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Evaluation of Older Driver Fitness-to-Drive Metrics and Driving Risk Using Naturalistic Driving Study Data

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ABSTRACT

In this study, we evaluated the relationship between older drivers' fitness assessment profiles and their driving risk, represented primarily by crash and near-crash (CNC) rate, and secondarily by high g-force (HGF) event rate, all recorded during a naturalistic study of senior drivers. Due to the relatively small sample size in this pilot investigation (20 primary drivers), principal component analysis was used for dimension reduction and classification of the 60 total fitness profile metrics. Negative binomial regression models were employed to model the CNC and HGF events. The results indicated that contrast sensitivity measures were significantly associated with CNC rate. The greater the sensitivity, the lower the CNC rate, as would be the expected nature of that association. In the HGF event analysis, we found that CNC rate was positively related to HGF rate. The fitness metric contrast sensitivity was also related to HGF event rate. In addition, two metrics related to metacognition, a measurement of one's perception of one's own cognitive status, were associated with HGF event rate. Higher HGF rates were associated with greater self-rating of cognitive status as well as greater disparities between that same self-rating and an objective metric of cognitive status. The results of this study provide crucial information on the metrics and protocols which could be applied by motor vehicle departments, physicians, occupational therapists, Certified Driving Rehabilitation Specialists, and others for whom determining seniors' fitness to drive is an important component of their work. Further, these results can be further investigated and validated using the much larger database of senior driver data collected in the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study.

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CHAPTER 1. INTRODUCTION AND BACKGROUND

The fitness-to-drive of seniors has been under discussion since at least the 1950s. In a letter to the editor of the *British Medical Journal*, Martin Stratford, presumably a general practitioner (GP), laments being put between the ostensibly competing interests of the insurance company and the elderly driver and his or her family. He suggests that an independent and specifically trained physician would be better suited to make the fitness-to-drive determination, or at least that the GPs who currently make such decisions be furnished with a better, more objective set of tools for this purpose (Stratford, 1959). This is remarkable because the identical concerns articulated in his letter are still very much with us and largely unresolved more than a half century later. Some forty years after the appearance of Stratford's letter, Marshall and Gilbert (1999) conducted a survey of physicians in Saskatchewan, Canada, who were likely to be involved in making fitness-to-drive determinations. They found that while 57.6% of the respondents indicated that they do not hesitate to report patients whom they believe to be medically unfit to drive, an even greater percentage (59.5%) felt as Stratford did, that while necessary, this type of reporting harms the physician-patient relationship. Although physicians around the turn of the century did have better tools and information available than Stratford and his peers, Marshall and Gilbert still concluded that physicians' understanding regarding the relationship between specific medical conditions and the resulting increments in driving risk tended to be poor.

This study is a direct follow-up to the work of Antin, Lockhart, Stanley, and Guo (2012), in which the fitness profiles of seniors who were still driving were compared with those of a matched cohort of seniors who had recently ceased driving in an effort to devise fitness-to-drive assessment models. Results of that study showed that the fitness profiles of the drivers and non-drivers were, not surprisingly, very different, with the drivers demonstrating better functional abilities than their non-driving counterparts for virtually all the metrics where there was a statistically significant difference. In addition, Antin et al. (2012) developed parsimonious models to see if driver or non-driver group membership could be predicted based solely upon the individual's fitness profile. A five-factor model was 100% successful at predicting group membership. An even more parsimonious three-factor model was nearly perfect at predicting group membership; this model included the following factors (Table 1):

Table 1. Three-factor driver/non-driver categorization model factors (from Antin et al., 2012).

Functional Dimension	Factors
Perceptual – Vision	Dynamic visual acuity (24°/s)
Physical – Strength	Average Upper Body Maximum Torque
Visual-Cognitive	Trail Making (Part B)

1.1 OBJECTIVE

The current study sought to determine if the profile data used in Antin et al. (2012) could also be used to successfully predict safety-related outcomes observed in that same study's naturalistic driving record. To the best of the authors' knowledge, this study represents the first ever attempt to relate seniors' functional assessments to safety-related outcomes observed in naturalistic driving data. In the current study, the safety-related data include crash and near-crash (CNC) event rates as well as high g-force (HGF) event rates.

1.2 DATA OVERVIEW

Note that among 27 initially recruited driving participants who provided assessment data, only 20 of them completed the naturalistic driving study (NDS) data collection. The data sources used and which data were provided by each group are illustrated in Table 2.

Table 2. Project data source structure.

	Number of Participants with…	
Participant Group	**Functional Assessment Metrics**	**NDS Data**
Drivers	27	20
Non-drivers	23	–
Totals	**50**	**20**

There are 80 CNC events, including 6 crashes and 74 near-crashes, found in the 4,158 driving hours for these 20 drivers. As crashes are a rare event, Guo et al. (2010) suggested that near-crashes (which tend to occur with a frequency 10 times that of crashes) are valid crash surrogates. In this analysis, we combined crash and near-crash events to represent crash risk.

However, even when near-crashes are included, crash-related events are still relatively rare. Therefore, we were also interested in a more frequently occurring safety-related event, high g-force (HGF) events. HGF events include longitudinal and/or latitudinal acceleration or deceleration, and rapid change of driving direction (yaw rate). Guo and Fang (2013) showed that critical incidents are closely associated with CNC risk at the driver level. In this study, we used HGF to represent the risky driving behaviors. In summary, this study mainly focuses on exploring the relationship between senior driver fitness profiles and CNC events and, secondarily, their relationship to HGF events.

CHAPTER 2. DATA

2.1 FITNESS PROFILE DATA

Sixty fitness-to-drive assessments were performed as the first step in the study (and the only step for the non-drivers); these are listed in Appendix A. In this analysis, 12 of the 60 metrics (i.e., the seven color vision metrics and left eye contrast sensitivity [CSL] metrics) were dropped from the analyses for various reasons. For example, the color vision metrics have essentially identical values for almost all participants, thus providing no modeling-relevant information; the CSL metrics are suspected to possibly have data quality issues and must be explored further to be used in any subsequent analyses. Details of the 48 metrics used are shown in Appendix A. The 48 remaining assessment metrics measured from the 50 participants (27 drivers, 23 non-drivers) were included in the analyses. Note that among the 27 participants in the "drivers" category who contributed assessment data, only 20 of those individuals actually participated as drivers in the naturalistic driving data collection and were included in the driving-risk-related modeling.

There are several missing values in the fitness profile data. A complete data analysis that only includes participants with a full data record would greatly reduce the sample size. Therefore, a data imputation approach was used whereby missing values were replaced with the means drawn from the non-missing values. Because Antin et al. (2012) suggested that older driver and non-driver groups may have very different fitness profiles, the missing values were therefore imputed by the group mean of either drivers or non-drivers, depending on which group the individual represented.

2.2 CRASH AND NEAR-CRASH (CNC) EVENT DATA

A *crash* is defined as any contact with an object, either moving or fixed, at any speed in which kinetic energy is measurably transferred or dissipated. Crashes include a participant's vehicle making contact with other vehicles, roadside barriers, objects on or off the roadway, pedestrians, cyclists, or animals. A *near-crash* is defined as any circumstance requiring a rapid, evasive maneuver by the participant (or his/her vehicle) or any other vehicle, pedestrian, cyclist, or animal to avoid a crash. The crashes and near-crashes were identified through a multiple-step process of automatic trigger identification followed by visual confirmation by experts as described in Dingus et al. (2006).

