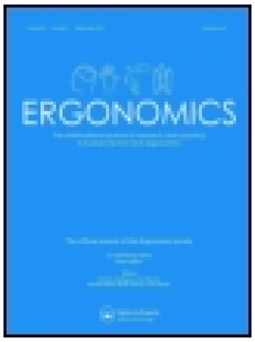

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Personal factors influencing the visual reaction time of pedestrians to detect turn indicators in the presence of Daytime Running Lamps.

Antonio Peña-García[a,*], Rocío de Oña[b], Pedro Antonio García[c] and Juan de Oña[b]

[a] Research Group 'Lighting Research for Safety and Sustainability', Department of Civil Engineering, ETSICCP, University of Granada, 18071 Granada, Spain.

[b] TRYSE Research Group, Department of Civil Engineering, ETSICCP, University of Granada, 18071 Granada, Spain.

[c] Department of Statistics and O.R., University of Granada, 18071 Granada, Spain.

* Corresponding author. Phone: +34 958 24 94 35, pgarcia@ugr.es

ABSTRACT

Daytime Running Lamps (DRL) on vehicles have proven to be an effective measure to prevent accidents during the daytime, particularly when pedestrians and cyclists are involved. However, there are negative interactions of DRL with other functions in automotive lighting, such as delays in pedestrians' visual reaction time (VRT) when turn indicators are activated in the presence of DRL. These negative interactions need to be reduced. This work analyses the influence of variables inherent to pedestrians, such as height, gender and visual defects, on the VRT using a classification and regression tree as an exploratory analysis and a generalized linear model to validate the results. Some pedestrian characteristics, such as gender, alone or combined with the DRL color, and visual defects, were found to have a statistically significant influence on VRT and, hence, on traffic safety. These results and conclusions concerning the interaction between pedestrians and vehicles are presented and discussed.

PRACTITIONER SUMMARY

Visual interactions of vehicle Daytime Running Lamps (DRL) with other functions in automotive lighting, such as turn indicators, have an important impact on a vehicle's conspicuity for pedestrians. Depending on several factors inherent to pedestrians, the Visual Reaction Time (VRT) can be remarkably delayed, which has implications in traffic safety.

Keywords

Perception, Vision and lighting, Product safety, Injury risks.

INTRODUCTION

The Visual Reaction Time (VRT) can be defined as the interval of time between the application of a visual stimulus and the detection of a response from an observer (Luce 1986). The impact of the VRT on road safety is very important. For example, a vehicle travelling at 60 km/h is advancing at 17 m per second. Hence, even a short delay in a driver's VRT means that the vehicle can travel a significant distance (e.g., 5 m in 0.3 s), sufficient to cause a fatal accident under some circumstances. For this reason, it is a critical task for both researchers and the automotive industry to identify potential factors that increase the VRT in drivers and pedestrians and, hence, affect critical manoeuvres such as braking (Green, 2000). However, the VRT is not an isolated parameter depending only on an individual's reflexes; it remarkably depends on the environment where the detection task must be carried out. Hence, it is easy to understand that there is an inverse dependence on variations in luminance during detection tasks, known as Piéron's law (Luce 1986), in terms of vehicle traffic, where light signals are the main way to inform the users of the road about the presence of a vehicle (Daytime Running Lamps, Position Lamps), direction changes (Turn Indicators), obligations or permissions to proceed (traffic lights), etc.

Therefore, it is extremely important to ensure that these light signals are correctly perceived by the users of the road. This means that the signals must be intense enough but also that any distortion or mixture among light signals will not impair their perception or delay the reaction to them (Sivak 2001). For example, the regulations dealing with turn indicators in the countries added to the United Nations Economic Commission for Europe (UNECE), such as Regulation ECE Nr. 6 (UNECE 2011) and Regulation ECE Nr. 48 (UNECE 2013), establish different categories of turn indicators depending on their distance from the dipped-beam and/or front fog lamp in order to avoid light mixing. Hence, the nearer to the dipped-beam or front fog lamp a light is, the more intense the light for the turn indicators must be. The same division into categories is necessary with other more complex vehicle functions such as the Adaptive Front-lighting Systems (AFS) (Peña-García et al., 2012).

For this reason, studying the visual interactions among different users of the road has been an active field within traffic safety. Interesting conclusions on pedestrian conspicuity have been reached and summarized (Shinar, 1984; Langham and Moberly, 2003; Whetsel Borzendowski, Stafford Sewall, Rosopa, Tyrrell, 2015), whereas vehicle conspicuity has been considered from several perspectives over the past few decades (Hörberg and Rumar, 1979; Hole, Tyrrell and Langham, 1996; McIntyre, 2008; Pinto, Cavallo and Saint-Pierre, 2014). However, vehicle perception from the perspective of pedestrians was not a hot topic until the Daytime Running Lamp (DRL) became popular in automotive signalling. Indeed, the relatively recent requirement of the compulsory installation of these lights in new models sold in the ECE market has made DRL a trending topic in many communication media. Before this function was known to non-specialists, it was studied in depth in several research projects that highlighted it as an effective countermeasure to traffic accidents, especially those involving pedestrians and cyclists (Theeuwes 1995; Williams 1995; Farmer 2002; Elvik 1993, 1996; Koornstra 1997; Tofflemire 1997).

Within this field, only a few researchers (e.g., Palmer 1994 and Sivak 2001) have addressed the issue of the visual interactions between DRL and other signalling functions. This apparent gap prompted us to question how the activation of other signalling functions in the presence of DRL could affect the VRT in road users.

