A COGNITIVE TOOL TO PREDICT INDIVIDUAL ACCIDENT PRONENESS OF VEHICLE DRIVERS

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Abstract: Cognitive abilities are believed to be highly correlated with driving safety (Anderson et al., 2005). Developing cognitive tasks to predict individual traffic accident proneness could benefit both driver screening and traffic accident prevention. In this study we designed four tasks to measure vehicle drivers' cognitive abilities consisting of attention span, attention distribution, spatial working memory span, multiple object tracking and speed estimation. Significant correlation was found between these cognitive indexes and the drivers' crash frequency in a simulated driving task. Then the drivers were divided into high accident-prone group and low accident-prone group based on their crash frequency. Discriminant analysis using cognitive indexes as discriminant variables revealed an up to 94.4% highly accurate classification pattern, which approved the validity of our cognitive tool as a useful predictor of individual driver's accident proneness.

Key words: *cognitive tool, accident proneness, transportation security*

1 Introduction

Among a population, a small proportion of people are much more likely to get involved in accidents than others, this phenomenon is called accident proneness (AP), first noted by Greenwood & Woods (1919). The existent of AP has been proved in many contexts such as road transportation (Visser et al., 2007). To differentiate high accident-prone (HAP) drivers from low accident-prone (LAP) drivers is useful for driver selection and training, which benefits transportation security. The traditional way to identify HAP drivers usually relies on post hoc statistics of accident records in reality across several years. However, this does not prevent accidents from occurrence. A more effective way is to predict AP using other related factors. Psychological studies on AP mainly focus on its personality source (Trimpop & Kirkcaldy, 1997; Ulleberg & Rundmo, 2003). The relatively of less interests, but not less important, is the cognitive aspect. Large amount of evidences show that cognitive deficits caused either by normal aging or aging-related disease may increase the risk of driving (for reviews, see Anstey et al., 2005; Reger et al., 2004). And the effect of cognitive screening has been tested among old drivers with cognitive degeneration (Withaar et al., 2000). The basic assumption of this study is that the correlation between cognitive abilities and driving safety is a more general phenomenon not limited to aging people. So we tried to find some driving-related cognitive indexes to predict AP among younger drivers. We expected to observe cognitive differences between HAP drivers and LAP drivers on these indexes.

2 Methods

18 drivers (all males) from a transportation team participated the cognitive assessment for monetary payment. 4 PC-based tests programmed by E-Prime 1.1 were carried out. Considering the space we cannot describe every detail of the assessment in this paper. Only general methods of test and data collection will be described below, in the order of tasks.

(1) Attention span task

Several traffic signs were displayed simultaneously on the screen (Fig. 1.a) for 100ms. Participants were asked to judge how many targets they had seen. For each trial, the signs were randomly selected from a pool of 14 familiar equal sized round-shaped traffic signs, and their positions on the screen were randomized with the constraints that the distance between any two signs or from any sign to the screen's edge was larger than the diameter of the sign itself. The number of signs has 5 levels, varied within {4, 6, 8, 10, 12} across trials. *Attention span* was calculated via Eqs. 1 and 2 for each participant. *X* represents the set of sign number. *Y* is the set of corresponding mean accuracy. *n* is the number of elements within the set.

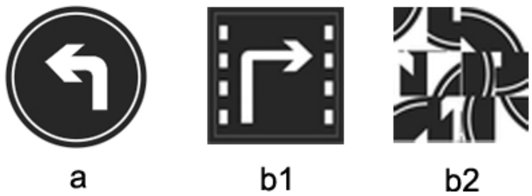

Figure 1. Samples of target stimuli used in task 1 and task 2

$$\begin{cases} \bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \\ \bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i \\ L_{XX} = \sum_{i=1}^{n}\left(X_i - \bar{X}\right)^2 \\ L_{XY} = \sum_{i=1}^{n}\left(X_i - \bar{X}\right)\left(Y_i - \bar{Y}\right) \end{cases} \quad (1)$$

$$Span = \left(0.5 - \bar{Y} + \bar{X} * L_{XY} / L_{XX}\right) / \left(L_{XY} / L_{XX}\right) \quad (2)$$

