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The influence of functional health on seniors' driving risk

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ABSTRACT

Driving safety is important for the growing population of seniors, as driving remains their primary mode of travel in the U.S., and declines in functional health are often associated with driving cessation. As some seniors may have limited or inaccurate insight into their own driving capabilities, a set of objectively measured functional health assessments is needed that could help them and other stakeholders to determine fitness-to-drive. The purpose of the current study was to examine the relationships between senior drivers' functional health and crash risk. This analysis used data from 723 senior drivers enrolled in the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS). Participants' functional health capabilities were measured using 58 metrics encompassing cognitive, perceptual, physical, psychomotor, and psychological abilities as well as driving knowledge. The mileage driven and crashes were identified from objective NDS data. Twenty-two of the metrics were statistically significantly associated with crash risk. Deteriorated functional health was uniformally associated with increased crash rate. These findings provide key information to support the development of a battery of functional assessments for senior drivers who may need to have fitness-to-drive screening.

1. Introduction

As our society continues to age, the issues facing seniors will continue to grow in importance from a public health perspective, not only for aging individuals, but also for the many social institutions striving to cope with this substantial and continuing demographic shift. As driving still accounts for the majority of seniors' trips in the U.S. (Federal Highway Administration, 2013), it is crucial to maintaining mobility and quality of life in the U.S. — but only to the extent that driving safety can also be maintained.

Therefore, it is imperative to provide seniors, as well as other stakeholders a simple and reliable screening method to determine, at a first approximation, fitness-to-drive (Marshall et al., 2012). Finding such a tool has proven to be elusive, though much research has been conducted to associate seniors' driving risk with a variety of dimensions of functional health related to fitness-to-drive. These have included cognitive (Aksan et al., 2015; Hemmy et al., 2016), perceptual (Anstey et al., 2012; Owsley and McGwin, 1999), visual-cognitive (Papandonatos et al., 2015; Roy and Molnar, 2013), physical (Chen et al., 2015; Marmeleira et al., 2012), and psychological (Dingus et al., 2016; Zhang and Chan, 2016) abilities. Hakamies-Blomqvist (2006) argued that the entire notion of screening senior drivers for fitness-to-drive is fraught with difficulties such as politics intruding on science and the difficulty of associating a specific metric of driving risk to a particular individual.

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While many seniors may self-restrict their driving in a variety of ways (e.g., avoiding bad weather, night driving, or freeway speeds (Naumann et al., 2011)), some voluntarily give up driving altogether (Kowalski et al., 2012). Others may lack such insight into their own functional status (Wood et al., 2013). Furthermore, while such self-restriction may reduce crash risk by reducing exposure in general and to particular driving challenges in specific, it may also result in reduced independence. The American Academy of Neurology recommends that for patients with dementia self-reported situational avoidance is useful for identifying patients at increased risk for unsafe driving; however, they also note that a lack of situational avoidance in this same patient group is not useful for identifying increased risk for unsafe driving (Iverson et al., 2010). Charlton et al. (2006) found that self-restriction is related to functional health in that those most likely to restrict had specific characteristics, including vision problems.

Studying the individual effects of particular impairments may often be limited. To truly address risk, one must examine the pattern of impairment across the multiple dimensions of functional health crucial to safe driving (Kowalski et al., 2012). Antin et al. (2012) examined a broad array of driving-related functional health dimensions and developed a parsimonious model based solely on these capabilities. The model was able to almost perfectly categorize individual seniors into active drivers or seniors who had recently given up driving. Guo et al. (2015) analyzed a broad array of prospectively collected functional health assessment data in conjunction with safety-related outcomes observed in naturalistic driving data collected from a group of 20 senior drivers. Their results supported the idea that seniors' visual contrast sensitivity (CS) is important for driving safety.

