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Using the Attention Network Test to predict driving test scores

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ABSTRACT

Driving is a complex multi-factorial task that taps underlying mechanisms of cognition and attention. Not surprisingly, therefore, many tests of cognition and attention are significantly associated with driving outcomes. In this article, we introduce driving researchers and clinicians with an interest in driving to the Attention Network Test (ANT), which to our knowledge has not previously been used in driving research. It is a recently developed test that is based on a neural network model of the human attention system. It combines elements of Posner's cuing paradigm [Posner, M.I., 1980. Orienting of attention. Quarterly Journal of Experimental Psychology 32, 3–25.] with the Eriksen & Eriksen flanker task [Eriksen, B.A., Eriksen, C.W., 1974. Effects of noise letters upon the identification of a target letter in a nonsearch task. Perception & Psychophysics 16, 143–149.], and provides measures of three distinct functions of attention: alerting, orienting, and executive function. Our results demonstrate that the ANT has very good concurrent validity with the Useful Field of View (UFOV), and that it is comparable to UFOV in its ability to predict road test scores for a simulated drive. These findings suggest that further investigation of the usefulness of the ANT as a tool for driving researchers and clinicians is merited.

1. Introduction

Driving is a complex multi-factorial task that taps underlying mechanisms of cognition and attention, among other things. It is not surprising, therefore, that many tests of cognition and attention are significantly associated with driving outcomes. Examples include: the trail-making test (De Raedt and Ponjaert-Kristoffersen, 2001; Hunt et al., 1993; Odenheimer et al., 1994); the mini-mental state exam (Marottoli et al., 1994); the motor-free visual perception test (Mazer et al., 1998); and the PC version of the Useful Field of View,[1] or UFOV (Ball et al., 1993, 2006; Clay et al., 2005; Owsley et al., 1998; Sims et al., 1998, 2000).

One recent development in the field of attention research that has not yet made its way into the toolkits of driving researchers or clinicians who assess fitness to drive is the Attention Network Test (ANT). An advantage of the ANT over some other cognitive tests is that it is based on a well-developed neural network model of the human attention system (Fan et al., 2002; Posner and Petersen, 1990). We begin with a brief overview of the model and description of the ANT, and then discuss how they may be relevant to driving.

1.1. The Human Attention Network Model

The human attention network model (Fan et al., 2002; Posner and Petersen, 1990) postulates three distinct functions of attention—alerting, orienting, and executive function—that are subserved by three distinct and relatively independent neural networks. Alerting is defined as achieving and maintaining alertness, or readiness to respond to incoming signals; orienting concerns the shifting of attention from one location or object to another in order to select information from sensory input; and executive attention concerns resolution of response conflicts. The brain structures and primary neurotransmitters thought to be involved in the three networks are shown in Table 1. Evidence for the model comes from studies that use functional magnetic resonance imaging (fMRI) (Corbetta et al., 2000; Fan et al., 2005), event-related potentials (ERP) (Neuhaus et al., 2007; Rueda et al., 2005), and genetics (Fan et al., 2001; Rueda et al., 2005).

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[1] See Edwards et al. (2005) for information on the differences between the original, or standard version of UFOV and the PC versions.

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Table 1
Brain structures and neurotransmitters subserving the three attentional networks.

Function	Structures	Primary neurotransmitter
Alerting	• Locus Coruleus • Right frontal cortex • Parietal cortex	Norepinephrine
Orienting	• Superior parietal lobe • Temporal-parietal junction • Frontal eye fields • Superior colliculus	Acetylcholine
Executive function	• Anterior cingulate cortex • Lateral ventral cortex • Prefrontal cortex • Basal ganglia	Dopamine

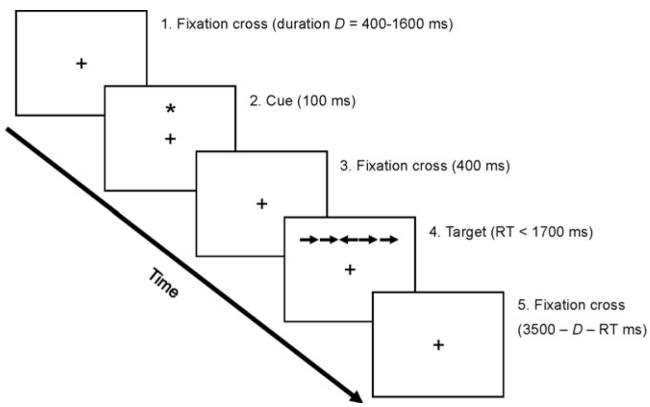

Fig. 1. Sequence of events during one trial of the Attention Network Test.

1.2. *The Attention Network Test (ANT)*

The ANT, provides measures of all three functions of attention within a single task. It combines Posner's cueing paradigm (Posner, 1980) with the Eriksen flanker task (Eriksen and Eriksen, 1974; Eriksen and Schultz, 1979). As shown in Fig. 1, each trial begins with the presentation of a fixation cross in the middle of the computer screen. (Subjects are instructed to keep their eyes fixed on the cross throughout the test.) Then, at some variable interval *D* (ranging from 400 to 1600 ms),[2] a cue is presented for 100 ms. Four hundred ms after the offset of the cue, a target display appears, and remains on until response (i.e., a key-press indicating the direction of the target arrow), or for 1700 ms if no response is made. Then the fixation cross alone is displayed for a duration of 3500 – response time (RT) – *D*, and is followed by the start of the next trial.

There are 4 cue conditions and 3 target conditions, as shown in Fig. 2A and B respectively. Targets can appear either above or below the fixation cross. The first three cue conditions (no cue, center cue, and double cue) provide no information about the location of the impending target. By way of contrast, spatial cues indicate with 100% validity where the impending target will appear: If the spatial cue appears above fixation, the target will also appear above fixation; and if the spatial cue appears below fixation, the target will also appear below fixation.