In one previous study (Peña-García 2010), the VRT was evaluated in a large sample of observers in different situations involving the activation of turn indicators in the presence of DRL. The results showed that the color of the DRL (compulsorily white in the countries following the regulatory ECE framework and amber or white in the USA and Canada) and the relative angle between the observer and vehicle have a remarkable influence on the pedestrians' VRT and, hence, on the vehicle conspicuousness.

When that study was published, the automotive lighting community was paying attention to topics such as constraining the distance from the turn indicator to the DRL, comparisons of the ECE and USA in terms of color of DRL, and various other topics. The work by Peña-García (2010) was focused on vehicle-related variables. Some years later, the interest of the researchers has started to move towards the interaction between people and vehicle lighting. In general terms, almost the entire lighting community is now interested in the effects of light on psycho-physiological parameters (melatonin inhibition by lighting, cortisol release, etc.). Hence, we decided to look for factors affecting people’s VRT because beyond vehicle- and other traffic-related circumstances, such as the environment, other conditions inherent to pedestrians may affect vehicle conspicuity (height, gender or visual defects). In this work, we analyse the influence of these variables upon the VRT. These variables more closely related to ergonomics have not been considered in the literature so far, nor in the first analysis (Peña-García et al., 2010), which mainly focused on the parameters related to the vehicle, not the pedestrians, that are the main 'leit motivs' of DRL.

In summary, this work analyses the influence of some variables inherent to pedestrians on their visual reaction time when turn indicators and DRL are both activated. Several interesting new findings are discussed.

MATERIALS AND METHODS

Human and material resources

In this study, we used data from an experiment that measured the VRT in several situations involving DRL and Turn Indicators. The aim of the experiment was to evaluate the pedestrians' reaction time in the presence of a Turn Indicator that was suddenly and randomly switched on in different situations.

For this purpose, 148 volunteers (50 women and 98 men) were recruited among the students in the 'Lighting Technology' course of the Civil Engineering degree (University of Granada, Spain). The participants received no financial remuneration but a little compensation in the final qualification as long as they completed all of the required tests (all of them finished all tests successfully). The mean age of the students was 20.0 years with extreme values of 18 and 26 years and a standard deviation of 1.37. The mean height was 1.75 m with extreme values of 1.52 and 1.91 m and a standard deviation of 0.09. The main visual defect among the participants was myopia (n=81). There were many participants with no defects (n=48), while the rest of the participants had other less common visual defects (e.g., far-sightedness, astigmatism, etc.) or a combination of these (e.g., myopia and astigmatism, etc.). The homogeneity in the visual perception is more remarkable among young people than older individuals (even with similar disability glare rates, good and similar spectral sensitivities, no cataracts, etc.). This means an important advantage to avoid potential hidden variables.

The device used for the experiment was a headlamp with a DRL and a Turn Indicator, both fulfilling the relevant photometric requirements for the ECE and USA: ECE Regulation 87 (UNECE 2013), ECE Regulation 6 (UNECE 2013) and North American FMVSS 108 (NHTSA 2011). The DRL was set on a stand that reproduced the conditions of a vehicle and was mounted 900 mm from the ground. The module housing the Turn Indicator was attached to the same stand and placed under the headlamp. The mounting height could be changed by moving it up and down the bar with no angular deviation from the optical axis. A schematic representation of the experimental set-up is shown in Fig. 1.

Fig. 1. A schematic diagram of the experimental setup. Taken from (Peña-García 2010)

The DRL used a P21W bulb when it was white and a PY21W bulb when it was amber, both powered at 13.5 V. An H21W bulb with the same voltage was used for the Turn Indicator. All of the bulbs were approved for use according to Regulation ECE 37 (UNECE 2008).
The DRL was fitted with a round concave reflector made of small mirrors that directed the beams to distribute the light correctly. The reflector used for the Turn Indicator was similar, but its shape was rectangular and it included a piece of polycarbonate with optical grooves (Fresnel) to help re-direct the light by refraction. Inside the module, there was a Position Lamp (consisting of a bulb and reflector) that remained turned off during the whole experiment.

Measurements

The experiment was carried out on a closed street in daytime on a very sunny day (Illuminance on the ground, 85.000 lux) with the sun in its highest position in order to reproduce the most unfavourable conditions for the pedestrian detection of vehicles. In all cases, the distance between the participants and the experimental device was 25 m, which is the standard distance of measurement required by the ECE regulations.

Participants set their eyes on an object placed behind the experimental device and slightly higher than it, while the DRL in the experiment device was continuously lit. Under these conditions, they had to detect the activation of the Turn Indicator, which was remotely and suddenly switched on. The experiment was designed to study the impact of several factors on the participants' VRT, such as the color of the DRL (white or amber), distance between the Turn Indicator and DRL (5 cm and 50 cm), and the various angular positions between the observer and the experimental device (0º and 20º). Hence, each participant made eight observations under different combinations of these factors, as summarized in Table 1. Moreover, participant details such as the gender, height and whether they had visual defects (i.e., myopia, far-sightedness, astigmatism, etc.) were taken into consideration to study whether such variables had an impact on the VRT. After the experiment, we asked the participants for their height without shoes. All participants with visual defects performed the experiment with corrected vision (i.e., glasses or contact lenses).

