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Measuring errors and violations on the road: A bifactor modeling approach to the Driver Behavior Questionnaire

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ABSTRACT

The Driver Behavior Questionnaire (DBQ) is a self-report measure of driving behavior that has been widely used over more than 20 years. Despite this wealth of evidence a number of questions remain, including understanding the correlation between its violations and errors sub-components, identifying how these components are related to crash involvement, and testing whether a DBQ based on a reduced number of items can be effective. We address these issues using a bifactor modeling approach to data drawn from the UK Cohort II longitudinal study of novice drivers. This dataset provides observations on 12,012 drivers with DBQ data collected at .5, 1, 2 and 3 years after passing their test. A bifactor model, including a general factor onto which all items loaded, and specific factors for ordinary violations, aggressive violations, slips and errors fitted the data better than correlated factors and second-order factor structures. A model based on only 12 items replicated this structure and produced factor scores that were highly correlated with the full model. The ordinary violations and general factor were significant independent predictors of crash involvement at 6 months after starting independent driving. The discussion considers the role of the general and specific factors in crash involvement.

1. Introduction

Road traffic crashes continue to present a serious public health challenge. According to the World Health Organization there were approximately 1.24 million deaths on the road in 2010 across the world, equating to almost 3400 a day, with estimates of injuries arising from road traffic crashes rising from the eleventh to the eighth leading cause of mortality from 2002 to 2010 (Peden et al., 2004; World Health Organisation, 2013). Human behavior is a key factor in crash risk. Based on Reason's extensive work on the human contribution to disaster across a wide range of situations (Reason, 1990), the Driver Behavior Questionnaire (DBQ) was designed as a self-report measure of the behaviors that may increase risk of crash involvement (Reason et al., 1990). The measure distinguishes unintentional cognitive failures from deliberate violations of the accepted principles of safe driving. Cognitive failures are often further categorized into slips and lapses, "the unwitting deviation of action from intention" (Reason et al., 1990 page 1315), such as getting into the wrong lane at a junction, and errors, which involve "the departure of planned actions from some satisfactory path towards a desired goal" (Reason et al., 1990 page 1315), such as missing a give-way sign. Violations may also be subcategorized. Ordinary violations, such as speeding and crossing red lights, may be distinguished from violations that involve aggression towards other road users, for example, sounding the horn to display aggression (Lawton et al., 1997). Since its publication the DBQ has been very influential, with more than 174 papers using the measure (de Winter and Dodou, 2010).

Despite this volume of research, a number of questions remain about the DBQ. A key issue for its utility is the extent to which the DBQ subscales relate to crash involvement. Relevant evidence has been mixed, with some early work concluding violations were good predictors of self-reported crashes whereas cognitive failures were not (Parker et al., 1995). However, a recent meta-analysis concluded that there were simple correlations between self-reported crash involvement and both cognitive failures (r = .10,

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based on 35 studies) and violations (r = .13 based on 42 studies) (de Winter and Dodou, 2010).

The estimates of the relationships between the DBQ scales and crash involvement calculated in the meta-analysis cannot adjust for the positive correlation between cognitive failures and violations that has been reported to range from .3 to .7 across studies (de Winter and Dodou, 2010). A relationship of this magnitude is unexpected given that cognitive failures and violations are hypothesized to relate to separate psychological processes. Part of the correlation may reflect exposure, in that both cognitive failures and violations may be reported more frequently by higher mileage drivers. Shared or correlated risk factors may also contribute to the association. For example, hyperactivity is associated with both risk-taking and errors in children's minor injury involvement (Rowe and Maughan, 2009). A similar situation may exist in driving: the inattentive component of hyperactivity may lead to increased rates of cognitive failures and the impulsivity component may lead to more frequent violations. It is also likely that a component of the correlation is due to shared method variance, as discussed by de Winter and Dodou (2010) and af Wahlberg and Dorn (af Wahlberg and Dorn, 2012). Scales which are completed by the same reporter may be spuriously correlated for a number of reasons, including individual differences in response style such as locating answers on particular points of a scale consistently across measures (Podsakoff et al., 2003).

Effectively modeling the relationship between cognitive failures and violations may be key to understanding the nature of their relationship to crash involvement. One approach has been to specify a second-order factor structure. For example, Lajunen et al. (2004) fitted a second-order model in which a general violations factor accounted for the association between aggressive and ordinary violation factors and a general cognitive failures factor accounted for the association of slips and errors. This model fitted the data well across large British, Dutch and Finnish samples. More recently, Martinussen et al. (2013) fitted a second-order factor structure using confirmatory factor analysis (CFA). This model was based on a somewhat different item set from Lajunen et al. (2004). The model contained only three first order factors (errors, lapses and violations) as well as a single "aberrant behavior" second-order factor onto which all three first order factors loaded.