In the congruent and incongruent target conditions, the target is the central arrow in a string of 5 arrows. In the congruent condition, all 5 arrows point in the same direction. In the incongruent condition, the arrows that flank the target point in the opposite direction to the target arrow (i.e., target points left and flankers point right, or vice versa). Thus, there is response conflict in the incongruent condition, but not in the congruent condition. In the neutral condition, no flanker arrows appear.

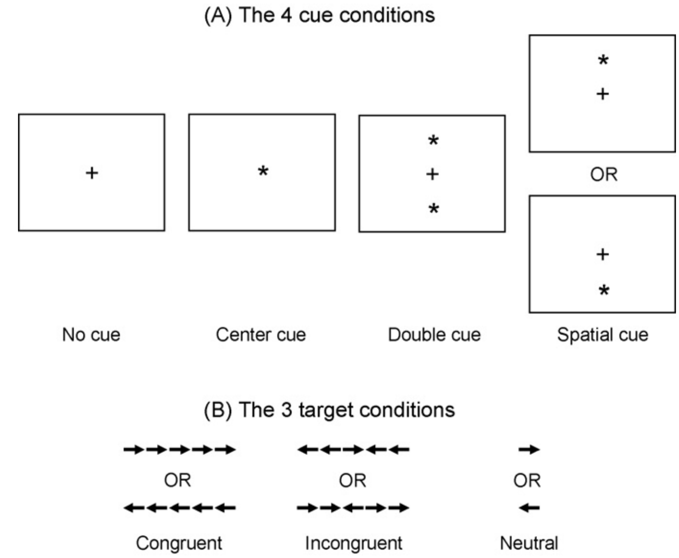

Fig. 2. The 4 cue conditions (A) and three target conditions (B) in the Attention Network Test.

When the target display appears, the task is to indicate as quickly and accurately as possible which way the target arrow is pointing. Responses are made via spatially compatible key-presses (e.g., the left and right cursor keys), and RT is recorded to the nearest millisecond.

At the conclusion of the experiment, a median RT is computed for each of the 12 cue condition × target condition combinations (using correct trials only). Then means of median RTs are computed for each of the 4 cue conditions (averaging across the 3 target conditions), and for the congruent and incongruent target conditions (averaging across the 4 cue conditions). And finally, estimates of the three functions of attention are computed as follows[3]:

$$\text{Alerting efficiency} = RT_{\text{no-cue}} - RT_{\text{double-cue}} \quad (1)$$

$$\text{Orienting efficiency} = RT_{\text{center-cue}} - RT_{\text{spatial-cue}} \quad (2)$$

$$\text{Conflict efficiency} = RT_{\text{incongruent}} - RT_{\text{congruent}} \quad (3)$$

Notice that alerting and orienting efficiency both represent *benefits* (i.e., decreases in RT) that occur due to information present in the cues. Alerting efficiency represents the benefit that one derives from knowing *when* the target will appear (i.e., 500 ms after cue onset); and orienting efficiency represents the benefit one derives from knowing both *when and where* the target will appear versus knowing only *when* it will appear. Conflict effi-

[2] This interval is variable so that subjects cannot easily predict when the target will appear in the no cue condition. That uncertainty is needed to obtain a measure of alerting.

[3] One might ask why both double- and center-cues are needed, as both provide no information about where the impending target will appear. Fan et al. (2002) argue that the double-cue is most appropriate for computing alerting efficiency because it "tends to keep attention diffused between the two potential target locations", which is presumably what also happens in the no-cue condition. But the center-cue is used to compute orienting efficiency because "like the single [spatial] cue, it encourages orienting attention to one location". Having said that, the difference between the double- and center-cue conditions is probably quite subtle. Indeed, one version of the ANT on Fan's website excludes the double-cue and neutral target conditions, and computes alerting efficiency as $RT_{\text{no-cue}} - RT_{\text{center-cue}}$.

ciency (or executive function), on the other hand, represents the *cost* that is incurred (increased RT) when the incongruent flanking arrows call for a different response than the central target arrow.[4]

1.3. Relevance to driving

An attractive feature of the human attention network model is that it gives rise to well defined and testable hypotheses. For example, given the association of a specific neurotransmitter with each network (see Table 1), one might be able to predict with some confidence how particular medications would affect the three attention networks, and thereby driving performance. To illustrate, one would expect dopamine agonists or antagonists to have greatest impact in driving situations that require one to deal with distraction from irrelevant stimuli (executive function). On the other hand, medications that affect cholinergic and noradrenergic systems primarily would be expected to have greatest impact in situations that require scanning the environment (orienting) and vigilance (alerting) respectively.

Similar expectations arise for clinical conditions that selectively affect the three neurotransmitter systems. For example, both Parkinson's disease (PD) and schizophrenia affect dopaminergic systems (Seeman, 2007), so one would expect greatest impact on executive function (Gooding et al., 2006; Muslimovic et al., 2005). Alzheimer's disease (AD) affects cholinergic systems primarily (Geula and Mesulam, 1995), so one would expect greatest impact on orienting efficiency. Attention-deficit hyperactivity disorder (ADHD) affects both noradrenergic and dopaminergic systems (Biederman and Spencer, 1999; Clarke et al., 2005), so one might expect to see disturbances to both alerting efficiency and executive function (Konrad et al., 2006).

Finally, it may be possible to use knowledge of clients' individual patterns of attentional dysfunction, as determined via the ANT, to create driving rehabilitation programs tailored to their specific needs. For example, someone who has impaired executive function, but is within the normal range for alerting and orienting might well benefit from extra practice at dealing with distraction, whereas someone who is selectively deficient in alerting might benefit from practice on vigilance tasks.

1.4. Can we predict driving outcomes from the ANT?

The purpose of this article is to explore the possibility of using measures derived from the ANT to predict driving outcomes. To do that, we will first assess the *concurrent validity* of the ANT by determining how well it predicts the UFOV total score. UFOV is widely used, and is considered by some to be the current gold standard of cognitive tests for driving researchers. Second, we will determine how well the ANT predicts driving evaluation scores, and whether prediction improves when the UFOV total score is added to the model. Finally, because age is known to be strongly associated with various driving outcomes, we will determine whether measures derived from the ANT account for variability beyond that which is explained by age.

