AN EXAMINATION OF THE RELATIONSHIP BETWEEN ATTENTION PROFILES AND SIMULATED DRIVING PERFORMANCE

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Summary: This study examined whether attention profiles from a computerized test battery relate to simulated driving performance. Five attention abilities were examined in the study: sustained, divided, selective, switching, and scanning. Participants completed eight tasks in a computer-based test battery and four driving scenarios designed to tap the same attention abilities. Physiological measures were collected during the test battery and the driving scenarios. Principal components analysis (PCA) with varimax rotation extracted seven components from the test battery, including the five proposed abilities along with speed and orienting components. Component scores were used as predictors of simulated driving performance in stepwise regressions and explained a significant proportion of variance (ranging from 7% - 26%) for most measures of driving performance. The speed, visual search, and divided attention components appeared as significant predictors more often than did the sustained, switching, orienting, and selective components. When physiological measures were added to the regressions, they explained additional variance beyond that explained by the component scores, but there was no consistent relation between simulated driving performance and any particular physiological measure.

INTRODUCTION

The purpose of this study was to begin development of an attention battery that will be used to assess driving performance. This study examined the relationship between attention abilities assessed with a computer-based test battery and a driving simulator. The goal of this study was to investigate if some specificity could be found between an attention ability from the test battery and a driving scenario designed to tap the same ability. A relationship between attention abilities (selective, scanning, switching, sustaining, and divided) and driving performance would support the utility of determining a person’s attention profile to provide information about their driving. It is the hope that this attention battery will be useful for examining driving skills in the elderly and cognitively impaired populations. This study also sought to investigate how physiological measures (i.e., heart period, pre-ejection period, respiratory sinus arrhythmia, respiration rate, and respiration amplitude) correlate with driving performance.

METHOD

Sixty-seven undergraduates from Central Michigan University completed this study. The average miles driven per year were 10,732 miles, with a range of 1,000 to 50,000 miles. Forty-three of the participants were female (64.2%) and 24 were male (35.8%). Participants ranged in age from 18 to 27 years old, with an mean of 19.5 years old. Approximately 79% of the participants were Caucasian, 6% African American, 4.5% Hispanic, 4.5% Oriental, 3% Native American, and 3%

classified themselves as other. The experiment lasted approximately three hours and participants were tested individually. Half of the participants began the study with the ASAP tasks and the other half began with simulated driving.

A computer-based attention battery, Assessment Software for Attention Profiles (ASAP; Washburn & Putney, 1997), was used to obtain performance measures for seven different attention tasks: a Stroop task (Stroop, 1935), an Attention Network Task (ANT; Fan et al., 2002), a two-choice reaction time task (CRT), a continuous performance task (CPT), a letter-search task (Neisser, 1963), and pro- and anti-saccade tasks (Hallett, 1978). All of the tasks in the ASAP required the participant to respond by pushing buttons on a mouse. A dual-task, which was a CRT using a mouse and a single-axis compensatory tracking task using a joystick, was added to the ASAP to assess divided attention. Participants also completed six simulated driving scenarios, four of which were designed to demand the attention abilities from the ASAP but be ecologically valid to driving. Participants completed a baseline driving scenario (6 min) to familiarize them with the simulator, the four attention-demand scenarios, followed by another baseline driving scenario. The four attention-demand driving scenarios were switching (9 min, modeled after the Gopher and Kahneman (1971) dichotic listening task but using the visual modality), sustained attention (15 min, respond to cow crossing signs among horse crossing signs), visual search (10 min, detect police cars among other parked cars), and selective attention (4 min, respond to one letter on an overhead road sign and ignore other letters). During the driving scenarios, speed was fixed and participants only controlled lateral lane position. Participants responded to stimuli by pushing buttons located on the steering wheel. The driving scenarios were created using Hyperdrive simulation programming software (version 1.9.25). The virtual driving worlds were presented using a DriveSafety desktop driving simulator. Baseline physiological measures were taken prior to beginning both the ASAP and the driving tasks. Physiological data were collected for 3 min during the ASAP in the first task of each of the five blocks (i.e., during the ANT, anti-saccade, search, and dual tasks) and 15 min in the CPT. Participants were allowed three minutes to rest between each block during both the ASAP and driving scenarios. Physiological data were collected continuously during the driving scenarios.

