



# Novice drivers' individual trajectories of driver behavior over the first three years of driving



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## ABSTRACT

Identifying the changes in driving behavior that underlie the decrease in crash risk over the first few months of driving is key to efforts to reduce injury and fatality risk in novice drivers. This study represented a secondary data analysis of 1148 drivers who participated in the UK Cohort II study. The Driver Behavior Questionnaire was completed at 6 months and 1, 2 and 3 years after licensure. Linear latent growth models indicated significant increases across development in all four dimensions of aberrant driving behavior under scrutiny: aggressive violations, ordinary violations, errors and slips. Unconditional and conditional latent growth class analyses showed that the observed heterogeneity in individual trajectories was explained by the presence of multiple homogeneous groups of drivers, each exhibiting specific trajectories of aberrant driver behavior. Initial levels of aberrant driver behavior were important in identifying sub-groups of drivers. All classes showed positive slopes; there was no evidence of a group of drivers whose aberrant behavior decreased over time that might explain the decrease in crash involvement observed over this period. Male gender and younger age predicted membership of trajectories with higher levels of aberrant behavior. These findings highlight the importance of early intervention for improving road safety. We discuss the implications of our findings for understanding the behavioral underpinnings of the decrease in crash involvement observed in the early months of driving.

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## 1. Introduction

Road traffic crashes are one of the top ten causes of mortality, resulting in almost 3400 deaths per day worldwide (Peden et al., 2004; World Health Organization, 2013). A range of evidence indicates that younger/novice drivers are at greater risk of crash than older/experienced drivers (Evans, 2004). Age and driving experience are confounded risk factors as the majority of drivers begin driving at the same age and gain experience across development. However, a body of research on crash risk for novice drivers who begin driving at different ages indicates that age and experience have independent effects, with some evidence that the effect of experience is greater than the effect of age (e.g., McCartt et al., 2009). Experience is particularly important in the

first few months of independent driving, with crash risk declining steeply over this period for drivers who acquire a license at any age.

Identifying the changes in driving behavior that underlie the decrease in crash risk over the first few months of driving is key to efforts to reduce young driver injury and fatality risk. This information could be used as a focus for pre-driving education programs. These programs might then be able to equip novices with the appropriate driving behaviors that would be learnt during the first few months of motoring without exposing them to the period of high risk independent driving that currently is required. In theory it would also be able to hone Graduated Driving Licensing rules to focus on the key risky driving behaviors that are most important to novice driver safety.

These efforts may be usefully informed by classification schemes of driving behaviors that increase crash risk. Many such schemes highlight a distinction between driving skill and style (e.g., Elander et al., 1993). Driving skill involves the behaviors involved in controlling the car, including the perceptual-motor skills of steering and gear-control as well as higher order cognitive

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skills such as hazard perception. Driving style reflects the way drivers choose to drive, such as speed choice, following distance and gap acceptance. It has been argued that both driving errors and driving style are correlates of crash involvement (de Winter and Dodou, 2010). Therefore, improvements in the safety of either or both of these factors across the first few months of driving could underlie the decrease in crash risk observed during this period.

While there is evidence that violations become less common with maturation from adolescence to adulthood (Jessor et al., 1997), few studies have focused specifically on the effects of driving experience on behavior during the early stages of driving. In the United Kingdom Department for Transport Cohort II study, from which the data used in the present analyses are drawn, violation frequency increased over the first three years of driving, although no formal statistical analyses were conducted (Wells et al., 2008). A pattern of increase was observed for ordinary violations, such as speeding and close following, and aggressive violations, such as using the horn and giving chase to other drivers, with a similar direction of effect for both males and females, and younger and older novice drivers. Similarly, an increase in traffic offences was observed over the first 3 years of driving in a study of more than 13,000 new drivers in Michigan, USA (Waller et al., 2001). Cross-sectional studies provide corroborating evidence that style becomes riskier over the early stage of driving careers. Cross-sectional analyses of the G1219 study that includes almost 1000 young drivers provides corroborating evidence; driving experience (from 0 to 3 years after licensure) was positively correlated to risky attitudes towards driving violations, largely focusing on speed (zero-order correlation  $r = .13$ , Rowe et al., 2013). Wells et al. (2008) also assessed self-report errors while driving, such as missing give-way signs, and slips, which include getting into the wrong lane at a junction. Error rates appeared to be very similar across different stages of experience and any change that was present was in the direction that they became more frequent as experience was gained.

The studies discussed above identify behaviors that become more risky with development. Therefore, they offer few clues to the improvements in road safety behaviors that might underlie the reductions in crash involvement observed during the early months of driving. This is somewhat surprising, as the behavioral measures used are well-documented correlates of crash involvement. The Attitudes to Driving Violations Scale, used in the G1219 study, is related to crash involvement (West and Hall, 1992). Cohort II used the Driver Behavior Questionnaire (Reason et al., 1990) to measure violations and errors. A recent meta-analysis concluded that there were simple correlations between self-reported crash involvement and both cognitive failures ( $r = .10$ , based on 35 studies) and violations ( $r = .13$  based on 42 studies) (de Winter and Dodou, 2010). This meta-analysis found that violations were more strongly correlated with crash involvement in young drivers than in other age groups.