[4] As noted by one of the reviewers, the conflict efficiency effect could also be viewed as a benefit—i.e., the benefit of having congruent versus incongruent flanking arrows. We have chosen to describe it as a cost for two reasons. The first reason is consistency with the literature on flanker interference effects. Second, calling it a benefit suggests that larger difference scores reflect better performance. That is the case (within limits) for the alerting and orienting effects, which is why they are described as benefits. But for conflict efficiency, better performance is shown by a smaller flanker interference effect.

2. Methods

2.1. Participants

Both ANT and UFOV data were collected for $n = 95$ individuals. Their mean age was 45.3 years (range, 18–83), and 62 (65.3%) were female. On-road driving evaluations were done for $n = 15$ participants (10 females, 66.7%) with a mean age of 73.5 (range, 59–83). A total of $n = 42$ participants drove a simulation of the road test circuit. Their mean age was 35.2 years (range, 18–81), and 23 (54.8%) were female. Manitoba Road Test scores are available for 38 (90.5%) of that subgroup.

2.2. The measures

UFOV data were collected using the PC version of UFOV (version 6.0.7), and a total score was computed by summing the threshold scores for the 3 subtests. ANT data were collected using a free java program downloaded from Jin Fan's website (http://www.sacklerinstitute.org/users/jin.fan/). This version of the ANT consists of 312 trials (1 block of 24 practice trials and 3 blocks of 96 test trials), and takes about 20 min to complete. However, in one of the studies that contributed data to our analysis, the ANT was terminated after 10 min in order to reduce the load on participants, who had several other tests to complete. But analyses of data from participants who completed the entire test show clearly that performance does not change systematically over time.

On-road driving evaluations took about 35 min, and were done in participant's own vehicles on a circuit in Thunder Bay, Ontario that contained all of the elements needed for a G2 license test in the province of Ontario (e.g., various types of roadways and speeds, left and right turns at controlled and uncontrolled intersections, lane changes, parallel parking, a three-point turn, etc.). The Manitoba Road Test form, a demerit-based scoring system, was completed by a trained evaluator approved by the Ministry of Transportation. Demerit points were assessed for infractions falling in five general categories (starting/stopping/backing, signal violations/right of way/inattention, moving on roadway, passing/speed, and turning). Either 5 or 10 demerits were assessed for each infraction, depending on severity. Simulated drives were done on a fixed base driving simulator (STISIM 400) with three 17-in. monitors and a 135° field of view. The driving scenario was a simulation of the on-road circuit described above, and also took about 35 min to complete. It included all of the same elements as the road course except for parallel parking and the three-point turn, because backing is not possible on the simulator. The Manitoba Road Test form was also completed for 90.5% of the simulated drives, but not by a trained evaluator in most cases. For both on-road and simulated drives, we examined the total number of demerit points for the Manitoba Road Test.

2.3. Statistical analysis

All of the variables of interest are quantitative and reasonably well distributed. Therefore, associations between variables were explored via scatter-plots and linear regression models. Because UFOV is intended primarily for older drivers, we used different symbols for younger and older drivers in scatter-plots. All analyses were performed with SPSS version 16.

3. Results

Descriptive statistics for the main variables are given in Table 2. A few points are noteworthy. First, all measures exhibit a fair degree of variability, which is useful when one is looking for associations

Table 2
Descriptive statistics for UFOV, ANT, and the Manitoba Road Test.

Variable	N	Minimum	Maximum	Mean	S.D.
UFOV-1: Processing speed	95	16.7	376.8	29.0	44.40
UFOV-2: Divided attention	95	16.7	500.0	99.6	134.93
UFOV-3: Selective attention	95	23.4	500.0	211.7	157.50
UFOV Total	95	56.8	1206.6	340.3	290.23
ANT: Mean RT, No-cue	95	465.7	1133.2	676.0	128.40
ANT: Mean RT, Double-cue	95	439.0	1106.5	643.1	129.12
ANT: Mean RT, Center-cue	95	455.7	1069.8	654.3	134.79
ANT: Mean RT, Spatial-cue	95	430.3	1001.5	611.9	129.98
ANT: Mean RT, Congruent	95	414.3	1176.5	615.7	127.96
ANT: Mean RT, Incongruent	95	531.9	1423.3	779.2	179.73
ANT: Mean RT, Neutral	95	387.1	763.5	545.2	93.64
ANT: Alerting efficiency	95	−68.8	382.0	33.0	46.40
ANT: Orienting efficiency	95	−78.7	183.5	42.4	37.36
ANT: Conflict efficiency	95	16.3	659.6	163.5	90.02
ANT: Overall Mean RT	95	447.7	1077.8	646.5	128.40
ANT: % errors	95	0.0	57.5	2.8	6.74
Mb Road Test Total (simulator)	38	30.0	235.0	113.2	50.56
Mb Road Test Total (on-road)	15	15.0	115.0	45.0	29.46

between variables. Second, notice that the minimum values for alerting and orienting efficiency are negative. Thirteen subjects had negative alerting scores (mean = −21, range = −69 to −2), and 6 subjects had negative orienting scores (mean = −29, range = −79 to −2). No subjects had negative scores for both. Negative alerting scores indicate slower responding when a warning signal appears 500 ms prior to the onset of the target. Negative orienting scores indicate slower responding following spatial cues versus centre cues. It is somewhat unusual for alerting and orienting scores to be negative, and we can only speculate about what they signify. It may be that participants with negative alerting and orienting scores are distracted by the informative cues rather than helped by them. If so, one would expect them to also exhibit greater flanker interference effects. And indeed, the data bear out that expectation: The 19 participants for whom either alerting or orienting was negative had a mean conflict effect of 237 ms versus 145 ms for the other 76 participants, $t(19.2) = 2.64$, $p = .016$.[5]

Finally, notice that the Manitoba Road Test scores are substantially higher for the simulated drive than for the on-road test. This is what we typically find. We suspect that it is largely due to relative unfamiliarity with the simulator. For the $n = 8$ subjects who did both, the correlation was .685.