2.3 HIGH G-FORCE (HGF) EVENT DATA

The HGF data are recorded by accelerometers installed in participants' vehicles. The accelerometers measured longitudinal and latitudinal acceleration at a temporal resolution of 10 Hz. The direction of the g-force is indicated by the "plus or minus" sign "±". There are over 127.5 million syncs in the 3,542 hours of recorded g-force data. Because of the high sensitivity of the accelerometers, g-force values often fluctuate rapidly. This impacts identification of HGF events, as they are defined such that each begins when the g-force value first exceeds a predetermined threshold and ends when the value returns below the threshold. Rapid fluctuation will unnecessarily result in an excessive number of HGF events caused by noise in signals.

A remedy is to apply a smoothing method to reduce the number of spurious events in the data. In this study, we employed the centered moving average (CMA) method with a moving window of 10 syncs. There is a trade-off in choosing the moving window: too small a window cannot effectively remove spurious HGF events; too large a window will mask actual HGF events of interest. The SAS EXPAND procedure with the (CMOVAVE *n*) command was used to compute the centered moving average. It computed the mean of *n* values of X_i for observation $\mathrm{t} - (\mathrm{n} - 1)/2 \leq \mathrm{i} \leq \mathrm{t} + (\mathrm{n} - 1)/2$. Because n = 10 is an even number, the formula will compute the mean of X_i's for $\mathrm{t} - 4 \leq \mathrm{i} \leq \mathrm{t} + 4$ (i.e., 9 entries). The 10-sync averaged g-force value in a particular sync *t* is computed as:

$$X_t^{CMA10} = \frac{X_{t-4}+X_{t-3}+\cdots+X_t+\cdots+X_{t+3}+X_{t+4}}{9}$$

A graphical example with 200 syncs taken from a trip file is shown in Figure 1 to demonstrate the smoothing effect. The raw data have a high frequency component that would yield an excessive number of false safety events. The data after the CMA is applied are much smoother, while still retaining sufficient detail. The figure shows that four HGF events will be identified (during sync number 3904–3924) when *raw* data are evaluated, whereas there will be only one HGF event identified if using CMA *smoothed* data.

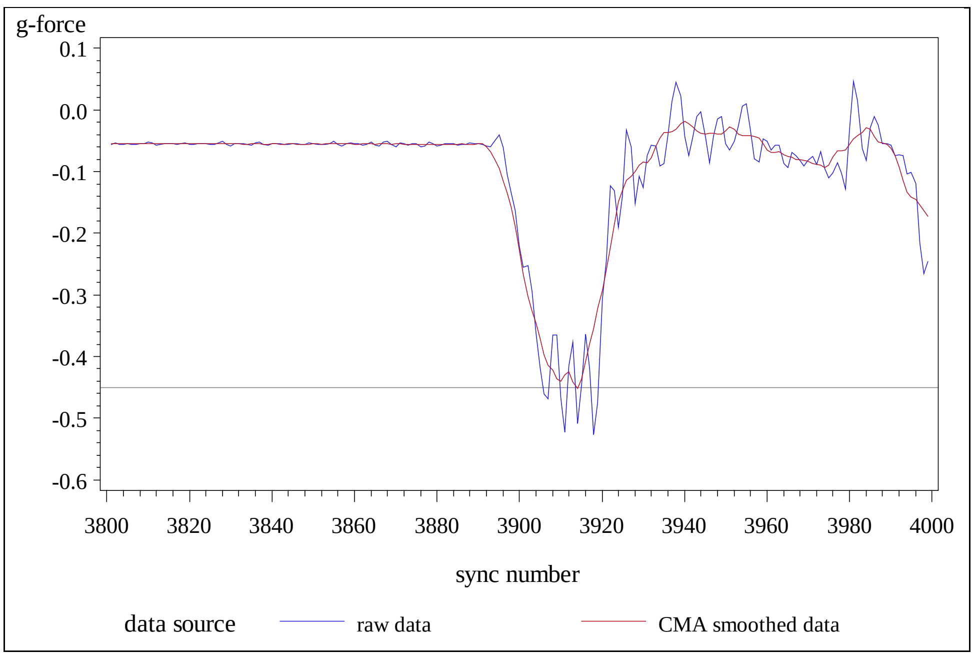

Figure 1. Graph. Example of the effect of the application of CMA10 smoothing on a sample of HGF data.

Another major challenge with HGF events is defining the threshold g-force values. Compared with the identification of CNC events, which relies on police reports, self-reports, algorithms, and video reduction, the identification of HGF events solely relies on the accelerometer data, and there is currently no standardized g-force threshold to define an HGF event. Thus, a trial-and-error approach was employed to choose a reasonable threshold. In all, we evaluated four combinations of threshold values as shown in Table 3.

In the preliminary analysis, we investigated longitudinal HGF, latitudinal HGF, and combined HGF events. The combined HGF events are defined such that either longitudinal or latitudinal (or both) exceed threshold values. Results suggested that the events in one dimension (longitudinal or latitudinal only) did not yield stable HGF event counts, while combined HGF events did yield more reliable, robust performance.

After four trials, we proposed the thresholds for HGF events as longitudinal ±0.45g and latitudinal ±0.45g. With this threshold, there were from 0 to approximately 100 HGF events for each driver, which is a reasonably good set of numbers for the subsequently developed negative binomial regression models.

Table 3. Summary of HGF threshold trials.

Threshold Values	Reasoning	Results
Long.: ± 0.2g Lat: ±0.1g	Use low values for older drivers	Ca. 5,000 to 50,000 HGF events for each driver
Long.: 0.35–0.45g Lat: ±0.4g	Adapted from Simons-Morton et al. (2012)	Ca. 100 to 2,500 HGF events for each driver
Long.: ± 0.6g Lat: ±0.7g	Adapted from Guo et al. (2010)	Too few HGF events identified
Long.: ± 0.45g Lat: ±0.45g	Trial and error	This is the combined threshold that was used in this analysis

2.4 CRASH/NEAR CRASH AND HIGH G-FORCE DATA BY DRIVER

The driving risk was measured by the CNC and HGF. The CNC and HGF rates are defined as the number of events per 100 hours of driving. Note that two drivers (subject IDs 1151 and 1171) have substantially higher HGF event rates (428.32 and 113.41 HGF events per 100 hours driven) compared with the other participants. Considering that older drivers typically demonstrate more conservative driving behaviors, such high HGF rates likely result from errors in the mounting or functioning of the accelerometer subassembly. Therefore, data from these participants were removed from further HGF event analysis. As shown in Table 4, there are 1,245 HGF events identified for the remaining 18 drivers. HGF rates are plotted across a lowest-to-highest ordered plot of CNC rates in Figure 2. A scatter plot of HGF and CNC rates is shown in Figure 3.

Table 4. CNC and HGF event summary table.

