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de Winter, J.C.F.

DOI

[10.1016/j.aap.2012.12.018](https://doi.org/10.1016/j.aap.2012.12.018)

Publication date

2013

Document Version

Final published version

Published in

Accident Analysis & Prevention

Citation (APA)

de Winter, J. C. F. (2013). Predicting self-reported violations among novice license drivers using pre-license simulator measures. *Accident Analysis & Prevention*, 52, 71-79. <https://doi.org/10.1016/j.aap.2012.12.018>

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Predicting self-reported violations among novice license drivers using pre-license simulator measures

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ARTICLE INFO

Article history:

Received 26 October 2011

Received in revised form

10 December 2012

Accepted 11 December 2012

Keywords:

Driving simulator

Validity

Novice drivers

Young drivers

Long-term prediction

ABSTRACT

Novice drivers are overrepresented in crash statistics and there is a clear need for remedial measures. Driving simulators allow for controlled and objective measurement of behavior and might therefore be a useful tool for predicting whether someone will commit deviant driving behaviors on the roads. However, little is currently known about the relationship between driving-simulator behavior and on-road driving behavior in novice drivers. In this study, 321 drivers, who on average 3.4 years earlier had completed a pre-license driver-training program in a medium-fidelity simulator, responded to a questionnaire about their on-road driving. Zero-order correlations showed that violations and speed in the simulator were predictive of self-reported on-road violations. This relationship persisted after controlling for age, gender, mileage, and education level. Respondents with a higher number of violations, faster speed, and lower number of errors in the simulator reported completing fewer hours of on-road lessons before their first on-road driving test. The results add to the literature on the predictive validity of driving simulators, and can be used to identify at-risk drivers early in a driver-training program.

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1. Introduction

Road traffic crashes are a leading cause of death, accounting for 22% of all fatal injuries worldwide (World Health Organization, 2009). Crashes not only cause loss and grief on a personal level, but have serious consequences for society as well. If countries could prevent all crashes and associated costs, the result would be a socioeconomic benefit of some 2.5% of the gross national product (Connelly and Supangan, 2006; Elvik, 2000; European Transport Safety Council, 1997).

Novice drivers, that is, drivers in their first few years of independent driving and most of whom are in their late teens or early twenties, are overrepresented in crash statistics (Evans, 1987; Lee, 2007; Organisation for Economic Co-operation and Development [OECD], 2006; Williams, 2003). Research has shown that formal on-road driver training is not consistently effective for reducing their crash risk (Beanland et al., 2013; Christie, 2001; Groeger and Banks, 2007; Mayhew and Simpson, 2002) while scores of on-road driving tests bear little association with crash rates once drivers are licensed (Senserrick and Haworth, 2005). More effective measures to prevent crash-prone drivers from entering traffic may need to be considered to enhance safety and reduce the number of crashes.

There are many tools used to predict a driver's crash involvement. One well known tool is Useful Field of View (UFOV), a test capturing the visual area over which information can be extracted in a brief glance (Ball et al., 1993; Clay et al., 2005). The UFOV is particularly used for testing older drivers, as its outcome is a strong correlate of age-related cognitive decline (Sekuler et al., 2000). Driving simulators are another promising means to assess safe driving ability, as they provide objective measures with a high degree of controllability (Hancock et al., 1990; Medeiros et al., 2012; Underwood et al., 2011). Simulators offer several advantages over on-road driving, such as cost-effectiveness, ease of data collection, reduction of stress and nerves during initial driver training, and the ability to deal with dangerous tasks and learn from mistakes without putting road users at risk (Bédard et al., 2010; De Winter, 2009; Santos et al., 2005; Vlakveld, 2005). There is a growing body of evidence indicating that simulator measures can reliably predict on-road performance (Bédard et al., 2010; Godley et al., 2002; Lee and Lee, 2005; Mayhew et al., 2011; Shechtman et al., 2009) and individual differences in crash involvement (Cox et al., 1999; Hoffman and McDowd, 2010; Lee et al., 2003a; Reimer et al., 2006; Rosen et al., 2011).

The validity of simulators for predicting the on-road performance of older drivers and patients is relatively well established. The available research indicates that measures obtained in a simulator have a high correlation with those from on-road studies with respect to performance on sensory/cognitive tasks. For example, a study of 129 older drivers by Lee et al. (2003b) showed that a

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composite index of simulator driving correlated well with a composite index of on-road driving ($r=.72$). The composite indexes consisted of criteria such as average driving speed on a straight road segment, stopping in the right place, correct use of indicators, stable steering and speed maintenance, and recalling the route and street names. All assessment criteria correlated negatively with age (r s between $-.25$ and $-.66$), suggesting that bodily aging is a common cause of individual differences in driving skill. Lee et al. (2003b) explained that age-related deterioration of driving skill might involve such factors as “loss of visual processing ability on the periphery, deficits due to medical conditions, cognitive decrements and sensory impairment” (p. 802). In another study, Lew et al. (2005) tested 11 patients with moderate to severe traumatic brain injury and found that a 12-measure simulator index predicted on-road driving performance observed 10 months later with a significant correlation of .66. The authors concluded that automatic assessment by means of a simulator could provide measures that may be more sensitive in detecting some drivers’ vulnerabilities than a traditional on-road test.