3.1. Concurrent validity: associations between ANT and UFOV

Fig. 3 shows a series of scatter-plots, each with Y = the UFOV total score. The X-axis variables are all derived from the ANT. For panels A–E respectively, they are: alerting efficiency, orienting efficiency, conflict efficiency, overall mean RT, and overall % errors. R^2 values from linear regression models are also displayed. It is clear from visual inspection that the best individual predictors of the UFOV total score are overall mean RT (D), conflict efficiency (C), and overall % errors (E). But note that for % errors, the strength of the association is somewhat inflated by one or two influential points in the upper right quadrant of the scatter-plot.

Because we did not have strong a priori expectations about which components of the ANT would be most predictive of the UFOV total score, we entered all 5 of the variables into a multiple linear regression model, and used backward elimination with the p-value for removal set at .20.[6] The step 1 model (with all 5 variables) had $R^2 = .687$. The final model, with overall RT and % errors as the only predictors, had $R^2 = .685$.[7] That translates to a multiple correlation of $R = .828$. By way of comparison, Edwards et al. (2005) reported correlations of .772 and .874 respectively for the mouse and touch-screen PC versions of UFOV versus the standard version. Therefore, the concurrent validity of the ANT vis-à-vis the PC version of UFOV is very comparable to the validity of the PC version of UFOV vis-à-vis the standard version.

3.2. Predicting driving evaluation scores from the ANT

Fig. 4 shows a series of scatter-plots with Y = the Manitoba Road Test total score (i.e., number of demerit points) for a simulated drive of the G2 test circuit. In panels A–E, the X-axis variables are the same five measures derived from the ANT that we examined earlier; and in panel F, X = the UFOV total. The only variables that are significantly associated with the driving evaluation score are the overall RT from ANT and the UFOV total. For RT, the functional relationship is linear, and $R^2 = .564$. For UFOV, the functional relationship is curvilinear, and $R^2 = .629$. A model with ANT RT, the UFOV total, and the UFOV total squared as predictors yields an R^2 of .662. When UFOV is added to ANT, the change in $R^2 = .098$, $F(2, 34) = 4.92$, $p = .013$; and when ANT is added to UFOV, the change in $R^2 = .033$, $F(1, 34) = 3.33$, $p = .077$.

Fig. 5 shows the same associations as Fig. 4, but with Y = the Manitoba Road Test total score for an on-road driving evaluation rather than for a simulated drive. As noted earlier, on-road tests were done for drivers aged 55+ only (range, 59–83). It is clear that individually, none of the six variables, including the UFOV total, are even moderately associated with the driving evaluation score for an on-road test. Because of that, and because of the small sample size ($n = 15$), we did not examine any models with multiple predictors.

3.3. Is prediction improved by adding ANT to age?

It is well known that driving outcomes of all sorts are related to age, as are scores on cognitive tests used to predict driving outcomes. It is often argued that the important factor is not age per se, but that age is a marker for other variables that change with age (Ball and Owsley, 2003). We do not dispute that. However, given the complexity and multi-factorial nature of driving, it is unlikely that one would ever have all of those other variables in hand; and even if one did have all of the relevant variables, the sample size needed to include all of them in a regression model would be prodigious.[8] Therefore, it would be ill-advised to exclude age from the model when attempting to predict driving scores.

Fig. 6 shows the relationship between age and the variables of most interest in this study: UFOV Total (panel A), ANT mean RT (panel B), and Manitoba Road Test total score for a simulated drive (panel C). Age is quite strongly associated with all of these variables. For both UFOV Total and ANT RT, the functional relationship is curvilinear, not linear. When age-squared was added to the model to allow for this, the change in R^2 was statistically significant, $F(1, 92) = 28.249$, $p < .001$ for UFOV, and $F(1, 92) = 4.186$, $p = .044$ for ANT RT. Therefore, R^2 values are shown for both a linear functional fit, and for a curvilinear (or quadratic) fit.

[5] We report the Welch–Satterthwaite t-test because the standard deviations differed by a factor of nearly 3, and Levene's test for equality of variances was highly significant, $p < .001$.

[6] We are aware of the problems associated with algorithmic selection methods (e.g., Harrell, 2001; Babyak, 2004), and therefore urge readers to treat these results as exploratory rather than confirmatory.

[7] As can be seen in Fig. 3, the R^2 for RT alone was .638. Therefore, R^2 increased by .047 when % errors was added, $F(1, 92) = 13.64$, $p < .001$.

[8] Problematic multicollinearity would also be likely.