Therefore, it appears that trends in crash involvement and these behavioral correlates of crash involvement are discrepant across the early months and years of driving; crash involvement becomes less frequent at the same time as violations and errors remain stable or increase. One possible explanation for this discrepancy is that the studies described above used developmental models that averaged across all drivers. It is likely that there is heterogeneity in the developmental course of driving behaviors and that this may not be well characterised by an overall mean. Instead there may be identifiable classes of drivers who follow very different developmental trajectories. For example, the overall drop in crash involvement over the first few months of driving may be the result of a minority of drivers who have very high levels of violations in the first months of their careers but quickly adopt much safer driving styles. Conversely, violations in the remainder

of the population may become more common over time accounting for the overall rise in violation frequency across development when these different developmental trajectories are averaged together.

Latent growth curve modeling is a technique that is ideally suited to exploring these issues; information about individuals' initial levels and trajectories of behavior over time can be obtained, therefore providing insight into both intra-individual change and inter-individual differences in this change. This technique also permits the examination of developmental heterogeneity. When used within latent class growth models, the technique can reveal identifiable categories of drivers who follow very specific trajectories of behavioral development. Models of this sort have been usefully applied to study developmental trajectories in other domains, for example, children's cognitive, emotional and social development (e.g., Goldberg and Carlson, 2014), well-being in clinical and non-clinical samples (e.g., Hughes et al., 2013) or propensities for criminal careers in adolescents and adults (for a review, see Erosheva et al., 2014). For example, with regards to the development of antisocial behavior, a number of studies provide evidence that there are four distinct trajectory classes. A large group of children who rarely engage in antisocial behavior through childhood and adolescence, a smaller group whose antisocial behavior onsets during adolescence, and two small groups who begin antisocial behavior early in development. One of these early onset groups maintains relatively high levels of antisocial behavior throughout adolescence while the other group desists from antisocial behavior before reaching puberty (Odgers et al., 2008).

While this modeling approach has been highly informative in other areas of public health, there has been limited application to driving behavior. Vassallo et al. (2013) used data from the Australian Temperament Project (ATP) to profile different subgroups of drivers whose risky driving behavior either increased, decreased or remained stable across two time points (19–20 years old to 27–28 years old) but the subgroups were constructed without formal analyses. To our knowledge, only one study has so far applied latent trajectory modeling to this field: The Naturalistic Teenage Driving Study (Simons-Morton et al., 2013). In this study, kinematic risky driving in instrumented vehicles, represented by high gravitational force events such as sudden acceleration and braking, was measured for 42 teenage novice drivers over the first 18 months of driving. Two main classes of risky driving emerged, representing higher and lower levels of risk, with risk in both groups remaining stable over development (Simons-Morton et al., 2013). This study has a number of strengths, including the naturalistic measurement of risky driving that is independent of any sources of reporter bias, but is limited by the small sample of only 42 drivers. The present study aims to extend this knowledge by relying on a sample of over 1000 drivers and by shifting the focus away from kinematic measures to self-reported aberrant driver behavior, where driving skill and style are distinguished.

While using self-report may have a number of weaknesses, a key advantage is that self-report allows insight into the human psychological processes that underlie the observed behaviors. Therefore self-report data can complement the information available from instrumented vehicles. For example, a recorded sudden acceleration might take place because the driver has raced away from (the) lights in order to beat another driver (i.e., an aggressive violation), or because the driver has misjudged the force needed to apply to the acceleration pedal in order to move away smoothly (i.e., a slip). Understanding individual trajectories of aberrant driving behavior through the lens of human intentions and abilities can further develop education programs designed to lead to behavior change. In this study we employed latent trajectory analytic techniques to answer three main questions:

1. What is the average trajectory of driver behavior over time, for different components of driver behavior?
2. Is it helpful to identify groups of drivers who follow specific developmental trajectories?
3. Which demographic characteristics known to be correlated to crash involvement differentiate identified latent trajectory classes?

## 2. Method

### 2.1. Sample

The present study used data from the Cohort II study, a six-year longitudinal study of UK novice drivers. The original sample included over 42,851 learner drivers recruited from November 2001 to August 2005. Those who passed their driving tests, a total of 12,012 participants, were followed up with questionnaires at 6, 12, 24 and 36 months after licensure. However, because the study terminated before all participants had completed their first three years of driving, some participants only received the questionnaire at the first 3 time-points and some only at the first 2 time-points. On the other hand, some participants were regained at later time-points. Therefore the sample size varied across time-points, with 10,064 (84% of the total number of 12,012 participants who provided data) drivers at 6 months, 7450 at 12 months (62%), 4189 at 24 months (35%) and 2765 at 36 months (23%). It should be noted that the low levels of participants at the final two contacts is not only a result of attrition, also due to the study finishing before all participants could to complete the last 2 waves.