Novice drivers are a crash-prone group with risk factors that are distinct from those of older drivers and patients. Reasons for the high crash rate of novice drivers include the following: novice drivers have not yet perfected their vehicle control skills, have low spare attentional capacity to deal with novel traffic situations, and have poor ability to anticipate and identify hazards (Deery, 2000; Lee, 2007; Underwood et al., 2011). Crash risk drops dramatically during the first 6 months of driving (Mayhew et al., 2003; OECD, 2006), and it appears to require several more years of driving experience to optimize higher-order skills such as hazard perception (Pradhan et al., 2005). Deviant driving styles such as deliberate violations and sensation-seeking are also known to contribute to the crash risk of novices (Clarke et al., 2005; OECD, 2006). These behaviors appear to be governed by a combination of social, neuro-behavioral, and biological mechanisms (Dahl, 2008; Evans, 2006; Jessor, 1987) and are resistant to change, as demonstrated by a longitudinal study among drivers in their first nine months of independent driving (Björnskau and Sagberg, 2005). This study showed that self-reported violating behavior did not show a learning curve pattern (while self-reported errors did); in fact, violations increased with months of experience. Summarizing, older and novice drivers have distinct risk factors. In older drivers, driving with higher mean speed and maintaining progress is a *positive* behavior and an indication of adequate driving ability (cf. Lee et al., 2003b), but in novice drivers, fast driving (particularly speeding) is seen as a *negative* behavior and a predictor of crash involvement (Gonzales et al., 2005; OECD, 2006).

There is only limited evidence for the predictive validity of driving simulators in the novice driver population with a focus on measuring violating behavior such as speeding. One exception is Allen et al. (2009), who calculated correlations between pre-license behavior in a driving simulator and state-registered crashes four years later in 488 teenagers. Twenty simulator performance variables were recorded, including root mean squared error of speed and lane-center error, improper turn signaling, and center-line crossings. Their results showed that of the 20 variables, average speed, number of speed limit exceedances, and number of stop sign tickets during initial training experience in the instrumented-vehicle simulator configuration were predictive of crashes ($n = 144$, of which 17 participants were involved in an on-road crash later on), while no predictive validity was demonstrated by desktop simulator systems ($n = 344$). Allen et al. (2009) concluded that their results “can be interpreted as suggesting that accident-prone novice drivers have a higher tendency to risk taking.” (p. 92).

The aim of this study was to investigate whether pre-license behavior in a driving simulator is predictive of post-license self-reported driver aberrations. A questionnaire was administered to

people who 2.3–4.1 years ago had followed a simulator-based driver-training program. Relationships were established between recorded pre-license driving behavior in a simulator (violations, errors, and speed) on the one hand, and self-reported risk-related variables, including violations, errors, crashes, and speeding tickets, on the other.

2. Methods

2.1. Questionnaire

E-mail addresses of individuals who had driven in a simulator as part of their driver training in the period 2007–2009 were obtained from Green Dino BV, a Dutch manufacturer of driving simulators. On 12 and 13 July 2011, e-mails were sent to these individuals with an invitation to participate in this research project with an explanation regarding the purpose of the research, and a link to an electronic questionnaire.

The multiple-choice questionnaire consisted of 15 items on individual characteristics and standard driving parameters (e.g., age, gender, education, month of obtaining driving license, number of hours of professional instruction on the road, mileage), 7 items on the respondents’ interests and driving style, 7 items on their opinion of driving simulators, and 4 items on their history of crashes and incurred speeding tickets. In addition, violations and errors were measured using 12 items from the Manchester Driver Behaviour Questionnaire (DBQ). The DBQ was originally published by Reason et al. (1990) and to date, has been used in over 174 studies (De Winter and Dodou, 2010). The DBQ violations and errors scores are predictive of self-reported accident involvement, both prospectively and retrospectively (De Winter and Dodou, 2010). The violations factor also correlates with speed/speeding recorded by in-vehicle recording systems and unobtrusive radar measurements (Åberg and Wallén-Warner, 2008; De Angeli et al., 1996; Palamara and Stevenson, 2003; Quimby et al., 1999a,b; Zhao et al., 2012).

To increase the response rate, two cash lottery incentives of 400 euro were offered (cf. Doerfling et al., 2010). The research was approved by the Delft University of Technology Human Research Ethics Committee, and all participants provided informed consent through a dedicated questionnaire item.

2.2. Simulator hardware and simulator curriculum

The medium-fidelity fixed-base simulators were stationed at Dutch driving schools. The simulator provided a simulation of a mid-class manual-transmission passenger car, using 180-degree field of view and surround sound. The steering wheel, pedals, ignition key, gear lever, indicators, and seat resembled those of an actual car. The steering wheel provided force feedback using a DC torque motor coupled to the steering shaft through an 8:1 gearbox. Vehicular acceleration cues were supplied by vibration elements on the steering column and the seat. The virtual world was projected by means of three LCD projectors. The resolution of the front projection was 1024×768 pixels, and the resolution of each side projection was 800×600 pixels. The dashboard, interior, and mirrors were integrated in the projected images. The simulation ran at approximately 50 Hz, and the frame rate depended on scene complexity, but was at least 30 Hz.