The physiological data were collected via a Mindware Technologies Impedance Cardiograph Model MW2000D using Mindware Acquisition data acquisition system (Mindware Technologies, Inc.). Electro- and impedance cardiography were used to obtain noninvasive indices of sympathetic and parasympathetic nervous system activity. Heart period was analyzed instead of heart rate because of its superior biometric properties and was calculated as the time in ms between successive R-peaks of the ECG (Berntson et al., 1994). A shortening of heart period results in an increase in heart rate. Respiratory sinus arrhythmia (RSA, the parasympathetic index) was calculated as the natural logarithm of the power in the high-frequency heart period variability frequency band (0.12-0.40 Hz) by applying Fast-Fourier Transform (FFT) to the resampled R-R intervals using Mindware HRV (ver. 2.2, Mindware Technologies, Inc.). Pre-ejection period (PEP, the sympathetic index), which is the time between the onset of ventricular depolarization and the onset of left ventricular ejection into the aorta, was obtained from the first derivative of pulsatile changes in transthoracic impedance (dZ/dt) using Mindware IMP (ver. 2.2, Mindware Technologies, Inc.). Respiration rate (peak frequency converted to breaths/minute) and amplitude (in arbitrary units) were found using an FFT of resampled respiration obtained from the dZ/dt data (Ernst et al., 1999). All physiological measures were analyzed as difference scores from baseline.

RESULTS

Manipulation checks revealed that the ASAP tasks exhibited the expected statistical effects with one exception, the ANT task, for which only a flanker effect was found. Seven components were extracted from ASAP performance data by principal components analysis (PCA) because each had an eigen value greater than one and explained more than 5 percent of the total variance. Table 1 provides the amount of total variance in the ASAP that is explained by each of the seven components before and after varimax rotation. Labels were given to the components in the rotated component matrix (see Table 2) based on the variables that had loadings beyond +/-.5.

Table 1. Total Variance Explained from PCA

	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Eigen Value	% of Variance	Cumulative %	Eigen Value	% of Variance	Cumulative %
1	6.196	26.939	26.939	5.036	21.897	21.897
2	2.365	10.281	37.220	2.874	12.495	34.392
3	1.935	8.412	45.633	2.018	8.773	43.165
4	1.823	7.924	53.557	1.884	8.211	51.367
5	1.557	6.770	60.372	1.745	7.585	58.961
6	1.219	5.300	65.628	1.434	6.233	65.194
7	1.148	4.990	70.617	1.247	5.423	70.617

Table 2. Rotated PCA Component Matrix

	Component						
ASAP Performance Measure	1	2	3	4	5	6	7
Anti-saccade accuracy	.000	.055	-.061	**.903**	.090	.027	.085
Anti-saccade RT	**.783**	.286	.142	-.051	.100	.062	-.174
Pro-saccade accuracy	.013	.058	-.055	**.912**	-.110	.105	-.061
Pro-saccade RT	**.704**	.354	.303	.082	.168	-.031	-.077
ANT alerting	.212	-.327	.015	.072	**-.540**	.133	.285
ANT orienting	.065	.203	.090	.033	-.077	**.749**	-.196
ANT executive	-.171	.205	**.511**	-.072	.297	-.110	-.076
Search accuracy	.362	-.073	-.017	-.243	**.616**	.041	.196
Search RT	**.607**	-.102	.314	.184	.157	.030	.223
CPT Seg 1 RT	.278	**.771**	.010	.081	.114	.190	-.080
CPT Seg 2 RT	.377	**.776**	-.035	.083	.011	-.062	.174
CPT Seg 3 RT	.275	**.872**	.009	-.012	-.077	-.040	-.063
Rt-2 accuracy	.260	-.152	-.260	.196	.391	-.086	-.262
CRT RT	**.779**	.391	.027	.107	-.118	-.045	.216
Stroop Neutral accuracy	-.026	-.021	-.098	.100	**.705**	.200	.144
Stroop Congruent accuracy	.057	-.172	-.092	.106	.231	**.775**	-.181
Stroop Incongruent accuracy	-.013	-.008	.039	.021	.083	.009	**.854**
Stroop Neutral RT	**.805**	.295	-.111	-.052	-.158	.008	.090
Stroop Congruent RT	**.888**	.035	-.061	-.021	-.005	.108	-.038
Stroop Incongruent RT	**.794**	.157	-.331	-.111	.091	.045	-.097
Tracking accuracy	-.114	.216	**-.665**	.075	.304	.266	-.130
Tracking/CRT RT	**.544**	.358	**.517**	.123	-.048	.048	-.093
Tracking RMSE	.035	-.052	**.779**	-.077	-.162	.209	.052

