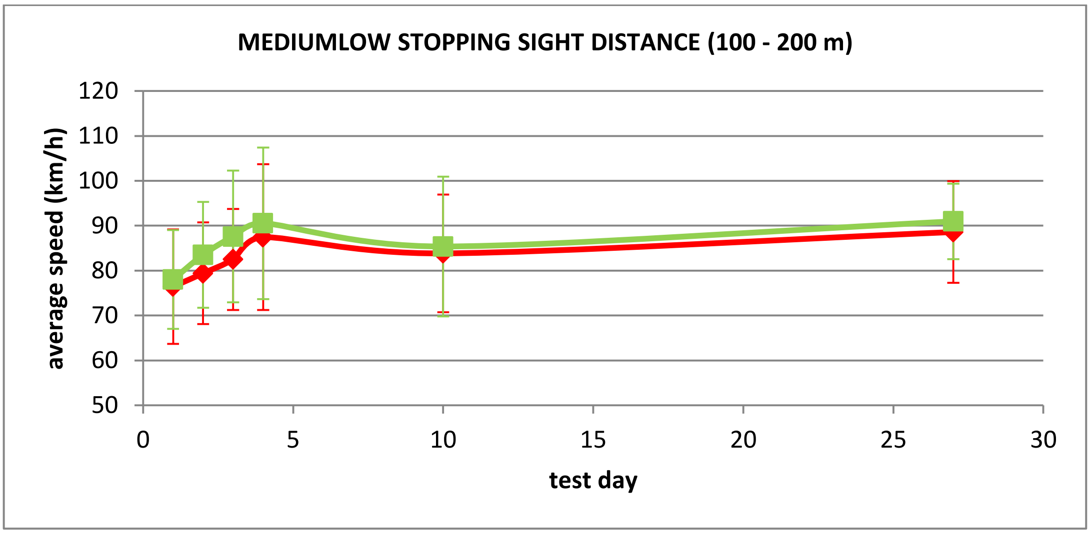
Values and significance of the β-coefficients of the two models are reported in Table 5.22 and Table 5.23. In order to compare the two experiments I had to consider only low and medium-low visibility classes. The comparison between the coefficients is shown in Table 5.24, by considering only equations 13 and 14. Coefficient values are not perfectly comparable with one another due to the lack of two visibility classes in Norwegian experiment, but trends could be discussed the same by looking at them. Discussion about coefficient values will be made in the last paragraph of the chapter.

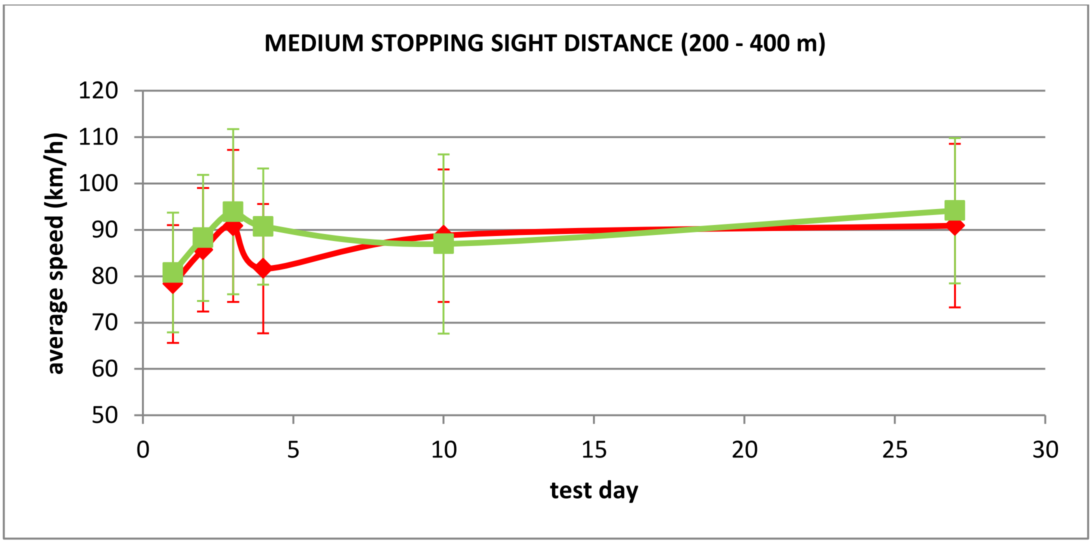
5.5.4 Effects of introduction of the variable "stated speeding"

In the paragraph 5.4 both the Italian and the Norwegian drivers were categorized by using measured speed as a variable. Instead, in the paragraph 5.5, both the Italian and the Norwegian drivers were categorized by using stated speeding as a variable.

Average speed/test days diagrams obtained by considering risk classes based on stated speeding are reported below.







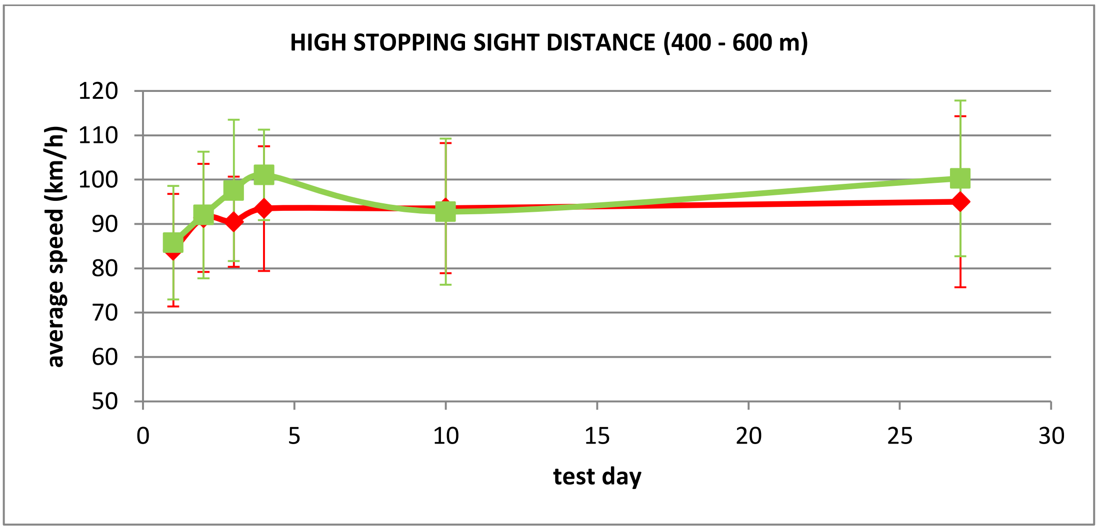
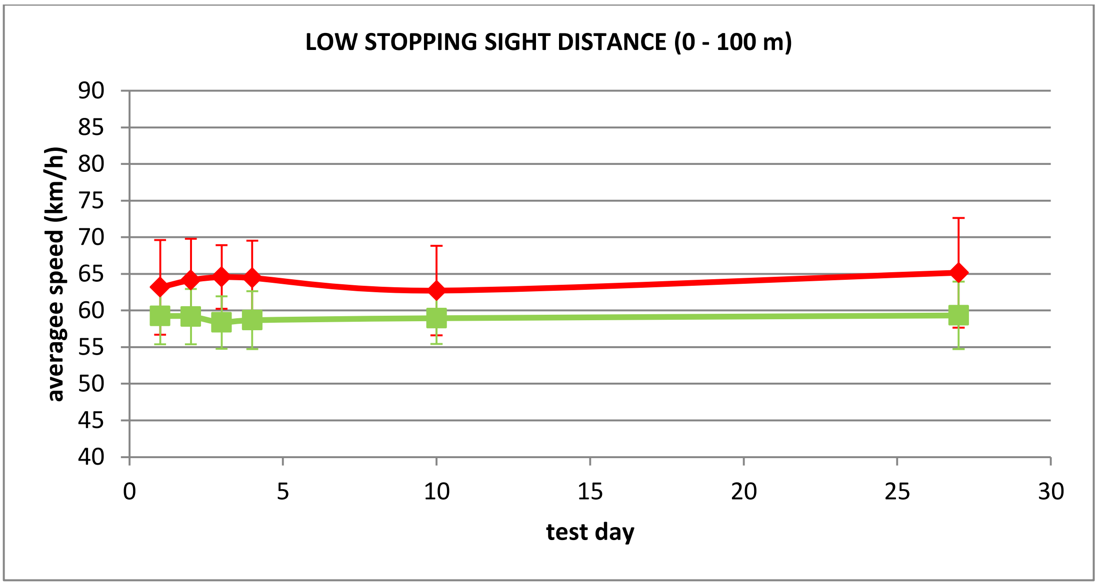