### 2.2. Measures

Information about driving behavior was self-reported through the Driver Behavior Questionnaire (Reason et al., 1990). The version used here includes 27 items (Lajunen et al., 2004) about the frequency with which a range of driving behaviors have been exhibited since the previous survey. The DBQ distinguishes between intentional violations of accepted safe driving practice, sub-categorised into ordinary violations (8 items) and aggressive violations (3 items), and unintentional cognitive failures, sub-categorised into errors and lapses (both 8 items each). Responses were on a 6-point Likert scale, ranging from 1 = 'never' to 6 = 'nearly all the time'. Additional measures included participant age and gender, as well as a measure of mileage (i.e., number of miles driven since previous survey).

### 2.3. Missing data

To capitalise on the availability of data, driver behavior was conceptualized as factor scores saved from a longitudinal confirmatory factor analysis applied to the entire sample of 12,012 participants. Regarding this analysis, we found that data were missing completely at random (MCAR) with respect to the four dimensions of aberrant driver behavior (aggressive violation, ordinary violations, errors and slips) across the four time-points, as indicated by a non-significant chi-square in Little's MCAR test:  $\chi^2 = 1951.21, p = .94$ . Saving factor scores of driver behavior from an analysis reliant on the maximum likelihood function (MLR; robust maximum likelihood) provided estimated factor scores for all participants and at all time-points. Where observed data was missing, factor scores were imputed based on the model's prediction. Mileage was measured using a single indicator at each contact. This meant that missing mileage data could not be replaced using the method applied to driving behavior. Therefore, analyses that included mileage were only available for the sub-

sample of 1148 drivers who reported their mileage at all time-points.

The sub-sample comprised slightly fewer men than the full sample of 12,012 drivers (32.2% in the sub-sample and 37.2% in the main sample). Also, the sub-sample included slightly fewer very young drivers than the main sample: under 20 year olds = 54.2% in the sub-sample vs 59.8% in the main sample; under 25 year olds = 68.9% in the sub-sample vs 76.9% in the main sample.

Multiple imputation for mileage was considered. However, a large number of participants were lost in the third and fourth waves by design, as noted above. In order to avoid artefacts that might be caused by using multiple imputation to correct for design imposed attrition and because a sample of over 1000 participants is sufficiently large for the proposed analyses, we decided to proceed using only the available data. Note, however, that additional analysis based on the full sample of 12,012 individuals using multiple imputation to replace all missing data yielded findings that do not differ substantively from those presented here. Therefore, the results reported here focus specifically on the sub-sample of 1148 participants who provided mileage data at all four time points.

### 2.4. Analytic strategy

Models were estimated using Mplus v.7.11 (Muthén and Muthén, 2013). Analyses were conducted using the robust maximum likelihood estimator, which accounts for data skewness. To investigate individual trajectories of driver behavior over time, we used latent growth curve models. Preliminary measurement invariance tests were also conducted, to ensure that the measure has functioned equivalently at each time-point, which is an essential requirement when conducting analyses reliant on the comparison of means, such as latent trajectory modeling. Values  $\geq .90$  on the comparative fit index (CFI) and the Tucker–Lewis index (TLI) and  $\leq .08$  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  $\leq .06$  indicated excellent model fit (Bentler, 1990).

To identify whether there were groups of drivers with specific trajectories of aberrant driver behavior and whether these were determined by gender and age, we used unconditional and conditional latent class growth analyses. The model fit indices used to compare models with various numbers of classes (i.e., non-nested models) were: the Akaike (AIC) and Bayesian (BIC) information criteria, the Vuong–Lo–Mendell–Rubin likelihood ratio test, the Lo–Mendell–Rubin adjusted likelihood ratio test, the parametric bootstrapped likelihood ratio test and entropy. A model was favored over other models when the AIC and BIC had low values, the likelihood ratio tests were not significant and entropy was high. Final models are normally selected based on information from fit indices and the interpretability of classes. Models with fewer classes are favored over models with multiple similar classes and models whereby a class represents a very small proportion of the population (<5%).