Driver ID	Gender	Hours Driven	CNC Events	CNC Rate	HGF Events	HGF Rate
1011	M	199.3	0	0.00	77	38.63
1021	M	59.7	2	3.35	20	33.52
1031	F	302.0	4	1.32	60	19.87
1041	M	313.3	10	3.19	252	80.43
1051	M	436.9	18	4.12	222	50.81
1061	M	184.6	2	1.08	31	16.80
1071	M	340.7	2	0.59	51	14.97
1081	M	437.6	9	2.06	118	26.97
1091	F	128.2	6	4.68	57	44.46
1101	M	114.2	2	1.75	60	52.56
1111	F	115.8	2	1.73	75	64.80
1121	M	369.1	2	0.54	54	14.63
1131	F	102.2	6	5.87	29	28.37
1141	F	39.7	1	2.52	3	7.55
1151	M	192.4	4	2.08	–	–
1161	F	69.1	1	1.45	28	40.53
1171	F	268.3	3	1.12	–	–
1181	F	189.4	2	1.06	41	21.65
1191	M	184.1	2	1.09	32	17.38
1201	F	111.2	2	1.80	35	31.47
Total	**–**	**4,158**	**80**	**–**	**1,245**	**–**

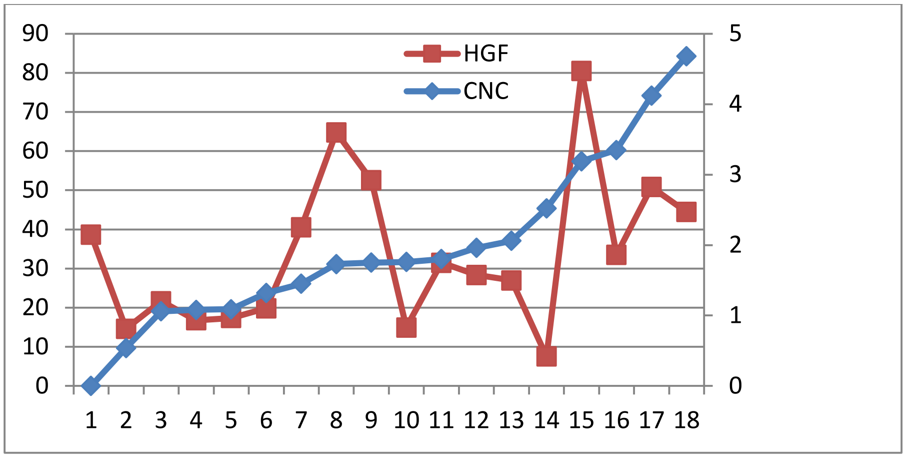

Figure 2. Graph. CNC (right y-axis) & HGF (left y-axis) rates (ordered by lowest to highest CNC rate) for each of the 18 remaining driving participants.

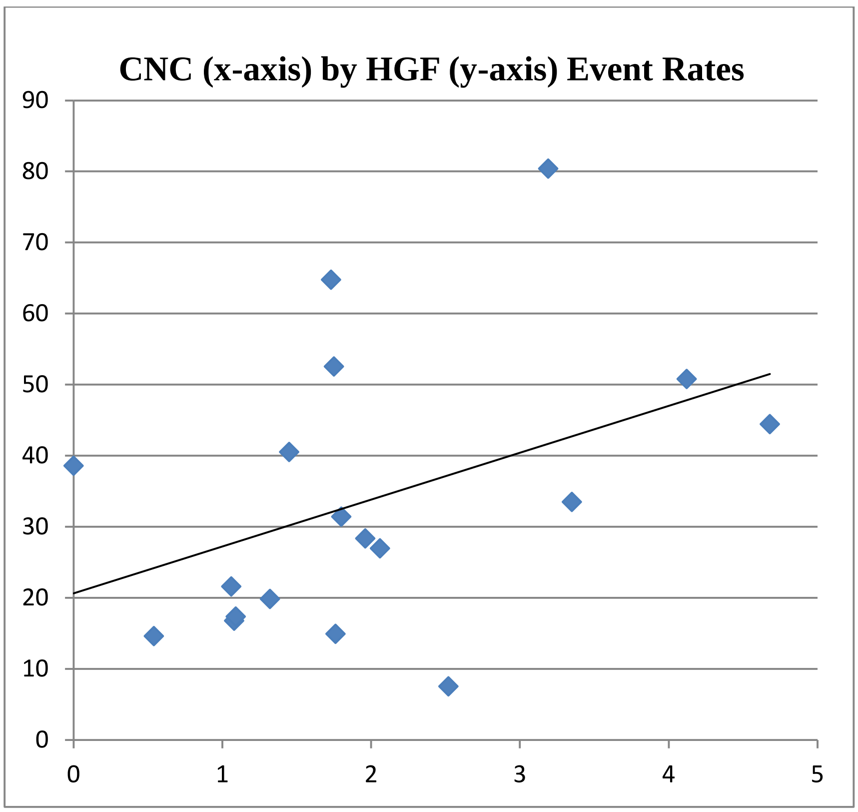

Figure 3. Graph. CNC by HGF scatter plot with linear trend line (*r* = 0.41, *p* = 0.0891).

CHAPTER 3. STATISTICAL METHODS

3.1 DIMENSIONALITY REDUCTION: PRINCIPAL COMPONENT ANALYSIS

Fitness profiles (Appendix A) comprised 48 assessment metrics (P = 48 columns) and 50 participants (N = 50 rows). Many of these metrics are highly correlated, as they measure very similar or related constructs. When performing the regression analysis, it is not possible to include all metrics as regressors, mainly because (1) the number of observations N is similar to than the number of regressors P; and (2) there is a severe multicollinearity issue due to the high correlations among many of the fitness metrics.

To address this issue, we applied principal component analysis (PCA) to reduce the dimensionality of the redundant and correlated fitness profile data (Jolliffe, 2002). PCA uses orthogonal transformation to convert correlated metrics into a set of uncorrelated principal components (PCs), which are linear combinations of optimally weighted observed metrics. The first PC has the highest variance and accounts for the highest proportion of the variability of the data. Each succeeding component in turn has the highest possible variance among the remaining components, while maintaining orthogonality with preceding components.

The advantages of PCA include: (1) it maximizes the useable information in the data through the dimension reduction activity; (2) the derived PCs are not correlated, which eliminates the multicollinearity issue in subsequent modeling; and (3) the factor loading pattern of the PCs can help detect which metrics are closely related and have significant impact on a particular PC.

3.2 MODELING CNC AND HGF EVENTS USING NEGATIVE BINOMIAL REGRESSION

Preliminary analysis has shown that the CNC event data have a moderate variance over-dispersion issue (chi-square/degree of freedom [DF] value at 1.7~2.0), while HGF data have an even more severe problem in this area (chi-square/DF larger than 10).

Negative binomial (NB) regression can be used to model over-dispersed count data (e.g., HGF events). For data with moderate over-dispersion, the additional dispersion parameter in the NB regression model accounts for extra heterogeneity much better (the chi-square/DF values for NB models are typically < 1.4). Therefore, NB regression was adopted to model both CNC and HGF events. In NB models, the number of CNCs or HGFs is assumed to follow a negative binomial distribution,

$$\mathrm{Y_i} \sim \mathrm{NB}(\mathrm{E_i}\lambda_\mathrm{i}, \gamma)$$

$$\text{with } \mathrm{E(Y_i)} = \mathrm{E_i}\lambda_\mathrm{i},\ \mathrm{Var(Y_i)} = \mathrm{E_i}\lambda_\mathrm{i} + (\mathrm{E_i}\lambda_\mathrm{i})^2 \times \gamma,$$

where Y_i is the number of CNCs or HGFs for driver i. λ_i is the expected CNC or HGF rate (the number of events per 100 hours driven) for driver i. The exposure E_i is measured by the number of hours driven, measured in a unit of 100 hours. γ is the dispersion parameter; when γ

converges to 0, the variance of Y converges to the mean of Y, and the NB model converges to a Poisson model.