Fig. 5.7a, b, c, d - Average speed-test day diagrams, differentiated by section category (risk classes based on stated speeding) – Italian experiment

COLOR LEGEND:

Stated speeding yes   Stated speeding no



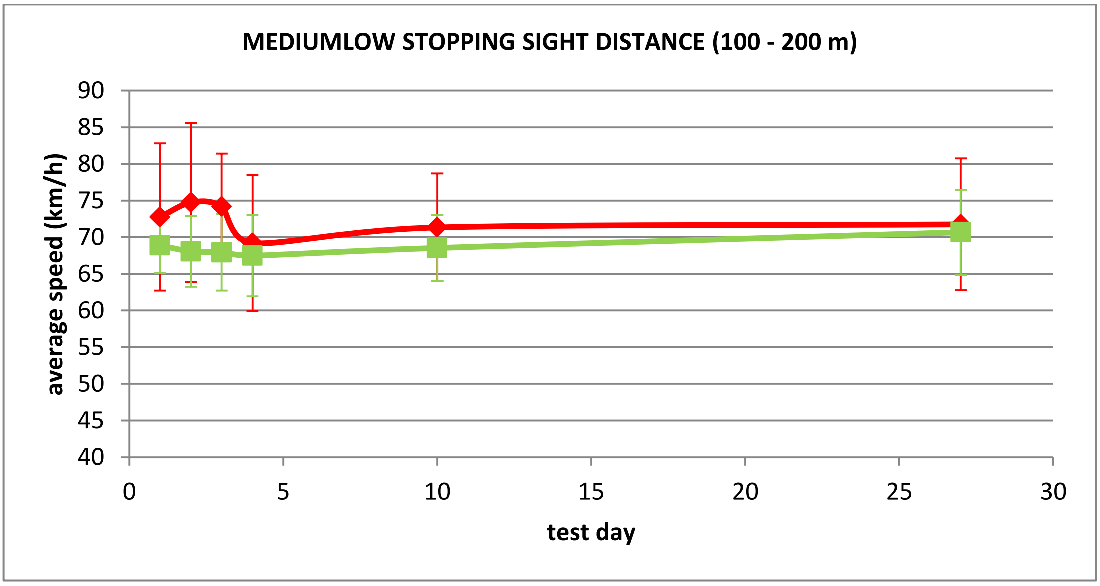
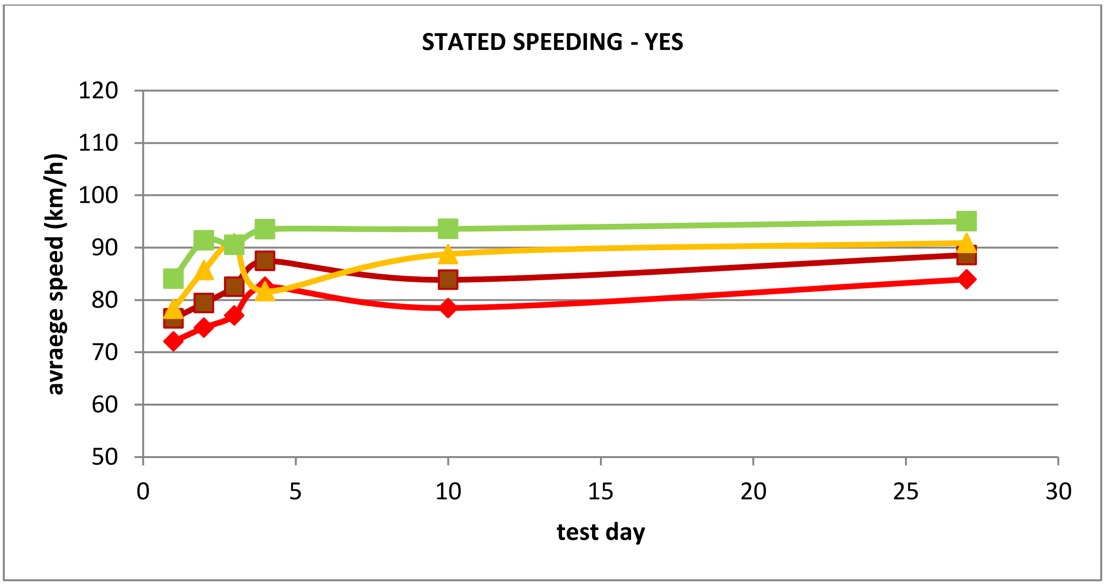


Fig. 5.8a, b - Average speed-test day diagrams, differentiated by section category (risk classes based on stated speeding) – Norwegian experiment

COLOR LEGEND:

Stated speeding yes

Stated speeding no



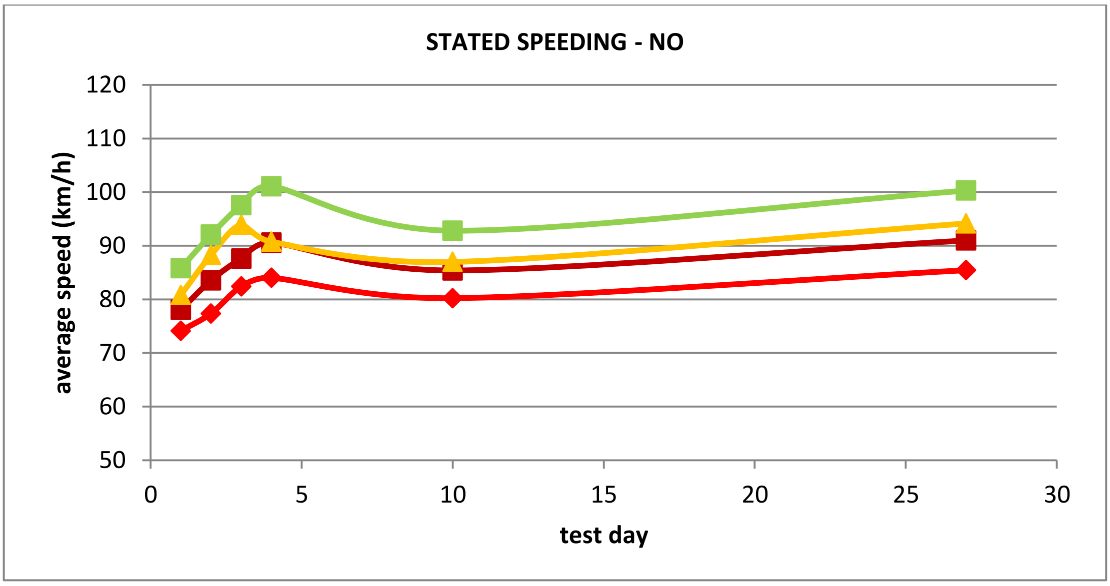
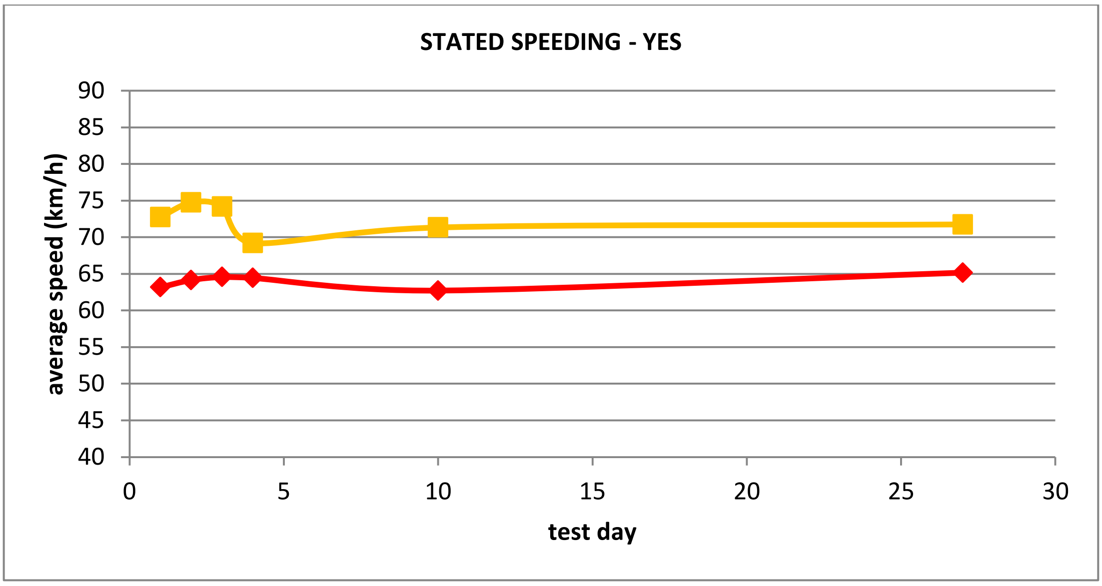