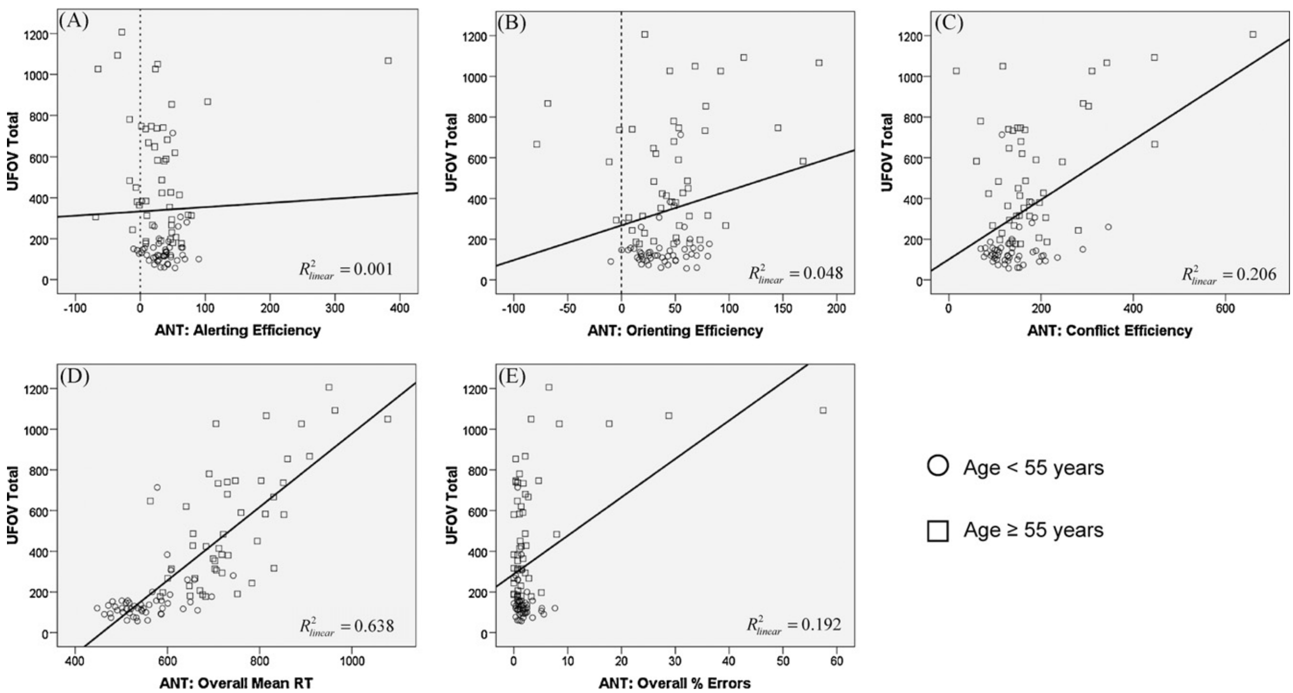

Fig. 3. Concurrent validity of the ANT versus UFOV. In each plot, Y = the UFOV Total. The X-axis variables are five different measures derived from the ANT. Round and square data points are for younger (<55 years) and older (55+ years) participants respectively.

The first question we addressed was whether the ANT explains any variance in the UFOV total beyond that accounted for by age. Recall from Section 3.1 that both RT and % errors from the ANT were predictive of the UFOV total. Therefore, we ran a hierarchical linear regression with age and age-squared as the step 1 variables, and the ANT RT and % errors as the step 2 variables. The change in R^2 (from .671 to .763) was statistically significant, $F(2, 90) = 17.39$, $p < .001$. In our sample, the two ANT variables accounted for an additional 9% of the variance in UFOV beyond that explained by age.

Next, we asked whether the ANT could account for additional variance in the Manitoba Road Test scores for the simulated drive beyond that explained by age. Recall that overall RT was the only ANT variable significantly associated with this outcome (Section 3.2), and notice that the functional relationship with age is linear,

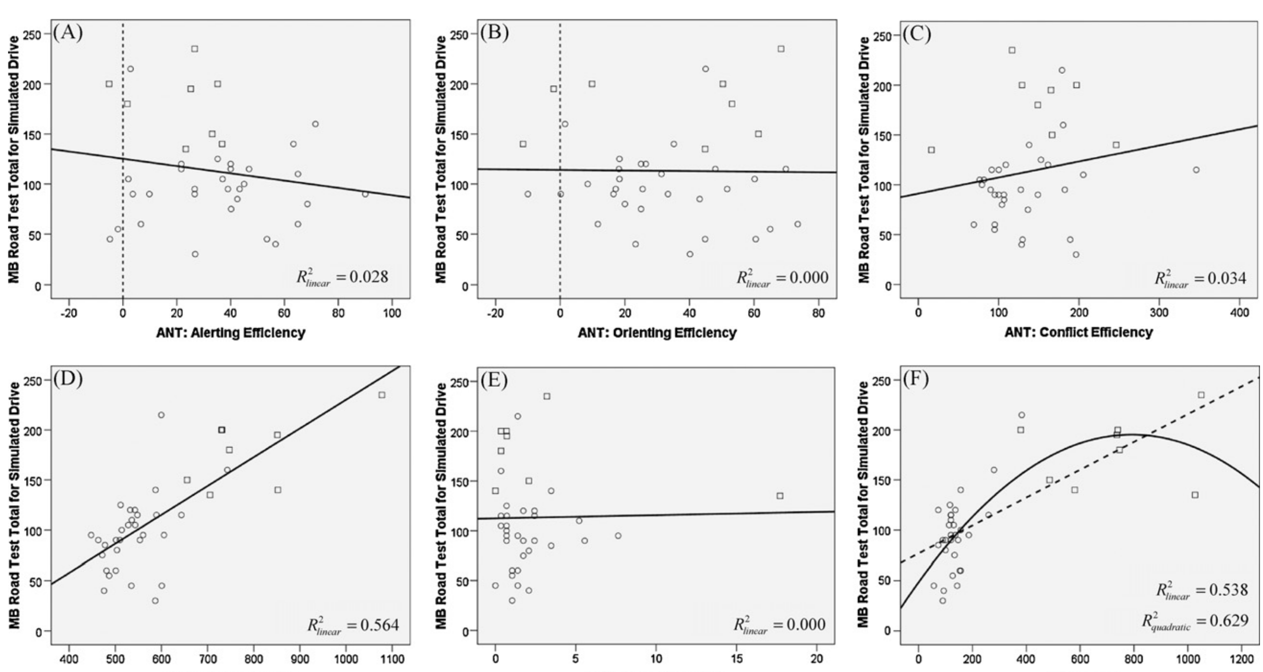

Fig. 4. Prediction of driving evaluation scores for a simulated drive. For each plot, Y = Manitoba Road Test Total Score (i.e., number of demerit points). The X-axis variables in panels A–E are five measures derived from the ANT. In Panel F, X = the UFOV Total. Round and square data points are for younger (<55 years) and older (55+ years) participants respectively.