## 3. Results

### 3.1. Preliminary analyses

As a preliminary step, we examined the factorial invariance of the Driver Behavior Questionnaire across the four assessment points. We used a longitudinal confirmatory factor analysis applied to data from all four time-points and specified four factors at each time-point: ordinary violations, aggressive violations, errors and slips. The factor loadings and indicator intercepts of corresponding items were constrained to equality across assessments. The error

**Table 1**  
Linear latent growth models of driver behavior over time.

	CFI	TLI	RMSEA	RMSEA 90% CI
Ordinary violations	.965	.956	.077	.065–.090
Aggressive violations	.986	.980	.053	.040–.066
Errors	.991	.988	.038	.025–.053
Slips	.998	.997	.020	.000–.037
	Mean intercept	Mean slope	Variance intercept	Variance slope
Ordinary violations	-.07*	.60**	.72**	.02**
Aggressive violations	-.11**	.46**	.64**	.01**
Errors	-.04 ( $p = .21$ )	.26**	.64**	.02**
Slips	-.03 ( $p = .37$ )	.43**	.71**	.01**
	Influence of mileage on driver behavior			
	6 months	12 months	24 months	36 months
Ordinary violations	.01 ( $p = .93$ )	.06**	.07**	.04*
Aggressive violations	.01 ( $p = .48$ )	.04**	.05**	.03 ( $p = .06$ )
Errors	.01 ( $p = .79$ )	.03*	.05*	.03 ( $p = .14$ )
Slips	.01 ( $p = .67$ )	.01 ( $p = .59$ )	.03 ( $p = .06$ )	.03 ( $p = .09$ )

Note: All values represent fully standardised coefficients, except for those referring to the variance around the mean intercept and slope, which are unstandardised.

\*  $p < .05$

\*\*  $p < .01$

variances of corresponding indicators were permitted to correlate across assessments. This model fitted the data well: CFI = .94; TLI = .93; RMSEA = .01 (90% CI = .01–.01). In other words, the assumption of scalar invariance (i.e., strong factorial invariance) held, demonstrating that the measure functioned equivalently across assessments. Therefore, we saved factor scores for use in further analyses.

### 3.2. Average trajectories of driver behavior over time

To investigate individual trajectories of driver behavior over time, we specified linear growth curve models across the four assessment points (6 months, 12 months, 24 months and 36 months), applied separately to the factor scores of ordinary violations, aggressive violations, errors and slips. Correlations were permitted between the intercept and slope in all models. To account for the effect of exposure, we included mileage as a time-varying covariate.

As shown in Table 1, a linear growth model fitted the data well in relation to each of the four dimensions of driver behavior. On

inspection of the plots, the average trajectories appeared slightly curvilinear, however, quadratic models showed poor fit to the data, especially as assessed by the TLI and RMSEA, which penalise overly complex models. This indicated that drivers' trajectories were, in fact, linear and the slight curvilinear appearance simply represented distortions introduced by variations in driving exposure.

Table 1 demonstrates that the average trajectories showed significant increases in aberrant driver behavior across time, in relation all four dimensions: ordinary violations, aggressive violations, errors and slips. The intercept and slope of ordinary violations were positively related:  $r = .15$ ,  $p < .01$  showing that participants with higher initial levels of ordinary violations had steeper increases in ordinary violations over time. In contrast, the intercept and slope of aggressive violations were marginally significantly negatively related:  $r = -.08$ ,  $p = .054$ , indicating a small regression to the mean effect whereby participants with lower initial levels of aggressive violations had steeper increases in aggressive violations over time. No correlation between the intercept and slope was noted with regard to either errors:  $r = .07$ ,  $p = .22$ ; or slips:  $r = -.03$ ,  $p = .59$ . Importantly, as shown in

**Table 2**  
Model fit of 2, 3, and 4 class models of aberrant driver behavior.

	AIC	BIC	BIC-adj	VLMR-LRT	LMR-LRT	PB-LRT	Entropy	Class %
Ordinary violations								
2 classes	9666.91	9737.56	9693.09	1883.71**	1798.62**	1883.71**	.90	74; 26
3 classes	8652.27	8738.05	8684.06	2904.35**	2773.16**	2904.31**	.94	63; 31; 6
4 classes	8210.31	8315.22	8251.69	3348.32 (.34)	3197.07 (.35)	3348.32**	.92	55; 29; 13; 3
Aggressive violations								
2 classes	8079.85	8150.49	8106.02	2098.75**	2003.95**	2098.75**	.95	85; 15
3 classes	7086.77	7172.54	7118.55	3097.84**	2957.90**	3097.84**	.93	67; 26; 7
4 classes	6517.55	6618.47	6554.94	3673.05 (.23)	3507.13 (.25)	3673.05**	.93	61; 26; 10; 3
Errors								
2 classes	9937.29	10007.93	9963.46	1731.89**	1653.66**	1731.89**	.91	77; 23
3 classes	9196.46	9282.24	9228.24	2478.72 (.21)	2366.75 (.22)	2478.72**	.91	65; 29; 6
4 classes	8809.03	8909.95	8846.42	2872.15**	2742.41**	2872.15**	.89	57; 27; 13; 3
Slips								
2 classes	8864.93	8935.57	8891.10	1776.52**	1695.88**	1776.11**	.89	70; 30
3 classes	8110.86	8196.64	8142.64	2536.18**	2449.27**	2536.18**	.86	45; 40; 15
4 classes	7573.26	7674.18	7610.65	3079.78**	2974.24**	3079.78**	.88	38; 37; 21; 4

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; VLMR-LRT: Vuong–Lo–Mendell–Rubin likelihood ratio test; LMR-LRT: Lo–Mendell–Rubin adjusted likelihood ratio test; PB-LRT: Parametric bootstrapped likelihood ratio test.