The curriculum taught learner drivers the basics of car driving, such as speed control, shifting gears, lane keeping, starting, and stopping the car, driving through intersections and roundabouts, and driving and maneuvering on highways. Lessons, including the introductory screens, were 30 min long. Each simulator lesson comprised two or three different lesson blocks. The simulator-based

training was automated, removing the need for a human driving instructor. Interaction with other vehicles was not based on pre-programmed scenarios. Much as they would in an on-road lesson with a human instructor, learners drove in the virtual environment with a virtual instructor providing route instructions and feedback on task performance. The virtual instructor adapted its feedback according to the learner's success rate on tasks and the situation in the virtual environment (Weevers et al., 2003a,b). Learners usually start on simulator-based training before transferring to lessons in a real car. The number of lessons per learner driver varied and was determined by the learner and the supervisor at the driving school.

2.3. Simulator predictor variables

For each respondent, simulator variables were extracted from the databases. A distinction was made between violations, errors, and task completion times. Extracted violations were: speeding on highways and in curves, following too closely on highways, and running red lights. Extracted errors were steering errors (not enough steer, too much steer), lateral position errors (too far to the left, too far to the right), and inaccurate tracking of speed during a speed-control exercise. Task completion times were calculated as the difference between the start time and end time of a task, averaged over successfully completed tasks. A distinction was made between time to complete a road segment (in highway and city environments), time following another car near intersections (note that faster drivers are expected to drive longer behind other cars than slow drivers because they are more likely to be held up by a vehicle ahead, see also De Winter et al., 2007), and time for basic vehicle control actions (starting the engine, shifting up a gear). Table 1 provides an overview of the simulator predictor variables. If a respondent had completed a particular lesson more than once, then the repeated lesson or lessons were considered as well.

Lesson blocks took place in different types of virtual environments, with different traffic demands, or different task instructions. For example, some lesson blocks had many intersections controlled by traffic lights, creating ample opportunity for red-light violations, while other lesson blocks had only a few traffic-light controlled intersections, resulting in a low number of recorded red-light violations. To account for such block-specific variation, standard scores were calculated per lesson block as follows:

$$z_i = \frac{x_i - \mu_i}{s_i}, \quad (1)$$

where z_i represents the variable's standard score for lesson block i , x_i represents the variable's value (number of task failures [violations or errors], or mean task completion time of successfully completed tasks) for the i th lesson block, μ_i represents the variable's arithmetic mean for the i th lesson block, and s_i represents the variable's standard deviation for the i th lesson block. Missing values, resulting from the fact that the participant did not complete a particular lesson block, were ignored in the standardization process.

Next, for variables 1–9, the arithmetic mean was calculated as:

$$V^* = \frac{1}{n} \sum_{i=1}^n z_i, \quad (2)$$

where V^* represents the transformed variable with block-specific information removed, i represents the lesson block number, and n represents the total number of lesson blocks for the particular variable. Lesson blocks where the standard deviation of number of task failures was equal to or less than 0.5 failures, signaling only limited individual differences, were excluded from Eq. (2) (see also De Winter et al., 2009).

A weighted average was used for variables 10–15, accounting for the number of tasks per lesson block:

$$V^* = \frac{\sum_{i=1}^n z_i c_i}{\sum_{i=1}^n c_i}, \quad (3)$$

where c_i represents the number of times the task completion time was recorded in lesson block i .

Because of updates to the simulator at regular service intervals resulting in slight programming differences in simulator software, a further correction was carried out. The V^* variables were divided into three groups (lesson before 21 June 2008, lesson between 21 June 2008 and 31 November 2009, and lesson after 31 November 2009) and standard scores were calculated for each group. All reported analyses of simulator variables are based on the thus obtained standardized variables.

2.4. Dependent variables

The aim of this study was to investigate whether driver behavior in the simulator predicts self-reported on-road behavior. In the DBQ, respondents rated from 1 (never) to 6 (nearly all the time) how often they make specific aberrations while driving. A distinction is made between violations and errors:

- DBQ-Violations (1–6). The DBQ-Violations score was calculated as the average of the responses on the following items: (1) "Sound your horn to indicate your annoyance with another road user", (2) "Disregard the speed limit on a residential road", (3) "Use a mobile phone without a hands free kit", (4) "Become angered by a particular type of driver, and indicate your hostility by whatever means you can", (5) "Race away from traffic lights with the intention of beating the driver next to you", (6) "Drive so close to the car in front that it would be difficult to stop in an emergency", and (7) "Disregard the speed limit on a motorway". These items were selected from the DBQ used by Wells et al. (2008) because they loaded highly on the violations factor.
- DBQ-Errors (1–6). The DBQ-Errors score was calculated as the average response on the following items: (1) "Change into the wrong gear", (2) "Forget to take the handbrake off before moving off", (3) "Get into the wrong lane when approaching a roundabout or junction", (4) "Incorrect steering so that you hit the curb", and (5) "Strayed from the middle of the lane into the verge or emergency lane". The first three DBQ items were taken from Wells et al. (2008) because they loaded highly on the errors factor, and the other two were included to capture lateral driving behavior, as lateral behavior in the simulator has been shown to be a sensitive predictor of on-road driving test performance (De Winter et al., 2009).

In addition, the following dependent variables were employed:

- NumberCrashes (#). This variable represents the response to "How many accidents were you involved in when you were driving a car or van in the last 12 months? (Please include all accidents, regardless of how they were caused, how slight they were, or where they happened)" (item taken from a survey study by Transport Research Laboratory, 2008).
- CrashesDamage (0 or 1). This variable represents the response to "Since my simulator training, I personally have caused damage in a traffic crash" (0 = no, 1 = yes). It has been suggested that personal responsibility is an important factor in crash prediction (Af Wählberg and Dorn, 2007). Af Wählberg (2003) stated that crashes for which a person is not culpable cannot be predicted

Table 1

Overview of variables extracted from the simulator databases, with description of automatic assessment criteria.

