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Short Communication

Rethinking Driving Assessment: A Hypothesis-Driven Proposal for Cognitive Evaluation

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Abstract

Driving is a critical aspect of personal mobility and autonomy, but ensuring road safety requires a comprehensive evaluation of driving abilities beyond self-reported behaviors and practical skills. This article emphasizes the importance of cognitive assessment in determining fitness to drive and explores the potential benefits of using digital tools for such evaluations to enhance road safety. Implementing these digital tools does come with challenges, such as unfamiliarity with digital cognitive reviews for some and the requirement of adaptability to evaluate cognitive skills across various age demographics. Additionally, the absence of standardization in driving assessments across different regions can result in inconsistencies in judging who is fit to drive. Despite these hurdles, integrating digital cognitive evaluations and training into conducting assessments and educational initiatives can more effectively comprehend and address mental aspects of driving, thereby potentially reducing crash risk and promoting road safety. This hypothesis-driven approach proposes that a thorough assessment of an individual's readiness to drive, focusing on vital cognitive domains associated with safe driving, can contribute to safer roads and yield substantial social, economic, and personal benefits. We encourage future research and educators to consider these insights when developing driving education programs and assessments of driving fitness.

Keywords
Driving assessment; fitness-to-drive; safe driving; driving performance; cognitive abilities; digital tools

1. Introduction

Driving is significant in today' 's society, especially in rural regions or areas lacking well-developed public transportation systems. It grants individuals the liberty to move freely and access resources that might otherwise be unattainable. This freedom enables essential everyday activities such as commuting to work, running errands, and exploring new places, all of which are integral to maintaining a high-quality life. Beyond personal benefits, driving also fuels economic growth and development. It bolsters various industries by facilitating the transportation of goods and services [1], thereby playing a significant role in the economic machinery. However, these benefits come with substantial risks. Motor vehicle crashes can lead to catastrophic consequences, resulting in personal tragedies and significant financial burdens on individuals, communities, and economies [2-4].

Road traffic crashes, including car users, cyclists, motorcyclists, and pedestrians, result in loss of life, physical injuries, psychological trauma, and property damage, all of which extend to far-reaching social and economic impacts. Globally, road traffic crashes cost an estimated $1.8 trillion annually, accounting for approximately 3% of the gross domestic product (GDP) in direct and indirect expenses [5]. The World Health Organization reports that over 1.35 million people die yearly due to road traffic crashes, while 20 to 50 million sustain non-fatal injuries [6, 7]. These crashes are a leading cause of death and injury worldwide, resulting in billions of dollars in medical expenses, property damage, and lost productivity [8, 9]. Beyond the monetary costs, crashes can also cause lasting psychological trauma for survivors and their families [10, 11].

Road traffic crashes are not solely a consequence of unfortunate circumstances; they stem from a complex interplay of numerous factors [12, 13]. These factors encompass environmental aspects such as road and weather conditions, technical elements such as the vehicles' state, and most importantly, human factors such as driver behavior and cognitive ability. Notably, car drivers and passengers of 4-wheeled vehicles account for the highest proportion of road traffic crashes and road user deaths globally [6]. Thus, identifying and understanding the numerous contributing factors to these incidents is critical, with the ultimate goal of developing effective strategies to predict and prevent these crashes and enhance overall road safety.

Many studies have attested to the efficacy of implementing measures for decreasing the frequency of road crashes, particularly among older drivers [14]. These measures range from cognitive training programs designed to enhance attention, memory, and decision-making [15-17], and physical fitness programs that target the improvement of strength and flexibility essential for operating a vehicle [18, 19] to the use of assistive driving devices like advanced driver-assistance systems (ADAS) which provide crucial environmental information to drivers [20, 21].

For decades, most licensing authorities have relied on single-construct assessment instruments to evaluate driving fitness, primarily focusing on visual and auditory acuity, manual dexterity, and on-road tests [22]. The latter often leads to subjective evaluation and relies on the judgment of an examiner or driving instructor [23]. Researchers assessing driving abilities or driver impairments have also used single-construct instruments [24-28]. The Manchester Driver Behaviour Questionnaire (DBQ) [29] and the Driver Skill Inventory (DSI) [30] are two of the most commonly used driving assessment instruments. The DBQ evaluates a driver's self-reported behavior on the road, including their tendency to take risks, compliance with traffic laws, and their level of aggression while driving. On the other hand, the DSI measures a driver's ability to control the vehicle, anticipate and respond to potential hazards, and navigate complex driving scenarios. Another standard driving assessment instrument is the Useful Field of View (UFOV), which gauges a driver's visual attention and processing speed [31]. The UFOV presents the driver with visual stimuli and measures their ability to detect and respond to them. However, despite their widespread use, these assessments fall short of accurately predicting road traffic crashes, as often claimed [32].