BOLD indicates high factor loadings. CPT=continuous performance task. CRT=choice reaction time. Component labels: 1= speed, 2= sustained, 3= divided, 4= switching, 5=visual search, 6=orienting, 7= selective.

Component scores on the seven components were computed for each participant and were correlated with their performance in the driving scenarios. As can be seen in Table 3, the components did not show specificity with the driving scenario that was designed to require particular attention ability more so than with the other scenarios; instead, the components tended to correlate with driving- or attention-demand performance variables. Component 1, the speed component, generally had significant positive correlations with RMSE and SWSD and significant negative correlations with side-task response accuracy. These patterns indicate that participants who performed well in the ASAP battery (i.e., had low scores on the speed component because they had fast RT in the test battery) also performed well during simulated driving (i.e., had small lateral deviations and steering wheel movements and high accuracy in the attention-demand scenarios). Component 2, the sustained component, did not consistently correlate with any measure across driving scenarios. Component 3, the divided attention component, had the same relation to RMSE as did Component 1, but did not correlate with SWSD. Component 3 had a more complex relation with accuracy than Component 1 in that participants who had good divided attention performance in the ASAP battery (low component score) had high accuracy in the selective scenario but tended to have low accuracy in the visual search scenario. Components 4 and 5, the switching and visual search components, indicated that participants who did well on the ASAP tasks (i.e., high accuracy in the pro- and anti-saccade and visual search tasks) had good driving performance (i.e., low RMSE). Component 5, visual search, showed the most specificity of the components in that it was the only component to correlate with accuracy in the visual search scenario, where high component scores went with high search accuracy. Components 6 and 7, the orienting and selective components, did not significantly correlate with performance in the driving scenarios, although Component 6 approached significance for accuracy in the selective and switching scenarios where higher component scores (i.e., better orienting) went with lower accuracy in the driving scenario.

Although the component scores are orthogonal to each other, we wanted to determine whether the bivariate correlations in Table 3 explained unique or merely the same variance in driving performance. Therefore, stepwise multiple regressions were performed for each driving performance variable using the seven component scores as predictors. Components had to have an F with $p<.05$ to enter and $p>.10$ to remove, but in fact all components reported below are significant at $p<.05$. Components are listed in the order in which they were entered and the adjusted R^2 and significance are reported for the final step in the analysis. For the first baseline driving scenario RMSE was predicted by Components 1, 5, and 3 (speed, visual search, and divided), adjusted $R^2 = .220$, $F = 6.74$, $p < .01$, and SWSD was predicted by Components 1 and 2 (speed and sustained), adjusted $R^2 = .203$, $F = 8.77$, $p < .01$. For the second baseline driving scenario, RMSE was explained by Components 5, 3, and 4 (visual search, divided, and switching), adjusted $R^2 = .235$, $F = 7.45$, $p < .01$. For the selective-attention driving scenario SWSD was predicted by the Components 1 and 5 (speed and visual search), adjusted $R^2 = .139$, $F = 6.07$, $p < .01$, and accuracy was predicted by Components 3 and 6 (divided and orienting), adjusted $R^2 = .259$, $F = 12.00$, $p < .01$. For the first segment of the sustained scenario, RMSE was predicted by Components 5 and 3 (visual search and divided), adjusted $R^2 = .153$, $F = 6.42$, $p < .01$, SWSD was predicted by Components 1 and 5 (speed and visual search), adjusted $R^2 = .144$, $F = 5.94$, $p < .01$, and accuracy was predicted by Component 1 (speed), adjusted $R^2 = .190$, $F = 15.04$, $p < .01$. For the second segment of the sustained scenario, RMSE was predicted by Components 3 and 1 (divided and speed), adjusted $R^2 = .107$, $F = 4.60$, $p < .05$, SWSD was predicted by Components 5, 1, and 4 (search, speed, and switching), adjusted $R^2 = .216$, $F = 6.52$, $p < .01$, and accuracy was predicted by Component 1 (speed), adjusted $R^2 = .067$, $F = 5.29$, $p < .05$. For the visual search scenario, RMSE was predicted by Component 1 (speed), adjusted $R^2 = .109$, $F = 8.72$, $p < .01$, SWSD was predicted by Component 5 (visual search), adjusted $R^2 = .109$, $F = 8.74$, $p < .01$, and accuracy was predicted by Components 1, 5, and 3 (speed, search, and divided), adjusted $R^2 = .247$, $F = 7.87$, $p < .01$. No regressions were significant in the switching scenario.