Fig. 5.9a, b - Average speed-test day diagrams, differentiated by risk category (risk classes based on stated speeding) – Italian experiment

COLOR LEGEND:

LS MLS MS HS



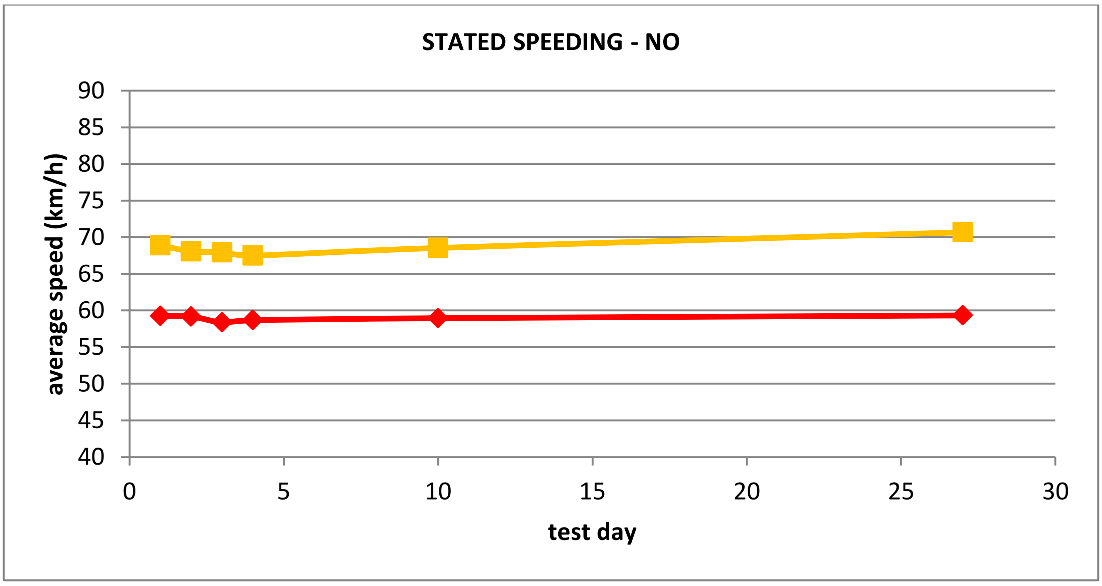
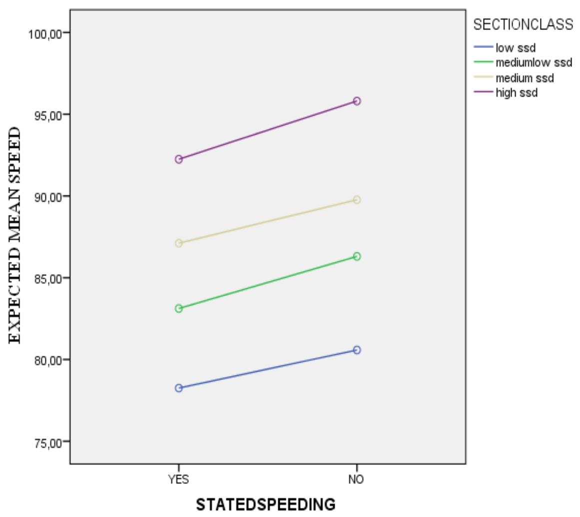


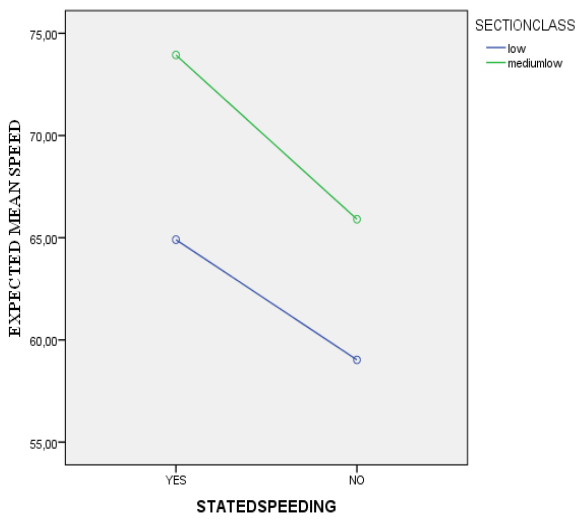
Fig. 5.10a, b - Average speed-test day diagrams, differentiated by risk category (risk classes based on stated speeding) – Norwegian experiment

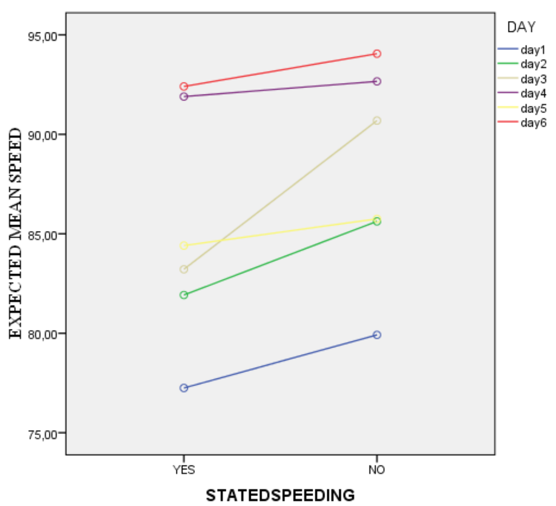
COLOR LEGEND:

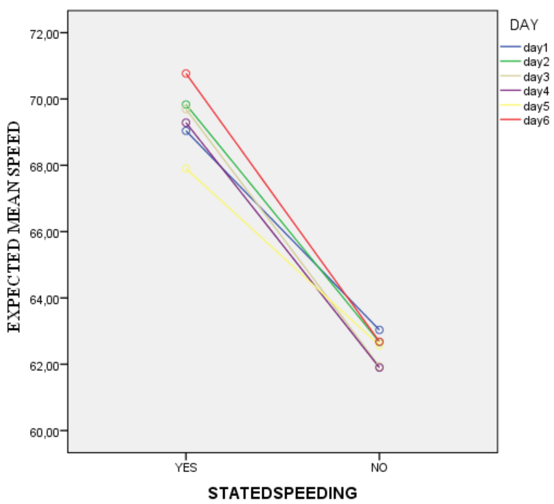
LS MLS

Furthermore, it is possible to make a qualitative comparison between results obtained using risk categories based on self-reported speeding in the Italian experimentation and in the Norwegian one by looking at the following diagrams. In each diagram, expected mean speed is on the y-axis, while variables used in categorizing drivers are on the x-axis. Furthermore, in each diagram there is more than one curve, because every variable is combined with one another. For each combination of variables, the diagram on the left is related to the Italian experimentation and the diagram on the right is related to the Norwegian one.









