Automated feedback on viewing skills lowers accident involvement

Abstract — The risk of being involved in an accident in the first year after licensing is greater for novice drivers who passed their driving exam the first time than for novice drivers who failed their first driving exam. Enhanced training programs can shorten the duration of training and can raise the passing rate on the first exam, but can also increase accident involvement after licensing. We propose automated feedback on viewing skills can contribute to safe driving after licensing. An intervention was made in a driving simulator curriculum of manufacturer Green Dino to study the transfer on the first driver exam and retention of driving skills for safe driving in the first year after licensing. A questionnaire was sent to 22,881 former students. The results of 2,439 subjects where used in this study. The driving skills of a control group were compared to the driving skills of subjects who followed driving lessons with automated feedback on viewing behavior. Analysis of simulator data and questionnaire data showed significant differences between the two groups. Novice car drivers who followed driving lessons on a simulator with automated feedback on viewing skills needed fewer lessons to pass the driving exam. The self-reported accident involvement of this group was 31% lower than the control group and 32% lower than the average accident involvement in the Netherlands. We suggest using automated feedback on viewing skills in driver training before and after passing driver examination to increase road safety.

1 Introduction

The risk of being involved in an accident in the first year after licensing is greater for novice drivers who pass their driving exam the first time than for novice drivers who fail their first driving exam (Renge 1983 [1], Fortsigth et al. 1997 [2], Wells et al. 2008 [3]). Enhanced training programs, like skid avoidance training, can shorten the duration of training and can raise the passing rate on the first exam, but can also increase accident involvement after licensing. The retention of skills necessary for safe driving, showed during the driver exam, is relative low in the first months after licensing. After licensing, the feedback of the driving instructor stops immediately. The loss of the external feedback directly leads to erosion of skills EOS (Kuipers 2014 [4]). Novice drivers in the Netherlands are 4 to 6 times more frequently involved in accidents compared to experienced drivers. This phenomenon is reported worldwide. It seems difficult for formal driver training programs to achieve positive retention on safe driving after licensing (Brown et al. 1987 [5], Mayhew et al. 1998 [6], Christie 2001 [7], Elvik & Vaa 2004 [8]).

Positive effects on safe driving where noted as result of training of recognition of dangerous traffic situations (Vlakveld 2011 [9]). We assumed that extra attention for viewing skills can have a positive effect on the retention of safe driving and can lower accident involvement. We proposed using automated feedback on viewing skills because it is too demanding – and unsafe – for a driving instructor to give consistent feedback on viewing behavior. We assumed not only the retention of safe driving skills will benefit from automated feedback on viewing skills, but also the transfer of training during examination. To test our hypotheses, we developed and implemented viewing feedback technology in a driving simulator curriculum. A learning theory was constructed that embraces EOS. We compared the driving skill performance of simulator students who were trained with the automated viewing feedback to students who followed driving lessons without the automated feedback. And we performed analysis between subjects to lower self-selection effects of the driving simulator. An online questionnaire was used to research the transfer and retention of safe driving skills.

2 Mental Transition

To have a better understanding of EOS, we constructed a new learning theory, Mental Transition (MT). MT is an abstract model, based on generally accepted learning theories from the field of neural psychology. We suggested that a better understanding of the biological principles underneath information processing in the human brain could result in improved retention of safe driving. MT has two pillars. The first one is automation of skills; the transition from information processing from the short term memory (STM) to the long term memory (LTM). New information is processed in the STM. STM is slow memory with a very limited capacity and therefor error prone. The shift from STM to LTM is necessary to quickly process large amounts of information without making mistakes. This mental transition is not stable. In case the permanent nerve structure is not stimulated frequently, the nerve connections become weaker and can vanish. EOS appears, the mental transition rolls back.

The second pillar of MT is based on the parameters that influence the mental transition. The frequency of sensory stimuli and the complexity of information are important parameters influencing the performance of information processing in the brain. Parameter management can optimize the process of mental transition and lower EOS. Speed for example, has strong correlation with frequency and complexity of information. Other parameters we distinguish are motivation (internal and external) and intelligence (information processing capacity). We tuned these parameters to achieve an optimal performance of the human brain related to the learning process. For example, 50 meters before a crossroads, a student receives the instruction to release the accelerator pedal and decrease speed. Normally, drivers maintain speed and use the brake to lower speed. Entering the crossroads at higher speed leads to tunnel vision. The mental effort needed to process information increases. The field of view decrease. Special attention was given to weak stimuli, like applying traffic rules. We tried to associate them with stronger stimuli such as vehicle handling. Slowing down not only results in an increased field of view, but it also supports the learning of skills for applying rules.

3 Automated feedback on viewing skills

In 2009, we introduced automatic facial recognition and visual feedback for learner drivers who followed driver training on a driving simulator (figure 1).