Table 1. A summary of the different configurations evaluated

The 148 participants were divided into eight groups with a maximum of 20 participants per group. They formed a line and the first person performed the detection task for one given configuration (example: Amber DRL, 0º observation, 5 cm between the DRL and Turn Indicator). Then, this participant returned to the last position and the second person took their place. Once the whole group had completed the detection in this configuration, we changed the configuration and repeated the tests.

Methodology

In this paper, we first used decision trees for an exploratory analysis then used a generalized linear model (GLM) to validate the results obtained from the decision trees.

One of the main advantages of using decision trees is that they are helpful for exploratory analyses because they are non-parametric models that do not require any pre-defined knowledge about the underlying relationship between the dependent (i.e., VRT) and independents (i.e., gender, height, visual defect, light color, angle or distance) variables. The classification and regression tree (CART) has been widely employed in business administration, agriculture, medicine, industry, and engineering. In road safety analyses, the application of CART has been advocated by many authors (Abdel-Aty 2005; Council 1996; Chang 2005, 2006, 2014; Chen 2000; De Oña 2012; Kuhnert 2000; Magazzù 2006; Pande 2010; Qin 2008; Sohn 2001; Yan 2006, 2010). Because it has the ability to automatically search for the best predictors and the best threshold values for all predictors to classify the target variable, CART has been proven to be a powerful tool for various types of analyses. A detailed description of the CART analysis and its applications can be found in Breiman (1984). Calculations were performed using the SPSS software program.

Finally, a generalized linear model (GLM) was used to validate the results obtained from the decision trees. A GLM is a flexible generalization of an ordinary linear regression that allows for the analysis of response variables that have other than a normal distribution. Additionally, the linear model can be related to the response variable via a link function. The link function provides the relationship between the linear predictor and the mean of the distribution function.

In a GLM, each outcome of the dependent variable, Y, is assumed to be generated from a particular distribution in the exponential family that includes the normal, gamma and inverse normal distributions, among others. The mean (μ) of the distribution depends on the independent variables, X, through $E(Y) = \mu = g^{-1}(X\beta)$, where E(Y) is the expected value of Y; $X\beta$ is a linear combination of unknown parameters, β; and g is the link function. The estimates for the coefficients (β) in the model are very sensitive to the presence of outliers (Lindsey 1997). Therefore, as a first approach, we included outlier detection in the context of analysing the reaction times (Baayen 2010) due to the non-symmetrical nature of the VRT. The *robustbase* software package (Rousseeuw 2012) provides a framework to detect/extract extreme values for skewed distributions. Calculations were performed using the R-statistical program.

For the remaining cases, we checked the adequacy of a probabilistic distribution of our data, as suggested by Baayen and Milin (2010), among others, as the log-normal, gamma or inverse-normal distributions to model the VRT. These three distributional assumptions were considered for the VRT and several link functions were used to better fit the linear model. The model included not only the so-called principal factor but also possible interactions between predictors. To avoid over-fitting the model, only second-order interactions were considered. Comparisons of alternative GLM models were performed using an F-ratio test (McCullagh 1989).

RESULTS

An association between predictive variables may change randomly in response to small changes in the model or the data. Therefore, we excluded height as a predictor due to its association with the categorical variable gender (point-biserial correlation -0.74). No other consideration was made for the rest of the independent variables.

The exploratory analysis using decision trees showed that the factors with the highest influence on the VRT were the angular position between the observer and the experimental device, the color of the DRL, the gender and the presence of a visual defect. The CART analysis noted that women had a higher VRT than men when the color of the DRL was amber. A more detailed description of this analysis can be found in Appendix.

The outlier detection identified 12 values that were out of the interval (0.5450522, 1.8589340) that could be considered extremes. Table 2 shows the best fit, with an inverse-normal distribution with an inverse link, (1/VRT), and the associated p-values for the considered predictors.

Table 2. The GLM coefficients and results of the Analysis of Deviance (Type II tests).

To illustrate the results provided in Table 2, we described the associated coefficients for some factors (angle, color, distance, gender, visual defects and color-gender) in the proposed models. Factors were coded 0,1,2,...,n-1 for n levels (e.g., for angle, level 0 corresponds to 0º whereas level 1 corresponds to 20º; in the case of color, level 0 is amber whereas level 1 is white; etc.). Due to the inverse link, the greater the expected estimate in the model, the lower the corresponding VRT. For the factor color, the model tested whether the group mean for white, Color(T.W), differed from the mean of the reference group (amber, that is, Color(T.A)). The estimated coefficient of 0.044 was significant (p=0.002) and positive contributed to the expected value of the dependent variable in the model. We can therefore conclude than the expected VRT for white is significantly lower than that for amber. However, in the general model, the Deviance Table shows that color was not a significant factor (p=0.176), so we could discard this factor in a reduced model.

Table 2 also shows that the observed differences for the levels of the factor color were due to the interaction between color and gender (p=0.006). The associated coefficient for the interaction, -0.051, decreased the expected estimation of the dependent variable for the crossing level Color(T.W):Gender(T.M). Therefore, only one of those primary factors really contributes to the estimation. As a result, the amber color will lead to a significantly higher expected VRT for women than men.

In the case of the factor angle (see row 3 in Table 2), using 0º as the reference category (T.0), the associated estimate was negative, with a value of -0.001. Hence, the estimated value of the VRT for an angle of 20º was significantly higher than for an angle of 0º (p=0.017). In this case, the angle was also a significant factor in the general model (p=0.018). The factor gender (see row 6 in Table 2), using female as reference category (T.F), resulted in an estimate of 0.053. This factor was significant in both models, reduced and general, with p-values of <0.001 in the reduced model and 0.002 in the general model. Table 2 also shows that the factor distance was not significantly different in either model.