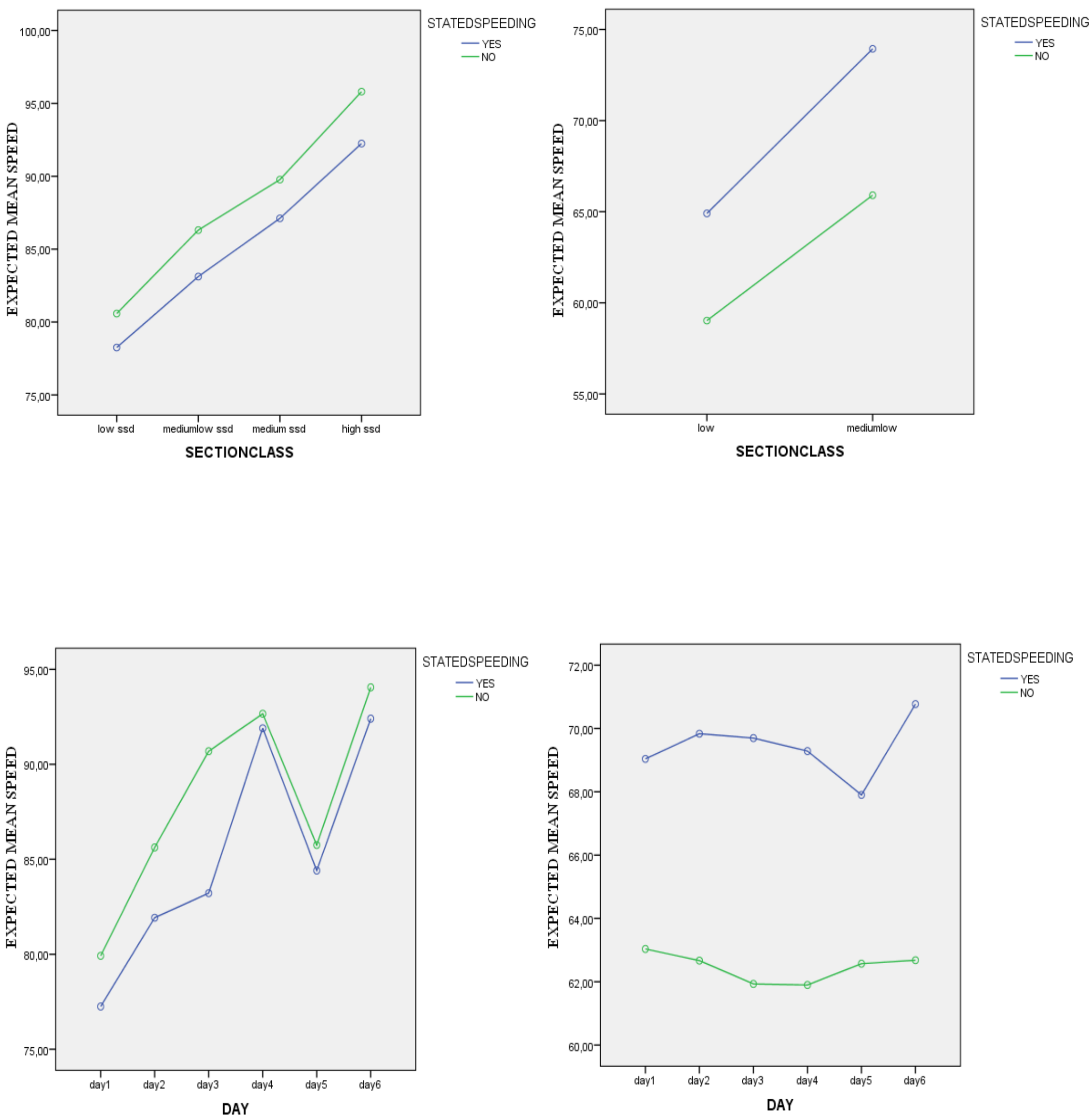


Fig. 5.6a, b, c, d – Comparison between Italy and Norway – two-ways interactions models based on stated speeding

We can see two different results. In Italy it seems that there is no relationship between risk classes and stated speeding: people who affirm to go above speed limits are more prudent than the ones who affirm to go below speed limits. Instead, in Norway, we can note the opposite behavior: people who affirm to go above speed limits are more risky than the ones who affirm to go below speed limits.

The possible conclusion is that Italian drivers have a wrong perception of their usual speed while the Norwegian drivers have, on average, a correct perception. This sentence is confirmed by looking at the expected mean speed-day diagrams: in Italy the variable stated speeding is not able to produce a division of speed data in two different risk clusters, while in Norway this phenomenon could be clearly noted.

5.6 Discussion

In light of the analysis of qualitative comparison and of the comparison made by using ANOVA analyses for the two experiments it is possible to draw some conclusions about the differences between them. In this sense, the most explanatory results are Figures 5.4 and Table 5.13, in which are shown speed trends and coefficients belonging to the two different developed models (considering measured speed as a variable able to classify users into risk categories).

In fact, coefficients and their related statistical significance give us an idea of the influence of each factor on the two models, influence that can be checked by considering diagrams-related qualitative comparison.

Value of the constant is equal to 95.13 km/h in the Italian experiment and it is equal to 64.97 km/h in the Norwegian experiment. This means that the overall average speed of all users is higher in Italy than in Norway. In fact, in this sense, we can look at the Table 5.1 and to the Table 5.6 in order to find mean values of speed. On average, among the six days, in the Italian experiment risky users have a speed of 85.84 km/h in low visibility sections and of 91.92 km/h in medium-low sections; while prudent users have a speed of 71.28 km/h in low visibility sections and of 76.99 km/h in medium-low sections. Instead, in the Norwegian experiment, the corresponding speeds are: 66.36 km/h, 77.72 km/h, 58.3 km/h and 65.3 km/h. Therefore, clearly, Italians drive faster than Norwegians in every visibility condition. However, I already stated that the two roads are quite different and so, apart from possible different risk perception, difference is also due to this dissimilarity. It is also interesting to look at the speeding phenomenon in the two countries, even if there are still the same problems in explaining speed choice information. Speed limit is set to 70 km/h in both the roads, and so it seems that Italians have a greater tendency to speeding than the Norwegians, even if speeding is widespread and socially accepted also in Norway, as stated in the chapter 'state of the art'. In fact, in example, Italian risky users have an average speed of 102.33 km/h on high visibility sections, a value that is 30 km/h higher than the fixed speed limit. However, we cannot make a comparison with high visibility sections on the Norwegian road and so judgment on speeding is incomplete and affected by the already explained problems.

If we look at obtained data, drivers could be well divided in two different groups according to their risk perception both in the two experiments. In fact, speed trends of risky users are considerably higher than the one of prudent users in all visibility conditions, especially in higher stopping sight distance sections. Instead, in low visibility conditions, this difference is lighter, due to intrinsic difficulties of roads that limit speed choice. More in detail, in the Norwegian experiment there is the minimum difference between speed of risky users and that one of prudent users in low visibility segments and this is due to the explained features of that road. However, the general logic result is that degrees of freedom of speed choice decrease in each driver in worse visibility conditions independently from the driver's country. In fact, in both the models, coefficients related to risky users are positive and significant in respect to coefficient related to the prudent ones ($\beta_{2,\ \text{Italy}} = 10.82$, $\beta_{2,\ \text{Norway}} = 14.31$). However, this evidence cannot be seen as a result because of the way in which risky users are defined (by considering measured speed as a parameter).

Visibility conditions have also a clear effect on speed choice in both the two experiments. This effect, already discussed in the previous paragraphs, is responsible of an almost linear decrease of speed while going from higher visibility sections to lower visibility sections in both the experiments. This trend is confirmed by looking, for example, at values of the β_3 coefficients of both models for low visibility sections: $\beta_{3,\ \text{Italy, low visibility}} = -15.86$, $\beta_{3,\ \text{Norway, low visibility}} = -6.55$. The Italian coefficient is calculated with respect to the value obtained in high visibility conditions, while the Norwegian one is calculated with respect to the value obtained in medium-low visibility conditions. However, both of them are significant and noticeably lower than zero. Furthermore, computed β_3 coefficient obtained considering only low and medium-low visibility classes for the Italian experiment is -7.33. Hence, the two values are comparable.

Instead, number of test day has a different effect on the two experiments. In the Italian experiment we can see a proof that an acquired knowledge of the road leads up to an increase of speed over time. On the other hand, in the Norwegian experiment this effect is practically absent. In fact, the effect of time on speed is the only not significant main factor in the Norwegian experiment, as we can see by looking at the Table 5.10. These sentences are confirmed by looking at β_4 coefficient values of the two models. In the Italian experiment those values are: $\beta_{4,\text{ Italy, day 1}}$ = -14.60, $\beta_{4,\text{ Italy, day 2}}$ = -10.67, $\beta_{4,\text{ Italy, day 3}}$ = -10.44. $\beta_{4,\text{ Italy, day 4}}$ = -4.32 $\beta_{4,\text{ Italy, day 5}}$ = -9.05, all calculated with respect to the value of day 6 set to zero and significant. Instead, in the Norwegian experiment, those values are very close to the zero and all of them are not significant. The β_4 coefficient takes into account time effect without considering visibility classes or risk classes and so it is referred to all the users. The analysis about the habituation effect and how it is influenced by risk attitude has been done in the devoted paragraph. Here, looking at those results, it is only important to notice that habituation effect could not be noted every time, everywhere and with different conditions. This sentence will be better analyzed in the last chapter.