Variable number	Variable name	Description
1	SpeedingViolations	Number of speeding violations on a highway. The criterion was driving faster than 130 km/h where 120 km/h was allowed.
2	HeadwayViolations	Number of times following too closely on a highway. The criterion was a time headway of less than 1.5 s with respect to the car in front.
3	RedLightViolations	Number of times driving through a red traffic light at a sign-controlled intersection.
4	CurveSpeedingViolations	Number of times driving too fast in a curve. The criterion was driving faster than 30 km/h in sharp curves or faster than 60 km/h in mild curves.
5	NotEnoughSteerErrors	Number of times not enough steering. The criterion was a lane-center error in a curve that was greater than 1.0 m and increasing for at least 0.3 s to the outside of the curve.
6	TooMuchSteerErrors	Number of times too much steering. The criterion was a lateral velocity on a highway that was greater than half a lane per second, or a lane-center error in a curve that was greater than 1.0 m and increasing for at least 0.3 s to the inside of the curve.
7	TooFarLeftErrors	Number of times lateral position too far to the left. The task was to drive on a road with various sharp curves during a 12.5 min lane-keeping exercise. The criterion was a lane-center error greater than 30% of the lane width for more than two consecutive seconds.
8	TooFarRightErrors	Number of times lateral position too far to the right. The assessing criterion was equivalent to TooFarLeftErrors.
9	SpeedTrackingErrors	Number of times deviating from instructed speed during a speed-control exercise. The task was to maintain speeds of 30, 50, and 80 km/h for 18 s periods during a 9 min exercise. Steering was automated. The criterion was deviating more than 5 km/h from the instructed speed.
10	AccessLaneTime	Mean time to approach access lane (s). This variable represents the time to complete a curved road segment leading to a highway access lane. This road segment was on average about 170 m long.
11	ExitLaneTime	Mean time to approach exit lane (s). This variable represents the time to complete a curved road segment leading to a highway exit lane. This road segment was on average about 330 m long.
12	CarFollowingTime	Mean time following another car when approaching/crossing an intersection or roundabout. The timing was activated when the time headway with respect to a car in front was less than 1.5 s, and deactivated when the time headway was greater than 1.5 s.
13	ShiftUpTime	Mean time to shift up a gear (s). This variable represents the time taken to shift to a higher gear including depressing and releasing of the clutch pedal. The task was initiated when the system determined that the gear was too low (based on current engine RPM, throttle position, and gear).
14	StartEngineTime	Mean time to start the engine (s). This variable represents the time from the start of a drive-away task to the turning of the ignition key with clutch depressed. Drive-away tasks were initiated automatically at the start of lesson blocks, after a collision, and during drive-away exercises.
15	IntersectionTime	Mean time to take intersection (s). This variable represents the time to cross an intersection together with the road segment prior to the intersection. The total distance covered depended on the type of intersection and road layout and was about 265 m on average.

by any variable, except exposure, as they are not consequences of any specific behavior.

- NumberSpeedingTickets (#). This variable represents the response to the item “How many speeding tickets have you received in the past 12 months?” The response “more than 3” was coded as 4.
- NumberHoursRoadLessons (0–101). “How many hours of professional driving tuition have you had? Count only the number of lessons until your first official driving test”. The response “more than 100” was coded as 101.

2.5. Extraneous predictor variables

Age, gender, mileage, and education level (intelligence quotient) are important predictors of self-reported violations and car crashes (De Winter and Dodou, 2010; O’Toole, 1990; Whitley et al., 2010). Therefore, the following variables were selected as additional predictors.

- Gender (0 = male, 1 = female).
- Age (years).
- Education (1–9). This item asked for the highest attended education level (1 = primary education, 2 = vocational education, 3 = special education, 4 = preparatory middle-level applied education, 5 = higher general continued education, 6 = preparatory scientific education, 7 = middle-level applied education, 8 = university of applied sciences, 9 = research university). Note that none of the respondents reported categories 1–3.
- Mileage (km). This represents the answer to the free response item: “How many kilometers did you drive in the past 12 months?

Count driving lessons as well as licensed-driving journeys. If you are not sure, give an estimate.”

- DriveFrequency (1–7). This represents the response to the item, “On average, how often did you drive in the past 12 months?” (1 = never, 2 = less than once a month, 3 = about once a month, 4 = about once a fortnight, 5 = 1–3 days a week, 6 = 4–6 days a week, 7 = every day).

It is important to statistically control for the date of the first simulator lesson to account for a possible trend in simulator scores due to the general population becoming more accustomed to computer simulation over time (De Winter et al., 2009). Furthermore, the number of completed simulator lessons might bear a relationship between the simulator variables and the dependent variables. Therefore, the following registered variables were also used as extraneous predictors:

- FirstSimDate (date). The date of the first simulator lesson.
- SimPeriod (days). The duration of driver training on the simulator, defined as the starting date of the last simulator lesson minus the starting date of the first simulator lesson.
- NumberSimLessons (#). Number of driving-simulator lessons completed.
- NumberSimBlocks (#). Number of unique lesson blocks completed (not counting repeated lessons).