For the factor visual defects, we used three levels (myopia, no defect, and others) and performed two comparisons to the reference level, myopia. Both comparisons showed statistically significant differences (p<0.001) with the same interpretation as above.

In brief, Table 2 shows:

- The statistically significant differences (p<0.05) between the VRT values for factor levels in the Angle, Color of DRL, Gender and Visual defects, as well as for the second-order interaction between Gender and Color of DRL.

- The associated Analysis of Deviance Table, which leads to the inference that the effect for the Color of DRL is actually due to the second order interaction with Gender. Therefore, only one crossing category for these factors, in our case, Female and Amber, has more statistical significance than the rest.

Finally, an analysis of the residuals was performed to check the usual model assumptions (independence, homoscedasticity, linearity and normality). Figure 2 shows that no relevant deficiencies were found.

Fig. 2. Basic plots for the GLM residuals

The results in terms of the VRT for the different experimental conditions are shown in Table 3.

Table 3. A summary of the VRT in the different configurations evaluated in the experiment where: A= Amber; W= White; F= Female; M= Male.

The statistically significant results (shown in Table 3) were the Gender (men compared with women), Gender combined with DRL color (men compared with women in the presence of amber DRL) and the presence of visual defects (corrected myopic people compared with people without visual defects). These findings are shown in Figure 3.

Fig. 3. A plot of the statistically significant configurations (VRT in seconds).

A careful analysis of the results in the section above showed that there were significant differences in the VRT in situations that were related to gender and visual defects.

Regarding gender, women showed a longer VRT in all of the situations tested. This finding supports other studies stating that females seem to have slower reaction times than males for both visual and acoustic stimuli (Noble, 1964; Welford, 1980; Adam, 1999; Dane & Erzurumlugoglu, 2003; Der & Deary, 2006; Kosinski, 2013) and also have worse visual acuity (Burg, & Hulbert, 1961). Besides the generality of this result independent from the color of DRL, the difference in the VRT between genders was more significant when the color of the lights was amber.

As a possible explanation for this fact, the different sensitivities to different colors of light are due to the participation of three different types of cones in the retina: L cones, which are more sensitive to shorter wavelengths of light, such as red or amber; M cones, which are more sensitive to medium wavelengths such as green and S cones, which are more sensitive to short wavelengths such as blue. These three cones have different opsines, the molecules (proteins) that participate in the photochemical reactions produced when the incident light strikes the cones. Hence, different molecules are involved in the optimal detection of different colors of light. For this reason, the biochemical differences due to gender (mainly hormones) may influence the detection of different colors of light.

Concerning the lower VRT (that is, better reactivity) of participants with corrected myopia, the main explanation is that the lenses used to correct myopia are divergent, and thus, the images formed on the retina are smaller, which could cause an image to be better located on the fovea. Another argument that could explain this decrease in VRT could be the fact that myopic subjects are corrected to 20/20 vision, whereas many drivers with nominally normal vision have only 20/30 vision or worse. This makes myopic but corrected pedestrians more reactive when the turn signal is switched on in presence of DRL.

Although the results obtained in this study can be at least partially explained, more research is needed, especially with regard to the physiological and biochemical explanations of the findings.

CONCLUSIONS

This paper studies some of the variables that may have an impact on pedestrians' VRT when they need to detect the activation of turn indicators while DRL are turned on. The current parameters considered when making regulations related to traffic safety should be revised in order to include the new factors identified in this work.

An analysis was made of several variables in this study: vehicle features (e.g., the color of the DRL and the distance between the DRL and Turn Indicators), inherent pedestrian characteristics (including height, gender and visual defects), and environment-related variables that cause an interaction between pedestrians and vehicles (such as the angle between the observer and vehicle). Therefore, beyond confirming the results concerning vehicle-related variables (Peña-García 2010), we herein reported new results concerning the variables inherent to pedestrians, which should be of interest to the automotive industry. Hence, the most relevant outcome of this analysis based on decision trees and a Generalized Linear Model is that certain pedestrian-related parameters show a clear correlation with the VRT as follows:

1. Women have longer visual reaction times than men. The long distance between observers and experimental device, which makes the small difference in height between the genders negligible, excludes a geometrical explanation of this fact. The difference may be hormone-related. There is abundant literature reporting slower VRT in women, which means that these visual differences do not take place only in exceptional cases, for example, pregnancy, when the correlation between vision and sexual hormones is well-known (Ness 2010). Moreover, although the visual system works in very different ways in a bright environment (i.e., photopic conditions, as in our experiment) than in a dark or poorly illuminated environments (i.e., scotopic or mesopic conditions, as in nighttime driving), significant gender-based

differences in accident rates have been found (De Oña 2013). These results suggest that a raise in the minimum luminous intensity emitted by DRL should be seriously considered by both, automotive industry and regulatory bodies.

2. There is an interaction between gender and the color of DRL: women have an even longer VRT when the color of the DRL is amber rather than white. This finding could provide an argument in favour of white DRLs opposed to the amber ones, which is a discrepancy between the ECE and North American regulatory frameworks with regard to automotive signals. Given that the distribution in of pedestrians should be 50% male – 50% female (and even if this ratio were different), the findings of this research clearly show that regulatory bodies should seriously consider using only white DRLs worldwide. Furthermore, although carmakers are allowed to use DRL with amber light in some countries, white light is allowed everywhere. Hence, it would not be even necessary to introduce any change in national regulations if the industry only manufactures headlamps whose DRL emit only white light. This measure, together with the raise in the minimum intensity proposed in the preceding conclusion, would improve the safety of millions of men and women, especially these last.
3. Myopic subjects with correction (glasses) had lower visual reaction times than the rest of the sample. As highlighted in the Discussion, this finding is not surprising due to the optical properties of the lenses used to correct myopia and to the optimized visual performance of people with visual correction.