\*\*  $p < .01$

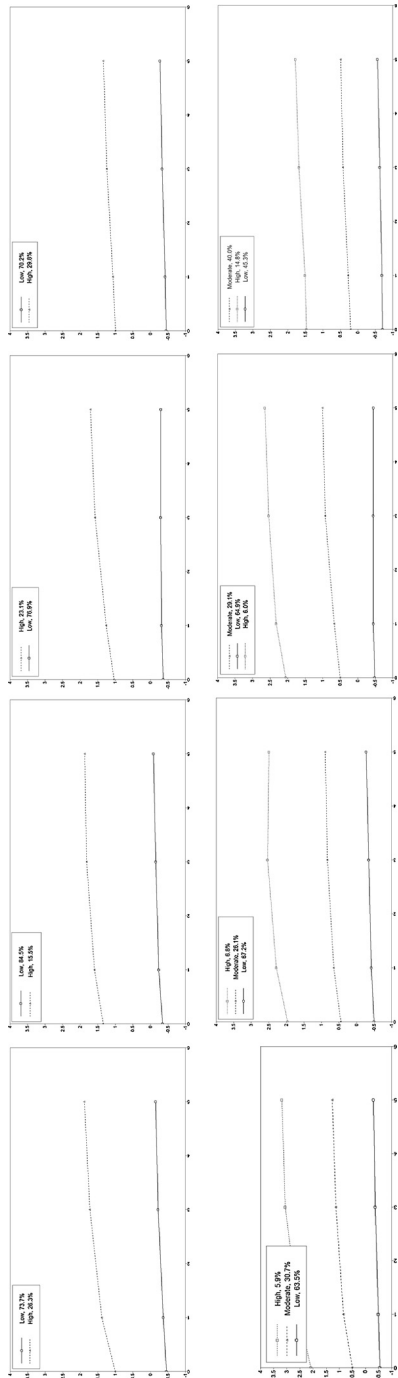


Fig. 1. Latent class growth analyses of driver behavior over time. The x-axis represents time (0 = 6 months; 1 = 12 months; 3 = 24 months; 5 = 36 months). The y-axis represents standard deviations from a baseline (i.e., time 1) score of zero.

Table 1, there was significant variation around the mean intercepts and slopes of all four components, an indication that participants differed significantly in terms of their initial levels and individual trajectories of aberrant driver behavior.

### 3.3. Subgroups of driver behavior trajectories

To test whether the observed heterogeneity in individual trajectories of aberrant driver behavior hides the presence of homogeneous subgroups of drivers following different trajectories, we used latent class growth analysis. Specifically, for each of the four components of aberrant driver behavior, we examined whether the linear growth curve model described in the previous section fitted the data well in models comprising 2, 3 and 4 classes. Here, intercept and slope variances within each group were fixed to zero (i.e., in order to identify homogeneous classes) and the intercept and slope means were freely estimated in each group. Table 2 provides comparative information for model fit and Fig. 1 depicts the trajectory groups identified in 2- and 3-class models.

As shown in Table 2, the 4 class model was discounted regarding all four behaviors based on limited improvements in AIC and BIC values, non-significant values in some of the likelihood ratio tests (i.e., adding an additional class did not appear to provide significant benefits relative to the 3 class model) and the fact that the fourth class comprised a small number of individuals (3–4%). As depicted in Fig. 1, the slopes differed slightly between the classes, with high risk classes exhibiting slightly steeper increases in aberrant driver behavior over time than low risk classes, but classes were mainly identified by differences in initial levels of aberrant driver behavior. Therefore, the more parsimonious 2 class model might be favored based on the similarity of trajectory shapes. In contrast, the 3 class model received support from the various fit indices and might be favored if the

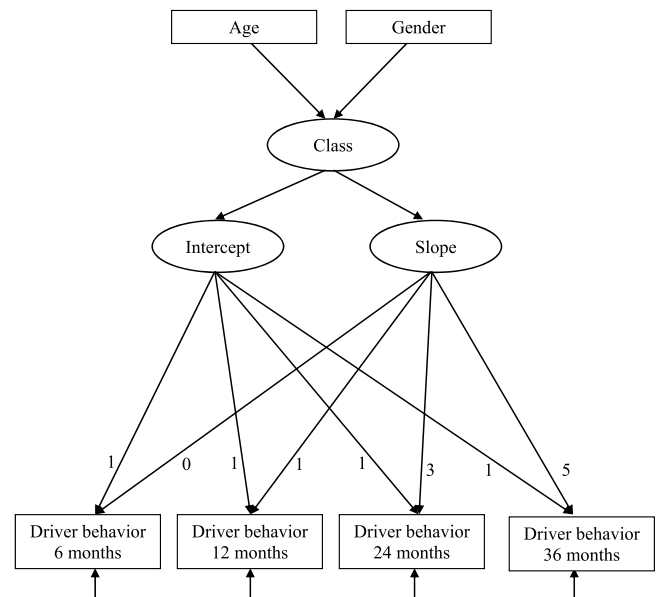


Fig. 2. Diagram of a conditional latent class growth model of aberrant driver behavior.