Second order models are useful data reduction techniques, but come at a loss of differentiation between factors. Once the first order factors of violations and cognitive failures have been specified to represent a single generic factor of aberrant behavior, they are no longer used as independent constructs. Bifactor modelling offers an alternative conceptualization of general and specific factors with both being defined by direct loadings of the observed items. Specific factors may be correlated with each other, but are assumed to be independent from the general factor (Chen et al., 2006). The bifactor modelling approach has recently been applied to understand the relationships between related constructs in a number of other domains including anxiety and depression within negative affect disorders (Simms et al., 2008), impulsivity and inattention within hyperactivity (Martel et al., 2010) and irritability and behavioral problems within oppositional behaviors (Burke et al., 2014). Chen et al. (2006) describe a number of advantages of the bifactor approach. One advantage is that the bifactor model explicitly demonstrates the strength of the specific factors. In a second-order factor model, on the other hand, it may not be readily apparent whether a specific factor is important independently from the relationship of the items to the higher order factor. This feature is particularly useful when examining the external correlates of the specific factors independently from the general factor. Therefore a bifactor modelling approach is well suited to testing the existence of separate violation and cognitive failures factors in the context of a general aberrant driving behavior factor and to identifying their independent correlates, for example in terms of crash involvement.

A final issue is that the DBQ takes a relatively long time to complete, limiting the applicability of the measure in many research and applied settings. The original DBQ contains 50 items (Reason et al., 1990). There have been several attempts to reduce the number of items since then such as a 24-item version that used the eight highest loading items on the 3 factors of ordinary violations, errors and lapses from the original 50-item version (Parker et al., 1995), and a 27-item version that included 3 additional items on aggressive violations previously identified as distinguishable from ordinary violations (Lawton et al., 1997). Recently, researchers have shown interest in using further shortened versions of the measure. For example, a 4-item version of the ordinary violations sub-scale (which usually has 8-items) was employed in the Genesis1219 study (Rowe et al., 2013). Furthermore, Martinussen et al. (2013) provided evidence on the validity of a 9-item version of the DBQ using confirmatory factor analysis. In this model, factors of violations, lapses and errors were measured with three items each.

In the present study we use the UK Department for Transport's Cohort II study of novice drivers to examine the fit of a bifactor model to DBQ data. We compare this to the fit of first-order and second-order factor models. We test whether a short version of the DBQ based on the best-fitting factor model provides adequate psychometric properties. Finally, we explore the external correlates of the best fitting model, including contemporaneous self-reported crash involvement.

2. Method

2.1. Sample

Detailed description of the study design may be found elsewhere (Wells et al., 2008). Briefly, the Cohort II study randomly sampled 128,000 practical test candidates between November 2001 and August 2005. The identified sample were sent an initial questionnaire 10–16 days after taking the final component of the driving test. The initial response rate was 33% (42,851 responses). Only 20,512 respondents (49%) that had passed their test were eligible to continue in the study. The study design allowed for follow-up questionnaires at 6, 12, 24 and 36 months. However, at the time of study termination not all participants had completed 36 months driving. All participants had been driving for 1 year, but only 77% had been driving for 2 years and 52% had completed the full follow-up period. The current analyses are based on 12,012 drivers who provided data at up to four time points: 10,064 participated at 6 months (49% response rate), 7450 at 12 months (36%), 4189 at 24 months (27%) and 2765 at 36 months (26%). The participants tended to be young; 59% were under the age of 20 years and 76% under the age of 25 years. The gender composition was 63% women and 37% men. The age distribution is comparable to the population of newly licensed drivers while females were over-represented in the sample. (Wells et al., 2008).

The Cohort II study was commissioned and funded by the UK Department for Transport and conducted by the Transport Research Laboratory, Crowthorne, UK (Transport Research Laboratory Safety Security and Investigations Division, 2008). The data collection protocol complied with Market Research Society and Department for Transport social research guidelines. Consistent with these guidelines, informed consent was inferred from return of completed postal questionnaires.

2.2. Measures

Information about driving behavior was self-reported through the Driver Behavior Questionnaire (Reason et al., 1990). The version used in our analyses followed that used by Lajunen et al. (2004). This includes 27 items, 8 ordinary violations, errors and lapses, and 3 aggressive violations. Responses were on a 6-point Likert scale, ranging from 1 = 'never' to 6 = 'nearly all the time'.

Additionally we utilized measures of self-reported mileage and number of public road crashes, both assessed at 6 months after licensure. Mileage was constructed as the number of miles driven in the first 6 months of driving. The median reported mileage was 2000. The number of crashes was self-reported on a scale from 0 to 3 (3 = three or more crashes). Only crashes on a public road were included here. Eighty-seven percent of the sample reported no crashes during this period, 12.1% reported one crash, 1.1% reported two crashes and .2% reported three crashes or more.

2.3. Analytic strategy

We employed confirmatory factor analysis (CFA) to systematically test four different factor structures. The first structure comprised a single factor of aberrant driving. The second structure comprised two factors: violations (combining aggressive and ordinary violations) and cognitive failures (combining errors and slips). The third structure comprised three factors: violations (combining aggressive and ordinary violations), errors and slips. Finally, the fourth structure comprised four factors: aggressive violations, ordinary violations, errors and slips. Three models were applied to each of these structures (except for the one-factor structure): a simple first-order structure with permitted inter-factor correlations, a second-order model and a bifactor model with no residual correlations. Following suggestions given by model modification indices, an additional bifactor model with a residual correlation between aggressive and ordinary violations was applied to the structure where ordinary and aggressive violations were separated. This procedure provided a total of 11 models, repeated at each of the four study time-points.