Beyond the necessity for potential changes expressed in conclusion 2, there are interesting implications of these findings on future research. For example, given the high variability in the visual systems among older people, future experiments should be extended to these age groups, to more severe climate conditions (although not in adverse weather conditions because the low beam is switched on and DRLs are off in such cases), colder or hotter environments, to scenarios with moving cars, etc. The chain of 'detection-decision-reaction' in a pedestrian intending to cross a street is complex and includes many variables so that the various constraints, especially in age, of this study should not be considered as limitations but as an starting point for further studies. In future research, these variables will be considered in depth in order to provide more general results.

In addition, the efforts of multidisciplinary teams with expertise in psychology, road safety, illumination and technical regulations should also determine why women generally present longer VRT in discriminations between turn indicators and DRL, especially when the latter are amber, as well as the implications of this finding for road safety and traffic regulation.

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Appendix: Data mining approach (Decision trees)

The collected data were used to build two different models for predicting the dependent variable (VRT of pedestrians) and identifying the attributes that had the most influence on predicting this variable. To that end, two different CARTs were developed and implemented using 10-fold cross-validation of the sample. The purpose of the first CART (CART 1, Figure 4) was to detect whether certain variables related to an individual could influence the VRT. In this case, two variables involving the individual's characteristics (gender and the existence of visual defects) were entered. The second tree (CART 2, Figure 5) was built using all the five variables considered in the experimental analysis (color of DRL, separation between the DRL and Turn Indicator, observation angle, gender and visual defects), in order to analyze the relative importance of each one in relation to the others.

Fig. 4. CART 1: VRT vs. (gender, visual defects).

Figure 4 shows the model for CART 1. The interpretation of the tree is given below. The root node (Node 0) is divided into two child nodes (Node 1 and Node 2). The variable that is able to maximize the "purity" of the two child nodes is used as a splitter. In this case, the splitter is Gender. Node 1 shows the data related to females. Node 1 is a terminal node, or leaf node, which predicts a VRT value of 1.000 seconds. The right brunch of the tree shows VRT for men. This tree shows that women present longer VRTs than men. In the second level of the tree, the variable Visual Defects is the splitter, sending the individuals who present myopia to the left branch (Node 3) and those who presents other visual defects (i.e. long-sightedness, astigmatism, etc.) or none to the right branch (Node 4). In this case, the individuals with myopia present lower VRT than all the others. This first decision tree produced two levels (depth below the root node), 4 nodes and 3 terminal nodes or leaves. A 10-fold cross-validation of the sample was used, which gave an estimated risk (or unexplained variance) for the model of 0.138, with a standard error in the estimation of risk of 0.086.

Fig. 5. CART 2: VRT vs. (color of DRL, separation between DRL and turn indicator, observation angle, gender, visual defects).

CART 2 (see Fig. 5), in which all the five variables are analyzed as a whole, produced 3 levels, 6 nodes and 4 terminal nodes, with an estimated risk of 0.137 and a standard error of 0.084. The splitter that divided the root node into two child nodes was Angle observer-device, with Node 1 being a terminal node. All the data that had an observation angle of 0º were concentrated in this terminal node, predicting the same VRT value of 0.953 seconds. This shows that even when all the variables are analyzed together (both the experiment-related variables and the individual-related variables), the other variables will lack importance and the individuals will have good VRT if the angle of observation between the observer and the experimental device is 0º.

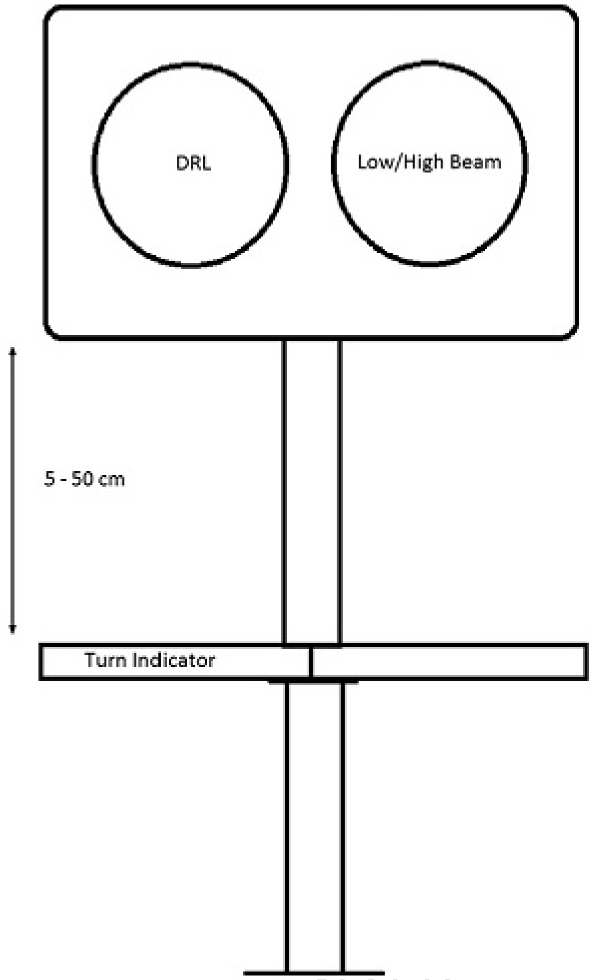
All the observations at a 20º angle were obtained after Node 2. It was found that the terminal nodes which started with an observation angle of 20º obtained worse VRT values than those for 0º observations. Node 2 was divided into two nodes, a child node (Node 3) and a terminal node (Node 4), using the variable Color of DRL as splitter. Node 4 described the experiment's conditions with 20º angle and a White DRL. This node predicted a VRT value of 0.972 seconds. This was the lowest value for a 20º angle. Node 3 was divided into two terminal nodes (Nodes 5 and 6) using the variable Gender as splitter. The terminal Node 5, corresponding to VRT for women with 20º angle and Amber DRL, describes the experiment's least favorable conditions, since it has the worst predicted VRT (1.100 seconds).

