Trajectories of older drivers' risky driving behavior over time: a clustering approach

Zhu Yuanfang (Nagoya University)　Jiang Meilan (Nagoya University)　Yamamoto Toshiyuki (Nagoya University)

1.Objectives

Older drivers' driving behaviors are likely to change with age because of the age-related decline in functional abilities and driving abilities. As the function describing within-person change is referred to as a "trajectory", road safety studies often use trajectories of driving behaviors to represent changes in driving behaviors over time (Simons-Morton et al., 2013). Utilizing the older driver dataset "DAHLIA" from Nagoya University COI project, this study aims to explore the trajectories of older drivers' risky driving with age. Drivers are classified into different groups based on the initial levels and trajectories of their risky driving behaviors. Predictors of the class membership are investigated.

2. Material and methods

Data used in this study are from the Data Repository for Human Life-Driving Anatomy (DAHLIA) database of the Nagoya University Center of Innovation (COI) project. All participants were active drivers who held valid driver's licenses and lived in the Nagoya Metropolitan Area. All participants provided informed consent to participate in the study, which was approved by the Nagoya University Ethics Committee (approval number: 2022-16).

A subsample of 44 drivers who have participated in the study for at least 2 years were used for the analysis. A driving recorder (Yupiteru BU-DRHD421) was installed in the participants' private vehicles to record their everyday driving behavior. It can identify two types of harsh events: sudden start/brake and sudden steering. Harsh event rate was used as the driving outcome and was calculated as the number of sudden start/brake/steering events per 1000 km driven. Demographics, personality traits (i.e., sensation seeking and impulsivity), functional abilities, and driving exposure were included as potential predictors of average risky driving behaviors over time and changes in driving behaviors with age. Measurement of these variables can be found in our previous work (Zhu et al, 2024).

Our dataset is an unbalanced panel data (i.e., number of participants varies across time-points). Therefore, the latent growth curve modeling approach used in previous studies is not suitable for our data. To address this issue, we proposed a clustering approach to classify individual trajectories of harsh event rates. The proposed method used Dynamic time warping (DTW) to measure the similarity between each pair of trajectories. A distance matrix that contains pairwise DTW distances between two trajectories was inputted into the hierarchical clustering algorithm. The number of clusters was determined depending on a combination of several factors, including the performance of the clustering algorithm (evaluated by Silhouette index), number of participants in each cluster, and interpretability of the results. Ordinal logistic regression model was used to examine the predictors of class membership identified by the clustering approach.

3. Results

Our analysis indicated that a three-cluster model is more appropriate considering the model performance, number of participants in each cluster and interpretability of the results.

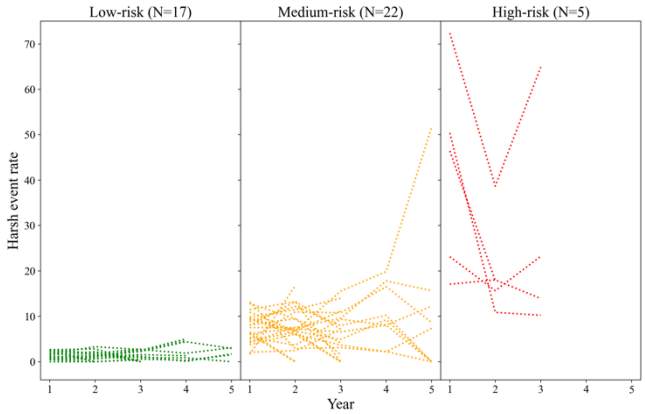

Figure 1 Individual trajectories of harsh event rates for the three subgroups

Figure 1 plotted the individual trajectories of harsh event rates for the three subgroups. The clusters were mainly identified by differences in initial levels of harsh event rates. Drivers in the low-risk group were characterized by low initial levels of risky driving behaviors, and they maintained a low level of risky driving behaviors with age. Drivers in the medium-risk group had moderate initial levels of harsh event rates. Drivers in the high-risk group were characterized by high initial levels of risky driving behaviors and a steeper decrease in risky driving behaviors with age, indicating a regression to the mean effect. Despite a steeper decrease, their harsh event rates remained higher than most drivers in low-risk and medium-risk groups over the study period.

Table 1 shows the estimation results of the ordinal logistic regression model. Female drivers were more likely to be higher-risk drivers (i.e., medium-risk and high-risk drivers). A higher sensation seeking score increased the likelihood of being a higher-risk drivers. A marginally significant association was observed between monthly driving distance and class membership, indicating that lower driving exposure increased the likelihood of being a higher-risk drivers.

Table 1 Estimation results of the ordinal logistic regression model

Variables	**Coefficients (95% CI)**	**OR**
Female	1.66* (0.23-3.26)	5.25
Sensation seeking score	0.20* (0.06-0.37)	1.23
Monthly driving distance (1000 km)	-1.87† (-3.93-0.03)	0.15
AIC value	77.67	

$^{\dagger}p \leq 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

4. Discussion

The cluster analysis indicated that the heterogeneity in individual trajectories of harsh event rates can be explained by the presence of three subgroups of drivers. Initial levels of risky driving behaviors were more important than time slopes in identifying subgroups of older drivers, indicating that differences between drivers existed at early stages and remained relatively consistent over the study period. This finding indicated that it might be important to identify high-risk older drivers and implement driving intervention at early stages to improve their driving safety. The regression analysis indicated that female drivers, sensation-seeking drivers, and lower driving exposure predicted a higher level of driving risk.

5. Reference

[1] Simons-Morton, B. G., Cheon, K., Guo, F., & Albert, P. (2013). Trajectories of kinematic risky driving among novice teenagers. *Accident Analysis and Prevention*, 51, 27–32.

[2] Zhu, Y., Jiang, M., & Yamamoto, T. (2024). Changes in older drivers' risky driving behavior over time: Insights from a naturalistic study. *Transportation Research Part F: Traffic Psychology and Behaviour*, *104*, 318-333.