2.6. Statistical analyses

All statistical analyses were performed with MathWorks’ MATLAB version 7.7.0.471. First, descriptive statistics (means and standard deviations) were calculated for all variables. Because of their ordinal scale and their occasionally severe

Table 2

Descriptive statistics and zero-order correlations between variables.

Variable	<i>M</i>	<i>SD</i>	#	<i>r</i> Gender	<i>r</i> DBQ- Violations	<i>r</i> DBQ- Errors	<i>r</i> Number Crashes	<i>r</i> Number Speeding Tickets	<i>r</i> Number Hours Road Lessons
Simulator predictor variables									
SpeedingViolations (#)	4.4	6.6		-.25	.27	-.01	.01	.20	-.11
HeadwayViolations (#)	10.5	8.9		-.37	.32	-.11	.09	.18	-.21
RedLightViolations (#)	1.8	2.4		.08	.05	-.03	.13	.04	.05
CurveSpeedingViolations (#)	19.9	12.1		-.26	.16	-.12	-.02	.00	-.04
NotEnoughSteerErrors (#)	14.7	13.0		.28	-.10	.11	-.07	-.23	.21
TooMuchSteerErrors (#)	28.0	18.6		.05	.05	.02	.20	.07	.08
TooFarLeftErrors (#)	0.2	0.5		.13	.03	.11	.00	.02	.06
TooFarRightErrors (#)	0.8	1.6		.26	-.14	-.02	-.05	-.11	.14
SpeedTrackingErrors (#)	1.7	1.9		.11	.00	.02	-.10	-.10	.12
AccessLaneTime (s)	8.9	1.9	30.2	.42	-.28	.19	-.01	-.12	.27
ExitLaneTime (s)	12.9	2.2	29.9	.38	-.23	.16	-.03	-.11	.31
CarFollowingTime (s)	4.3	1.4	53.4	-.32	.28	-.13	.01	.09	-.20
ShiftUpTime (s)	6.5	3.2	72.0	.30	-.18	.01	.04	-.06	.24
StartEngineTime (s)	4.6	2.4	60.7	.17	-.10	.00	.00	-.09	.28
IntersectionTime (s)	37.8	4.1	124.9	.37	-.24	.15	.02	-.10	.14
Dependent variables									
DBQ-Violations (1–6)	1.86	0.60		-.21	—	.00	.18	.35	-.09
DBQ-Errors (1–6)	1.60	0.42		.17	.00	—	.09	-.09	.13
NumberCrashes (#)	0.12	0.34		.00	.18	.09	—	.05	-.03
NumberSpeedingTickets (#)	0.39	0.76		-.20	.35	-.09	.05	—	-.04
NumberHoursRoadLessons (#)	36.4	16.7		.24	-.09	.13	-.03	-.04	—
Extraneous predictor variables									
Gender (0 = male, 1 = female)	0.55	0.50		—	-.21	.17	.00	-.20	.24
Age (years)	24.6	6.31		-.01	-.22	.18	-.09	-.01	.14
Education (1–9)	8.01	1.12		-.06	-.21	.19	-.08	-.06	-.05
Mileage (km)	8180	14,329		-.25	.45	-.22	.11	.43	-.17
DriveFrequency (1–7)	4.95	1.48		-.06	.43	-.18	.12	.33	-.08
FirstSimLessonDate	18 Feb 2008	144		-.08	-.14	.12	-.09	-.09	.00
SimPeriod (days)	34.6	29.3		.00	-.01	-.04	.09	-.03	-.16
NumberSimLessons (#)	17.5	5.7		.00	-.04	.01	-.03	-.08	-.16
NumberSimBlocks (#)	31.6	9.5		-.04	-.02	.00	-.06	-.07	-.14

Note. The reported means (*M*), standard deviations (*SD*), and numbers of tasks (#) are uncorrected. The reported correlations are based on standardized simulator predictor variables and rank-transformed self-reported variables. Correlation coefficient in italics when $.001 \leq p < .05$. Correlation coefficient in boldface when $p < .001$.

skew distribution, all self-reported variables (i.e., DBQ-Violations, DBQ-Errors, Crashes, CrashesDamage, NumberSpeedingTickets, NumberHoursRoadLessons, Age, Education, Mileage, DriveFrequency) were converted to ranks (Conover and Iman, 1981) using MATLAB's *tiedrank* function. Zero-order Pearson correlation coefficients between the predictor variables and the dependent variables were then established.

Because the simulator predictor variables were correlated with one another, exploratory factor analysis was conducted using principal axis factoring as the extraction method (Malec et al., 2007). Exploratory factor analysis was carried out on simulator variables 1–9 to extract a violations factor and an errors factor (see also De Winter et al., 2007, 2009). These two factors were rotated using oblique quartimin (i.e., oblimin with $\gamma = 0$; Bernaards and Jennrich, 2005), one of the most common oblique rotation techniques. Oblique rotation was used because it provides a more accurate and realistic representation of how constructs are related to each other than orthogonal rotation does (Fabrigar et al., 1999). Factor analysis was also conducted on the mean task completion times (simulator variables 10–15) to extract a generic speed factor (cf. De Winter et al., 2009). Standardized (i.e., z-transformed) Bartlett factor scores were calculated, and zero-order Pearson correlations were established between the factor scores and dependent variables.