CART 1 shows that Visual Defects and Gender are weighty variables in reaction times. The analysis of CART 2 shows that Angle observer-device and Color of DRL are key variables, followed by Gender.

Personal factors influencing the visual reaction time of pedestrians to detect turn indicators in the presence of Daytime Running Lamps.

List of Figures

List of Tables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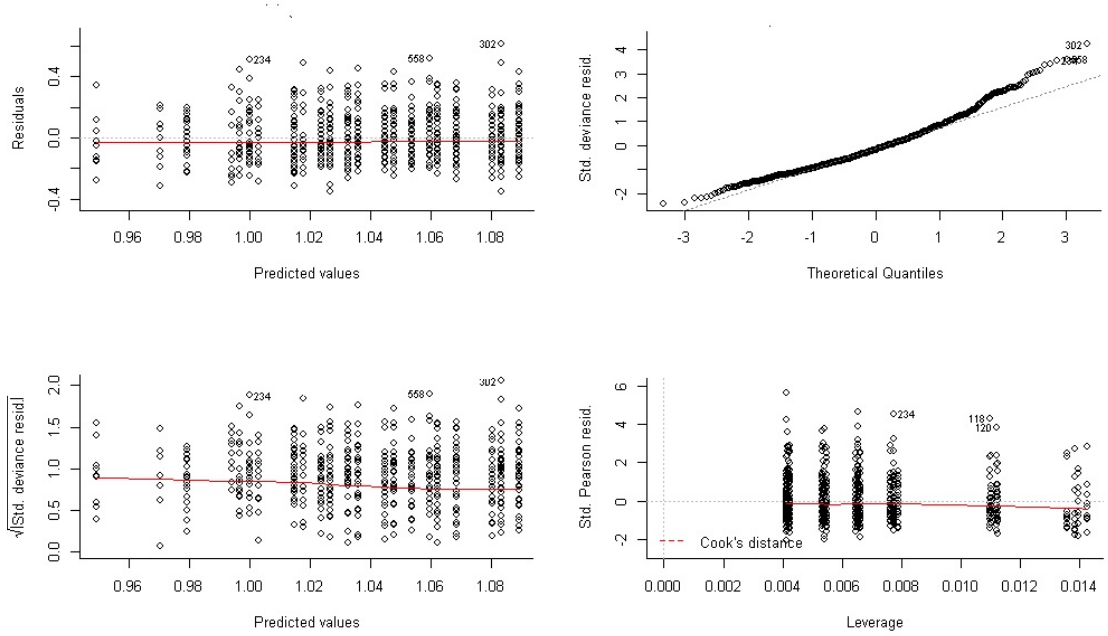