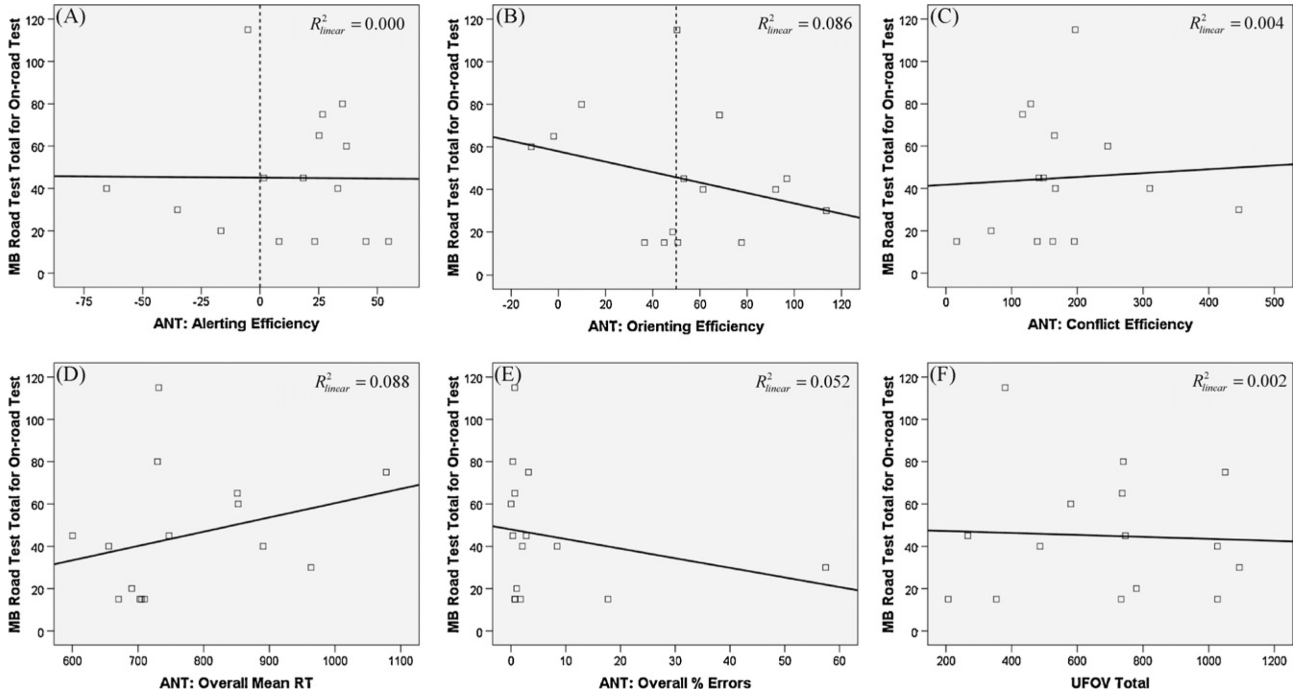

Fig. 5. Prediction of driving evaluation scores for an on-road test. For each plot, *Y* = Manitoba Road Test Total Score (i.e., number of demerit points). In panels A–E, the *X*-axis variables are five measures derived from the ANT. In Panel F, *X* = the UFOV Total. All drivers were 55 years of age or older.

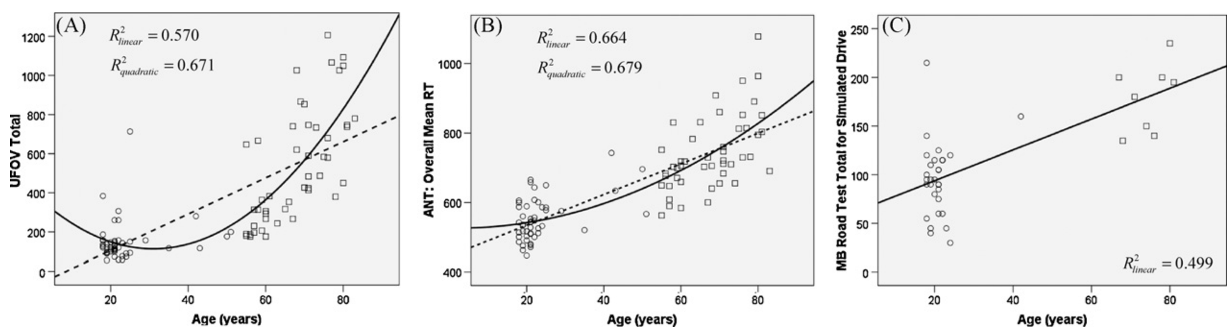

Fig. 6. Associations between age and the main variables. For each plot, *X* = age in years. In panels A–C respectively, *Y* = the UFOV total score, overall mean RT from the ANT, and total score on the Manitoba Road Test for a simulated drive.

not curvilinear (Fig. 6C). Therefore the step 1 and 2 variables in the hierarchical linear regression were age and ANT RT respectively. The change in R^2 (from .499 to .588) was statistically significant, $F(1, 35) = 6.80$, $p = .013$. When we added the UFOV total in a third step, R^2 increased to .597, but the change was not statistically significant, $F(1, 34) = 1.40$, $p = .245$.

We then repeated that exercise, but entered UFOV on step 2 and ANT RT on step 3. In this case, R^2 changed from .499 to .554 on step 2, and from .554 to .597 on step 3. The first change was statistically significant, $F(1, 35) = 4.35$, $p = .044$; and the second change approached, but did not reach statistical significance, $F(1, 34) = 3.61$, $p = .066$.

4. Discussion

4.1. Summary of findings

The goal of this article was to explore the feasibility of using the ANT to predict driving outcomes. We began by assessing the concurrent validity of the ANT using the PC version of UFOV as the gold standard, and found it to be as good as the concurrent validity of the PC version of UFOV versus the original (standard) version. The multiple correlation for a regression model with ANT RT and % errors as predictors of UFOV Total ($R = .828$) was comparable to the correlations between PC versions of UFOV and the standard version ($r = .772–.874$) reported by Edwards et al. (2005).