(2) Spatial working memory and attention distribution task

This part contained one single task and one dual task. First was the tracing task. At the beginning of each trial, a car laid at the center of a 9*9 grating region taking a random heading. Participants was asked to follow a red dot appeared one grid either up, down, left or right next to the car by pressing the direction keys. Once the car went to the right grid, the red dot disappeared. And after 300-500ms it reappeared one grid next. The total steps participants traced every trial was either 4, 6, 8, 10 or 12, with 2 step/turning on average. After tracing, participants had to restore the traced route from memory by pressing direction keys. The restore accuracy was defined as the number of overlaid grids of restored route and the traced route in proportion of the total steps of traced route. Using X represents the set of traced steps, Y represents the corresponding mean restore accuracy, we can compute *spatial working memory span* via Eqs. 1 and 2.

In the dual task, participants had to respond to one prompted stimuli in each tracing trial. They judged whether the prompted sign was a normal one (Fig.1.b1) or a scrambled one (Fig.1.b2). The sign might appear within any grid except the ones adjacent to the car. Participants had to restore route after tracing ensuring that the memory load keep the same, though their restore accuracy wasn't used in analysis. We calculated geometric mean of tracing and judging accuracy in dual task as each participant's *attention distribution score.*

(3) Multiple objects tracking task

Before each trial was launched, eight cars parked on the remote end of four legs of a cross road. Three cars among them were highlighted by flashing red circles. Participants were asked to pay attention to these target cars during the trial. Then all the cars started to move at a constant speed in straight line for 5000ms before the scene disappeared. Among the eight cars, a random one would accelerate to a new constant speed at about 2500 to 3500ms after the motion started. Participant's task was to answer whether or not the target cars had changed their speed after the whole animation. The mean judge accuracy is their *score of multi-object tracking (mot).*

(4) Speed estimation task

Sheltered TTC paradigm was used in this task (Fig. 2). A car parked at the left side of the screen while a blue shelter was at the right side. A red bar positioned on the shelter indicated the target position of the car. Once participant pressed the "space" key, the car started to move at a constant speed towards right and became invisible behind the shelter. They had to press the "space" key again when they felt it's just the right time when the head of the car contact the red bar. The speed of the car had three levels (fast, medium, slow) and the position of the red bar also varied (far, medium, near), which generated 9 combinations randomized across trials. The estimation error for each condition was obtained by subtracting the target position from the final car position at the moment of key pressed in unit of pixel. *Speed estimation error* was defined as the square root of mean square error of each condition, which didn't account the direction of estimation bias.

Figure 2. Configuration of speed estimation task

3 Results and Discussion

3.1 Descriptive results of cognitive tasks

Descriptive statistical results of the five indexes referred in the methods part are shown in Table 1. The performances of the drivers are subjected to normal distribution on all the five cognitive indexes according to one sample Kolmogorov-Smirnov test. In order to put different indexes into one assessment system, all the data are normalized and unified scale direction (larger score for good performance and smaller score for bad performance) in the later analysis.

Table 1. Descriptive statistics of unstandardized cognitive indexes

	Mean	SD	Minimum	Maximum	K-S sig.
atten_span	8.126	1.257	6.420	11.750	0.246
memo_span	7.389	1.335	6.000	10.500	0.843
atten_distribution	0.766	0.073	0.640	0.950	0.789
mot	0.759	0.121	0.570	0.960	0.524
spd_esti_err	55.434	30.429	13.920	123.460	0.761

3.2 Cognitive indexes correlate with accident occurrence

The aim of this study is to predict AP of common drivers. Since it's almost impossible to design field experiment to cause traffic accident, on-vehicle performances of the drivers in this study were collected on a QJ-4B driving simulator with a FOV up to 180 degree and 6D kinesthetic feedback. High fidelity driving simulator has been proved to be a good substitution of real on-road test for its ecological efficiency and safety (Lee et al., 2003). Crash frequency of each driver averaged by 10 roads was transformed into standardized score within the population and regressed with the five cognitive indexes.