Models were estimated using Mplus v.7.11 (Muthen and Muthen, 1998–2012Muthen and Muthen, 1998–2012). To account for data skewness and missingness, the robust maximum likelihood estimator was used. Values $\geq$.90 on the comparative fit index (CFI) and the Tucker-Lewis index (TLI) and $\leq$0.08 on the root mean square error of approximation (RMSEA) indicated adequate model fit (Hu and Bentler, 1999). Additionally, CFI and TLI values $\geq$.95 and RMSEA values $\leq$0.06 indicated excellent model fit (Bentler, 1990).

3. Results

3.1. Factorial structure of the DBQ

Across all time-points, the four factor structure was superior to the one, two and three factor structures (Table 1). Only the four factor bifactor model reached adequate fit consistently across the four time points. Further improvements in fit were observed when a residual correlation was permitted between the factors of aggressive and ordinary violations.

Table 2 provides the item loadings from the best fitting model. Most of the items showed a similar pattern of loadings across time-points. All 27-items loaded significantly onto the General factor. The three aggressive violations loaded significantly onto the specific Aggressive violations factor. The two speeding items were consistently strong loading items on the Ordinary violations factor as was the racing away from traffic lights item. Other items showed positive and significant loadings consistently over time with the exception of pulling out of a junction so far that other drivers have to let you out. This item was non-significant at 6 months and the loadings were relatively low, though significant, at other time points. Getting into the wrong lane and taking the wrong turning from roundabouts were the strongest loading items on the Slips factor. The other items also loaded significantly with the exception of hitting something unseen when reversing. This item was significant at 6 and 12 months and not at later time points and all loadings were .06 or below. Item loadings on the Errors factor were generally weaker than on the other factors. Only three items showed significant loadings at all time points (nearly hit a cyclist on the inside when turning left, missed give way sign, attempt to overtake and hadn't noticed signaling right).

3.2. DBQ short version

Next we tested whether a shortened version of the DBQ provides adequate psychometric properties within a bifactor

Table 1
Model fit for first-order, second-order and bifactor models, at the four time-points.

Model	df	6 months				12 months				24 months				36 months			
		χ^2	CFI	TLI	RMS EA	χ^2	CFI	TLI	RMS EA	χ^2	CFI	TLI	RMS EA	χ^2	CFI	TLI	RMS EA
N = 1	324	7320.25	.76	.73	.05	6850.84	.76	.74	.05	4593.92	.75	.73	.06	3462.66	.73	.71	.06
–																	
N = 2																	
Simple	323	5235.49	.83	.81	.04	4748.45	.84	.82	.04	2972.29	.84	.83	.05	2205.76	.84	.83	.05
2nd order	322	5219.29	.83	.81	.04	4733.76	.84	.82	.04	–	–	–	–	2198.93	.84	.83	.05
Bifactor	297	3087.52	.90	.88	.03	–	–	–	–	1903.96	.91	.89	.04	1453.80	.90	.88	.04
–																	
N = 3																	
Simple	321	4567.21	.85	.84	.04	4139.80	.86	.84	.04	2661.44	.86	.85	.04	1926.22	.86	.85	.04
2nd order	Fit statistics are the same as N = 3 Simple structure																
Bifactor	297	3012.39	.91	.89	.03	2898.90	.90	.89	.04	1979.40	.90	.88	.04	1411.88	.91	.89	.04
–																	
N = 4																	
Simple	318	3184.25	.90	.89	.03	3162.05	.89	.88	.04	1947.37	.90	.89	.04	1506.77	.90	.89	.04
2nd order	320	3584.88	.86	.87	.03	3601.84	.88	.87	.04	2275.51	.89	.87	.04	1766.15	.88	.87	.04
Bifactor	297	2578.15	.92	.91	.03	2397.43	.92	.91	.03	1682.09	.92	.90	.03	1284.31	.92	.90	.04
Bifactor2	296	2086.68	.94	.93	.03	1908.99	.94	.93	.03	1321.61	.94	.93	.03	1029.42	.94	.93	.03

"-" indicates model non-convergence. N = 2: a single factor of aberrant driving. N = 3: two factors (violations and cognitive failures). N = 3: three factors (violations, errors and slips). N = 4: four factors (aggressive violations, ordinary violations, errors and slips).

Table 2
Factor loadings for the four factor bifactor model with a residual correlation between the aggressive and ordinary violations factors.