Note: Four models were conducted, with one model per type of driver behavior. The fixed paths from the intercept to the 4 time-scores (all values fixed to 1) indicate that the intercept is centered at the first time-point, thus representing initial levels of aberrant driver behavior. The fixed paths from the slope to the 4 time-scores (0, 1, 3 and 5) represent a linear growth, accounting for the unequal intervals between time-points (i.e., the intervals between the second and third assessments and between the third and fourth assessments were twice as long as the interval between the first two assessments).



**Table 3**  
Comparative model fit information for 2 and 3 class models.

	AIC	BIC	BIC-adj	VLMR-LRT	LMR-LRT	PB-LRT	Entropy	Class %
Ordinary violations								
2 classes	9551.04	9631.77	9580.95	2003.59**	1948.29**	2003.59**	.90	73; 27
3 classes	8501.20	8607.17	8540.46	1059.84**	1030.58**	1059.84**	.94	63; 31; 6
Aggressive violations								
2 classes	8031.23	8111.96	8061.14	2151.30**	2091.99**	2151.30**	.95	84; 16
3 classes	6993.72	7099.68	7032.98	1047.52*	1018.60*	1047.52**	.93	67; 26; 7
Errors								
2 classes	9895.15	9975.88	9925.06	1778.04**	1728.96**	1778.04**	.91	76; 24
3 classes	9142.96	9248.92	9182.22	762.19 (.50)	741.15 (.51)	762.19**	.91	64; 30; 6
Slips								
2 classes	8856.74	8937.48	8886.66	1788.29**	1738.93**	1788.29**	.88	70; 30
3 classes	8098.05	8204.01	8137.31	768.69 (.13)	747.48 (.13)	768.69 (1.0)	.86	45; 40; 15

Note: AIC: Akaike information criterion; BIC: Bayesian information criterion; VLMR-LRT: Vuong–Lo–Mendell–Rubin likelihood ratio test; LMR-LRT: Lo–Mendell–Rubin adjusted likelihood ratio test; PB-LRT: Parametric bootstrapped likelihood ratio test.

\*  $p < .05$

\*\*  $p < .01$ .

identification of a very high risk group (i.e., 2 standard deviations above the mean) is desirable.

### 3.4. Adding demographic variables to the trajectory modeling

To examine whether men and young drivers were more likely to belong to the groups with heightened aberrant driver behavior, we conducted conditional latent class growth analyses for each of the four dimensions: ordinary and aggressive violations, errors and slips. In a conditional latent class growth model, external correlates are included as ‘determinants’ of classes and the models are re-estimated. The introduction of external correlates might change the number of classes and the shape of the trajectory within each class. Here, we used the 2 and 3 class models described in the previous section and regressed the class component onto indicators of age and gender. Fig. 2 depicts the general model, Table 3 provides comparative information on the model fit, Table 4 presents the mean intercepts and slopes and Table 5 presents odds ratios for the regression paths from gender and age to class membership.

For each of the four aspects of aberrant driver behavior, the 2 class models revealed a group of drivers with low initial levels of aberrant behavior and slightly increasing trajectories of aberrant behavior over time (except for errors, where no increase was

noted) and a group of drivers with moderate/high initial levels of aberrant behavior paired with somewhat sharper increases in aberrant driver behavior over time. The group of drivers with heightened levels of aberrant behavior was more likely to comprise younger drivers and men than the low group (except for slips, where both genders were represented equally).

The 3 class models largely confirmed the results of the 2 class models. In relation to ordinary violations, the ‘low’ group was more likely to contain women than the other two groups, whereas the ‘moderate’ and ‘high’ groups were more likely to contain men than the ‘low’ group. The effect of age was graded, with younger participants increasingly more likely to be in the ‘moderate’ and ‘high’ groups than in the ‘low’ group. The pattern was highly similar with respect to aggressive violations, except that the ‘high’ group did not contain more men than women than the ‘low’ group.

In relation to errors, the ‘low’ group was more likely to contain older drivers and women. The ‘moderate’ and ‘high’ groups were more likely to contain younger drivers. In contrast to the ‘low’ group, the ‘moderate’ group included more men. The gender composition of the ‘high’ group did not differ to either of the other two groups. In relation to slips, drivers in the ‘low’ group tended to be younger than those in the other two groups, whereas gender was distributed evenly between the three groups.