Generally, individual driver's crash frequency has a linear correlation with his cognitive scores. The regression function is marginally significant, R^2=0.559, F (5, 12) =3.043, p=0.053. Contribution of each variable is shown in Table 2. *Attention span* and *speed estimation error* are strong predictors of crash frequency, the p values are both at 0.01 level. However, no significant correlation with crash is found among other indexes obtained from task 2 and task 3. Three possibilities may explain the invalidity: one is that the indexes are insensitive to driving; a more reasonable alternative may be the difficulties of the tasks per se, since the two paradigms are relatively complex and new, improper settings might be used; small sample size may also contribute to statistical insensitivity.

Table 2. Regression coefficients of cognitive indexes

	Coefficients	Std. Error	t	Sig.
(Constant)	-0.071	0.200	-0.355	0.729
atten_span	0.758	0.256	2.959	0.012
memo_span	-0.230	0.221	-1.038	0.320
atten_distribution	0.007	0.294	0.025	0.981
mot	-0.405	0.379	-1.069	0.306
spd_esti_err	0.832	0.253	3.288	0.006

3.3 Discriminant analysis

To further examine the validity of the cognitive assessments, we want to see if the results can predict AP directly. Here we divided the 18 drivers into two equal groups according to their crash frequency while driving along ten preset roads with different difficulties (Fig. 3).

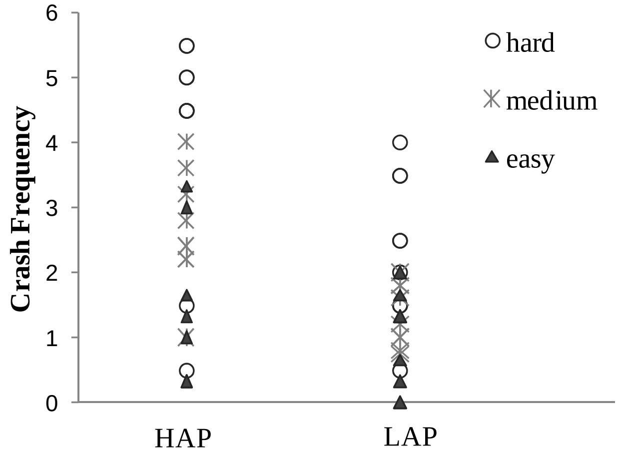

Figure 3. Crash frequency of HAP and LAP drivers on different roads

Discriminant analysis was done with the five cognitive indexes as discrimant variables. Classification results and canonical discriminant function is shown in Table 3. The total classification rate is 94.4% with only one case goes into the wrong category. The group centroids of HAP group and LAP group based on the function is -0.842 and 0.842 respectively.

Table 3. Classification results of discriminant analysis

		Prior defined group membership	Predicted Group Membership		
			HAP	LAP	Total
Original	Count	HAP	9	0	9
		LAP	1	8	9
	%	HAP	100.0	0.0	100.0
		LAP	11.1	88.9	100.0

Discriminant function: Y=-0.025+1.501X_1 -0.556X_2 -0.177X_3 -0.803X_4 +1.006X_5

4 Conclusions

Using individual cognitive capabilities to predict AP is meaningful for traffic safety. In this study we developed a suit of cognitive tests and an assessment method to discriminate HAP drivers from LAP drivers. Cognitive indexes like attention span and speed estimation error are proved to be sensitive predictors of one's accident rate. The AP discriminant function with cognitive indexes as discriminant variables is proved to be quite accurate in this study.

5 Recommendations for Future Research

Here we developed a useful cognitive tool for traffic AP prediction. However, before it's put into use, we suggest larger sample size studies to set up more objective criteria for real extreme high and low accident proneness among general populations rather than the relative high and low we used in this study. Future studies should also try to find more sensitive cognitive indexes besides that used in this study. With more indexes and larger data bank, we believe the method described in this paper would yield more adaptive discriminant function for practical use.

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