Table 3. Correlations between ASAP Component Scores and Driving Simulator Task Performance

Driving Task	N	Variable	Component 1	2	3	4	5	6	7
Baseline 1	65	RMSE	**.35****	-.09	**.26***	.09	**-.27***	-.11	-.03
		SWSD	**.36****	**-.32***	.20	-.21	-.07	-.02	-.00
Baseline 2	64	RMSE	.14	-.03	**.27***	**-.23+**	**-.38****	-.06	.10
		SWSD	.04	-.11	-.10	-.19	-.13	-.17	.08
Selective	65	RMSE	**.25+**	-.13	.02	-.13	**-.23+**	-.08	.04
		SWSD	**.30***	-.12	.03	-.20	**-.28***	-.14	.11
		Accuracy	.02	.18	**-.48****	-.12	-.05	**-.22+**	-.14
		RT	.18	.05	-.10	**.23+**	-.14	.01	-.05
Sustained	63								
Segment 1		RMSE	**.22+**	-.06	**.24+**	-.10	**-.35****	-.03	.03
		SWSD	**.32***	-.08	.17	-.13	**-.27***	-.16	-.05
		Accuracy	**-.45****	.13	.06	-.00	-.03	.00	.09
		RT	.19	.03	-.03	.00	.09	.14	-.01
Segment 2		RMSE	**.25+**	.02	**.27***	**-.21+**	-.20	.02	-.05
		SWSD	**.28***	.04	.12	**-.27***	**-.32***	-.13	-.00
		Accuracy	**-.29***	.01	.19	-.03	.15	.00	.05
		RT	.11	-.04	-.04	.13	-.02	.05	-.17
Switching	55	RMSE	.07	.10	.22	-.20	-.17	.05	.05
		SWSD	.13	-.00	.04	-.06	-.15	-.11	.05
		Accuracy	.09	-.13	-.07	-.20	.22	**-.23+**	-.01
		RT	-.15	-.03	.00	.06	.14	-.11	.11
Visual Search	66	RMSE	**.35****	.16	.07	-.12	**-.21+**	.07	.11
		SWSD	.15	.01	-.01	-.04	**-.35****	-.04	-.11
		Accuracy	**-.34****	.06	**.23+**	-.02	**.34****	-.08	.16
		RT	.15	.02	.05	.06	-.12	-.06	-.04

+=p<.10; * p<.05; ** p< .01. RMSE = root mean square error in lateral lane deviations. SWSD = standard deviation of steering wheel angle. Component labels: 1= speed, 2= sustained, 3= divided, 4= switching, 5=visual search, 6=orienting, 7= selective.