Naturalistic driving evaluation tools, such as the eDOS (Electronic Driving Observation Schedule), provide a more comprehensive and objective assessment of driving abilities [33]. The eDOS system employs in-vehicle sensors and cameras to monitor and record real-time driving behavior, providing valuable data on a driver's performance under various driving conditions. This data can help identify risky driving behaviors and provide targeted interventions to boost driving safety. Another tool suitable for naturalistic driving evaluation is the Long Short-Term Memory (LSTM) model. Based on a deep-learning architecture, this model has been used to classify the risk levels of near-crashes, demonstrating high performance in terms of accuracy, recall, and precision [34]. The LSTM model can improve the classification accuracy and prediction of most near-crash events and reduce false near-crash classification, providing valuable insights for predicting and classifying driving risk and offering helpful suggestions for reducing the incidence of critical events and forward road crashes. However, while these tools provide a nuanced understanding of observable driving behaviors and environmental conditions, these machine learning models fail to consider cognitive aspects influencing driving performance input as reliable predictors.

2. What Does Driving Involve?

Driving is often perceived as a simple and automatic task; however, it is, in reality, a complex and multifaceted process that involves integrating various cognitive skills, such as attention, perception, memory, and decision-making [35]. For safe navigation in a driving environment, drivers must continuously evaluate and analyze their surroundings, visualizing and anticipating the trajectory of other vehicles, pedestrians, or obstacles [36].

Cognitive flexibility is vital for swiftly adapting to changes while working memory is essential for recalling recent driving events and navigating intricate traffic situations [37]. Attention is fundamental to safe driving, enabling drivers to concentrate selectively on relevant stimuli while disregarding distractions [38]. Perception and situational awareness are also critical, allowing drivers to accurately perceive their environment and anticipate potential hazards [39]. Visuo-spatial skills are critical in this context. They enable drivers to perceive their environment in three-dimensional space accurately, anticipate the movements of other road users, and make appropriate driving decisions [40-42].

Effective decision-making demands integrating multiple cognitive skills, including attention, perception, and working memory [43]. Memory plays a crucial role in retaining information about traffic rules and the spatial layout of the driving environment [44]. The significance of these cognitive components becomes apparent in the high crash rates resulting from distracted or impaired driving [45-48].

In addition to these cognitive processes, the substantial roles of impaired and distracted driving in road traffic crashes cannot be overlooked. For instance, alcohol-impaired driving significantly contributes to road traffic crashes, leading to severe injuries and fatalities [49, 50]. Similarly, drug use can significantly impair driving performance and increase the risk of road crashes [51].

Regarding distracted driving, mobile phone use emerges as another critical factor contributing to road traffic crashes [52-54]. Even secondary tasks, such as interacting with in-vehicle technologies, can be a distraction source leading to traffic crashes [55]. Additionally, a driver's personality and sociodemographic characteristics can significantly influence the driving behavior and the likelihood of crashes [56].

3. Predicting Future Crash Involvement

Rear-end collisions are common on roads, accounting for roughly 20-30% of all driving collisions, mainly when the leading vehicle is stationary or moving at a slower speed [57]. Therefore, understanding perceptual or estimation errors in driving situations could help reduce many traffic crashes. By accounting variables such as the objects' final position, initial position, velocity, and time course position of each object, it is relatively simple to predict the convergence of two objects within a controlled environment where computational resources are readily available. However, the driving experience is on another level; we are constantly and unconsciously making predictions and approximate calculations that provide us with the final position data of the vehicles around us. This leads to questions about potential failures in the cognitive skills that allow us to anticipate the distance to the leading car, necessary braking time, and crash occurrence.

In the literature, the time it will take to hit an obstacle, or the time available to react and take evasive action, is referred to as time-to-contact/collision (TTC) or time-to-arrival (TTA) [58-63]. Although they are sometimes used interchangeably, TTC implies that both objects are in motion (observer and target). At the same time, TTA indicates that the target is stationary and only the observer is moving [64]. While both TTC and TTA aim to determine if two objects will collide, the equation for TTC is more complex, requiring more sensory information (velocity, distance, and acceleration of both objects) and more significant cognitive effort. TTC is directly related to anticipatory behaviors such as braking, turning, staying within the lane, maintaining a safe distance from the vehicle ahead, and so on. Given the potential for devastating consequences, factoring in cognitive variables related to TTC when evaluating driving proficiency is crucial.