The interpretation of the influence of main factors on speed is immediate, but also two-ways interaction effect analysis could be interesting. In the Italian experiment, all the interactions are significant, while in the Norwegian experiment only the interaction between risk class and visibility class is significant (cf. Table 5.10). For instance, if we want to search for the influence of these interactions on speed, we could look at the two remarkable β_6 coefficient values for the combination risky user-day 3 (10.22) and risky user-day 5 (10.79), that lead up to a remarkable increase of the speed output of the Italian model.

The more frequent presence of non-significant coefficients in the Norwegian model than in the Italian one could be explained by the fact that Norwegian sample size is smaller than the Italian (Norwegian drivers are 10 while the Italian ones are 19; Italian measurement is made section by section while Norwegian measurement is made on road segments). However, as expected, influence of risk class and that of visibility class on speed are significant also in the Norwegian experiment. Another important symptom is that, in the same experiment, interactions are not significant if they contain the day factor.

Therefore, we must conclude that also the Norwegian experiment is reliable, even if the size of the sample is small, because the influence of all main factors but day factor are very similar.

Afterwards, the study was repeated by dividing drivers into risk categories based on stated speeding. The first evident effect on the two models is the decreasing of the R-squared values in both the Italian and the Norwegian model. (0.189-0.337) In particular the R-squared value of the Italian experimentation decreases from 0.385 to 0.189 (-45 %) and the R-squared value of the Norwegian experimentation decreases from 0.467 to 0.337 (-28%). Therefore, other conditions being equal, considering stated speeding as a variable in order to classify users into risk categories, leads up to a less reliable model.

Nevertheless, also the initial developed model could be not considered as reliable because of the risk classification based on measured speed.

However, even if globally the model is less reliable both for the Italian experimentation and for the Norwegian one, there is a remarkable difference between the two models developed in this way. In fact, in the Norwegian model it is possible to note that the variable “stated speeding” is a good predictor of risk perception, while in the Italian model this consideration is not possible. Hence, it’s not possible to clearly use the self-reported speeding as a variable in order to classify users into risk categories and to predict speed.

Finally, next step will be the inquiring why habituation trend is different in the two experiments.

6 CONCLUSIONS

The main aim of this work is to understand the learning process that occurs in drivers and to comprehend how driver's behaviour changes over time after more acquired knowledge of the road. This purpose derives from the will of a deepened examination of matters related to risk perception, driving behaviour and speed choice; which are crucial fields for traffic safety studies and related with one another. These topics and the relations between them were examined in the chapter 2.

In particular, in order to look into changes in driving behaviour, speed measurements have been used as the main parameter representing driver's behaviour and its changes over time. In this sense, the two experiments were conducted in Italy and Norway by using a similar method, which were discussed in the chapter 3 and the chapter 4. Speed of a sample of drivers was measured over time in six different days and after, data were processed by dividing users into risk categories and by dividing road into sections with similar visibility conditions. A comparison between the two experimentations based on qualitative considerations and statistical elaboration was shown in the chapter 5.

Main results could be explained as follows:

- division of drivers in risk classes by considering measured speed on both experiments is a good way to highlight users' habituation patterns;
- speed increases almost linearly with visibility for both experiments but in different ways for different risk classes;
- habituation effect could be noted in the Italian experiment, while in the Norwegian one it is almost completely absent.

The first two results could be easily explained by looking at theories discussed in the Introduction and in the State of the Art. In fact, speed choice depends on many variables among which are road features and risk perception. In particular, road features influence speed choice in a different way according to different risk classes. A clear habituation effect was noted in the Italian experiment: speed increases over time due to the acquired road knowledge. However, speed increasing tendency is different among the drivers: risky users seem to understand road differences sooner than the prudent ones and so they show a better short-term learning effect. Furthermore, risky users seem to be able to transform short-term memory into long-term memory by keeping the same confidence in the road until the last test. Instead, prudent users seem to become confident in the road only after a long time. In fact, the transformation from their short-term learning to long-term learning is inefficient because they need to test again the road after a certain period of time without driving on that road. On the other hand, in the Norwegian experiment we cannot see the same habituation effect.

First, we have to say that instruments employed in the Norwegian experimentation have an accuracy of about 10 m, while the Italian instruments have an accuracy of about 0.1 m. Therefore, probably comparison is affected by this difference.

However, apart from the discrepancies between the two instrumentations, there are some possible explanations about the differences between the two experimentations:

- roads used for the two experimentations are significantly different;
- there could be cultural differences between different countries affecting drivers' speed choice;
- variable weather and traffic conditions in the Norwegian experiment made not possible the fulfillment of habituation effect.

The road used for the Norwegian experiment was very winding and it was characterized by some small-radius curves. Therefore, even if visibility classes are defined in the same way of the Italian experimentation, on average visibility conditions in the Norwegian road are worse than in the Italian one. Hence, the first explanation could be that the habituation effect cannot be possible on roads with very poor visibility conditions or it could be possible in more than one month. This sentence is supported by the fact that also in the Italian experimentation habituation effect is less evident in low visibility conditions and that speed trends of Norwegian risky users seem to increase after the fifth test day. Given that, as already stated, risky users increase their speed faster than the prudent ones, a light habituation effect could happen very slowly also in poor visibility conditions. However, the increase of speed in the Norwegian experiment could be not statistically significant and so we cannot be sure if speed increases very slowly or if speed does not increase at all.

Speed choice is related to risk perception, risk perception is related to the chosen safety risk budget and this one depends from many variables. Surely, one of the variables influencing it is the culture of the drivers. This means that risk perception and speed choice could be different in different countries and this is a problem that we must consider while analyzing the two experiments. For example, Italians seem to show a greater tendency to speeding and this could be taken into account while comparing the two situations. However, the already stated differences in the road do not allow us to state surely that Norwegians have a smaller tendency to speeding because their speed choice is limited by poor visibility conditions.

Finally, we found in literature that the habituation effect in response to a given stimulus can occur only if the stimulus is exactly the same over time. In the Norwegian experiment users drove also with bad weather and traffic conditions during some tests, while in the Italian users drove almost always with fine weather and traffic conditions. Therefore, the third explanation could be that the habituation effect could be not possible if the road is not driven in the same conditions for a certain period of time.

Hence, even if explanation of the results of comparison is difficult and maybe could be a mix of the proposed solutions, the comparison between the two experiments lead us up to the evident conclusion that there are a lot of variables that can determine if the habituation effect will be noticed or not. Moreover, other variables not considered in those experiments could influence speed choice as well as visibility and drivers' risk attitude. In fact, models proposed in chapter 5 are able to explain only a quantity between one third and one half of the speed variations. However, the visibility variable was always found as statistically related to speed in both experiments and this is a confirmation about how good the employed experiment method is.

Finally, it is clear that there is a lot of work to do by investigating better on the habituation effect while driving on the same road. First of all, in order to have a good comparison and to let the possible variations decrease, experiments should be repeated on the same or, if this is not possible, on very similar roads and by using instruments with a similar accuracy. Furthermore, weather and traffic conditions should be also the same in order to have not speed choice being affected by them. These aims could be achieved by using driving simulators in which road features and surrounding conditions could be well defined and they could be the same for every users. In the end we still have to study cultural differences in order to understand the real influence of this feature on speed choice.

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ATTACHMENT I

MASTER DEGREE THESIS

Spring 2014
for

Student: Paolo Intini

Changes in speed behaviour due to acquired road familiarity

BACKGROUND

In order to study whether and how speed choice changes as drivers become familiar with the road infrastructure, an experiment has been conducted in Italy, in which 19 drivers participated. GPS-technology was used by the drivers who travelled along a given road section six times according to a given schedule covering four weeks. Initial analyses suggest that both a short-term and a long-term memory effect can be found.

TASK

The candidate shall plan and administer a similar experiment in Norway. The collected data from both countries shall be analysed and compared.