**Table 4**  
Means of intercepts and slopes of driver behavior.

	Class 1 mean (intercept; slope)	Class 2 mean (intercept; slope)	Class 3 mean (intercept; slope)
Ordinary violations			
2 class model	-.478; .056	1.049; .160	
3 class model	-.579; .046	.551; .139	2.135; .215
Aggressive violations			
2 class model	-.352; .042	1.357; .099	
3 class model	-.510; .038	.464; .084	2.017; .103
Errors			
2 class model	-.373; .009 <sup>a</sup>	1.045; .135	
3 class model	-.487; .002 <sup>a</sup>	.515; .102	2.101; .111
Slips			
2 class model	-.468; .035	.984; .069	
3 class model	-.721; .025	.200; .057	1.448; .065

All  $p$ -values significant at .001 level, unless otherwise stated.

<sup>a</sup> Not significant.

**Table 5**  
Odds ratios for the regression paths from age and gender to class membership.

Model	Class specification	Age OR (95% CI)	Gender (male = 1) OR (95% CI)
Ordinary violations			
2 class model	Moderate/high vs low	.92*** (.90–.94)	2.48*** (1.84–3.35)
3 class model	High vs low	.86*** (.80–.92)	2.23*** (1.30–3.82)
	High vs moderate	.93* (.86–.99)	.99 (.57–1.71)
	Moderate vs low	.93*** (.91–.94)	2.26*** (1.68–3.04)
Aggressive violations			
2 class model	Moderate/high vs low	.92*** (.90–.95)	1.50* (1.04–2.18)
3 class model	High vs low	.89*** (.84–.94)	1.10 (.65–1.85)
	High vs moderate	.94* (.89–.99)	.56* (.32–.96)
	Moderate vs low	.94*** (.93–.96)	1.97*** (1.45–2.67)
Errors			
2 class model	Moderate/high vs low	.95*** (.93–.97)	1.57*** (1.16–2.35)
3 class model	High vs low	.95*** (.93–.96)	1.38 (1.07–2.16)
	High vs moderate	1.01 (.97–1.04)	.95 (.54–1.69)
	Moderate vs low	.95*** (.91–.98)	1.45* (.81–2.37)
Slips			
2 class model	Moderate/high vs low	.98*** (.96–.99)	1.04 (.78–1.39)
3 class model	High vs low	.97*** (.95–.99)	1.19 (.81–1.75)
	High vs moderate	1.00 (.98–1.02)	1.34 (.89–2.02)
	Moderate vs low	.97*** (.96–.99)	.88 (.65–1.32)

\* $p < .05$ , \*\* $p < .01$ , \*\*\* $p < .005$ .

#### 4. Discussion

The current study set out to determine the average trajectory of aberrant driver behaviors over time, identify groups of drivers who follow different developmental trajectories, and explore whether identified groups can be differentiated by demographic characteristics known to be correlated to crash involvement. The first main study finding was that all four dimensions of aberrant driving behavior significantly increased across development: aggressive violations, ordinary violations, errors and slips. This confirms results from the very few studies that have investigated changes in risky driving over time, which have also found no overall change or a slight increase in aberrant driver behavior over time (Wells et al., 2008; Waller et al., 2001). As noted in the introduction, these findings are at odds with models of the development of crash risk, which decreases dramatically over the early driving period (e.g., McCartt et al., 2009), given the repeated reports of a relationship between aberrant driver behavior and crash involvement (e.g., de Winter and Dodou, 2010). In this paper we explored the possibility that there might be heterogeneity in developmental trajectories and that a latent class of drivers might be identified with a trajectory of behavioral development that matches the well-documented decrease in crash involvement during the early stages of driving. While our analyses did identify separable trajectory classes, none of the trajectories identified matched a pattern compatible with a decrease in crash involvement.

One explanation of the apparent mismatch between overall trajectories of behavior and crash involvement found in the wider literature is simply that changes in the aspects of driving behavior tapped by the DBQ are not related to the behavioral changes that underlie the decrease in crash involvement observed over the early

stages of driving. If this is true then it raises the question of which aspects of driving behavior do underlie the reduced crash risk. Hazard perception, the ability to identify potential sources of crash risk in the driving environment is one aspect of driving that may not correlate with DBQ self-report (e.g., Horswill and McKenna, 2004). Further research is needed to assess the possibility that development of these skills underlie improvements in novice driver safety over the first few months of driving.

An alternative possibility is that trajectories of driver behavior are related to trajectories of crash involvement, but this relationship is nuanced by intervening factors which may moderate the relationship. For example, while overall levels of violation increase during early driving, drivers might also be learning the road situations where violations are particularly hazardous and desisting from violation in these situations only. This study therefore, calls for future research to investigate whether drivers become more selective in the situations in which they will violate across development.