Finally, linear multiple regression analysis was applied to fit a predictive model and to investigate which of the predictor variables have a relationship with DBQ-Violations. A robust regression analysis was conducted using the *robustfit* function of MATLAB. Robust regression is less affected by outliers and deviations from normality than traditional least squares estimates for regression models. The simulator factor scores and the extraneous predictor variables were entered into the model. Predictor variables and the dependent

variable (i.e., DBQ-Violations) were standardized prior to running the regression analysis such that the regression analysis provided interpretable model coefficients.

3. Results

3.1. Descriptive statistics

There were 5554 people who drove at least four 30-min lessons. The questionnaire was sent to 2921 people with an available e-mail address. The mailing resulted in 336 bounced messages, leaving 2585 e-mails sent correctly and 334 people responding to the questionnaire. Respondents took on average 11 min to complete the questionnaire ($SD = 18$ min, median = 8 min). Three percent of the respondents indicated that they had not yet done an on-road driving test, and a further 1% (i.e., 4% in total) indicated that they did not have their driving license yet. These respondents were excluded, resulting in a final set of 321 respondents. One person did not fill in the DBQ items and therefore the analyses of DBQ-Errors and DBQ-Violations involve 320 respondents.

The 321 respondents consisted of 55.5% females and 44.5% males. The mean age at the time of responding was 24.5 years for females (median = 22 years, $SD = 6.47$ years, range = 20–52 years), and 24.7 years for males (median = 22 years, $SD = 6.14$ years, range = 19–57 years). The respondents had taken their simulator lessons at 40 driving schools, and drove their first simulator lesson between 22 May 2007 and 12 March 2009, which means that they had completed the first simulator lesson between 2.3 and 4.1 years ago (mean = 3.4 years). They drove on average 17.5 30-min lessons in the simulator (min = 4, max = 31). The mean time between the first and last simulator lesson was 34.6 days (median = 25.0 days, min = 0 days, max = 195 days). The mean self-reported pass rate

Table 3

Factor loadings for exploratory factor analysis with oblimin rotation of simulator violations and errors variables.

Variable	SimViolations	SimErrors
SpeedingViolations (#)	.69	.01
HeadwayViolations (#)	.78	–.04
RedLightViolations (#)	.15	.22
CurveSpeedingViolations (#)	.39	.10
NotEnoughSteerErrors (#)	–.14	.60
TooMuchSteerErrors (#)	.27	.54
TooFarLeftErrors (#)	–.16	.14
TooFarRightErrors (#)	–.06	.60
SpeedTrackingErrors (#)	.03	.29

Note. Factor loadings > .30 are in boldface.

at the first official driving-license test was 48.8%, which is in line with the national averages in 2007, 2008, and 2009 of 47.4, 46.4, and 47.4%, respectively (CBR, 2008, 2009). The respondents were highly educated, with 40% reporting research university and 36% reporting university of applied sciences as their highest level of attended education. The self-reported pass rate for the official theory test (i.e., a computerized test to confirm a person's knowledge of driving, road signs, and traffic laws) was 85%, considerably higher than the national average of about 50% (CBR, 2009). The mean number of self-reported hours of on-road driving lessons from a professional driving instructor was 36.4. Of the respondents, 11% reported involvement in a crash as a driver in the past 12 months (NumberCrashes variable greater than 0), and 18% reported having caused damage in a traffic crash since their simulator training (variable CrashesDamage). The number of crashes (NumberCrashes) correlated .18 with DBQ-Violations, .09 with DBQ-Errors, .05 with NumberSpeedingTickets, and .23 with CrashesDamage.

3.2. Zero-order correlations

Table 2 shows the descriptive statistics of the simulator predictor variables, dependent variables, and extraneous variables. Clearly, most simulator variables correlated with gender. Males committed more violations, fewer errors, and had lower task completion times than females in the simulator. Long task completion times as well as steering errors (NotEnoughSteerErrors) in the simulator predicted DBQ-Errors, whereas speeding violations and following-distance violations in the simulator predicted DBQ-Violations and NumberSpeedingTickets. The number of self-reported crashes in the past 12 months was predicted by specific behaviors in the simulator: steering too much and running red

Table 4

Factor loadings for exploratory factor analysis of simulator speed variables.

Variable	SimSpeed
AccessLaneTime (s)	– .74
ExitLaneTime (s)	– .67
CarFollowingTime (s)	.61
ShiftUpTime (s)	– .51
StartEngineTime (s)	–.25
IntersectionTime (s)	– .59

Note. Factor loadings < –.30 or > .30 are in boldface.

lights. A high number of driving lessons on the road was associated with long task completion times and NotEnoughSteerErrors in the simulator. The CrashesDamage variable was not predicted by any simulator variable ($p > .10$ for all 15 simulator variables; data not shown).

3.3. Factor analysis

The first four eigenvalues of the correlation matrix of simulator variables 1–9 were 1.95, 1.83, 1.17, and 0.92. Based on the Scree plot, a two-factor solution was deemed appropriate. The rotated factor loadings are shown in Table 3, and were interpreted as violations (SimViolations) and errors (SimErrors). The first three eigenvalues of the correlation matrix of simulator variables 10–15 were 2.64, 1.06, and 0.73. One factor, interpreted as a speed factor (SimSpeed), was extracted. Table 4 shows the factor loadings.