The expected CNC or HGF rate λ_i (per 100 hours driven) follows as:

$$\log(\lambda_i) = \beta_0 + \sum_{j=1}^{J} \beta_j X_{ij},$$

where X_{ij} is the j^{th} covariate, typically the PC for driver *i*; the β's are the regression coefficients. For regression models with a single PC, J = 1.

CHAPTER 4. CNC ANALYSIS RESULTS

A principal component regression (PCR) was conducted in which a PCA was used to reduce the dimensionality of the covariate matrix and followed by NB regression. The details of PCA for all 50 participants and 48 metrics is presented in Section 4.1. The subsequent NB regression models identified one PC that is significantly related to CNC risk. In Section 4.2, we use the five significant metrics identified in section 4.1 to conduct another round of PCR. Section 4.3 describes the use of NB regression analysis to screen all 48 individual metrics to recover any metrics that are individually significant but are not included the PCs in sections 4.1 and 4.2. In sections 4.4 and 4.5, we finalize the CNC analysis by proposing a final model and discussing the model's properties.

4.1 PCA AND NB REGRESSION ON 48 METRICS

4.1.1 PCA

The first step of PCA is to identify significant principal components for the set of correlated metrics. The eigenvalue-one criterion was used to choose the important or information-rich PCs (i.e., ones with eigenvalue > 1, Kaiser, 1960).

Although the PCA technique reduces the dimensionality of the covariate matrix, it is constrained by the ratio of N/P (i.e., the ratio between sample size and the number of variables). In general, N/P should be at least 2 and ideally be greater than 5 to 10 for the PCA to perform well. The fitness profile data comprise N = 50 participants and P = 48 assessment metrics. Therefore, it is not appropriate to conduct PCA for all metrics simultaneously. To overcome this obstacle, we divided the fitness metrics into four categories by the nature of the metrics: (1) physical ability, (2) visual ability, (3) health, and (4) cognitive ability. PCA was conducted for each of these categories and the N/P ratio was at least 2.

The PCs for each category identified by PCA are shown in Table 5–Table 8. There are three, seven, three, and three significant PCs for each category, respectively. These PCs account for 73%, 74%, 59%, and 75% of total variability for each category of data. In this study, we labeled these components as physical component 1–3, visual component 1–7, general health component 1–3, and cognitive component 1–3.

Table 5. Principal components for physical ability.

Component	Eigenvalue	Proportion Total Variability	Cumulative Proportion Total Variability
1	6.41	0.49	0.49
2	1.68	0.13	0.62
3	1.36	0.10	0.73

Table 6. Principal components for visual ability.

Component	Eigenvalue	Proportion Total Variability	Cumulative Proportion Total Variability
1	4.34	0.23	0.23
2	2.68	0.14	0.37
3	1.82	0.10	0.47
4	1.50	0.08	0.54
5	1.36	0.07	0.62
6	1.22	0.06	0.68
7	1.06	0.06	0.74

Table 7. Principal components for general health.

Component	Eigenvalue	Proportion Total Variability	Cumulative Proportion Total Variability
1	2.49	0.25	0.25
2	1.77	0.18	0.43
3	1.62	0.16	0.59

Table 8. Principal components for cognitive ability.

Component	Eigenvalue	Proportion Total Variability	Cumulative Proportion Total Variability
1	1.86	0.31	0.31
2	1.51	0.25	0.56
3	1.16	0.19	0.75

4.1.2 Negative Binomial Regression

Negative binomial regression was used to model the relationship between CNC rate and each of 16 PCs respectively. Results indicate that only one PC (the Visual-1 component) has statistically significant impacts on CNC rate.

The factor loading pattern of the metrics for the significant component (with respect to the NB model) is listed in Table 9. The magnitude (ranging between 0–100) of the numbers indicates the factor loading (relative contribution) of each metric for that particular component. The positive or negative sign of the numbers indicates the positive or negative relationship between the metric and the component. The metrics with magnitude greater than 40 (marked with an asterisk) are considered to have a substantial contribution to the particular component (Stevens, 1986). This way we can group the metrics based on their similar contributions to a particular component.

Table 9. Factor loading pattern of Visual-1 component.

Metric	Visual-1	
DVAC2	4	
DVAC4	7	
DVAC6	9	
DGR	-1	
Glare Acuity	16	
Glare CS 1	10	
Glare CS 2	-15	
Glare CS 3	2	
ACUITY	-22	
CSR 1.5	87	*
CSR 3	85	*
CSR 6	85	*
CSR 12	76	*
CSR 18	53	*
Color Sum	14	
OPT1	5	
OPT2	10	
OPT3	24	
OPT4	8	

From Table 9, we identified five metrics with substantial contributions to the Visual-1 component. The summary is shown in Table 10.

Table 10. Significant component and assessment metrics in NB regression.

Component	Number of significant metrics	Significant metrics with substantial factor loading
Visual-1	5	Right Eye Contrast Sensitivity (CSR 1.5, CSR 3, CSR 6, CSR 12, CSR 18)

In summary, PCA reduced the dimension of the fitness profile from 48 metrics to 16 PCs in four categories. Negative binomial regression indicated that one PC in the visual ability category has a significant relationship with the CNC rate. Five fitness assessment metrics have substantial contributions in the Visual-1 component.

4.2 PCA AND NB REGRESSION ON FIVE METRICS

The Visual-1 component identified in Section 4.1 contains a large number of metrics with minor contributions to the PC. If a metric is retained in the component, its value is required in order to compute the PC score in the future, even when it has only a minor contribution. These metrics with minor contributions do not lend much to the analysis. Therefore, we performed PCA with only the five significant metrics listed in Table 9. There is only one PC generated (Table 11); this is consistent with the result in Table 10. This PC accounts for 67% of the total variability.

Table 11. Principal component for five metrics.

Component	Eigenvalue	Proportion	Cumulative
PC-1	3.36	0.67	0.67

The factor loading pattern of the PC is listed in Table 12. The result indicated that all five metrics contributed significantly to only one PC with eigenvalue greater than 1. This is consistent with the results in Table 9. The grouping outcome can help to determine which metrics are closely related.

NB regression was performed on the newly generated PC. Results show that PC-1 is significantly related to CNC rate. The metrics with substantial contributions are summarized in Table 12. PC-1 represents right eye contrast sensitivity across all the spatial frequencies measured from 1.5 to 18 cycles per degree.

Table 12. Factor loading pattern of principal component.

Metric	PC-1	
CSR 1.5	79	*
CSR 3	78	*
CSR 6	91	*
CSR 12	90	*
CSR 18	72	*

4.3 NB REGRESSION SCREENING ON 48 METRICS

In Sections 4.1 and 4.2, the NB regression analyses were based on principal components. Because the four categories in Section 4.1 were predefined by the researchers, it is possible that the categorization was not optimal. There may be some individual metrics that are individually significant (with respect to the NB model) but that are not included in important components, or the important component is not statistically significant (with respect to the NB model). Either way, the potential significant metric will be masked in the PCs. To recover any potential significant metrics that are masked by the procedures discussed in Sections 4.1 and 4.2, we used NB models to screen all 48 metrics individually.

The NB regression analyses were performed on each of 48 individual metrics. Among 48 metrics, only 3 metrics (CSR 1.5, CSR 6, CSR 12) are individually significant (*p*-value smaller than 0.05). Note that CSR 3 and CSR 18 are in the principal components in Sections 4.1 and 4.2, but are not individually significant. However, because the five CSR measures are an integrated part in the fitness profile test and are highly related (Table 13), we chose to keep CSR 3 and CSR 18 in the model in order to stabilize the PCA computation and enhance the interpretability of the results.