While the current study does not support a simple role for DBQ-measured constructs in underpinning the intra-individual change in crash risk over time, we did find evidence consistent with a role for the DBQ constructs in identifying inter-individual variation in risky driving behavior amongst novice drivers. The second main finding of this study was that there was significant variability in initial levels and trajectories of aberrant driver behavior over time and that this heterogeneity in individual trajectories was successfully explained by the presence of multiple homogeneous groups of drivers, each exhibiting specific trajectories of aberrant driver behavior. The intercept was much more important than the slope in defining the modeled latent classes, indicating differences between drivers manifest early (i.e., within the first 6 months of driving) and remain relatively consistent.

Our identification of 2–3 classes of aberrant driver behavior is very similar to the results reported by the only study to have investigated latent trajectories of driver behavior (Simons-Morton et al., 2013). Similar to the findings of the current study, Simons-Morton et al. (2013) have reported that 3 classes were generally favored by model fit indices, but the more parsimonious 2 class models (higher risk and lower risk) also fitted the data very well. This similarity in results across the two studies is particularly reassuring given that each study adopted a unique perspective to driver behavior: the current study was focused on self-reported driver behavior that distinguishes between driving style (i.e., ordinary and aggressive violations) and skill (i.e., errors and slips), whereas the previous study was focused on risky driving as measured by high gravitational force events, such as rapid acceleration or deceleration.

The study conducted by Simons-Morton et al. (2013) decided in favor of the 2 class models, a decision informed mainly by the sample size of the third class (3 drivers, representing 7.14% out of a total of 42 drivers, a proportion similar to that in the current study). However, owing to the much larger sample size of the current study, all classes in the 3 class models presented here included a substantial number of drivers, with the smallest class comprising 67 drivers (the highest risk class along the dimensions of ordinary violations). The inspection of groups in terms of gender composition and age further indicated that 3 classes might, indeed, be more informative than 2 classes in some cases. In all four aspects of aberrant driver behavior, the 2 class models indicated that male gender and younger age were risk factors for trajectories of heightened aberrant driver behavior. While this remained the case for the 3 models of ordinary violations, slips and lapses, results for the 3 class model of aggressive violations contained one unexpected result. As expected, males were at increased risk of being categorised in the moderate group; 35% of males were classified to this group compared to 21% of females. However,

males were not at higher risk than females of being in the highest aggressive violation group; this class contained 7% of males and 7% of females. Further work will be required to test whether this gender equivalence in the higher level of aggressive violations may be replicated. More in keeping with the available literature, young age at licensure was a significant risk factor for membership of the high aggressive violations trajectory in the 3 class model.

The finding that young age is detrimental is not surprising. The most straightforward explanation, and the one most often cited, is that, during the teen years, there is a peak in propensity for novelty and sensation-seeking that is not mitigated by a parallel development of self-regulatory abilities and may thus result in a plethora of risky and antisocial behaviors (Steinberg, 2004). The teenage brain might not be sufficiently developed to tackle such a complex task as driving. Driving requires the recruitment of several cognitive functions, including working memory, attention control, planning and inhibitory control. These functions, collectively known as executive functioning (Hughes, 2011) are seated in the prefrontal cortex, which has a very protracted development that extends into adolescence. Neuropsychological tests have demonstrated that reduced EF is predictive of engagement in risky behavior, measured as a composite of multiple behaviors, including risky driving (Pharo et al., 2011). Indirect evidence of the role of the prefrontal cortex also comes from studies of the relationship between risky driving and disorders that involve deficits in EF, such as attention-deficit/hyperactivity disorder (ADHD) (e.g., Barkley and Cox, 2007).

Research focusing on the relative contribution of personality factors and cognitive ability (including the inhibition of responses that might be associated with aggression) to aberrant driver behavior remains a priority. The former may be best dealt with through early intervention targeting risky driving attitudes, whereas a higher age limit for licensure might be the most effective approach, ensuring driving does not begin until the brain is sufficiently mature. The DBQ attempts to address the distinction of personality and cognition through the identification of violations and cognitive failures, and there have been recent calls for an update to the theoretical structure that underpins the DBQ in order to better reflect recent advances in cognitive psychology (Mattsson, 2012). However, the DBQ is a questionnaire of general driver behavior, and not specifically novice driver behavior. Further development and implementation of measures designed to capture driver behavior early in the driving experience may prove a useful addition to the measures already available to driving researchers.

The current study provides suggestions for policy and practice. Initial levels of aberrant driver behavior appeared to be more important than slopes in identifying sub-groups of drivers, a result that favors early intervention and supports previous conclusions by Rowe et al. (2013) that the driver learning period might be a particularly good time for interventions. Additionally, the positive relationship between the intercept and slope of ordinary violations indicates that intervention programs aimed at preventing ordinary violations immediately after licensure may have additional long-term effects in improving drivers' trajectories of ordinary violations over time. In contrast, the lack of a significant relationship between initial levels and individual trajectories of errors, slips and aggressive violations suggests that improving trajectories along these dimensions might necessitate longer-term interventions, such as Graduated Driving Licensing programs (e.g., Williams, 2006), or other forms of prolonged supervised driving.

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