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Doctoral Dissertation

Study on Personalized Approach for Driver Assistance Based on Individual Driver Characteristics

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Abstract

Traffic accidents are a major social issue, and driver assistance systems (DAS) are an effective means of reducing them. In particular, DAS that provide support tailored to diverse drivers with differing accident risks and preferences have the potential to significantly enhance safety and driving comfort. The ultimate goal of this research is to realize a personalized DAS that adapts to individual drivers, reduces accident risk, and promotes comfortable driving. Achieving such a system requires a deep understanding of drivers and the selection of effective assistance strategies based on this understanding. In this context, stable driver characteristics, such as driving style, cognitive ability, workload sensitivity, and personality, represent fundamental, DAS-independent properties that can serve as a shared basis for personalization across multiple assistance functions. However, it remains unclear whether such driver characteristics can be reliably estimated from naturalistic driving data, and which characteristics are most effective for improving the performance and acceptance of personalized DAS. This thesis addresses these challenges by investigating methods for estimating stable driver characteristics from driving data and exploring their application to the personalization of DAS.

First, this thesis estimates driver characteristics from naturalistic on-road driving data collected along a fixed driving route. Psychological driver characteristics, including cognitive function, psychological driving style, and workload sensitivity, were estimated by explicitly considering road types and multiple temporal scales of driving behavior. The results demonstrate that several cognitive function measures, particularly the Trail Making Test (TMT (B)) and Useful Field of View (UFOV), can be estimated with relatively high accuracy from driving data collected under controlled route conditions (Pearson's correlation coefficients of $r = 0.57$ and 0.70, respectively).

Next, this thesis extends the estimation framework to driving data collected from different routes in order to examine the robustness of driver characteristic estimation under varying driving environments. By focusing on driving scenarios that commonly appear across routes, the results show that cognitive function can still be estimated with moderate accuracy even when route conditions differ (Pearson's correlation coefficients of $r = 0.34$ and 0.48). Although estimation performance decreased compared to the fixed-route setting, the findings indicate that cognitive function represents a driver characteristic that can be robustly inferred from driving data across diverse driving routes.

While the first two studies focus on estimating driver characteristics from driving data, the third study examines whether personalized driving assistance based on driver characteristics is effective. The third study particularly focuses on driving support for speeding and sudden acceleration and deceleration, which represent high-risk driving behaviors and can be reliably measured from driving data. The results show that the effectiveness of such support differs depending on individual driver characteristics. In particular, drivers with high hesitation for driving or low confidence in driving skill exhibited limited behavioral improvements in response to speeding warnings. These findings indicate that speeding-related driving support should be adapted according to driver characteristics.

Fourth, this thesis investigates which driver characteristics are most effective for improving the performance and acceptance of personalized assistance at stop sign intersections, where accident risk is particularly high among older drivers. By comparing multiple assistance strategies that differed in both the amount and content of information provided, it was shown that drivers' responses varied systematically according to cognitive function, personality traits, driving style, and workload sensitivity. Drivers with reduced cognitive function benefited from instructive support, whereas drivers with high neuroticism or high hesitation for driving were negatively affected by information-rich assistance. These results demonstrate that the effectiveness of intersection-related driving support strongly depends on individual driver characteristics.

On the basis of these findings, this thesis provides a unified discussion on personalized DAS. Stable, DAS-independent driver characteristics, especially cognitive function and personality traits, were shown to be influential in determining the effectiveness of driving support and estimable from naturalistic driving data. These properties make them promising foundations for consistent personalization across multiple assistance functions. At the same time, the results of the estimation of driver characteristics highlight that not all relevant driver characteristics can be estimated with sufficient accuracy. For example, in a binary classification setting, confidence in driving skill and hesitation toward driving achieved F1 scores of 0.41 and 0.64, respectively, indicating important challenges for future research.

These results will lead to the development of techniques for understanding drivers on the basis of driving data from psychological and cognitive perspectives, and provide insights into how such techniques can be applied to the design of DAS. Then, the proposed approach enables implicit personalization without imposing additional burdens on drivers, while maintaining interpretability of the personalization process, making it suitable for real-world deployment.