We then assessed the ability of the ANT to predict Manitoba Road Test scores for a simulated drive, and again found it comparable to the UFOV Total. UFOV was somewhat better than ANT RT at predicting the driving score (R^2 values of .629 and .564 respectively). And when UFOV and ANT RT were both in the model, the variance unique to UFOV was somewhat greater than the variance unique to ANT RT; but the difference was not large (9.8% versus 3.3%).

Neither the ANT nor UFOV were strongly associated with the MB Road Test for on-road tests. This may have been due to restriction of range, given that on-road tests were done for older drivers only. The sample size ($n = 15$) was too low to support multi-variable models. Of course, for the ANT to be useful in driving research, it will ultimately be necessary to demonstrate a relatively strong association between it and actual driving outcomes. But given that UFOV was also only weakly associated with the on-road test score, we are not terribly alarmed by the failure to find such an association here.

4.2. Associations between the three functions of attention and other variables

In this study, overall RT was the most consistently useful variable from the ANT. Except for conflict efficiency and UFOV (Fig. 3C; $R^2 = .206$, $F(1, 93) = 24.147$, $p < .001$), there was no evidence of any associations between the three individual functions of attention (alerting, orienting, and conflict efficiency) and UFOV or the driving scores. We found that somewhat surprising. In the case of orienting efficiency, we were surprised because there is a clear connection between orienting of attention and inhibition of return (IOR) (Posner and Cohen, 1984),[9] and we *did* observe an association between IOR and a driving evaluation score in an earlier study (Bédard et al., 2006). However, the outcome variable in that study was a different driving test that included a measure of how well drivers scan the environment; and IOR was most strongly associated with the scanning score. Given that scanning does entail shifting of attention around the environment—i.e., orienting of attention—we expect that orienting efficiency would be more strongly associated with a measure of scanning.

Similarly, we would expect to see an association between conflict efficiency (or executive function) and driving performance in situations that require one to deal with distraction or response conflict (e.g., distraction from pedestrians while following another vehicle that slows suddenly). And we would expect an association between alerting efficiency and driving performance in situations that require vigilance (e.g., a brake pedal reaction time task). We would also expect alerting efficiency to be associated with fatigue, and driving outcomes that are related to fatigue. Certainly other driving outcomes such as these ought to be explored before we abandon the individual measures of alerting, orienting, and conflict efficiency.

4.3. Summary

In summary, the ANT is based on a very well developed and well supported neural network model of the human attention system. It has very good concurrent validity with UFOV; and it is comparable to UFOV in its ability to predict the driving outcome we examined here. On these grounds, we believe that further exploration of its utility as a tool for driving researchers and clinicians is certainly merited. Future investigations might address questions such as the following:

1. Do associations between the individual functions of attention (alerting, orienting, and executive function) and driving performance emerge when more specific driving outcomes (e.g., measures of scanning) are used?
2. Are the specific functions of attention affected in the manner one would expect by particular neurological disorders or medications (e.g., selective impairment of alerting efficiency in people with AD)? And if so, do those specific effects on the attention system translate to corresponding effects in driving situations (e.g., do people with impaired orienting efficiency score poorly on measures of scanning)?
3. Are driving rehab programs that are tailored to address specific attentional problems identified via the ANT more effective than more general programs?
4. Can we establish screening cut-offs for the ANT similar to those that have been proposed for UFOV (Edwards et al., 2006)?
5. Are there specific driving outcomes (e.g., situations that require quick reactions) for which the RT-based measures from the ANT have better predictive utility than the threshold-based measures from UFOV?[10]

We hope and expect that such investigations will prove to be fruitful for both researchers and clinicians with an interest in driving.

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References

Babyak, M.A., 2004. What you see may not be what you get: a brief, nontechnical introduction to overfitting in regression-type models. Psychosomatic Medicine 66 (3), 411–421.
Ball, K., Owsley, C., 2003. Driving competence: it's not a matter of age. Journal of the American Geriatrics Society 51 (10), 1499–1501.
Ball, K., Owsley, C., Sloane, M.E., Roenker, D.L., Bruni, J.R., 1993. Visual attention problems as a predictor of vehicle crashes in older drivers. Investigative Ophthalmology & Visual Science 34 (11), 3110–3123.
Ball, K.K., Roenker, D.L., Wadley, V.G., Edwards, J.D., Roth, D.L., McGwin Jr., G., Raleigh, R., Joyce, J.J., Cissell, G.M., Dube, T., 2006. Can high-risk older drivers be identified through performance-based measures in a department of motor vehicles setting? Journal of the American Geriatrics Society 54 (1), 77–84.
Bédard, M., Leonard, E., McAuliffe, J., Weaver, B., Gibbons, C., Dubois, S., 2006. Visual attention and older drivers: the contribution of inhibition of return to safe driving. Experimental Aging Research 32 (2), 119–135.
Biederman, J., Spencer, T., 1999. Attention-deficit/hyperactivity disorder (ADHD) as a noradrenergic disorder. Biological Psychiatry 46 (9), 1234–1242.
Clarke, S., Heussler, H., Kohn, M.R., 2005. Attention deficit disorder: not just for children. Internal Medicine Journal 35 (12), 721–725.
Clay, O.J., Wadley, V.G., Edwards, J.D., Roth, D.L., Roenker, D.L., Ball, K.K., 2005. Cumulative meta-analysis of the relationship between useful field of view and driving performance in older adults: current and future implications. Optometry and Vision Science: Official Publication of the American Academy of Optometry 82 (8), 724–731.
Corbetta, M., Kincade, J.M., Ollinger, J.M., McAvoy, M.P., Shulman, G.L., 2000. Voluntary orienting is dissociated from target detection in human posterior parietal cortex. Nature Neuroscience 3 (3), 292–297.
De Raedt, R., Ponjaert-Kristoffersen, I., 2001. Short cognitive/neuropsychological test battery for first-tier fitness-to-drive assessment of older adults. The Clinical Neuropsychologist 15 (3), 329–336.
Edwards, J.D., Ross, L.A., Wadley, V.G., Clay, O.J., Crowe, M., Roenker, D.L., Ball, K.K., 2006. The useful field of view test: normative data for older adults. Archives of Clinical Neuropsychology: The Official Journal of the National Academy of Neuropsychologists 21 (4), 275–286.
Edwards, J.D., Vance, D.E., Wadley, V.G., Cissell, G.M., Roenker, D.L., Ball, K.K., 2005. Reliability and validity of useful field of view test scores as administered by personal computer. Journal of Clinical and Experimental Neuropsychology: Official Journal of the International Neuropsychological Society 27 (5), 529–543.
Eriksen, B.A., Eriksen, C.W., 1974. Effects of noise letters upon the identification of a target letter in a nonsearch task. Perception & Psychophysics 16, 143–149.
Eriksen, C.W., Schultz, D.W., 1979. Information processing in visual search: a continuous flow conception and experimental results. Perception & Psychophysics 25, 249–263.
Fan, J., McCandliss, B.D., Fossella, J., Flombaum, J.I., Posner, M.I., 2005. The activation of attentional networks. NeuroImage 26 (2), 471–479.
Fan, J., McCandliss, B.D., Sommer, T., Raz, A., Posner, M.I., 2002. Testing the efficiency and independence of attentional networks. Journal of Cognitive Neuroscience 14 (3), 340–347.