Table 13. Correlation matrix of five CSR measures.

	CSR 1.5	CSR 3	CSR 6	CSR 12	CSR 18
CSR 1.5	1	0.69 (< .001*)	0.60 (< .001)	0.57 (< .001)	0.36 (.010)
CSR 3		1	0.69 (< .001)	0.52 (< .001)	0.27 (.062)
CSR 6			1	0.79 (< .001)	0.59 (< .001)
CSR 12				1	0.76 (< .001)
CSR 18					1

*The numbers inside parentheses are *p*-values.

4.4 PROPOSED MODEL FOR CNC ANALYSIS

The results of the analyses thus far indicate that, among 48 older driver fitness-to-drive profile matrices, only five metrics related to the right-eye contrast sensitivity (CSR 1.5, 3, 6, 12, 18) have a statistically significant impact on CNC rate ($p < 0.05$). One principal component generated by these five metrics accounts for 67% of total data variability (Table 11 and Table 12). Therefore, we propose this model (Section 4.2) to be our best model for CNC data analysis.

The NB model estimation results for the proposed model are shown in Table 14–Table 17. Table 15 and Table 16 indicate that the PC is statistically significant in the regression model ($p < 0.05$). The CNC risk rate ratio is shown in Table 17. As the value of PC increases by 1 unit, the CNC risk rate decreases by 23%. The higher or better the contrast sensitivity score is, the lower the associated CNC risk.

Table 14. Model goodness-of-fit for proposed model.

Criterion	DF	Value	Value/DF
Deviance	18	22.92	1.27
Scaled Deviance	18	22.92	1.27
Pearson Chi-square	18	24.91	1.38
Scaled Pearson X2	18	24.91	1.38
Full Log Likelihood		-42.82	
Akaike Information Criterion (AIC) (smaller is better)		91.64	
Bayesian Information Criterion (BIC) (smaller is better)		94.63	

Table 15. Parameter estimation for proposed model.

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		*p*-value
Intercept	1	0.585	0.148	0.296	0.875	< 0.001
Component-1	1	-0.263	0.103	-0.465	-0.061	0.011
Dispersion	1	0.086	0.145	0.003	2.385	

Table 16. LR statistics for Type III analysis.

Parameter	DF	Chi-square	P-value
Component-1	1	4.49	0.034

Table 17. Risk rate ratio for proposed model.

Risk Rate Ratio	95% Lower Confidence Limit (LCL)	95% Upper Confidence Limit (UCL)
0.769	0.628	0.941

4.5 CALCULATION OF PREDICTED RISK RATE BASED ON PROPOSED MODEL PARAMETERS

To predict the CNC risk rate for future data, the first step is to obtain measurements of CSR 1.5, 3, 6, 12, and 18 (here written as $x_{1,future}$ to $x_{5,future}$). The principal component score for this observation is computed by summing the products of the standardized scoring coefficient α_i and the standardized values of x_{0i}.

$$PC_{future} = \sum_{i=1}^{5} \alpha_i \times \frac{x_{i,future} - \bar{x}_i}{s_i},$$

where α_i is the standardized scoring coefficient for the i^{th} metric; $\bar{x}_i$ and s_i are the mean and standard deviation of the i^{th} metric. Table 18 shows the coefficients for $\alpha_i, \bar{x}_i,$ and s_i derived in the current study. They can be used to calculate the PC value for data collected in the future.

Table 18. Coefficients for computing PC Score for CNC proposed model.

Metric	α_i	$\bar{x}_i$	s_i
CSR 1.5	0.234	4.440	0.907
CSR 3	0.231	4.880	1.350
CSR 6	0.270	3.640	1.156
CSR 12	0.267	2.720	1.429
CSR 18	0.214	1.920	1.794

The predicted CNC risk rate (i.e., the number of CNC events per 100 hours driven) is computed as:

$$\text{CNC rate}_{pred} = \exp(\beta_0 + \beta_1 \times PC_{future}),$$

where β_0 and β_1 are the estimated regression coefficients presented in Table 15 above.

CHAPTER 5. HIGH G-FORCE ANALYSIS RESULTS

The HGF event analysis was performed in a similar manner to the CNC analysis described above. To construct statistical models for HGF events, the first step is to screen and identify HGF events from raw data. In section 5.1, we model the relationship between CNC rate and HGF rate using NB regression modeling. In section 5.2, we use NB regression to model the relationship between HGF rate and the 16 PCs generated in the PCA part of Section 4.1. In Section 5.3, we use the eight significant metrics identified in section 5.2 to conduct PCR. Section 5.4 describes the use of NB regression analysis to screen through all 48 metrics to recover any metrics that are individually significant but that are not included in the PCs in sections 5.2 and 5.3. In section 5.5, we finalize the HGF analysis by proposing a final model and discussing the model's properties.

5.1 THE RELATIONSHIP BETWEEN CNC AND HGF EVENT RATE

Both CNC and HGF events are undesired safety outcomes and it is of interest to explore the relationship between them. It is widely accepted that the CNC rate directly reflects driving risk under any particular set of circumstances. Whether high g-force events indicate potentially dangerous or higher risk driving behavior is still up for debate. Several studies have shown that high g-force events or critical incidents are a predictor for CNC (Guo and Fang, 2013; Simons-Morton et al., 2012). Others argue that drivers who drive a sports car may tend to have more HGF events, attributable more to driving style than a genuine increase in driving risk. In the case of the older driver population, which tends to have a more conservative driving style, increased HGF event rates may truly reflect their physical and mental states rather than an aggressive driving style (though the final impact on safety may be similar).

We assessed whether there is a connection between CNC rate and HGF rate among older drivers. The scatter plot (Figure 4; data labels correspond to the index in Table 4) indicates a strong positive trend between CNC rate and HGF rate. We use negative binomial regression to model such a relationship. The response variable is the CNC frequency, and the covariate is the HGF event rate.

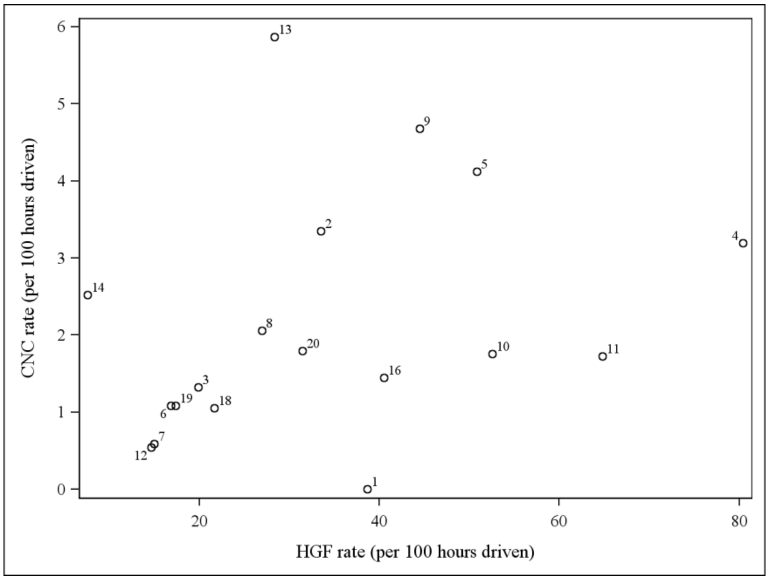

Figure 4. Graph. Scatter plot of CNC rate vs. HGF rate.