Recent studies have shown that machine learning and classification algorithms can effectively predict traffic crashes. For instance, a study by Akin et al. [65] used supervised machine learning techniques such as binomial logistic regression and other models to forecast the likelihood of traffic crashes involving driver error on a major highway. According to the study, the possibility of crashes caused by driver mistakes dropped as the number of lanes and daily average speed of traffic flow increased. However, the likelihood of driver-related traffic crashes increased as the yearly average daily traffic climbed and straight and horizontal curve sections became more prevalent. These findings underscore the importance of considering various factors, including road features and traffic flow parameters, in predicting traffic crashes.

Moreover, machine learning algorithms have been used to analyze data, extract hidden patterns, predict the severity level of crashes, and summarize the information in a helpful format. For example, Megnidio-Tchoukouegno and Adedeji [13] modeled the accuracy of traffic incidents in the UK using different algorithms. They showed that it is possible to anticipate the seriousness of a traffic crash and provide a guide to the crucial parameters that must be kept under close observation to lower the number of hits on the roads.

4. Cognitive Assessment

Psychological assessment is crucial in understanding individuals' cognitive abilities, emotional functioning, and behavioral patterns [66-69]. Traditional methods, such as self-report questionnaires, structured interviews, and observational techniques, have been used for decades [70]. However, recent advancements in cognitive evaluation have emphasized the importance of directly assessing cognitive functions, leading to a paradigm shift in psychological assessment [71].

Cognitive assessment evaluates an individual's cognitive abilities, including memory, attention, perception, executive functions, and reasoning [72]. While standardized paper-based tests were initially employed, digitization has enabled computerized administration, resulting in highly quantifiable, precise, and objective measurements of various cognitive abilities [73-77]. This approach offers a deeper understanding of an individual's cognitive strengths and weaknesses and helps identify potential cognitive impairments [78].

One key area of cognitive assessment that has gained attention in recent years is evaluating visuospatial skills. These skills are critical for safe driving as they allow drivers to perceive their environment in three-dimensional space accurately, anticipate the movements of other road users, and make appropriate driving decisions. Traditional paper-and-pencil tasks, such as the Rey-Osterrieth Complex Figure Test, the Complex Figure Test, or the Benton Visual Retention Test, have been used to assess visuospatial skills [40, 79, 80]. However, these tasks often fall short in ecological validity as they fail to capture the dynamic and complex nature of driving [81, 82]. To address this, computerized tasks have been developed, offering a more realistic and comprehensive assessment of these skills [83-85].

Recent research has underscored the effectiveness of computerized tasks in predicting driving performance. For instance, Anstey' 's study [86] demonstrated a significant correlation between on-road driving performance and automated tasks assessing visuospatial skills, such as the Useful Field of View (UFOV) scheme and the Hazard Perception Test (HPT). Similarly, a study by Roca et al. [87] found that tasks measuring visuospatial attention, such as the Attention Network Test (ANT), could predict driving simulator performance and self-reported driving errors.

However, many evaluations focus on a single variable, overlooking others. A comprehensive review by Bennett and colleagues [88] examining 28 studies on cognitive function and driving in people with dementia found no single cognitive domain consistently reliable in determining driving capability. These findings align with previous research showing that various cognitive domain fields' effect sizes range from weak to moderate [89]. Similarly, assessments based on brief mental examinations have proven inadequate in distinguishing between safe and unsafe drivers [90, 91]. These findings suggest that a deficit in a single cognitive ability does not reliably predict driving performance. As a result, there is a growing need to emphasize the use of multi-domain assessment tools. A combined battery of tests, each assessing different cognitive domains, seems to have a higher potential to predict driving performance.

Digital assessments also capture personal variables such as behavioral patterns, offering insights into an individual's capabilities and crash risks [92-94]. Furthermore, digital tools often feature tasks that closely resemble real-life situations, enhancing the ecological validity of the assessment [95-100]. Real-time data collection also enables continuous monitoring of cognitive performance and identification of at-risk areas [101].