Task description

The candidate is expected to:

- Perform a literature study to summarise existing knowledge about driving behaviour regarding: 1) risk perception, 2) factors affecting speed choice, 3) theories on adaptation to new situations/environments, 4) cultural differences between drivers from different countries
- Plan and administer data collection in Norway
- Analyse the data sets from both Italy and Norway in order to reveal and describe any adaptation effects when choosing speed.
- Based on the literature study and the analysis: discuss the results, their strengths and limitations, and give recommendations for future research.

General about content, work and presentation

The text for the master thesis is meant as a framework for the work of the candidate. Adjustments might be done as the work progresses. Tentative changes must be done in cooperation and agreement with the professor in charge at the Department.

In the evaluation thoroughness in the work will be emphasized, as will be documentation of independence in assessments and conclusions. Furthermore the presentation (report) should be well organized and edited; providing clear, precise and orderly descriptions without being unnecessary voluminous.

The report shall include:
- Standard report front page (from DAIM, http://daim.idi.ntnu.no/)
- Title page with abstract and keywords.(template on: http://www.ntnu.no/bat/skjemabank)
- Preface
- Summary and acknowledgement. The summary shall include the objectives of the work, explain how the work has been conducted, present the main results achieved and give the main conclusions of the work.
- The main text.
- Text of the Thesis (these pages) signed by professor in charge as Attachment 1.

The thesis can as an alternative be made as a scientific article for international publication, when this is agreed upon by the Professor in charge. Such a report will include the same points as given above, but where the main text includes both the scientific article and a process report.

Advice and guidelines for writing of the report is given in “Writing Reports” by Øivind Arntsen, and in the departments “Råd og retningslinjer for rapportskriving ved prosjekt og masteroppgave” (In Norwegian) located at http://www.ntnu.no/bat/studier/oppgaver.

Submission procedure
Procedures relating to the submission of the thesis are described in DAIM (http://daim.idi.ntnu.no/). Printing of the thesis is ordered through DAIM directly to Skipnes Printing delivering the printed paper to the department office 2-4 days later. The department will pay for 3 copies, of which the institute retains two copies. Additional copies must be paid for by the candidate / external partner.

On submission of the thesis the candidate shall submit a CD with the paper in digital form in pdf and Word version, the underlying material (such as data collection) in digital form (e.g. Excel). Students must submit the submission form (from DAIM) where both the Ark-Bibl in SBI and Public Services (Building Safety) of SB II has signed the form. The submission form including the appropriate signatures must be signed by the department office before the form is delivered Faculty Office.

Documentation collected during the work, with support from the Department, shall be handed in to the Department together with the report.

According to the current laws and regulations at NTNU, the report is the property of NTNU. The report and associated results can only be used following approval from NTNU (and external cooperation partner if applicable). The Department has the right to make use of the results from the work as if conducted by a Department employee, as long as other arrangements are not agreed upon beforehand.

Tentative agreement on external supervision, work outside NTNU, economic support etc.
Separate description is to be developed, if and when applicable. See http://www.ntnu.no/bat/skjemabank for agreement forms.

Health, environment and safety (HSE) http://www.ntnu.edu/hse
NTNU emphasizes the safety for the individual employee and student. The individual safety shall be in the forefront and no one shall take unnecessary chances in carrying out the work. In particular, if the student is to participate in field work, visits, field courses, excursions etc. during the Master Thesis work, he/she shall make himself/herself familiar with "Fieldwork HSE Guidelines". The document is found on the NTNU HMS-pages at http://www.ntnu.no/hms/retningslinjer/HMSR07E.pdf

The students do not have a full insurance coverage as a student at NTNU. If you as a student want the same insurance coverage as the employees at the university, you must take out individual travel and personal injury insurance.

Startup and submission deadlines
Startup and submission deadlines are according to information found in DAIM.

Professor in charge: Eirin Ryeng

Other supervisors: Thomas Jonsson

Department of Civil and Transport Engineering, NTNU
Date: dd.mm.yyyy, (revised: dd.mm.yyyy)

____
Professor in charge (signature)

ATTACHMENT II

QUESTIONNAIRE N.

General informations

Age ______ Gender ☐ M ☐ F

Part A: MOBILITY

A.1 Which mode of transportation do you use more frequently?

On foot	
Bycicle	
Motorcycle	
Urban bus	
Non-urban bus	
Train	
Car (passenger)	
Car (driver)	

A.2 Generally, do you choose the same mode of transportation used in the morning to come back home?

☐ yes ☐ no

A.3 Which are the main reasons of your mode choice?
(3 answers maximum)

☐ cheapness
☐ problems in finding parking
☐ safety
☐ health
☐ less stressful choice
☐ other ______________________________
☐ travel time
☐ comfort
☐ going with someone
☐ freedom of movement
☐ lack of direct connections
☐ lack of public transport
☐ bad connections
☐ frequently late rides
☐ distant bus stops
☐ have no alternative

A.4 Which mode of transportation do you usually use when you move within your city?

☐ by foot
☐ by bycicle
☐ by motorcycicle
☐ by own car
☐ by public transport
☐ by business car
☐ by taxi

A.5 Do you usually move outside your city? If yes, specify your chosen mode of transportation

☐ no

☐ yes, by foot
☐ yes, by bycicle
☐ yes, by motorcycicle
☐ yes, by own car
☐ yes, by public transport
☐ yes, by business car
☐ yes, by taxi

A.6 How much time do you use for travelling everyday? ______________
in minutes

A.7 How much time do you devote on average to mobility and travels every day?
-including longer trips (holidays)-

☐ zero ☐ short time ☐ enough time ☐ long time ☐ very long time

A.8 For your obligated moves (home to work or home to school) you need:

☐very short time ☐ short time ☐ standard time ☐ long time ☐ very long time

A.9 Do you think that there are some elements limiting your travels?
- age, health problems, other (specify______________________________)-

☐ I have no limitations (I can move every time that I want)
☐ I have few limitations
☐ I have some limitations
☐ I have a lot of limitations
☐ I can't move

Part B: DRIVING BEHAVIOR

B.1 How long have you been driving?

☐ < 6 months ☐ < 1 year ☐ 1 - 5 years ☐ 5 - 10 years ☐ > 10 years

B.2 Have you always got a car at your disposal? ☐ yes ☐ no

B.3 On average, how much time do you drive every day? ______________
in minutes

B.4 On average, how long is your driving travel every day? Km______________

B.5 Do you like to drive? ☐ yes ☐ no

B.6 Have you ever driven after a very tiring day? ☐ yes ☐ no

B.7 Illustrate your driving feelings in that conditions

____

____

____

B.8 Is your driving behavior changing in that conditions?

☐ no

☐ yes, I go faster
☐ yes, I go slower
☐ yes, other ______________________________

B.9 Have you ever driven after drinking alcohol? ☐ yes ☐ no

B.10 Illustrate your driving feelings in that conditions

____

____

____

B.11 Is your driving behavior changing in that conditions?

☐ no

☐ yes, I go faster
☐ yes, I go slower
☐ yes, other ______________________________

B.12 Have you ever gone faster than the speed limit? ☐ yes ☐ no

☐ never ☐ sometimes ☐ enough times ☐ a lot of times ☐ very frequently

B.13 In how many accidents have you been implicated in your life? N______________

B.14 In how many of them were you the driver? N______________

B.15 Do you consider yourself a risky driver? ☐ yes ☐ no

B.16 Evaluate your driving skills

☐low ☐lower than average ☐average ☐ little higher than average ☐very higher than average

Part C: REMARKS AND SUGGESTIONS

Thank you for participating in this study
Data will be nameless and it will be used for scientific aims