[9] IOR manifests as slower responding to targets that appear in a previously but no longer attended location (or object) relative to those appearing in a novel, not previously attended location (or object). Thus, it occurs in locations/objects to which attention was oriented, but then withdrawn.

[10] UFOV is not a response time task. For each subtest, PC versions of UFOV determine the minimum display duration for which 75% correct responding can be maintained. The maximum score for any subtest is 500 ms. When the maximum score is recorded for a subtest, any subsequent subtests are skipped and are assigned a score of 500 ms automatically.

Fan, J., Wu, Y., Fossella, J.A., Posner, M.I., 2001. Assessing the heritability of attentional networks. BMC Neuroscience 2, 14.

Geula, C., Mesulam, M.M., 1995. Cholinesterases and the pathology of alzheimer disease. Alzheimer Disease and Associated Disorders 9 (Suppl 2), 23–28.

Gooding, D.C., Braun, J.G., Studer, J.A., 2006. Attentional network task performance in patients with schizophrenia-spectrum disorders: evidence of a specific deficit. Schizophrenia Research 88 (1–3), 169–178.

Harrell, F.E., 2001. Regression Modeling Strategies: With Applications to Linear Models, Logistic Regression, and Survival Analysis. Springer, New York.

Hunt, L., Morris, J.C., Edwards, D., Wilson, B.S., 1993. Driving performance in persons with mild senile dementia of the alzheimer type. Journal of the American Geriatrics Society 41 (7), 747–752.

Konrad, K., Neufang, S., Hanisch, C., Fink, G.R., Herpertz-Dahlmann, B., 2006. Dysfunctional attentional networks in children with attention deficit/hyperactivity disorder: evidence from an event-related functional magnetic resonance imaging study. Biological Psychiatry 59 (7), 643–651.

Marottoli, R.A., Cooney Jr., L.M., Wagner, R., Doucette, J., Tinetti, M.E., 1994. Predictors of automobile crashes and moving violations among elderly drivers. Annals of Internal Medicine 121 (11), 842–846.

Mazer, B.L., Korner-Bitensky, N.A., Sofer, S., 1998. Predicting ability to drive after stroke. Archives of Physical Medicine and Rehabilitation 79 (7), 743–750.

Muslimovic, D., Post, B., Speelman, J.D., Schmand, B., 2005. Cognitive profile of patients with newly diagnosed parkinson disease. Neurology 65 (8), 1239–1245.

Neuhaus, A.H., Koehler, S., Opgen-Rhein, C., Urbanek, C., Hahn, E., Dettling, M., 2007. Selective anterior cingulate cortex deficit during conflict solution in schizophrenia: an event-related potential study. Journal of Psychiatric Research 41 (8), 635–644.

Odenheimer, G.L., Beaudet, M., Jette, A.M., Albert, M.S., Grande, L., Minaker, K.L., 1994. Performance-based driving evaluation of the elderly driver: safety, reliability, and validity. Journal of Gerontology 49 (4), M153–M159.

Owsley, C., McGwin Jr., G., Ball, K., 1998. Vision impairment, eye disease, and injurious motor vehicle crashes in the elderly. Ophthalmic Epidemiology 5 (2), 101–113.

Posner, M.I., 1980. Orienting of attention. Quarterly Journal of Experimental Psychology 32, 3–25.

Posner, M.I., Cohen, Y.A., 1984. Components of visual orienting. In: Bouma, H., Bouwhuis, D.G. (Eds.), Attention and Performance X. Erlbaum, Hillsdale. NJ.

Posner, M.I., Petersen, S.E., 1990. The attention system of the human brain. Annual Review of Neuroscience 13, 25–42.

Rueda, M.R., Rothbart, M.K., McCandliss, B.D., Saccomanno, L., Posner, M.I., 2005. Training, maturation, and genetic influences on the development of executive attention. Proceedings of the National Academy of Sciences of the United States of America 102 (41), 14931–14936.

Seeman, P., 2007. Dopamine and schizophrenia. Scholarpedia 2(10), 3634. http://www.scholarpedia.org/article/Dopamine_and_schizophrenia.

Sims, R.V., McGwin Jr., G., Allman, R.M., Ball, K., Owsley, C., 2000. Exploratory study of incident vehicle crashes among older drivers. The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences 55 (1), M22–M27.

Sims, R.V., Owsley, C., Allman, R.M., Ball, K., Smoot, T.M., 1998. A preliminary assessment of the medical and functional factors associated with vehicle crashes by older adults. Journal of the American Geriatrics Society 46 (5), 556–561.