Model results are shown in Table 19 –Table 22. Table 19 details the negative binomial model's goodness of fit. Table 20 and Table 21 indicate that the CNC rate is strongly associated with the HGF rate (p-values less than 0.05). The risk rate ratio of CNC risk is shown in Table 22. It indicates that as the value of the HGF rate increases by 1 unit, the CNC risk rate increases by 1.8%. This indicates that a higher HGF rate is associated with a higher CNC risk.

Table 19. Goodness-of-fit for negative binomial model.

Criterion	DF	Value	Value/DF
Deviance	16	19.30	1.21
Scaled Deviance	16	19.30	1.21
Pearson Chi-square	16	19.94	1.25
Scaled Pearson X2	16	19.94	1.25
Full Log Likelihood		-38.94	
AIC (smaller is better)		83.87	
BIC (smaller is better)		86.55	

Table 20. Parameter estimation for NB model comparing CNC and HGF rates.

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		*p*-value
Intercept	1	0.010	0.340	-0.656	0.677	0.976
HGF rate	1	0.018	0.008	0.002	0.033	0.024
Dispersion	1	0.148	0.146	0.021	1.031	

Table 21. LR statistics for Type III analysis, CNC rate vs. HGF rate.

Parameter	DF	Chi-square	Pr > Chi-square
HGF rate	1	4.02	0.045

Table 22. Risk rate ratio for NB model comparing CNC and HGF rates.

CNC Risk Rate Ratio	95% LCL	95% UCL
1.018	1.002	1.034

5.2 NB REGRESSION ON 16 INDIVIDUAL PCS

We used NB regression to model the relationship between HGF rate and each of 16 PCs identified in Section 4.1, which represent 48 fitness profile metrics across four categories. The results indicate that the principal components Cognitive-1 (*p*-value = 0.004) and Visual-5 (*p*-value = 0.016) are significant, and Visual-1 (*p*-value = 0.063) has a *p*-value close to 0.05. The factor loading patterns (Table 23 and Table 24) indicate that nine fitness profile metrics (marked by an asterisk) make a significant contribution to these three PCs.

Table 23. Factor loading pattern of Visual-1 and Visual-5 components.

Metric	Visual-1		Visual-5	
DVAC2	4		-8	
DVAC4	7		11	
DVAC6	9		-5	
DGR	-1		-33	
Glare Acuity	16		-50	*
Glare CS 1	10		-4	
Glare CS 2	-15		6	
Glare CS 3	2		-15	
ACUITY	-22		-3	
CSR 1.5	87	*	16	
CSR 3	85	*	5	
CSR 6	85	*	-4	
CSR 12	76	*	-4	
CSR 18	53	*	-25	
Color Sum	14		89	*
OPT1	5		25	
OPT2	10		10	
OPT3	24		-27	
OPT4	8		20	

Table 24. Factor loading pattern of Cognitive-1 component.

Metric	Cognitive-1	
Cog	2	
Meta	96	*
Ratio	95	*
MI	-5	
UFoV	14	
TM	-14	

5.3 PCA AND NB REGRESSION ON NINE METRICS

The PCA is performed on the nine metrics identified in Section 5.2. The factor loading patterns (Table 25) indicate three distinguishable PCs. The NB multiple regression is performed on all seven combinations of PCs (Table 26). Based on AIC, the BIC criteria, and the likelihood ratio test, Model 4 (with PC 2, 3) is the best model. The contributing metrics include Meta, Ratio, CSR 18, Glare Acuity, and Color Sum.

Table 25. Factor loading patterns for nine metrics, before variable screening.

Metric	PC-1		PC-2		PC-3	
CSR 1.5	82	*	-4		21	
CSR 3	80	*	22		14	
CSR 6	90	*	2		-11	
CSR 12	87	*	-4		-21	
CSR 18	67	*	-16		-48	*
Glare Acuity	23		12		-65	*
Color Sum	26		-4		77	*
Meta	0		95	*	-1	
Ratio	2		94	*	-13	

Table 26. NB regression model selection result.

Model	PC in the model	Significant PC	AIC	BIC	-2 log likelihood	Pearson chi-square/DF	Dispersion parameter
1	1,2,3	2	171.33	175.78	161.34	1.26	0.15
2	1,2	1	171.68	175.24	163.68	1.11	0.18
3	1,3	None	–	–	–	–	–
4	2,3	2, 3	170	173.56	162	1.15	0.16
5	1	None	–	–	–	–	–
6	2	None	–	–	–	–	–
7	3	3	172.19	174.86	166.2	1.26	0.21

5.4 NB REGRESSION SCREENING USING 48 METRICS

Similar to Section 4.3, we performed NB regression to recover any potentially significant metrics masked during PCA. The response variable is HGF frequency, and the covariate is each of 48 metrics. Results show that five individual metrics are statistically significant: Upper I RT (p-value = 0.019), Upper P RT (p-value = 0.020), CSR 1.5 (p-value = 0.019), CSR 3 (p-value = 0.03), and Color Sum (p-value = 0.012). In addition, two metrics have p-values close to 0.05: Meta (p-value = 0.06) and Ratio (p-value = 0.075). Note that CSR 18 and Glare Acuity are not significant by themselves, although they are contributing metrics in the PCs.

5.4.1 PCA and NB Regression on Nine Metrics after Variable Screening

We then performed PCA on the nine important metrics mentioned above. The factor loading patterns (Table 27) show four PCs. The NB regression results on all 15 combinations of PCs are shown in Table 28. AIC, BIC, and LRT criteria all suggest that Model 9 (with PC-2 and PC-3) is the best model. Note that although the results from Model 11 are significant, we did not include PC-3 and PC-4 in the final because these two metrics are not individually significant (Model 14, 15). The most important five metrics contributing to PC-2 and PC-3 are CSR 1.5/3/18, Meta, and Ratio.

Table 27. Factor loading patterns for nine metrics, after variable screening.

Metric	PC-1		PC-2		PC-3		PC-4	
Upper I RT	97	*	-3		-3		-13	
Upper P RT	99	*	-5		-8		-1	
CSR 1.5	-10		90	*	-9		-5	
CSR 3	6		87	*	18		3	
CSR 18	-16		50	*	-16		51	*
Color Sum	-15		35		-7		-76	*
Glare Acuity	-22		21		10		71	*
Meta	-8		2		95	*	-1	
Ratio	-3		1		95	*	10	

Table 28. NB regression model selection summary.

Model	PC in the model	Significant PC	AIC	BIC	-2 log likelihood	Chi-square/ DF	Dispersion
1	1,2,3,4	2	170.09	175.43	158.08	1.51	0.12
2	1,2,3	2	168.12	172.57	158.12	1.40	0.12
3	1,2,4	2	171.23	175.68	161.22	1.32	0.16
4	1,3,4	None	–	–	–	–	–
5	2,3,4	3	170.07	174.53	160.08	1.27	0.14
6	1,2	2	169.48	173.05	161.48	1.24	0.16
7	1,3	None	–	–	–	–	–
8	1,4	None	–	–	–	–	–
9	2,3	2, 3	168.23	171.79	160.24	1.17	0.14
10	2,4	None	–	–	–	–	–
11	3,4	3, 4	171.52	175.08	163.52	1.10	0.18
12	1	1	171.84	174.51	165.84	1.10	0.21
13	2	2	170.53	173.20	164.52	1.17	0.19
14	3	None	–	–	–	–	–
15	4	None	–	–	–	–	–

5.5 PROPOSED BEST MODEL FOR HGF ANALYSIS

The PCA (Table 29) was performed on the five significant metrics discussed above. The first two PCs account for 75.6% of the total data variability. NB regression was performed on all three combinations of PCs (PC-1 only, PC-2 only, and both PC-1 and PC-2). AIC, BIC, and LRT criteria were used for model selection. The results indicated that the model with both P-1 and PC-2 provided the best fitting.