Scale	DBQ items[a]	Time 1 β*	Time 2 β*	Time 3 β*	Time 4 β
General factor					
O	Drive so close to car that would not be able to stop	.56(.53, .59)	.58(.56, .60)	.58(.55, .61)	.58(.55, .62)
E	When queuing to turn left nearly hit car in front	.55(.52, .57)	.60(.57, .62)	.59(.56, .62)	.62(.58, .66)
E	Failed to notice people crossing when turned into side street	.53(.50, .55)	.56(.53, .59)	.56(.52, .59)	.62(.58, .66)
E	Failed to check rear-view mirror before maneuvering	.51(.49, .54)	.53(.50, .56)	.55(.51, .58)	.50(.45, .55)
O	Disregard speed limit on residential road	.50(.48, .53)	.49(.47, .52)	.47(.44, .51)	.46(.42, .51)
E	Missed give way signs and avoided colliding with traffic	.49(.45 .53)	.48(.43, .53)	.49(.45, .53)	.51(.46, .57)
E	Speed of oncoming vehicle when overtaking	.49(.46, .52)	.53(.50, .57)	.53(.50, .56)	.55(.51, .60)
O	Crossed junction knowing lights have turned against you	.47(.44, .50)	.51(.48, .54)	.51(.48, .55)	.50(.46, .55)
E	Brake too quickly on slippery road or steer wrong in skid	.47(.44, .50)	.51(.47, .54)	.50(.47, .53)	.52(.47, .57)
S	Get into wrong lane when approaching roundabout/junction	.46(.43, .48)	.46(.43, .48)	.48(.45, .51)	.49(.45, .54)
O	Pull out of junction so far that driver has to let you out	.45(.43, .48)	.49(.47, .54)	.48(.45, .51)	.48(.43, .53)
S	Realized have no recollection of road been travelling	.42(.40, .45)	.43(.40, .45)	.44(.40, .47)	.45(.40, .50)
O	Have disregarded speed limit on motorway	.39(.37, .42)	.38(.35, .41)	.38(.35, .42)	.33(.28, .38)
S	Misread signs and taken wrong turning off roundabout	.39(.37, .42)	.39(.36, .41)	.42(.39, .46)	.48(.43, .52)
S	Noticed on different road to destination want to go	.38(.35, .41)	.39(.36, .42)	.40(.36, .43)	.42(.38, .47)
O	Raced away from traffic lights to beat other driver	.37(.34, .40)	.38(.35, .41)	.38(.34, .41)	.41(.36, .46)
E	When turning left have nearly hit cyclist on inside	.34(.30, .38)	.43(.36, .49)	.38(.34, .43)	.41(.36, .46)
O	Stay in motorway lane know will be closed	.34(.30, .37)	.39(.35, .43)	.37(.33, .41)	.32(.27, .37)
A	Become angered by driver and indicate hostility	.34(.31, .37)	.38(.35, .41)	.32(.28, .36)	.32(.26, .37)
E	Drive away from traffic lights at too high a gear	.33(.30, .36)	.37(.34, .40)	.39(.36, .43)	.37(.32, .41)
S	Hit something when reversing that hadn't seen	.32(.28, .35)	.39(.33, .44)	.35(.31, .40)	.37(.30, .43)
S	Switch on one thing when meant to switch on other	.31(.29, .34)	.35(.32, .38)	.39(.35, .42)	.36(.31, .40)
E	Attempt to overtake and hadn't noticed signaling right	.31(.27, .35)	.35(.29, .41)	.38(.34, .42)	.41(.35, .47)
S	Forget where left car in car park	.29(.26, .32)	.30(.27, .33)	.29(.25, .32)	.32(.27, .37)
A	Become angered by driver and given chase	.27(.23, .31)	.35(.29, .40)	.26(.21, .30)	.26(.20, .32)
O	Overtake a slow driver on inside	.26(.23, .29)	.31(.27, .35)	.29(.24, .33)	.27(.22, .32)
A	Sound horn to indicate annoyance	.26(.23, .28)	.29(.25, .32)	.29(.25, .33)	.29(.24, .34)
–					
Aggressive violations					
	Become angered by driver and indicate hostility	.72(.68, .74)	.71(.68, .74)	.75(.71, .79)	.69(.64, .74)
	Sound horn to indicate annoyance	.59(.55, .62)	.59(.56, .63)	.62(.58, .66)	.63(.58, .68)
	Become angered by driver and given chase	.45(.41, .49)	.43(.39, .47)	.44(.38, .49)	.48(.42, .54)
–					
Ordinary violations					
	Have disregarded speed limit on motorway	.56(.52, .60)	.61(.57, .65)	.59(.54, .63)	.62(.57, .68)
	Raced away from traffic lights to beat other driver	.54(.50, .58)	.55(.50, .59)	.56(.51, .60)	.55(.50, .60)
	Disregard speed limit on residential road	.48(.45, .52)	.51(.47, .54)	.53(.49, .58)	.52(.47, .58)
	Overtake a slow driver on inside	.27(.23, .31)	.32(.28, .37)	.41(.36, .46)	.43(.38, .49)
	Stay in motorway lane know will be closed	.24(.19, .29)	.31(.27, .36)	.35(.30, .41)	.41(.35, .47)
	Crossed junction knowing lights have turned against you	.23(.19, .26)	.25(.22, .29)	.29(.24, .34)	.28(.23, .34)
	Drive so close to car that wouldn't be able to stop	.21(.18, .24)	.25(.21, .28)	.27(.22, .31)	.26(.21, .31)
	Pull out of junction so far that driver has to let you out	.04 [.095] (−.01, .08)	.05 [.021] (.01, .10)	.12(.07, .17)	.13(.07, .20)
–					
Slips					
	Misread signs and taken wrong turning off roundabout	.49(46, .53)	.53(.50, .57)	.38(.30, .46)	.45(.38, .53)
	Get into wrong lane when approaching roundabout/junction	.42(.39, .45)	.46(.42, .49)	.38(.30, .45)	.42(.34, .50)
	Noticed on different road to destination want to go	.33(.29, .36)	.32(.28, .36)	.38(.30, .45)	.37(.28, .45)
	Forget where left car in car park	.28(.25, .32)	.31(.26, .35)	.35(.27, .43)	.32(.23, .41)
	Switch on one thing when meant to switch on other	.25(.22, .28)	.26(.22, .30)	.24(.18, .29)	.25(.18, .31)
	Realized have no recollection of road been travelling	.19(.15, .22)	.15(.11, .19)	.23(.16, .31)	.18(.10, .27)
	Drive away from traffic lights at too high a gear	.14(.10, 17)	.15(.12, .19)	.19(.14, .24)	.12(.06, .19)
	Hit something when reversing that hadn't seen	.06 [.001] (.03, .10)	.05 [.021] (.01, .10)	.05 [.088] (−.01, .11)	.06 [.098] (−.01, .13)
–					
Errors					
	Attempt to overtake and hadn't noticed signaling right	.25(.16, .35)	.29(.21, .37)	.28(.16, .39)	.17 [.002] (.07, .28)
	When turning left have nearly hit cyclist on inside	.22(.11, .33)	.26(.15, .37)	.40(.26, .54)	.35(.21, .49)
	Missed give way signs and avoided colliding with traffic	.21(.11, 31)	.21(.12, .31)	.23(.14, .31)	.43(.29, .57)
	Failed to notice people crossing when turned into side street	.15(.07, .22)	.06 [(.077] (−.01, .12)	.18(.11, .26)	.10 [.049] (.00, .19)
	Speed of oncoming vehicle when overtaking	.13(.06, .20)	.10 [.001] (.04, .15)	.08 [.042] (.00, .16)	.10 [.113] (−.02, .21)
	When queuing to turn left nearly hit car in front	.07 (.074) (−.01, .22)	.05 [.135] (−.02, .11)	.04 [.246] (−.03, .12)	.03 [.536] (−.06, 12)
	Brake too quickly on slippery road or steer wrong in skid	.03 [.688] (−.10, .16)	.04 [.356] (−.04, .11)	.09 [.031] (.01, .17)	.21 [.00]1 (.08, .34)
	Failed to check rear-view mirror before maneuvering	.−20 [.035] (−.38, 01)	−.22(−.31, −.13)	−.08 [.066] (−.17, .01)	.08 [.127] (−.02, .17)