When applied to driving scenarios, computerized cognitive assessment provides accurate and reliable data, reduces the likelihood of biases and inaccuracies, and offers a comprehensive approach to assessing driving fitness [102-106]. Several commercially available cognitive assessment tools have been developed in fitness to drive, each offering a unique approach to assessing mental fitness to drive, focusing on different cognitive domains. The Neuropsychological Assessment Battery (NAB) - Driving Scenes Task sets cognitive functions related to fitness to drive, concentrate on selective attention, visual scanning, and visuospatial working memory. The Driver Assessment Cognitive Testing developed by Top Driver Acquisition, LLC, in partnership with SafeWay Driver Fitness Centers, measures multiple skills and abilities regarding safe driving, including the ability to estimate distances and speeds, manual dexterity, time perception, attention, and auditory and visual perception. The DriveABLE Cognitive Assessment (DCAT) by Impirica Inc. is a computer-based system designed to evaluate some cognitive abilities needed for safe driving. It predicts real-world driving behavior, providing a fair and objective assessment, focusing on motor speed and control, a span of attentional field, spatial judgment and decision making, speed of attentional shifting, coordination of mental abilities, and identification of driving situations.

Furthermore, the DCAT considers an individual's capability to initialize and react, track and process visual events, encode, retrieve, and respond to stimuli, judge spatial relations, control guided movements, and react swiftly to complex information. Another promising tool that offers a holistic approach to determining driving fitness is the Driving Assessment Battery (DAB) developed by Cognifit® (CogniFit Ltd., San Francisco, US). The DAB incorporates real-time simulations of driving scenarios, challenging individuals to navigate complex environments, estimate distances and speeds, and respond to sudden changes. It provides a more accurate reflection of their real-world driving abilities. It engages up to 10 cognitive skills, including estimating distances, speeds, time, perception, attention, reaction time, and processing speed. Additionally, it considers other relevant factors such as driving styles, rule compliance, and mental adaptability. It also measures capacities directly related to driving, such as manual dexterity, hand-eye coordination, and a wide field of view.

5. Forward-Looking Outlook

The current approach to evaluating driving skills primarily focuses on practical abilities and knowledge of traffic regulations, often neglecting the importance of cognitive capabilities [107-110]. Reliance on self-report measures, such as questionnaires, in driving assessments can be problematic due to their subjective nature and susceptibility to biases, including social desirability and recall bias [111]. These biases may result in inaccurate evaluations of driving competency, and self-report measures may not effectively capture an individual's ability to handle unexpected or complex driving situations, limiting their predictive validity [112]. It is necessary to develop and incorporate objective measures that are not subject to biases. Recent advancements in cognitive evaluation techniques have led to a growing consensus that digital approaches may offer valuable insights beyond what classical tests can provide [113, 114]. However, it's important to note that these tools primarily evaluate cognitive abilities related to driving and may not fully capture other crucial aspects of driving fitness. For instance, factors such as lack of practical driving training or risky behavior due to unfamiliarity with potential consequences may not be accurately assessed through cognitive evaluation tools alone.

Cognitive evaluation through digital tools could properly assess cognitive domains and personal variables that account for most in-car crashes. In this sense, computerized cognitive assessments can be adapted to evaluate driving-related cognitive skills, providing a more comprehensive evaluation of a driver's functioning. Digital cognitive assessments offer greater precision and objectivity in measurement and the ability to capture real-time data and provide immediate feedback. They also allow for the evaluation of a broader range of cognitive abilities and can be easily adapted to suit different populations and settings. However, these assessments may be less familiar to some individuals, particularly older adults or those with limited computer literacy, potentially affecting their performance.

Although age-related cognitive, motor, and perceptual skill changes can significantly impact an individual's driving abilities [115-118], annual statistics indicate that young people have the highest crash rate [119-121]. However, most studies on driver fitness have focused on the elderly, populations with psychiatric disorders or those who have suffered a brain injury [88, 122]. Therefore, it is essential to assess younger drivers' capabilities properly.

Furthermore, it is crucial to acknowledge that basing cognitive assessments on individuals' self-perceived abilities and behavior may introduce inherent biases and lead to potentially misleading results. Various studies have highlighted that individuals overestimate or underestimate their cognitive capacities, which can influence their decision-making and behavior. For instance, research by Hay et al. [123] demonstrated that older drivers who overestimated their cognitive abilities may place themselves in risky situations. In contrast, those who underestimated their abilities might prematurely discontinue driving.

A more reliable and objective approach is warranted to address these limitations and enhance the accuracy of cognitive assessments for driving fitness evaluations. An automated process of computerized cognitive assessment that relies on extended tests and paradigms could be implemented, thus capturing a broader range of cognitive functions relevant to safe driving. Moreover, these digital cognitive assessments could be tailored to assess differential cognitive abilities that might be distinct across various sociodemographic groups regarding safe driving. For instance, younger drivers might require an evaluation that focuses more on their hazard perception and decision-making abilities. In contrast, older drivers might necessitate an assessment that emphasizes their reaction time and attention span [124].