Table 29. Factor loading pattern on proposed HGF model.

Metric	PC-1		PC-2	
CSR 1.5	90	*	-6	
CSR 3	85	*	20	
CSR 18	61	*	-11	
Meta	-1		95	*
Ratio	-1		95	*

The model estimation results (Table 30–Table 33) show that some of the contrast sensitivity metrics (CSR 1.5, 3, 18) and two metrics related to metacognition (self-estimated mental sharpness [Meta] and metacognition ratio [Ratio]) are strongly associated with HGF events. When PC-1 increases by 1 unit, the HGF rate decreases by 22%, indicating that high CSR scores are related to lower HGF rate. In contrast, when PC-2 increases by 1 unit, the HGF rate increases by 50%, indicating that high Meta and Ratio scores are associated with higher HGF rate.

Table 30. Goodness-of-fit for proposed NB model for HGF analysis.

Criterion	DF	Value	Value/DF
Deviance	15	19.27	1.28
Scaled Deviance	15	19.27	1.28
Pearson Chi-square	15	17.05	1.14
Scaled Pearson X2	15	17.05	1.14
Full Log Likelihood		-80.48	
AIC (smaller is better)		168.96	
BIC (smaller is better)		172.52	

Table 31. Parameter estimation for proposed HGF model.

Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		*p*-value
Intercept	1	3.347	0.113	3.127	3.568	< .0001
PC-1	1	-0.252	0.092	-0.433	-0.072	0.006
PC-2	1	0.411	0.172	0.073	0.749	0.017
Dispersion	1	0.149	0.058	0.069	0.320	

Table 32. Risk rate ratios for proposed HGF model.

Parameter	Risk Rate Ratio	95% LCL	95% UCL
PC-1	0.777	0.649	0.931
PC-2	1.508	1.076	2.115

Table 33. LR statistics for Type III analysis for proposed HGF model.

Parameter	Numerator DF	Chi-Square	Pr > Chi-square
PC-1	1	6.97	0.008
PC-2	1	4.85	0.028

The constants required to compute the new HGF rate are listed in Table 34.

The computation procedure is similar to that in Section 4.5. The new PC-1 and PC-2 based on new observed values ($x_{1,new} \sim x_{5,new}$) are computed as:

$$PC_{1,new} = \sum_{i=1}^{5} \alpha_{1i} \times \frac{x_{i,new} - \bar{x}_i}{s_i}$$

$$PC_{2,new} = \sum_{i=1}^{5} \alpha_{2i} \times \frac{x_{i,new} - \bar{x}_i}{s_i}$$

where α_i's are the standardized scoring coefficients for the i^{th} metric in PC-1 and PC-2; $\bar{x}_i$ and s_i are the mean and standard deviation of the i^{th} metric in the original study data, i.e., the current study data, not related to future observations. The values of the related coefficients are shown in Table 34.

Table 34. Constants for computing new principal component score for HGF proposed model.

Metric	α_{1i}	α_{2i}	$\bar{x}_i$	s_i
CSR 1.5	0.471	-0.041	4.440	0.907
CSR 3	0.445	0.098	4.880	1.350
CSR 18	0.322	-0.063	1.920	1.794
Meta	-0.016	0.510	4.648	1.375
Ratio	-0.014	0.509	0.551	0.206

Then the new HGF risk rate (i.e., the number of HGF events per 100 hours driven) is computed as:

$$\text{CNC rate}_{new} = \exp(\beta_0 + \beta_1 \times PC_{1,mew} + \beta_2 \times PC_{2,new}),$$

where β's are estimated regression coefficients presented in Table 31.

CHAPTER 6. SUMMARY AND DISCUSSION

The goal of this study was to evaluate the relationship between senior drivers' fitness profiles and driving risk represented by CNC and HGF rate. Principal component analysis was used for metric dimensionality reduction and group classification. Due to the moderate variance over-dispersion issue in the CNC and HGF data, an NB regression model was applied to model the relationship between CNC and HGF rates and participants' fitness profiles, as well as the relationship between CNC rate and HGF rate.

With respect to the CNC analysis, contrast sensitivity (CSR 1.5 ~ CSR 18) has a significant impact on crash risk. The better the contrast sensitivity (higher the CSR scores), the lower the crash risk. There is also some statistical evidence that CNC rate is positively associated with HGF rate among senior drivers. With respect to the HGF analysis, some contrast sensitivity (CSR 1.5, 3, 18) and metacognition measures (self-estimated mental sharpness [Meta] and metacognition ratio [Ratio]) are associated with HGF rate. Lower contrast sensitivity scores and higher Meta and Ratio scores are related to elevated HGF event rate.

A recent study sponsored by the National Highway Traffic Safety Administration (NHTSA) looked at the degree to which a variety of metrics of functional ability could be used to proscriptively predict crash and serious traffic violation rates (Staplin, Lococo, Gish, & Joyce, 2012). Assessment metrics, mostly in the cognitive domain, were chosen for inclusion based on successful evaluations in prior research efforts or more novel metrics which appeared promising based mainly on face or construct validity. Results of that study showed greatest promise for a route-planning/maze-solving assessment. In addition, a metric related to contrast sensitivity was also significantly related to crash involvement.

While the current study did not employ a maze-based metric per se, results for the contrast sensitivity-based metrics did support the results for similar metrics found by Staplin, Lococo, Gish, and Joyce (2012), as this dimension of visual ability was also the most strongly related to CNC and HGF event rates among all metrics evaluated in the current study. Others using retrospective methods have also found positive results in terms of relating contrast sensitivity to crash rate (see Owsley, Stalvey, Wells, Sloane, & McGwin, 2001). Contrast sensitivity refers to the eye's ability to resolve information presented with limited contrast (i.e., where there is relatively little difference between the light and dark aspects of a stimulus—the lower the difference in contrast from which the information or content can reliably be retrieved, the greater the contrast sensitivity of that observer).

In addition, two metacognition metrics in the current study were also related to HGF event rate. Metacognition refers to the individual's insight into his/her current cognitive status. The first metacognition metric was represented by simply asking participants how sharp they felt relative to how they were in their 40s and 50s ("Meta"). The second ("Ratio") was represented by the ratio of "Meta" to the participant's actual score on the Abbreviated Mental Test Score (AMTS). The higher the "Ratio" metric, the greater the discrepancy between perceived and actual levels of cognitive functioning. Lundqvist and Alinder (2007) also found positive results related to metacognitive abilities and driving in evaluating 30 drivers with acquired brain injury (i.e., not an older sample per se). These individuals were assessed concerning cognitive functions and driving performance. In addition, the drivers assessed their driving performance through self-rating. Researchers concluded that the members of the group that made a more realistic evaluation of their driving performance were more aware of their cognitive abilities and were better able to adjust their driving performance. De Raedt and Ponjaert-Kristoffersen (2009) showed that older drivers may inherently compensate for loss of functional abilities, but their results did not indicate that metacognition was a mediating factor in this process. Methodological issues may have played a role in this outcome.