3.4. Correlation matrix

Table 5 shows the correlation matrix of factor scores (SimViolations, SimErrors, and SimSpeed), dependent variables, and extraneous predictor variables. SimViolations and SimSpeed correlated positively with DBQ-Violations and NumberSpeedingTickets. Illustratively, drivers who reported more than one speeding ticket (NumberSpeedingTickets ≥ 2 , $n = 25$) had a mean SimViolations factor score of 0.94 ($SD = 1.40$), which is considerably higher than the score of those who reported having received one ($n = 63$, $M = 0.02$, $SD = 0.92$) or zero speeding tickets ($n = 233$, $M = -0.11$, $SD = 0.92$). People with higher SimViolations and SimSpeed and lower SimError scores reported having completed fewer hours of on-road lessons before their first on-road driving test.

Table 5

Correlation matrix between simulator predictor variables, dependent variables, and extraneous predictor variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. SimViolations	–															
2. SimErrors	.01	–														
3. SimSpeed	.60	– .21	–													
4. DBQ-Violations	.32	–.08	.32	–												
5. DBQ-Errors	–.10	.06	–.17	.00	–											
6. NumberCrashes	.09	.02	.00	.18	.09	–										
7. NumberSpeedingTickets	.20	–.14	.13	.35	–.09	.05	–									
8. NumberHoursRoadLessons	–.18	.22	– .32	–.09	.13	–.03	–.04	–								
9. Gender	– .36	.28	– .48	– .21	.17	.00	– .20	.24	–							
10. Age	–.14	.05	– .21	– .22	.18	–.09	–.01	.14	–.01	–						
11. Education	–.15	–.08	–.08	– .21	.19	–.08	–.06	–.05	–.06	.11	–					
12. Mileage	.23	–.10	.28	.45	– .22	.11	.43	–.17	– .25	–.04	– .23	–				
13. DriveFrequency	.19	.00	.20	.43	–.18	.12	.33	–.08	–.06	–.11	– .40	.73	–			
14. FirstSimLessonDate	–.06	.04	.01	–.14	.12	–.09	–.09	.00	–.08	– .20	.11	–.16	–.15	–		
15. SimPeriod	–.03	–.02	.08	–.01	–.04	.09	–.03	–.16	.00	–.05	–.06	.06	.09	–.07	–	
16. NumberSimLessons	–.09	.04	.05	–.04	.01	–.03	–.08	–.16	.00	.08	.07	.04	.02	–.03	.48	–
17. NumberSimBlocks	–.07	–.03	.09	–.02	.00	–.06	–.07	–.14	–.04	.04	.10	.04	.01	.03	.42	.92

Note. Correlation coefficient in italics when $.001 \leq p < .05$. Correlation coefficient in boldface when $p < .001$.

Table 6

Results of robust regression analysis for predicting self-reported violations (DBQ-Violations) (N = 320).

Predictor variable	Coefficient	Standard error	t	p
Constant	−0.008	0.050	−0.17	.865
SimViolations + SimSpeed	0.197	0.059	3.32	.001
SimErrors	−0.016	0.052	−0.30	.767
Age	−0.072	0.060	−1.20	.229
Gender	−0.172	0.053	−3.25	.001
Education	−0.032	0.054	−0.59	.557
DriveFrequency + Mileage	0.392	0.055	7.06	.000
FirstSimDate	−0.116	0.052	−2.21	.028
SimPeriod + NumberSimLessons	−0.047	0.050	−0.94	.350

Note. Total strength of prediction: $r = .57$, $p < .001$. The dependent variable (DBQ-Violations) and predictor variables were standardized (i.e., z-transformed) prior to running the regression analysis. SimViolations and SimSpeed, DriveFrequency and Mileage, and standardized SimPeriod and standardized NumberSimLessons were summed because these pairs of variables were substantially correlated ($r = .60$, $.73$, and $.48$, respectively).

3.5. Regression analysis

Because SimViolations and SimSpeed were substantially inter-correlated ($r = .60$, see Table 5) these two variables were summed and included as a single predictor variable. DriveFrequency and Mileage ($r = .73$), and SimPeriod and NumberSimLessons ($r = .48$) were summed as well. Aggregating the variables prevents multicollinearity and provides a more parsimonious prediction as compared to including the predictor variables separately. The results of the regression analysis (Table 6) revealed that DBQ-Violations were predicted by SimViolations plus SimSpeed ($p = .001$) even when controlled for age, gender, DriveFrequency plus Mileage, and education level. All other variables held constant, males and people with more on-road driving (higher mileage and driving frequency) reported more violations, in line with earlier research on the DBQ (De Winter and Dodou, 2010). The overall correlation between predictor variables and the DBQ-Violations criterion was $.57$. Fig. 1 illustrates this correlation.

4. Discussion

Novice drivers are overrepresented in crash statistics, suggesting the need for remedial measures. Driving simulation may be useful in predicting future on-road driving behavior as simulators accurately (though not perfectly) mimic the sensations of real driving, while providing a high degree of controllability and repeatability of the environment for all participants.

This study showed that violations and speed during simulation-based driver training prior to completing on-road driving lessons are predictive of post-license violations and speeding tickets self-reported several years later. Self-reported crashes as a driver in the past 12 months were predicted using zero-order correlations with a number of behaviors in the driving simulator, including driving through red traffic lights. However, the relationships were insignificant when the respondents were asked about crashes involving damage they had caused themselves.