[a] Items are ordered according to factor loading at Time 1. Values in round parentheses represent 95% confidence intervals.
* p-value < .001 unless exact p given in square parentheses. A=Aggressive violations O=Ordinary violations E=Errors S=Slips.

framework. The three items with the highest loadings on each specific factor were chosen. The model fit was excellent at each time point, with CFI ≥ .98, TLI ≥ .96 and RMSEA ≤ .03. All items loaded significantly onto their respective specific factors and onto the General factor (Table 3). The factor loadings of each item were strikingly similar at each time-point. Item loadings were moderate to strong in relation to the Ordinary violations and Aggressive violations factors, moderate in relation to the Slips factor and the General factor and fairly low in relation to the Errors factor.

Table 3
Model fit and factor loadings for the four factor bifactor model applied to the short version DBQ.

Scale		Time 1	Time 2	Time 3	Time 4
	χ^2	192.13	251.41	154.88	107.68
	CFI	.99	.98	.98	.99
	TLI	.98	.96	.97	.98
	RMSEA	.02	.03	.03	.03
–					
General factor		β	β	β	β
E	Missed give way signs and avoided colliding with traffic	.46(.42, .51)	.46(.40, .52)	.45(.40, .50)	.49(.41, .56)
S	Get into wrong lane when approaching roundabout/junction	.46(.41, .50)	.44(.40,.48)	.48(.42, .53)	.48(.40, .56)
O	Disregard speed limit on residential road	.45(.42, .48)	.45(.41, .48)	.44(.39, .49)	.43(.37, .48)
S	Misread signs and taken wrong turning off roundabout	.42(.38, .46)	.42(.38, .46)	.47(.42, .53)	.51(.44, .57)
S	Noticed on different road to destination want to go	.41(.37, .46)	.41(.37, .45)	.44(.38, .50)	.47(.40, .53)
O	Have disregarded speed limit on motorway	.36(.33, .40)	.35(.32, .39)	.36(.31, .40)	.29(.23, .34)
O	Raced away from traffic lights to beat other driver	.34(.30, .38)	.34(.30, .38)	.34(.29, .39)	.37(.31, .43)
A	Become angered by driver and indicate hostility	.32(.28, .36)	.38(.34, .42)	.31(.26, .36)	.27(.21, .34)
E	When turning left have nearly hit cyclist on inside	.32(.27, .37)	.40(.32, .48)	.36(.31, .41)	.41(.35, .47)
E	Attempt to overtake and hadn't noticed signaling right	.27(.22, .32)	.32(.26, .39)	.34(.29, .40)	.38(.30,.47)
A	Become angered by driver and given chase	.26(.20,.32)	.35(.27, .42)	.22(.16, .29)	.24(.14, .33)
A	Sound horn to indicate annoyance	.24(.20, .28)	.27(.23, .31)	.29(.24, .34)	.29(.22, .36)
–					
Aggressive violations					
	Become angered by driver and indicate hostility	.72(.68,.75)	.70(.67, .74)	.74(.70, .79)	.72(.67, .77)
	Sound horn to indicate annoyance	.60(.56, .63)	.60(.56, .64)	.63(.58, .67)	.62(.57, .67)
	Become angered by driver and given chase	.46(.42,.50)	.44(.39, .49)	.45(.40, .51)	.49(.42, .56)
–					
Ordinary violations[a]					
	Raced away from traffic lights to beat other driver	.70(.65, .74)	.70(.67, .74)	.70(.65, .76)	.69(.63, .75)
	Have disregarded speed limit on motorway	.44(.40, .48)	.48(.43, .52)	.47(.42, .52)	.51(.45, .56)
	Disregard speed limit on residential road	.40(.36, .44)	.41(.36, .45)	.43(.37, .49)	.42(.35, .48)
–					
Slips					
	Misread signs and taken wrong turning off roundabout	.49(.43, .55)	.55(.49, .62)	.39(.27, .50)	.50(.39, .61)
	Get into wrong lane when approaching roundabout/junction	.47(.40, .53)	.49(.42, .56)	.49(.37, .61)	.45(.32, .58)
	Noticed on different road to destination want to go	.25(.20, .30)	.25(.19, .30)	.21(.12, .29)	.24(.15, .34)
–					
Errors					
	Attempt to overtake and hadn't noticed signaling right	.34(.21, .47)	.30(.20, .40)	.31(.20, .41)	.22(.11, .32)
	When turning left have nearly hit cyclist on inside	.24(.13, .34)	.33(.20,.46)	.40(.27, .53)	.37(.20, .54)
	Missed give way signs and avoided colliding with traffic	.23(.13, .32)	.25(.15, .35)	.29(.19, .40)	.43(.26, .61)