The main objective of the current study was to examine a broad array of prospectively collected metrics of functional health and their relationship to safety outcomes (measured as senior crash risk) objectively observed from a large-scale naturalistic driving study (NDS), the Second Strategic Highway Research Program (SHRP 2). Comparing such metrics to driving-safety outcomes observed in a full-scale naturalistic study, including video data, is a novel approach. We hypothesized that senior drivers' fitness to drive, as represented by key metrics of functional health, would be associated with the crash risk observed in the SHRP 2 data.

2. Material and methods

2.1. SHRP 2 naturalistic driving study data

The NDS methodology has provided a unique opportunity to collect objective *in situ* driving data and the ability to evaluate driving exposure and risk for a wide variety of driver behaviors and driving scenarios (Dingus et al., 2016; Guo et al., 2016; Klauer et al., 2014; Ouimet et al., 2014; Qing et al., 2017). The SHRP 2 NDS (Dingus et al., 2015) collected driving data from volunteers in real-world, non-experimental settings, following an observational prospective cohort study design from October 2010 to December 2013. Volunteers' vehicles were instrumented with a sophisticated yet unobtrusive automated data collection system which included a Global Positioning System (GPS), 3-dimensional accelerometer, speedometer, forward radar, and 4 video cameras providing views of the forward roadway, rear roadway, driver's face, and the participant's interactions with the steering wheel and center stack. The system continuously collected data from ignition-on to ignition-off. No experimenters were present, specific driving instructions were not given, and participants drove their car as they preferred along daily commutes or for any other purposes (Dingus et al., 2015).

SHRP 2 data were collected from more than 3500 participants living in the vicinity of six geographically distributed sites across the United States for one to two years each. The analysis included 723 participants who were screened into the analysis based on the following criteria: aged 65 or older and possessing complete trip and crash records, substantially complete functional health assessment data, and a minimum of six months of driving data. These 723 individuals comprised 81.4% (723/888) of all drivers 65 and older in the SHRP 2 study. The six-month minimum driving data criterion was implemented to provide a fair basis of driving exposure. Crashes were identified by screening for segments of driving data with abnormal kinematic values, such as high deceleration, and then confirmed via visual examination of the video record. Crashes were classified by severity from the most severe (e.g., air-bags deployed with possible injuries, Level I) to the least severe (e.g., tire-curb strikes, Level IV) (Dingus et al., 2016, 2015). Only Severity Level I, II, and III crashes were included in the analysis. Crashes were neither filtered nor analyzed by fault assignment; however, the participant was deemed to be at fault in approximately 75% of the crashes in the sample.

A total of 58 functional health metrics were evaluated, virtually all collected prospectively. Functional health was represented by the following dimensions: 12 cognitive, 3 visual-cognitive, 1 driving knowledge, 2 physical ability, 6 psychological, and 34 visual, with details listed in Table 1. As some of the metrics have mild missing data issues (1–3%), mean imputation was performed to replace the missing values. For a complete description of all of these metrics of functional health, see "Chapter 2: Study Preparation" of SHRP 2 technical report (Dingus et al., 2015).

2.2. Statistical analysis

The relationship between crash risk and functional health metrics was evaluated using negative binomial (NB) regression models, which is commonly used to model driver-level crash rate for NDSs (Chen et al., 2016; Guo et al., 2014, 2015). NB regression models are preferred to Poisson models in the presence of over-dispersion. The number of crashes by driver is assumed to follow an NB distribution:

$$Y_i \sim NB(E_i\lambda_i,\ \gamma) \text{ with } E(Y_i) = E_i\lambda_i \text{ and } Var(Y_i) = E_i\lambda_i + (E_i\lambda_i)^2 \times \gamma, \tag{1}$$

where Y_i is the number of crashes for driver i; λ_i is the expected crash rate (e.g., number of crashes per million miles driven) for driver i; E_i is the exposure (miles traveled by driver i, in the unit of million miles) during study period; γ is the dispersion parameter. A log link function connects the expected crash rate λ_i with