Low/High Beam
5 - 50 cm
Turn Indicator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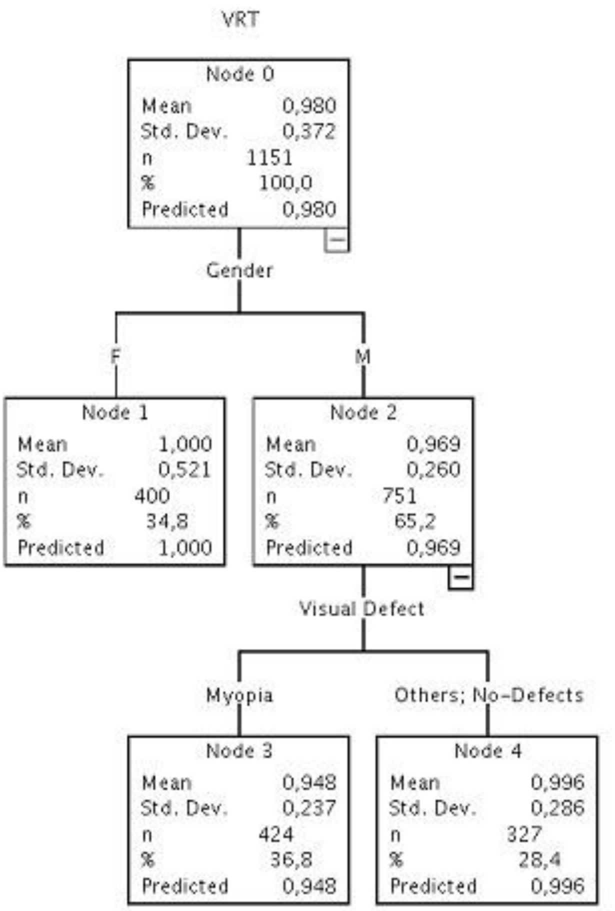
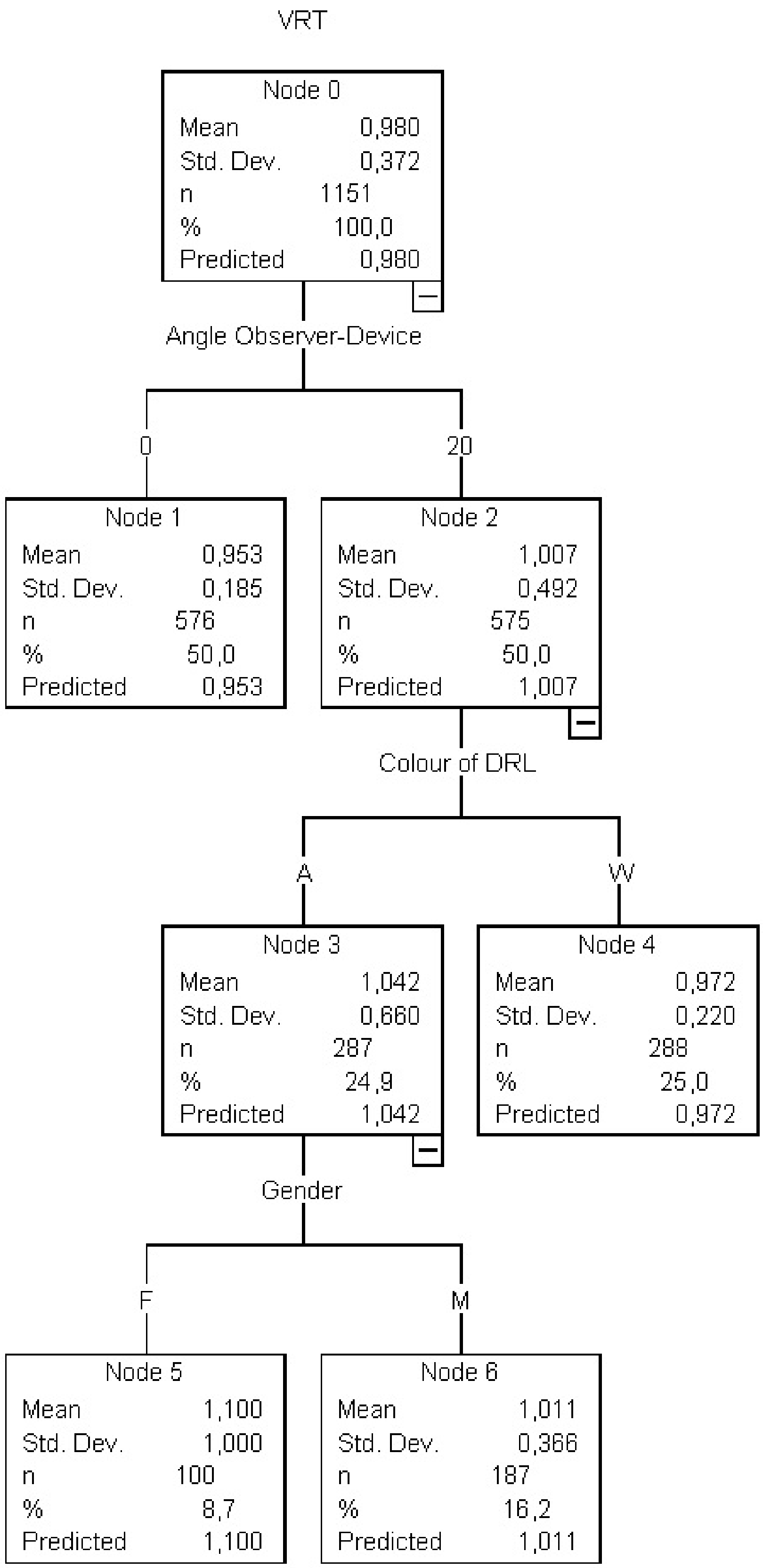
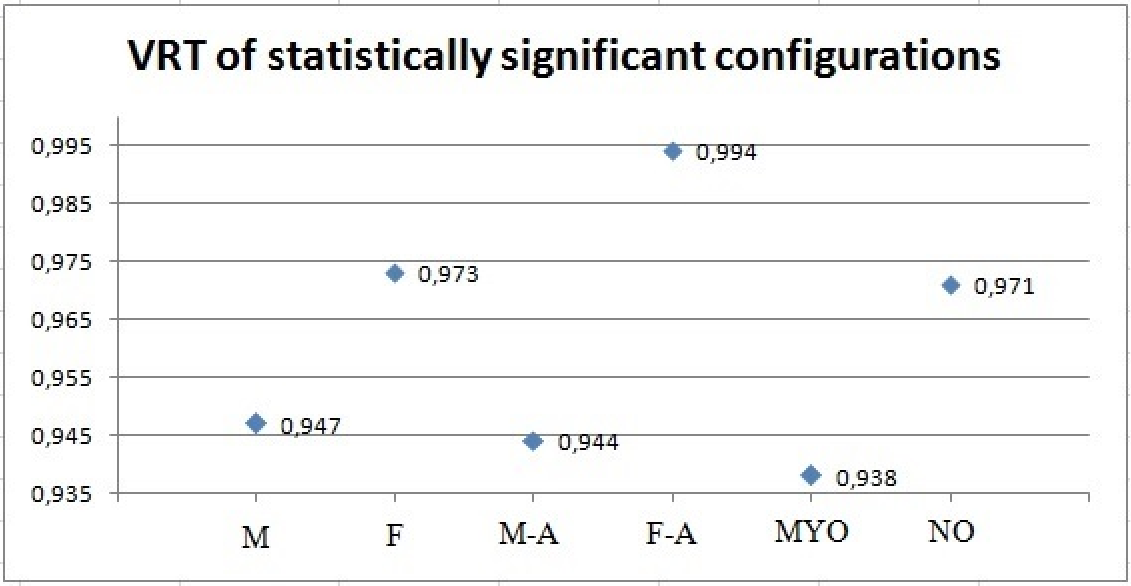
Predicted values
Std. deviance resid.
Theoretical Quantiles
√|Std. deviance resid.|
Predicted values
Std. Pearson resid.
Cook's distance
Leverage