ATTACHMENT III

TRAFFIC AND WEATHER CONDITIONS – NORWEGIAN EXPERIMENT

WEATHER CONDITIONS						
USERID	1	2	3	4	10	27
1	RAIN	RAIN	CLOUDY	CLOUDY	CLOUDY	CLOUDY
2	RAIN	RAIN	CLOUDY	CLOUDY	LITTLE FOG	CLOUDY
3	SUNNY	SUNNY	LITTLE RAIN	SUNNY	FOG	LITTLE RAIN
4	CLOUDY	CLOUDY	SUNNY	CLOUDY	SUNNY	DARK/SUNNY
5	CLOUDY/SUNNY	LITTLE RAIN	DARK/LITTLE RAIN	TWILIGHT	CLOUDY	CLOUDY
6	OK	RAIN	OK	OK	SNOW	OK
7	OK	OK	OK	OK	OK	OK
8	CLOUDY/SUNNY	CLOUDY	SNOW	CLOUDY	cloudy	cloudy
9	CLOUDY	CLOUDY	ok	ok	OK	(TWILIGHT)
10	RAINY	LITTLE RAIN	SUNNY	CLOUDY	SUNNY	
TRAFFIC CONDITIONS						
USERID	1	2	3	4	10	27
1	OK	TRAFFIC	OK	OK	TRAFFIC(AB)	WORKZONE
2	LOW	OK	LOW(BA)	TRAFFIC(BA)	TRAFFIC	WORKZONE
3	OK	OK	OK	OK	OK	OK
4	LOW	OK	LOW	OK	OK	OK
5						
6	OK	TRAFFIC	OK	LOW	OK	LOW
7	OK	OK	LOW	OK	OK	OK
8	OK	OK	OK	LOW	ok	ok
9	LOW	LOW	ok	traffic/wrong	TRAFFIC	OK
10	OK	OK	OK	TRAFFIC(BA)	OK	
ROAD SURFACE CONDITIONS						
USERID	1	2	3	4	10	27
1						
2						
3						
4	WET	DRY	DRY	DRY	WET	DRY
5	MOISTY	WET	WET	DRY	MOISTY	
6				MOISTY	WET	
7	MOISTY					
8	DRY	DRY	WET	WET		
9	MOISTY	WET			OK	OK
10	WET	MOISTY	MOISTY	MOISTY	DRY	

ATTACHMENT IV

COMPLETE DESCRIPTIVE STATISTICS

Descriptive statistics (Dependent variable: SPEED) ITALIAN EXPERIMENT RISK CLASS BASED ON MEASURED SPEED					
RISKCLASS	**SECTIONCLASS**	**DAY**	**Mean**	**Std. Deviation**	**N**
1 = risky	1 = low ssd	day1	77.0654	10.99398	371
		day2	82.0832	13.77602	424
		day3	88.9867	12.74506	424
		day4	88.2915	14.12869	424
		day5	89.7313	14.01588	263
		day6	89.3045	15.10678	419
		Total	85.8402	14.30123	2325
1 = risky	2 = mediumlow ssd	day1	81.0785	12.08806	660
		day2	88.1954	13.18043	770
		day3	95.6889	12.40004	770
		day4	95.4576	13.96685	770
		day5	95.7030	15.34200	440
		day6	95.5027	14.27172	760
		Total	91.9176	14.53649	4170
1 = risky	3 = medium ssd	day1	83.7817	14.88179	190
		day2	95.5101	17.25216	228
		day3	104.0766	15.58434	228
		day4	100.9122	14.55167	228
		day5	104.5570	16.11639	114
		day6	98.9863	17.57324	209
		Total	97.7777	17.38380	1197
1 = risky	4 = high ssd	day1	87.5371	16.01441	365
		day2	99.9255	15.65860	438
		day3	106.0729	17.59488	438
		day4	106.5587	15.66025	438
		day5	110.5349	14.65144	219
		day6	105.3899	14.67731	410
		Total	102.3692	17.32945	2308
1 = risky	Total	day1	81.9499	13.70276	1586
		day2	90.4610	15.85542	1860
		day3	97.6345	15.60411	1860
		day4	97.1068	15.85240	1860
		day5	98.2966	16.75252	1036
		day6	96.7178	15.97141	1798

		Total	93.6183	16.61612	10000
3 = prudent	1 = low ssd	day1	67.3705	12.01105	318
		day2	68.5780	12.44060	361
		day3	71.3818	11.71914	424
		day4	74.1612	14.85748	212
		day5	71.9071	14.79475	424
		day6	77.6277	14.81667	206
		Total	71.2845	13.63547	1945
3 = prudent	2 = mediumlow ssd	day1	72.9801	11.88033	660
		day2	74.1539	12.75112	738
		day3	76.5777	11.89189	880
		day4	80.1224	11.68841	440
		day5	76.9084	13.91584	880
		day6	85.8127	10.49567	431
		Total	76.9916	12.89020	4029
3 = prudent	3 = medium ssd	day1	75.1009	11.29318	228
		day2	78.2252	13.45673	228
		day3	77.1238	12.35285	304
		day4	85.3279	12.14000	114
		day5	78.7264	13.07644	304
		day6	88.0119	10.19258	134
		Total	79.1599	12.91539	1312
3 = prudent	4 = high ssd	day1	81.8041	10.62565	438
		day2	84.3364	11.97147	438
		day3	84.4319	10.21944	583
		day4	90.9426	8.70129	292
		day5	85.0121	11.29290	580
		day6	96.0002	11.95160	265
		Total	86.0153	11.62830	2596
3 = prudent	Total	day1	74.5401	12.53528	1644
		day2	76.0662	13.74457	1765
		day3	77.7379	12.34901	2191
		day4	82.4751	13.20072	1058
		day5	78.3400	14.08175	2188
		day6	87.0755	13.34057	1036
		Total	78.5267	13.71234	9882
Total	1 = low ssd	day1	72.5908	12.44449	689
		day2	75.8725	14.79265	785
		day3	80.1843	15.07598	848
		day4	83.5814	15.83557	636
		day5	78.7306	16.88693	687

		day6	85.4558	15.97414	625
		Total	79.2100	15.76601	4270
Total	2 = mediumlow ssd	day1	77.0293	12.64639	1320
		day2	81.3236	14.74671	1508
		day3	85.4962	15.42876	1650
		day4	89.8812	15.10465	1210
		day5	83.1732	16.91000	1320
		day6	91.9961	13.83539	1191
		Total	84.5830	15.64561	8199
Total	3 = medium ssd	day1	79.0467	13.73068	418
		day2	86.8676	17.71132	456
		day3	88.6750	19.21304	532
		day4	95.7175	15.61822	342
		day5	85.7711	18.09115	418
		day6	94.6989	16.03042	343
		Total	88.0421	17.82730	2509
Total	4 = high ssd	day1	84.4100	13.64105	803
		day2	92.1310	15.96423	876
		day3	93.7157	17.52308	1021
		day4	100.3122	15.35712	730
		day5	92.0077	16.76140	799
		day6	101.7035	14.41282	675
		Total	93.7120	16.71873	4904
Total	Total	day1	78.1785	13.63258	3230
		day2	83.4522	16.51341	3625
		day3	86.8733	17.10435	4051
		day4	91.8017	16.51642	2918
		day5	84.7528	17.65109	3224
		day6	93.1930	15.76051	2834
		Total	86.1173	17.00739	19882

Descriptive statistics (variable: SPEED) NORWEGIAN EXPERIMENT RISK CLASS BASED ON MEASURED SPEED					
RISKCLASS	**SEGMENTCLASS**	**DAY**	**mean**	**standard deviation**	**N**
1 = risky	1 = low	day1	66.55	8.31	63
		day2	65.68	6.85	64
		day3	66.13	6.03	55
		day4	65.78	6.67	61
		day5	65.28	7.67	59
		day6	68.73	8.11	61
		Total	66.36	7.38	363
1 = risky	2 = mediumlow	day1	78.03	8.96	27
		day2	77.98	13.04	30
		day3	78.31	8.88	29
		day4	78.06	4.61	20
		day5	75.79	9.82	25
		day6	78.15	9.53	21
		Total	77.72	9.59	152
1 = risky	Total	day1	69.99	9.98	90
		day2	69.60	10.86	94
		day3	70.34	9.17	84
		day4	68.81	8.17	81
		day5	68.41	9.61	84
		day6	71.14	9.39	82
		Total	69.72	9.60	515
3 = prudent	1 = low	day1	58.15	5.27	116
		day2	58.79	5.46	115
		day3	58.06	5.28	109
		day4	58.20	5.32	102
		day5	58.37	5.56	114
		day6	58.14	5.81	85
		Total	58.30	5.43	641
3 = prudent	2 = mediumlow	day1	65.23	6.93	30
		day2	65.65	6.70	29
		day3	64.65	6.58	28
		day4	64.94	5.81	26
		day5	65.48	7.04	30
		day6	65.79	7.19	29
3 = prudent	Total	day1	59.61	6.31	146
		day2	60.17	6.33	144
		day3	59.41	6.15	137

		day4	59.57	6.05	128
		day5	59.85	6.55	144
		day6	60.09	7.01	114
		Total	59.78	6.38	813
Total	1 = low	day1	61.11	7.63	179
		day2	61.25	6.83	179
		day3	60.77	6.72	164
		day4	61.04	6.90	163
		day5	60.73	7.14	173
		day6	62.57	8.62	146
		Total	61.21	7.31	1004
Total	2 = mediumlow	day1	71.29	10.18	57
		day2	71.92	12.05	59
		day3	71.60	10.38	57
		day4	70.64	8.42	46
		day5	70.17	9.82	55
		day6	70.98	10.22	50
		Total	71.13	10.24	324
Total	Total	day1	63.57	9.37	236
		day2	63.90	9.58	238
		day3	63.56	9.13	221
		day4	63.15	8.27	209
		day5	63.00	8.83	228
		day6	64.71	9.75	196
		Total	63.63	9.17	1328