All p values <.001.
[a] Items are ordered according to factor loading at 6 months. Values in parentheses represent 95% confidence intervals. A=Aggressive violations O=Ordinary violations E=Errors S=Slips.

Bivariate correlations between factor scores obtained from the 27-item version and from the 12-item version revealed that, at each time-point, the short version accurately reproduced the full version with regard to the General factor (r = .82–.84; p < .001), the Ordinary violations factor (r = .83–.86; p < .001) and the Aggressive violations factor (r = .93–.95; p < .001). High agreement in scores were also obtained for the Slips factors (r = .76–.90; p < .001) and moderate agreement was obtained for the Errors factor (r = .65–.83; p < .001).

Table 4 shows the correlations between factor scores generated from the bifactor model of the shortened DBQ. All factor scores were significantly associated, with the majority showing small to moderate correlations. As expected from the model specification, the correlation between Aggressive and Ordinary violations was more substantial. There were also more substantial correlations between the specific errors and slips factors and between the slips and the general factor.

3.3. Covariates and outcomes of the short version DBQ

To examine the relationship between driver behavior, as conceptualized in the bifactor model of the short version DBQ, and known covariates and outcomes, we saved factors scores from the model using the six-month time point. All variables were standardized. Nonparametric bivariate correlations indicated that, at 6 months after licensure, younger participants had higher levels of general aberrant behavior (r = −.20, p < .001), ordinary violations (r = −.31, p < .001) and aggressive violations (r = −.21, p < .001), but slightly lower levels of errors (r = .14, p < .001) and slips (r = .02, p = .04) than older participants. Nonparametric independent-

Table 4
Non-parametric bivariate correlations between factor scores of driver behaviour dimensions from the short version DBQ at 6 months.

	General behavior	Aggressive violations	Ordinary violations	Errors	Slips
General behavior	–				
Aggressive violations	.10**	–			
Ordinary violations	.19**	.68**	–		
Errors	−.23**	−.13**	−.23**	–	
Slips	.55**	−.26**	−.28**	−.42**	–

Table 5
Ordinal Logistic Regression models predicting public road crash involvement at 6 months from the Driver Behavior Questionnaire factor scores.

	Odds ratio (95% confidence interval)[a]	
	Single DBQ factor models	Joint DBQ predictor model
General behavior	1.23*** (1.17, 1.31)	1.21*** (1.09–1.11)
Ordinary violations	1.28*** (1.21, 1.35)	1.15** (1.06, 1.26)
Aggressive violations	1.21*** (1.5, 1.27)	1.04 (.96, 1.12)
Errors	.95 (.89, 1.01)	.91* (.83, .99)
Slips	1.08* (1.02, 1.15)	1.01 (.92, 1.10)

[a] All models control for age, gender and mileage.
* $p < .05$
** $p < .01$
*** $p < .001$

samples *t*-tests indicated that men exhibited higher levels of general aberrant behavior ($Z = 7.25$, $p < .001$), ordinary violations ($Z = 21.50$, $p < .001$) and aggressive violations ($Z = 15.74$, $p < .001$), but lower levels of errors ($Z = 3.68$, $p < .001$) and slips ($Z = 6.53$, $p < .05$) than women. Mileage was positively related to ordinary violations ($r = .24$, $p < .001$), aggressive violations ($r = .22$, $p < .001$) and general aberrant driving ($r = .12$, $p < .001$), but was negatively related to errors ($r = -.10$, $p < .001$) and unrelated to slips ($r < .01$, $p = .65$).