Driving simulators are used worldwide for training, assessment, entertainment, and research (Boyle and Lee, 2010; Carsten and Jamson, 2011; De Winter et al., 2009; Goode et al., in press; SVOV Institute for Road Safety Research, 2012). Simulators can range in sophistication from low-fidelity desktop computer systems to high-fidelity devices with a fully instrumented cabin, motion base, and surround view. High-fidelity simulation is typically used when a close physical match between simulator and reality is required, for example in automotive development or human perception research (Kemeny and Panerai, 2003; Yan et al., 2008). Low and medium-fidelity systems can provide validated measures

Fig. 1. Observed DBQ-Violations score (standard score of mean of the seven DBQ-Violations items in questionnaire) versus predicted DBQ-Violations score in robust multilinear regression analysis. Participants were sorted on their predicted DBQ-Violations score in ten groups of 32. The solid black squares represent the mean scores per group. The thick gray vertical lines illustrate the 95% confidence intervals of observed DBQ-Violations. The thin black vertical lines illustrate the mean observed DBQ-Violations plus and minus one standard deviation.

of driving behavior and are especially useful tools for driver assessment and other applications for which comparisons of individual differences are of interest. The present results add to the literature by showing that a relationship exists between driving behavior in a medium-fidelity driver-training simulator and self-reported driving behaviors of novice drivers.

Besides demonstrating significant relationships between violating behavior in the simulator and self-reported violating behavior on the roads, this study also showed that the number of hours of on-road driving lessons up to the first driving test could be predicted from measures collected in a simulator. People who made more errors and drove slower in the simulator required more hours of on-road driving lessons. Note that the relation between number of driving lessons required to obtain a driving license and road safety is complex. Results of a cohort study by Maycock and Forsyth (1997) indicated that less competent drivers take more lessons with professional tuition to pass the test, and despite having passed are more likely to become involved in a crash. Hatakka et al. (2002) cite a Japanese study that found that the fewer hours of training males had (i.e., the faster they had achieved a required level of skill), the more often they were involved in subsequent crashes and violations. In other words, a large number of driving lessons may be predictive of skill-related crash involvement, while a low number of driving lessons might signal increased crash risk due to a deviant driving style (Hatakka et al., 2002; cf. Williams and O'Neill, 1974).

The current findings indicate that individual differences in violating behavior in on-road driving are detectable very early in the driver-training program, even before a driver takes lessons in a real car. Being able to identify at-risk drivers during pre-license training would be valuable in identifying violation-prone individuals and providing them with the necessary corrective training or guidance before they obtain their driving licenses. Traditionally, human driving instructors are inclined to focus on improving specific vehicle-maneuvering skills with little consideration for monitoring

long-term violating behaviors and reasons and motives for driving (Hatakka et al., 2002). Based on the present results, it would be possible to create an evidence-based profile that indicates the trainee driver's propensity for making future traffic violations. Concurrent feedback can be provided to educate the driver (Donmez et al., 2010) or alternatively, an alert can be issued to a supervisor/trainer when a disproportionately high number of violations is detected. With targeted interventions, such as group discussions and self-reflection, violations can be dealt with before the novice begins to drive unsupervised.

One obvious limitation of this study is that it may have been preferable to use objective data as a criterion, for example data from an in-vehicle data recording system. It is known that self-reported data are susceptible to various biases, including social desirability, acquiescence, and forgetfulness. On the other hand, one may argue that self-reported behaviors are in fact powerful, as questionnaires can uncover behaviors that are difficult to detect by direct observation (cf., Reason et al., 1990). It is extremely unlikely that the present findings were generated by common method effects, because the simulator recorded driving behavior objectively, the respondents did not know their composite simulator scores, and there was a large time gap between the simulator-based training and questionnaire (see Podsakoff et al., 2003 for a review on common method variance, and for discussion see Af Wählberg and Dorn, 2012; Af Wählberg et al., 2012; De Winter and Dodou, 2012a,b).

A second limitation is the relatively low response rate of 13%, which may have biased the results. Note that the true response rate may be higher since it is not known how many of the e-mails that did get through were actually opened. Although response rates in Internet-based questionnaires are known to be low, completeness of data has been found to be considerably higher compared to paper-based surveys (Kongsved et al., 2007). The sample size was still sufficiently large to detect zero-order correlations of .11 with a 95% confidence interval not overlapping with zero. Previous research shows that the simulator metrics were relatively invariant for subgroups of drivers (De Winter et al., 2009). Because the present sample consisted mainly of people who attended higher education, the results are affected by range restriction, and the true correlations between simulator variables and questionnaire results may therefore be even stronger than those observed in the present study.

The results of this study demonstrate the predictive validity of the simulator. Further research is recommended into developing training interventions that aid violation and crash prevention in the long term. Another recommendation is to investigate how risky behavior in the driving simulator is related to other factors, including sensation seeking in other types of daily tasks, emotion regulation, hormonal factors, and social development (Boyer, 2006). Cognitive and affective neuroscience could provide insight into the biological basis of risk taking, and individual differences in such.

Acknowledgements

This research was supported by the Dutch Technology Foundation (Stichting voor de Technische Wetenschappen, STW), the Applied Science Division of the Netherlands Organization for Scientific Research (Nederlandse Organisatie voor Wetenschappelijk Onderzoek, NWO) and the Technology Program of the Ministry of Economic Affairs. I wish to thank Green Dino BV, manufacturer of driving simulators, for their support.

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