Descriptive statistics (Depdendent variable: SPEED) **ITALIAN EXPERIMENT** **RISK CLASS BASED ON STATED SPEEDING**					
STATEDSPEEDING	SECTIONCLASS	DAY	Media	Standard deviation	N
YES	low ssd	day1	72,1107	13,53527	424
		day2	73,8205	13,89668	361
		day3	77,4983	13,70227	424
		day4	84,0217	14,50055	265
		day5	78,0456	16,95597	424
		day6	83,7215	17,50826	254
		Total	77,4655	15,54144	2152
	mediumlow ssd	day1	76,4515	14,04557	770
		day2	77,7127	14,72724	629
		day3	82,2316	14,53106	770
		day4	89,5861	12,87874	440
		day5	81,5663	15,85821	770
		day6	91,3307	12,62651	421
		Total	82,0372	15,22729	3800
	medium ssd	day1	77,0988	14,92056	266
		day2	85,4253	18,08256	190
		day3	83,9799	16,51500	266
		day4	96,9862	13,89499	114
		day5	86,7479	16,57650	266
		day6	93,1654	14,78344	115
		Total	85,3929	17,06720	1217
	high ssd	day1	82,5463	14,72461	511
		day2	91,9415	16,14652	365
		day3	88,3191	13,26921	510
		day4	97,8419	12,88100	292
		day5	92,3378	15,85026	508
		day6	100,7255	12,88899	238
		Total	90,8550	15,57363	2424
	Total	day1	77,1852	14,68439	1971
		day2	81,1132	16,78942	1545
		day3	83,0249	14,80644	1970
		day4	91,1880	14,39227	1111
		day5	84,2886	17,05205	1968
		day6	91,8309	15,43412	1028
		Total	83,6655	16,34957	9593

NO	low ssd	day1	73,3591	10,44429	265
		day2	77,6196	15,31546	424
		day3	82,8702	15,90259	424
		day4	83,2670	16,73624	371
		day5	79,8351	16,74816	263
		day6	86,6432	14,73978	371
		Total	80,9826	15,79846	2118
	mediumlow ssd	day1	77,8381	10,33373	550
		day2	83,9075	14,21614	879
		day3	88,3528	15,63142	880
		day4	90,0498	16,24585	770
		day5	85,4230	18,05693	550
		day6	92,3599	14,44864	770
		Total	86,7820	15,67035	4399
	medium ssd	day1	82,4555	10,56264	152
		day2	87,8978	17,40231	266
		day3	93,3702	20,55904	266
		day4	95,0831	16,40450	228
		day5	84,0618	20,42028	152
		day6	95,4724	16,60154	228
		Total	90,5376	18,17120	1292
	high ssd	day1	87,6716	10,77390	292
		day2	92,2663	15,84723	511
		day3	99,1018	19,49871	511
		day4	101,9591	16,61763	438
		day5	91,4315	18,25753	291
		day6	102,2362	15,16621	437
		Total	96,5045	17,32020	2480
	Total	day1	79,7335	11,63565	1259
		day2	85,1896	16,09074	2080
		day3	90,5165	18,29775	2081
		day4	92,1790	17,68959	1807
		day5	85,4803	18,53440	1256
		day6	93,9683	15,89548	1806
		Total	88,4032	17,28891	10289
Total	low ssd	day1	72,5908	12,44449	689
		day2	75,8725	14,79265	785
		day3	80,1843	15,07598	848
		day4	83,5814	15,83557	636

		day5	78,7306	16,88693	687
		day6	85,4558	15,97414	625
		Total	79,2100	15,76601	4270
	mediumlow ssd	day1	77,0293	12,64639	1320
		day2	81,3236	14,74671	1508
		day3	85,4962	15,42876	1650
		day4	89,8812	15,10465	1210
		day5	83,1732	16,91000	1320
		day6	91,9961	13,83539	1191
		Total	84,5830	15,64561	8199
	medium ssd	day1	79,0467	13,73068	418
		day2	86,8676	17,71132	456
		day3	88,6750	19,21304	532
		day4	95,7175	15,61822	342
		day5	85,7711	18,09115	418
		day6	94,6989	16,03042	343
		Total	88,0421	17,82730	2509
	high ssd	day1	84,4100	13,64105	803
		day2	92,1310	15,96423	876
		day3	93,7157	17,52308	1021
		day4	100,3122	15,35712	730
		day5	92,0077	16,76140	799
		day6	101,7035	14,41282	675
		Total	93,7120	16,71873	4904
	Total	day1	78,1785	13,63258	3230
		day2	83,4522	16,51341	3625
		day3	86,8733	17,10435	4051
		day4	91,8017	16,51642	2918
		day5	84,7528	17,65109	3224
		day6	93,1930	15,76051	2834
		Total	86,1173	17,00739	19882

Descriptive statistics (dependent variable: SPEED) NORWEGIAN EXPERIMENT RISK CLASS BASED ON STATED SPEEDING					
STATEDSPEEDING	**SEGMENTCLASS**	**DAY**	**mean**	**Std. deviation**	**N**
YES	low	day1	64,3478	9,06546	63
		day2	64,8583	7,25589	66
		day3	64,6212	6,63633	64
		day4	64,7282	7,13439	61
		day5	63,4182	8,09332	68
		day6	67,5259	9,04850	56
		Total	64,8482	7,94515	378
	mediumlow	day1	73,6990	10,85192	37
		day2	74,9667	12,64518	40
		day3	74,9293	10,36002	38
		day4	74,1141	7,47012	30
		day5	72,2802	10,68243	35
		day6	73,4617	10,97422	30
		Total	73,9520	10,63155	210
	Total	day1	67,8077	10,71823	100
		day2	68,6728	10,78053	106
		day3	68,4615	9,58510	102
		day4	67,8225	8,46155	91
		day5	66,4296	9,94258	103
		day6	69,5965	10,10767	86
		Total	68,0996	9,99235	588
NO	low	day1	59,3488	6,06907	116
		day2	59,1492	5,60157	113
		day3	58,3061	5,52713	100
		day4	58,8317	5,75272	102
		day5	58,9813	5,85364	105
		day6	59,4821	6,72821	90
		Total	59,0195	5,90564	626
	mediumlow	day1	66,8439	7,09517	20
		day2	65,4964	7,58643	19
		day3	64,9360	6,65699	19
		day4	64,1335	5,96294	16
		day5	66,4687	6,85697	20
		day6	67,2672	7,84242	20

		Total	65,9294	6,98776	114
	Total	day1	60,4510	6,74985	136
		day2	60,0629	6,30372	132
		day3	59,3647	6,19175	119
		day4	59,5505	6,03734	118
		day5	60,1793	6,59835	125
		day6	60,8976	7,53540	110
		Total	60,0840	6,57219	740
Total	low	day1	61,1082	7,62588	179
		day2	61,2543	6,82626	179
		day3	60,7706	6,71746	164
		day4	61,0384	6,90485	163
		day5	60,7253	7,13845	173
		day6	62,5674	8,61659	146
		Total	61,2140	7,31047	1004
	mediumlow	day1	71,2937	10,18233	57
		day2	71,9170	12,05402	59
		day3	71,5982	10,38016	57
		day4	70,6426	8,42096	46
		day5	70,1669	9,81597	55
		day6	70,9839	10,22363	50
		Total	71,1292	10,24418	324
	Total	day1	63,5683	9,37236	236
		day2	63,8975	9,58348	238
		day3	63,5632	9,13240	221
		day4	63,1522	8,26948	209
		day5	63,0029	8,82726	228
		day6	64,7145	9,74695	196
		Total	63,6331	9,16983	1328