To investigate associations between driver behavior and self-reported crash involvement we used ordinal logistic regression, as appropriate to the ordered categorical nature of the public road crashes outcome variable (scored from zero to three). Preliminary tests indicated that the proportional odds assumption was not violated, as the parallel lines test revealed a non-significant chi-square: $\chi^2(16) = 17.95$, $p = .33$. Table 5 shows the results from models including each DBQ factor score separately and from a model containing all five DBQ factor scores as joint predictors. We found there were no multicollinearity problems in the joint model despite the correlations between predictors discussed above. Coefficients are presented in the form of odds-ratio where 1 standard deviation represents a unit change in continuous predictor variables.

Age gender and mileage were entered as covariates in all models. In the joint predictor model, risk for public road crashes decreased with age (OR = .83, $p < .001$; 95% CI = .77–.90) and increased for drivers with higher reported mileage (OR = 1.06, $p = .004$; 95% CI = 1.02–1.11), but was not significantly heightened for men as opposed to women[1] (OR = 1.09, $p = .17$; 95% CI = .96–1.25). As shown in Table 5, with regard to driver behavior, the risk for public road crashes was increased in the presence of heightened levels of general aberrant behavior and ordinary violations both in the single and joint predictor models. Aggressive violations and slips were significantly related to crash involvement in the models where they were the only DBQ predictors. However, they were not significant predictors when the other DBQ factor scores were included in the joint model. Conversely, errors did not significantly predict crash involvement in a single DBQ predictor model and higher levels of errors of were significantly negatively related to crash risk in the joint predictor model, where the correlations between the DBQ factors were taken into account.

4. Discussion

The DBQ has been used in many studies of driving behavior, with various factor structures being proposed. In this study we fitted a bifactor model to DBQ data across the four contact points of the large scale Cohort II novice drivers study. At all time points a bifactor model, containing a general factor and specific factors for ordinary violations, aggressive violations, errors and slips provided a better fit to the data than first order and second-order factor models. A bifactor model based on the highest loading items on the specific factors provided an excellent fit to the data with very similar item loadings across time points. Factor scores from this model of our short version of the DBQ correlated highly with factor scores from the full factor model.

In order to understand the nature of the factors extracted in the bifactor model derived from the short version DBQ, we examined their correlates from the first 6 months of driving. Interpretation of these relationships provide a novel perspective on the aspects of the DBQ that are associated with risk for crash involvement in novice drivers. We found that ordinary and aggressive violations were more common in younger people and in males. These demographic factors are well-documented correlates of crash involvement (Evans, 2004). In addition, ordinary violations were a significant independent correlate of crash involvement. These results confirm the importance of ordinary violations as a correlate of crash involvement as indicated in a wide range of other studies, summarized in de Winter and Dodou's (2010) meta-analysis. Our current results show that this remains the case once ordinary violations are modeled as a specific factor, independent from aggressive violations, slips and errors factors and from a general factor of aberrant driving.

Aggressive violations were significant correlates of crash involvement but were reduced to non-significance once their relationship with other DBQ factor scores was accounted for; as expected the correlation was strongest with ordinary violations. One possibility is that aggressive and ordinary violations are part of a single violations construct and should not be scored separately. However, our confirmatory factor analyses supported modeling aggressive and ordinary violations as separate though correlated factors. Another interpretation of these results is that aggressive violations are only related to crash involvement due to their correlation with ordinary violations. For example, it may be that the aggressive state underlying aggressive violations also leads to ordinary violations and it is the ordinary violations that confer risk for crashing. Exploring this possibility will be important, because aggressive states of mind are still hypothesized to be causal to crash involvement in this model, with the effect mediated by ordinary violations. If this is correct then aggressive violations remain a legitimate target for interventions to reduce crash involvement, even though they do not predict crash involvement independently from ordinary violations.

In contrast, the specific errors and slips factors showed a different pattern of correlations to the specific violation factors; both factors were more commonly reported by females than males, and both were significantly more common in older novice drivers, although the correlation coefficient for slips was of a small magnitude. Slips showed a weak positive relationship to crash involvement when modeled separately from the other DBQ scales but was unrelated when the correlations with other DBQ factors were accounted for. The specific errors factor was negatively, though non-significantly, related to crash involvement when modeled separately from the other DBQ factors. This relationship became significant once the correlation with other DBQ factor scores was taken into account; drivers that scored highly on the errors factor were less likely to report crash involvement.

At first sight, the results regarding the slips and errors specific factors might appear inconsistent with the findings of de Winter and Dodou (2010) meta-analysis where a general composite of cognitive failures comprising both errors and slips were associated with increased crash involvement. The reason for this different

[1] Gender is non-significant here due to its correlation with the DBQ scores. In a model predicting public road crashes from gender only, males have greater crash involvement (OR = 1.27 $p < .001$, 95% CI: 1.13–1.43).

pattern of results does not lie in any quirks of the Cohort II data set. de Winter and Dodou (2010) included analyses of the links between cognitive failures and crash involvement in Cohort II as well as their meta-analysis of results published elsewhere. These analyses found that a composite cognitive failures scale, albeit containing somewhat different items from the slips and errors factors used here, were positively related to crash involvement in cross-sectional and longitudinal analyses. It is likely that our results do not show the same relationships of slips and errors with crash involvement because our bifactor approach models them independently from violations and a general aberrant driving factor. Once the components of variance shared with these constructs has been removed, the variance unique to slips and errors was not associated with increased risk of crash involvement. The variables available in Cohort II are not well placed to investigate the mechanisms through which the specific errors factor was negatively related to crash involvement. One possibility is that more cautious people are likely to report more errors, either because they commit more errors or are more likely to remember them, but that their caution in other aspects of their behavior reduces their risk of crash involvement.