Fig. 1 Drive Master LT driving simulator

The learning theory Mental transition and the interface design methodology Data Centered Design DCD (Kuipers 2014 [4]) were used to construct an automated feedback mechanism. The feedback mechanism contains an adaptive information management system and a user interface for communication with the driver. The information management system contains information on driving procedures, peer group performance, and mental effort. In case viewing behavior is part of a driving task, the view assessment is activated. 8 visual areas are specified (front, front sides, inside mirror, outside mirrors, and sides). By showing student a red field in the area where he/she should have looked, in combination of a displayed warning, the student receives necessary feedback to solidify his/her knowledge (figure 2).

Fig. 2 Visual feedback with red areas, symbols and text. Left side, left side mirror, and inside mirror are not viewed by the student and turned red.

Auditive feedback on the driving speed before entering a crossroads is part of the feedback mechanism for viewing skills. The infrastructure was designed to support the feedback frequency threshold of maximum 1 minute. Within one minute, the student enters the next crossroads and rehearses the driving task. The student receives the instruction and warning to release the gas pedal 50 meters before entering the crossroads. We thought this way, the student could associate the frequency of red areas with the vehicle speed. We tried to teach them the relations between speed and viewing behavior. After the lesson, scores for parameters like speed before crossroads and viewing behavior are displayed on screen and reported by email to support self-reflection and motivation to rehearse and improve safe driving skills, like viewing. The safety report shows correlations between parameters involved in safe driving (figure 3). Students and supervisors can use this information to learn/ teach the consequences of specific driving styles, like high speed before crossroads results in tunnel vision. In the simulator, the student consistently receives the advice to release the accelerator pedal in case of an unsafe speed. After seeing the safety scores, the student gets a better understanding of the negative relation between speed and viewing. Paying attention to the visual and auditive feedback directly results in higher scores on both parameters.

Fig. 3 Safety report: assessment scores on safety parameters. Correlation between safe speed and view behavior.

4 Effect study

In 2015, we started an effect study among former students who followed driving lessons on driving simulators with automated feedback. An e-mail was sent between November 9th and 13th, 2015 to 22,881 people whose e-mail addresses were in the databases of driving schools with a Green Dino simulator. In this e-mail, the researcher first introduced herself and explained the subject and main goal of the questionnaire. The importance of the recipient filling out the questionnaire was also highlighted. The (former) driving students were then asked to complete the online questionnaire by clicking on the provided link and answering the questions. As a reward, 10 x 2 cinema tickets were promised to be raffled among interested participants. People could also indicate if they would like to be sent a summary of the results once the research had finished. The raffle and sending the summary took place in March 2016.

In December 2015, several driving schools were approached and asked if they could forward the aforementioned e-mail message to their (former) students, so more regular students could be reached and serve as a control group. To maximize the control group, the researcher also shared the link to the questionnaire on social media. After merging the questionnaire data with simulator data, people who had participated in 0 or 1 simulator lessons were also added to the control group.

The online questionnaire was closed on February 10th, 2016.

Eventually, 6,729 people have viewed the questionnaire, 5,142 people started answering questions and 3,761 people actually completed the questionnaire. After inspection of the data, 1,322 completed questionnaires (35.1%) appeared not to be useful for analysis. 2,439 subjects remained, of which 72.2% were simulator students (had lessons on a driving simulator during their driver's education). Only fully completed questionnaires were taken into account, and only when the participant was in the possession of a driving license since 2007 or later (because previous research on this topic was about 2007 and before). A short summary of subject data is listed in Table 1.

Participants were removed if they were younger than 18; the legal age for having a driving license. Because age differed significantly between the simulator group and the control group, age categories were computed to examine separately if necessary. Participants were divided in 3 age groups: 17-19, 19-24, and 24 or older (when they got their license).

Participants' education (they were given 8 different education options and a 'Different, namely…' option) was dichotomized into lower education and higher education. People who filled in the 'Different, namely…' option were manually divided in this new variable. 11 of them were not specific enough, and were not included in analyses about education level.

Participants were asked to give an estimation of how many kilometers they had driven in the first, an in the most recent year they had had their license. Answers of 120,000 km or higher were marked as missing because they were very improbable (10,000 or more km each month).

Outliers on driving lessons were removed (marked as missing), so no values over 200 remained. Which is still very high, but present in both the simulator group as the control group and not impossible. If the number of on-road driving lessons was 10 or lower, it was also marked as missing because that would be very unlikely and is possibly a typo.

Questions were asked about if and how many (severe) accidents participants had been involved within the first year of having a driving license, and in the most recent year of having a license. In analyses of accidents in the first year, only participants who had had their license for at least a year were included; in analyses of accidents in the most recent year only participants who had had their license for at least 2 years were included (to make sure these different periods did not overlap).