VRT
Node 0
Mean 0,980
Std. Dev. 0,372
n 1151
% 100,0
Predicted 0,980
Gender
F
M
Node 1
Mean 1,000
Std. Dev. 0,521
n 400
% 34,8
Predicted 1,000
Node 2
Mean 0,969
Std. Dev. 0,260
n 751
% 65,2
Predicted 0,969
Visual Defect
Myopia
Others; No-Defects
Node 3
Mean 0,948
Std. Dev. 0,237
n 424
% 36,8
Predicted 0,948
Node 4
Mean 0,996
Std. Dev. 0,286
n 327
% 28,4
Predicted 0,996


VRT
Node 0
Mean 0,980
Std. Dev. 0,372
n 1151
% 100,0
Predicted 0,980
Angle Observer-Device
0
20
Node 1
Mean 0,953
Std. Dev. 0,185
n 576
% 50,0
Predicted 0,953
Node 2
Mean 1,007
Std. Dev. 0,492
n 575
% 50,0
Predicted 1,007
Colour of DRL
A
W
Node 3
Mean 1,042
Std. Dev. 0,660
n 287
% 24,9
Predicted 1,042
Node 4
Mean 0,972
Std. Dev. 0,220
n 288
% 25,0
Predicted 0,972
Gender
F
M
Node 5
Mean 1,100
Std. Dev. 1,000
n 100
% 8,7
Predicted 1,100
Node 6
Mean 1,011
Std. Dev. 0,366
n 187
% 16,2
Predicted 1,011


VRT of statistically significant configurations
0,995
0,985
0,975
0,965
0,955
0,945
0,935
0,994
0,973
0,971
0,947
0,944
0,938
M
F
M-A
F-A
MYO
NO

Notation	Color of DRL*	Distance DRL-Turn Indicator (cm)	Observation angle (º)
A-5-0	A	5	0
A-50-0	A	50	0
A-5-20	A	5	20
A-50-20	A	50	20
W-5-0	W	5	0
W-50-0	W	50	0
W-5-20	W	5	20
W-50-20	W	50	20
*: “A” means amber and “W” means white.			

Table 1.- Summary of configurations.

Coefficients (1)	Estimate	Std.error	t	Pr(<|t|)	Analysis of Deviance Table (2) (Type II tests)			
					SS	Df	F	Pr(>F)
Intercept	1.033	0.013	78.87	**<0.001**				
Angle[T.20]	-0.001	0.0004	-2.376	**0.017**	0.1197	1	5.6432	**0.018**
Color[T.W]	0.044	0.015	3.014	**0.002**	0.0388	1	1.8285	0.176
Distance[T.50]	0.0001	0.0002	0.546	0.585	0.0063	1	0.2979	0.585
Gender[T.M]	0.053	0.012	4.119	**<0.001**	0.2003	1	9.4417	**0.002**
Visual Defect[T.No-defect]	-0.035	0.010	-3.668	**<0.001**	0.5768	2	13.5944	**1.465e-06**

Visual Defect[T.Others]	-0.064	0.014	-4.608	**<0.001**					
Color[T.W]:Gender[T.M]	-0.051	0.02	-2.75	**0.006**		0.1604	1	7.5627	**0.006**

(1) In brackets the contrasted categories for each factor levels.

(2) Analysis of Deviance columns shows significant factors in the model.

Bold text indicates p-value <0.05

Table 2. GLM coefficients and Analysis of Deviance (Type II tests).

		VRT (s)	
		Mean	**Std. Dev.**
Color of DRL	A	0,961	0,137
	W	0,950	0,142
DRL-Turn Indicator Distance (cm)	5	0,958	0,136
	50	0,953	0,143
Angle Observer-Device (º)	0	0,946	0,141
	20	0,965	0,138
Combinations Color-Distance-Angle	A-5-0	0,951	0,135
	A-50-0	0,950	0,143
	A-5-20	0,986	0,138
	A-50-20	0,959	0,131
	W-5-0	0,930	0,125
	W-50-0	0,954	0,159
	W-5-20	0,966	0,141
	W-50-20	0,951	0,140
Gender	F	0,973	0,152
	M	0,947	0,132
Combinations Gender-Color	F-A	0,994	0,156
	M-A	0,944	0,123
	F-W	0,952	0,144
	M-W	0,949	0,141
Visual defects	NO	0,971	0,140
	YES	0,948	0,139
Visual defects	MIOPYA	0,938	0,129

	NO	0,971	0,140
	OTHER	0,999	0,175

Table 3. Summary of the VRT in the different configurations involved in the experiment where:

A= Amber; W= White; F= Female; M= Male.