As is often found in the application of bifactor modelling (Burke et al., 2014; Martel et al., 2010), our general factor showed significant loadings from all items in the analysis. Therefore, all items loading on the specific factors, which were modeled as independent factors, also loaded onto the general factor. There was some variation in the strength of loadings onto the general factor. The confidence intervals on many of these estimates do not overlap, as shown in Table 2, illustrating that the variation in the loadings are not simply due to sampling error. Error items showed particularly strong loadings in the analyses based on the full DBQ. In the short version DBQ analyses, however, errors were less prominent among the highest loading items. Factor scores generated for the general factor from this model showed the largest correlation with the specific errors factor. Similar to the specific ordinary and aggressive violation factors, higher scores on the general factor were associated with younger ages, higher mileage, and were more common in males. The general factor was also an independent correlate of crash involvement, with an odds-ratio similar to that of ordinary violations. These findings indicate that the general factor is not simply measuring shared method variance but identifies a component of driving that is independently related to crash involvement.

As noted in the application of bifactor models in other domains, such as attention deficit hyperactivity (Martel et al., 2010), risk factors for general and specific factors may differ. With regard to the DBQ, risk factors for the general factor and specific ordinary violations factor are of most interest as these are independently related to crash involvement. The few risk factors studied here (age, sex, mileage) showed similar associations with these factors. Other potential risk factors include driver training experiences, socio-economic status, sensation-seeking and antisocial tendencies. Further work is needed to examine whether these factors are similarly related to the general factor and to the specific violations factor. It is also possible that the general factor and specific violations factor may be differentially affected by varied intervention approaches. For example, the general factor, with its inclusion of driving skill relevant items, may be amenable to change through interventions that improve driving skills. The specific violations factor, in contrast, may only be improved by attitude- or enforcement-based interventions (although see McKenna et al., 2006).

In our analyses the specific cognitive failure scales did not show characteristics to warrant inclusion in measurement of driving behaviors that increase crash risk. However, measurement of the relevant items is justified in order to measure the general factor that is made up from a combination of all the violation and cognitive failure items. It remains possible that cognitive failures do perform an important independent role in the crash involvement of young drivers but that this is not captured by the current cognitive failure items. More recent evidence on candidate driving errors that do increase crash risk may provide an impetus to develop new self-report items. For example, mobile phone use, which may itself be better conceptualized as a violation, has been shown to increase risk of crash (McEvoy et al., 2007). Cognitive failures resulting from the distraction of mobile phone use are likely to be the mechanism of this effect. Therefore, the types of errors that drivers make when using a mobile phone may provide the opportunity to identify cognitive failures that do increase risk of crashing and can be measured in self-report questionnaires. For example, one study identified greater speed fluctuations as a characteristic of drivers using a mobile phone in a driving simulator (Stavrinos et al., 2013). Therefore, an item measuring speed fluctuation might be effective in marking drivers at risk of crash through cognitive failure. Alternatively, it is possible that self-report does not allow access to many of the key processes involved in driving performance. For example, it is unlikely that self-report could provide an accurate assessment of hazard perception ability, where relatively large differences in skill might only result in response time improving by a few hundred milliseconds or less (Wetton et al., 2011). In addition, it might be inherently more difficult for drivers to identify and recall an inappropriate plan for a given situation, compared to identifying and remembering when a plan was not successfully executed (Reason et al., 1990). The difficulty with detecting errors may indicate that they are better measured by objective means such as driving simulations.

In addition to the novel bifactor approach to understanding the structure of driving behaviors that confer crash risk, we also present our short version of the DBQ as a potential new method of measuring and scoring the DBQ. A briefer form of the DBQ is desirable for many settings, for example the evaluation of road safety interventions. As noted in the introduction, other approaches to shortening the DBQ have been explored. The advantage of the approach taken here is that it allows scoring of both general and specific factors that have been identified in the modeling presented in this paper, while using only 12 items.

The results presented here must be interpreted in the context of a number of limitations. First, although the Cohort II study provides a unique large scale longitudinal study of novice drivers, it inevitably suffered from non-participation and attrition which may have colored the results. The results reported here replicate a number of well-documented findings in the literature, including identifying the expected correlates of the DBQ. This increases confidence that the novel findings identified here will also be replicable. Second, the sample only contains novice drivers, so we were unable to investigate whether the results reported here generalize to more experienced drivers. However, the novice driver period is one on the most important stages in which to understand driving behavior given their elevated rates of crash involvement. Third, crash involvement was measured using self-report only. It has been argued that self-report of crashes may be fallible and may be artificially linked to self-reports of driving behavior through shared-method variance (af Wahlberg and Dorn, 2011). While this position remains controversial and there may be some advantages of self-report data over officially recorded data (de Winter and Dodou, 2011), it would be a useful goal for further research to replicate these results using designs with different methods for recording crashes such as official records.

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