Table 1. Summary of subject data

		Simulator: 72.2% (N=1760)	Control: 27.8% (N=679)
Age when obtaining the driving license		Mdn=18.92	Mdn=19.67
Age when filling in the questionnaire		Mdn=22.00	Mdn=24.00
Months in possession of driving license		Mdn=28.00	Mdn=44.00
Sex	Male	37.0%	42.1%
	Female	63.0%	57.9%
Education level	Higher	75.1%	81.7%
	Lower	24.5%	17.8%
Distance driven in first year (km) – 12 or more months in possession of license		Mdn=1500.00 N=1368	Mdn=2000.00 N=622

5 Results

Only the results about the transfer on the first driver exam and the retention of safe driving skills are presented.

Students who followed simulator training (8 lessons and more) with automatic feedback on viewing skills performed significantly better on the first driver exam than simulator students who did not receive automated feedback on viewing skills (7 lessons and less). Simulator students who followed simulator training without automatic feedback on viewing skills had an average passing rate on their first exam of 51.8%. Simulator students who followed simulator training with automatic feedback on viewing skills had an average passing rate on their first exam of 59.6%. In combination with a hazard perception training, the passing rate was 81.8%. 33.8% higher than the Dutch national average of 48% (over the period between 2008 and 2015).

No significant effect on accident involvement was found for simulator students who only followed vehicle handling training. Simulator students who followed driving lessons (7 or less) without automated feedback on viewing skills had an average accident involvement of 13.8% in the first 12 months after licensing. Simulator students who followed driving lessons (8 or more) on a simulator with automated feedback on viewing skills had an average accident involvement of 5.1% in the first 12 months after licensing, 32% below the Dutch national average of 7.5%. The accident involvement of the control group of students who only followed driving lessons on road was 9.9% in the first 12 months after licensing. The control group drove 2,000 km in the first 12 months. Simulator students drove 1,500 km. After correction for the exposure, the risk of being involved in an accident for simulator students who followed driving lessons on a simulator with automated feedback was 31% lower than for students who only followed driving lessons on road.

Significant differences in accident involvement were also found between gender, age groups, education types, driving styles, and learning styles.

6 Conclusions

We assumed automated feedback on viewing skills during driver education could have positive effects on the transfer and the retention of safety related driving skills and lowered the effect of EOS. We developed and implemented view assessment technology in a simulator curriculum and added a hazard perception training. Our research showed significant differences in passing rates and accident involvement between (former) students who received automated feedback on their viewing skills and (for) students who did not get this feedback during training. Students who followed driving lessons with automated feedback on viewing skills had higher passing rates on the first driving exam and needed less lessons in total. Simulator students who got automated feedback on viewing skills were less involved in accidents than simulator students who did not get this feedback and students who only followed driving lessons on road. These transfer and retention differences had a positive correlation with the amount of simulator lessons followed by the (former) students. The more simulator lessons followed with automated feedback on viewing skills, the bigger the differences between the groups. These effects clearly indicate a positive effect of our new learning theory Mental Transition on transfer and retention of safe driving skills. However, influence of self-selection, self-reporting, and non-randomized testing should be taken into account.

7 Discussion

Our research showed passing the first driver exam does not have to lead to a higher risk of accident involvement. We suggest using automated feedback on driving skills in general, and viewing skills specifically, during driver training to lower accident involvement after licensing. Driving simulators offers several advantages in comparison with cars and human supervisors, like secure safety, easy data acquisition, uniform training and assessment, lower costs for students, higher profits for driving schools and no CO2 production. We also suggest to use automated feedback after licensing to decrease EOS and increase road safety. This could be done in vehicle but also using e-learning with driving simulation. Automated feedback on maneuvering skills during driving on roads could also lower erosion of driving skills due to automation with ADAS and use of self-driving vehicles (Kuipers 2014). Automated feedback offers great potential for training in general.

However, we also advise to conduct a retest in a more controlled environment with randomized, filtered subjects to validate our results.

8 Future work

In 2019 we start a longitudinal study under professional truck and bus drivers in cooperation with the Dutch Exam Authority. In a period of 5 years we will follow truck and bus drivers who follow their annual obligatory professional competence refresher training Code95 on a Green Dino simulator (figure 4) with automated feedback in combination with e-learning.

Fig. 4 Truck simulator type Crash Tender.

9 Acknowledgement

This research is supported by the Dutch Ministry of Economic Affairs, Green Dino BV, T. ter Morschhuizen, and J. De Winter.

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10 Author/Speaker Biographies

Jorrit Kuipers is founder of Green Dino (1992) and robotTUNER (2016). Green Dino offers an autonomous open platform for (driver) training and assessment based on artificial intelligence, big data and 3D simulation. robotTUNER develops a software driving license for autonomous vehicles in cooperation with the Netherlands Vehicle Authority and the Netherlands Driver Exam Authority. Jorrit is Vice president and treasurer of the Dutch Academy of Technology & Innovation. His PhD defense is planned for Q2 2019 (Man Machine Systems Delft Technical University). The subject of the thesis is the design of a new system architecture for autonomous training and assessment based on cognitive psychology. J.kuipers@greendino.nl.