This study successfully demonstrated that, even with a relatively small pilot sample, a certain parsimonious set of functional assessments can be used to reliably predict safety-related driving behaviors measured using the NDS paradigm. These functional assessments include contrast sensitivity as well as metrics related to the driver's metacognitive state. The safety-related driving behaviors include CNC and HGF rates. It is believed that this is the first fitness-to-drive study based on naturalistic driving data.

Future work can seek to utilize the far larger naturalistic data stores associated with the Second Strategic Highway Research Program (SHRP 2) NDS and other similar studies to further refine and validate these findings.

Once refined and validated, this work can support the application of particular assessments that can be meaningfully and efficiently applied in any environment where senior drivers are screened or assessed for fitness to drive.

One limitation of this study was the low number of driving participants relative to the number of metrics of functional ability assessed. This was addressed via the dimensionality reduction and modeling approaches used as described in the main body of the report.

Also with respect to the contrast sensitivity scores, only those scores from the right eye were related to the driving safety metrics. It is possible that there was a methodological problem with the collection of the left eye sensitivity metrics or that the truer metric is related to one's dominant eye (i.e., the one producing the best sensitivity score at a particular spatial frequency).

APPENDIX A. LIST OF 48 FITNESS ASSESSMENT METRICS USED

Physical Ability (13 total)

Ankle Torque Max/Plantar and Dorsiflexion (2)

Hip Torque Max/Flex and Extend (2)

Upper Body Torque Max/Left and Right (2)

Ankle Initial Reaction Time (RT, mean of Plantar and Dorsiflexion)(1)

Ankle Peak RT (mean of Plantar & Dorsiflexion) (1)

Hip Initial RT (mean of Flex and Extend) (1)

Hip Peak RT (mean of Flex and Extend) (1)

Upper Body Initial RT (mean of Left and Right) (1)

Upper Body Peak RT (mean of Left and Right) (1)

Head–neck–torso flexibility (1)

Visual Ability (19 total)

Dynamic visual acuity @ 12, 24, and 36 deg/s (DPS) (3)

Discomfort Glare Rating (1)

Glare Static Acuity (1)

Glare contrast sensitivity @ 4, 8, and 16 cycles/deg (3)

Static Visual Acuity (Snellen) (1)

Contrast sensitivity (Right Eye) @ spatial frequencies: 1.5, 3, 6, 12, and 18 cycles per degree (5); note: raw non-transformed scores, 1-9, were used for each frequency)

Total number of color vision plates correct (1)

Stereopsis (1)

Far acuity (Optec) (1)

Far vertical and lateral phoria (2)

General and Health-Related Info (10 total)

Height (in.) – self report (1)

Weight (lbs) – self report (1)

Total number of reported health problems (1)

Faces pain scale (1)

WHO (five) Well-Being Index 1998 Version (1)

Total number of sleep problems (1)

Total number of sleep disorders (1)

Total hours of sleep estimated per day (1)

Education (1)

Total years driving (1)

Cognitive Ability (6 total)

1. Abbreviated Mental Test Score (AMTS) (1)

2. Self Estimate: how mentally sharp compared w/ 40s and 50s (1)

3. Metacognition Ratio: SE/AMTS (1)

4. Visualizing Missing Information (1)

5. Useful Field of View™ (1)

6. Trail Making B (1)

APPENDIX B. LETTER TO THE EDITOR

[redacted]

Fitness to Drive

SIR,—The present position regarding the examination of the elderly for fitness to drive a car appears to be in need of review. The G.P. is frequently asked by the insurance company to give a certificate stating that their client is fit to drive a car, in view of his age—usually 70 or over. No physical standards are laid down and no specific questions are asked.

The family doctor is often placed in a very difficult position, as he may know the patient to be shaky, possibly old for his years, hard of hearing, and, in fact, a bad risk. In addition he so often has had visible evidence that the patient is an inadequate driver by personal observation on the road in the course of his daily rounds. Great pressure is sometimes brought to bear on the doctor by his patient or his relations, as the driver so often is the only means of transport for the family to and from the shops. An unfavourable certificate creates an unpleasant feeling between doctor and patient.

I believe that when an insurance company requires a certificate for fitness to drive they should arrange for one of their own medical officers or an independent practitioner to do the examination in the same way as for a life insurance examination, and that a thoroughly comprehensive examination should be undertaken. Failing this, at the very least the insurance company should ask the patient's G.P. for relevant details of his past history and to complete a questionary. With the greatly increased volume and speed of traffic at the present time this appears to be a matter of some importance and urgency.—I am, etc.,

Hatch End, Middlesex. MARTIN STRATFORD.

[redacted]

REFERENCES

Antin, J. F., Lockhart, T., Stanley, L. M., & Guo, F. (2012). Comparing the impairment profiles of older drivers and non-drivers: Toward the development of a fitness-to-drive model. *Safety Science*, *50*(2), 333–341.

De Raedt, R., & Ponjaert-Kristoffersen, I. (2009). Can strategic and tactical compensation reduce crash risk in older drivers? *Age and Ageing*, *29*, 517–521.

Dingus, T. A., Klauer, S.G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J., Perez, M. A., Hankey, J., Ramsey, D., Gupta, S., Bucher, C., Doerzaph, Z. R., Jermeland, J., and Knipling, R.R. (2006) 100 Car Naturalistic Driving Study – Phase II Results of the 100 Car Field Experiment. National Highway Traffic Safety Administration. DOT HS 810 593.

Guo, F., & Fang, Y. (2013). Individual driver risk assessment using naturalistic driving data. *Accident Analysis and Prevention*, *61*(1), 3–9.

Guo, F., Klauer, S. G., Hankey, J. M., & Dingus, T. A. (2010). Near crashes as crash surrogate for naturalistic driving studies. *Transportation Research Record: Journal of the Transportation Research Board*, *2147*, 66–74.

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). New York: Springer-Verlag.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, *20*, 141–151.

Lundqvist, A., & Alinder, J. (2007). Driving after brain injury: Self-awareness and coping at the tactical level of control. *Brain Injury*, *21*(11), 1109–1117.

Marshall, S. C., & Gilbert, N. (1999). Saskatchewan physicians' attitudes and knowledge regarding assessment of medical fitness to drive. *Canadian Medical Association Journal*, *160*(12), 1701–1704.

Owsley, C., Stalvey, B., Wells, J., Sloane, M., & McGwin, G. (2001). Visual risk factors for crash involvement in older drivers with cataract. *Arch. Ophthalmol.*, *119*, 881–887.

Simons-Morton, B. G., Zhang, Z., Jackson, J. C., & Albert, P. S. (2012). Do elevated gravitational-force events while driving predict crashes and near crashes? *American Journal of Epidemiology*, *175*(10), 1075–1079.

Staplin, L., Lococo, K. H., Gish, K. W., & Joyce, J. (2012). *Functional assessments, safety outcomes, and driving exposure measures for older drivers* (Report No. DOT HS 811 630). Washington, DC: National Highway Traffic Safety Administration.

Stevens, J. (1986). *Applied multivariate statistics for the social sciences*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Stratford, M. (1959, February 14). Fitness to drive [Correspondence to the editor]. *British Medical Journal*, p. 442.