Integrating cognitive evaluation into driving tests would have numerous positive implications for road safety. This approach would enable a more comprehensive assessment of an individual's readiness to drive safely by assessing their cognitive abilities, practical skills, and traffic knowledge. In addition, cognitive evaluation during driving tests could help identify individuals with cognitive deficits that could impair their driving abilities. Drivers can receive personalized feedback on their cognitive abilities and use cognitive training programs to improve their skills. Moreover, cognitive evaluation can identify high-risk drivers and provide targeted interventions to improve their driving safety. Early identification of cognitive weaknesses could prompt interventions such as cognitive training to address these issues before they interfere with driving and improve drivers' cognitive abilities.

By ensuring that licensed drivers possess the necessary cognitive abilities for safe driving, cognitive evaluation would improve road safety and reduce the number of crashes caused by cognitive deficits. Incorporating digital assessment and computerized mental training into driving education programs could significantly improve adolescents' cognitive variables associated with driving skills. These digital tools have the potential to complement current psycho-technical tests and contribute to a safer driving environment.

Digital evaluations are often more flexible than classical testing approaches, allowing for adaptations to suit diverse populations and settings. This flexibility can be particularly beneficial when assessing individuals from different cultural and linguistic backgrounds. Assessment methods and criteria for evaluating fitness to drive can vary significantly across jurisdictions, resulting in inconsistencies in determining who is deemed fit to drive. This lack of standardization can lead to confusion and discrepancies in identifying individuals who may pose a risk to road safety. An evaluation considering cognitive performance could overcome this limitation, as it is based on human development regardless of political or cultural environment. Moreover, cognitive assessment can also overcome possible acquiescence bias, response set bias, and deliberate deception.

We hypothesize that cognitive evaluation through digital tools can accurately assess cognitive domains and personal variables that impact driving safety. Implementing mental evaluation in fitness-to-drive assessments can provide a comprehensive review of driving ability and more accurately identify individuals with cognitive deficits that could impair their driving abilities, thus enabling early identification of individuals at risk of crashes. This improved identification can help target interventions and support services to those who need them most, reducing the risk of crashes involving cognitively impaired drivers. Incorporating cognitive stimulation into driving safety programs could lead to more effective training and education for drivers. By targeting driving-related cognitive skills, these programs can help individuals develop the cognitive abilities necessary.

6. Conclusions

This article emphasizes the critical role of cognitive evaluation in assessing fitness to drive and highlights the potential benefits of digital mental training in enhancing driving safety. By integrating these tools into existing driving assessments and educational programs, we can comprehensively understand an individual's readiness to go, identify cognitive deficits early, and inform targeted training initiatives.

However, the practical implementation of cognitive evaluation in driving assessments presents its own set of challenges. For instance, the unfamiliarity of cognitive digital evaluations for some individuals, particularly older adults or those with limited computer literacy, could potentially affect their performance and the accuracy of the assessment. Additionally, the cognitive abilities required for safe driving may differ between younger and older drivers, necessitating the adaptability of digital cognitive assessments to evaluate varying cognitive skills across different age groups.

Moreover, the lack of standardization in the methods and criteria for evaluating fitness to drive across jurisdictions can lead to inconsistencies in determining who is deemed fit to drive. This lack of uniformity can result in confusion and discrepancies in identifying individuals who may pose a risk to road safety. Therefore, a globally accepted standard for cognitive evaluation in driving assessments is needed to overcome these limitations.

Despite these challenges, implementing cognitive evaluation in fitness-to-drive assessments on a global scale can reduce traffic crashes and create safer roads. We propose that cognitive digital evaluations can accurately assess cognitive domains and personal variables that impact driving safety, thereby enabling early identification of individuals at risk of crashes. This improved identification can help target interventions and support services to those who need them most, reducing the risk of crashes involving cognitively impaired drivers.

We, therefore, advocate for further research to validate these hypotheses and explore the essential cognitive domains associated with safe driving. We urge policymakers to incorporate these findings into driving education programs and fitness-to-drive assessments. By doing so, we can move towards a future where cognitive evaluation becomes an integral part of driving assessments, ultimately contributing to safer roads and reducing traffic crashes.

Author Contributions

All authors contributed equally.

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Competing Interests

The authors have declared that no competing interests exist.

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