Only 47 participants had usable physiological data in all conditions. Internal consistency of the physiological measures was high. Across the ASAP tasks correlations ranged from r=.62-.81 for heart period, from r=.53-.76 for PEP, from r=.49-.72 for RSA, from r=.39-.68 for respiration rate, and from r=.01-.83 for respiration amplitude. All inter-task correlations were significant in the ASAP except for respiratory amplitude. Across the driving scenarios correlations were slightly higher than for the ASAP tasks (possibly because the recording epochs were longer) and ranged from r=.70-.91 for heart period, from r=.69-.88 for PEP, from r=.61-.85 for RSA, from r=.34-.70 for respiration rate, and from r=.24-.90 for respiration amplitude. All inter-scenario correlations were significant except for one of the respiration rate and two of the respiration amplitude correlations. Although the physiological data were reliable, these data did not consistently correlate with performance variables for either the ASAP tasks or the driving scenarios. Only 9% of the physiological/performance correlations were significant for the ASAP, and only 7% of the physiological/performance correlations were significant for the driving scenarios. Because there was no consistent pattern to these correlations and they barely exceeded the number of correlations expected by chance (5%), they were not interpreted further. However, we did try adding the physiological measures from the ASAP tasks to the stepwise regressions for the driving scenario performance measures performed above. For almost every one of the driving performance measures, there was at least one of the ASAP physiological measures added to the model beyond the component scores, even in the switching scenario where there were no significant regressions for the component scores. As with the correlations, though, there was no consistent pattern evident for the physiological measures that were significant predictors; therefore, the regressions including the physiological measures were not interpreted further.

CONCLUSIONS

This study was an initial attempt to create a comprehensive attention battery that can be used to predict driving performance by examining the relation between attention abilities assessed with a computer-based attention battery (the ASAP) and simulated driving performance. The goal was to ascertain whether specificity existed between an attention ability and a driving scenario created to address the same ability. Although we did not find specificity, this failure may have been due more to the design of the scenarios than to the estimation of attention abilities.

PCA with varimax rotation produced seven statistically independent components, which supported the a priori hypothesis of five attention abilities in the ASAP (with the divided task added), along with two more components that were not predicted, speed and orienting. Perhaps not surprisingly, Component 1 (speed) accounted for a large percentage of the variance in the ASAP data. Ackerman (1988; 1992; Ackerman et al., 1995) found that individual differences in perceptual speed contribute to differences in the learning of a complex skill. In the present study, the speed component also explained significant variance in simulated driving, which presumably reflects an individual's ability in the well-learned complex skill of on-road driving (e.g., Lee et al., 2003). Of the other components extracted, Component 3 (divided) and 5 (visual search) were most useful in predicting simulated driving performance.

The driving scenarios were designed to be as ecologically valid as possible but still tap the intended attention ability. However, some scenarios (e.g., baseline driving, visual search) more accurately reflected real-world driving than others. The switching scenario, in particular, did not approximate real-world driving in that we tried to replicate the Gopher and Kahneman's (1971) attention-switching task, and many participants did not understand what they were required to do. None of the components were able to predict performance in the switching scenario (although the physiological measures were able to).

In summary, the ASAP tasks were found to provide good measures for the extraction of attention abilities with one exception, the ANT task. In this study the ANT task was shortened from its original length, which resulted in significant flanker, but not the expected cue and cue by flanker, effects (Fan et al., 2002). Increasing the number of trials in future studies should improve estimation of the alerting, orienting, and executive measures that were important to the extraction of the divided and orienting components. Addition of the Trails A and B tasks, and perhaps other executive function tests such as the Wisconsin Card Sort task, should improve estimation of the visual search, divided, and switching components in future studies. The physiological measures did explain additional simulated driving performance variance beyond the attention components, but it is clear that much work remains to be done to improve physiological predictors.

The long-range goal is to use the attention battery to evaluate the driving skills of the elderly and cognitively impaired. Several companies have developed assessment batteries for driving similar to what we attempted. The best known of these is probably the Useful Field of View test (Ball et al., 2000). Others include a battery used in the DriveABLE™ assessment, the Multi-dimensional Attention Test (MAT), the Test for Attentional Performance-Mobility Version (TAP-M) (Moosbrugger et al., 2006). We believe that the multivariate approach used in the present study may provide more diagnostic information about a wider range of attention abilities than these other batteries.

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