Keywords: Driver Assistance Systems; Driving Behavior; Personalization; Machine Learning; Human-Computer Interaction

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Chapter 1

General Introduction

1.1 Research Background

The rapid development of the automobile industry has had a significant impact on human life. While it has brought many benefits to society, the automobile industry has also contributed to an increasing number of traffic accidents. Each year, approximately 1.19 million people lose their lives due to road traffic crashes [4]. Traffic accidents result from a wide variety of factors. The causes of traffic accidents can be classified into three categories: vehicular factors, environmental factors, and human factors [5]. Among these, human factors account for the majority of accidents, including improper lookout, excessive speed, inattention, and improper evasive action.

Since human factors account for the majority of traffic accidents, DAS are a promising solution to this problem and are currently contributing to accident prevention. Moreover, DAS are becoming increasingly widespread. The global DAS market size is calculated at USD 38.50 billion in 2025 and is predicted to increase from USD 42.74 billion in 2026 to approximately USD 107.79 billion by 2035 [6]. Existing DAS covers a wide range of functionalities, for example, adaptive cruise control (ACC), lane keeping assist (LKA), automatic emergency braking (AEB), blind spot detection (BSD), and parking assistance systems. Furthermore, DAS covers diverse levels of automation, ranging from warning-only systems to systems capable of longitudinal and lateral vehicle control. Even if the level of automation in DAS increases, human drivers are still required to operate the vehicle until fully autonomous driving is realized.

Accident risk varies significantly among individuals, with driver characteristics such as age, as well as personality [7, 8], driving experience [9], and cognitive ability [10]. In this thesis, driver characteristics are defined as relatively stable attributes related to the driver, including demographic, psychological, and cognitive factors that influence the driving process, consisting of perception, decision-making, and operation. For example, older drivers had the highest fatal crashes and younger drivers were involved more frequently in accidents [11]. In such diverse driver populations, one-size-fits-all DAS often does not meet individual needs. This mismatch can reduce driver comfort and acceptance, potentially leading drivers to disregard or misuse assistance systems over time. Since the acceptance of DAS is closely related to driver characteristics [12], drivers with different characteristics have distinct requirements and expectations for assistance systems. Therefore, DAS that adapt their support to individual drivers, which is referred to in this thesis as personalization of DAS, are expected to enhance both acceptance and safety, ultimately contributing to more effective accident prevention [13]. However, most existing DAS are still designed based on average driver characteristics [14], which limits their ability to meet diverse individual needs and to promote safe and comfortable driving.

The approaches of personalization are categorized into explicit and implicit personalization [15, 16]. Explicit personalization requires drivers to choose their preferred settings and change the system. This approach allows drivers to directly control system settings and prevents the selection of unwanted configurations. However, this approach has several drawbacks. Drivers are required to understand a large number of system functions and parameters. This abundance of options imposes a burden on drivers. Moreover, drivers may not always be able to select the system settings that truly match their preferences, and a discrepancy can arise between the settings chosen in advance and the preferences experienced during actual use. In contrast, implicit personalization does not require drivers to explicitly specify their preferences, but instead predicts and determines favorable configurations based on driver data. This approach reduces the burden of manual configuration. To avoid mismatches between implicitly selected assistance and driver preferences, the system must accurately model and understand driver profiles and behaviors.

Recent advances in sensing and data acquisition technologies have made it increasingly feasible to achieve a deeper understanding of drivers. Modern vehicles are equipped with a wide range of sensors, including in-vehicle cameras, physiological sensors, and vehicle dynamics sensors, which allow continuous observation of driver behavior and state. Vehicle dynamics and driver operation data can be reliably collected and synchronized via the Controller Area Network (CAN), which provides real-time access to signals from multiple electronic control units (ECUs), such as vehicle speed, acceleration, braking, and steering inputs [17]. In addition to built-in vehicle sensors, smartphones equipped with inertial sensors and GPS have also been increasingly used as sensing platforms for capturing vehicle dynamics and driving behavior [18]. Advances in vehicle-to-cloud connectivity allow these sensor data to be offloaded to cloud infrastructures, facilitating advanced analytics that would be difficult to perform solely on in-vehicle hardware. These developments provide rich data that can be leveraged to infer driver characteristics relevant to personalization. Furthermore, recent advances in machine learning techniques have significantly enhanced the ability to extract meaningful driver profiles and behaviors from such large-scale and heterogeneous sensor data.

1.2 Research Motivation

Many existing personalization approaches rely on driving behavior and driving style as driver profiles, benefiting from recent advances in sensing and data acquisition technologies. Despite these technological advances, it remains unclear which types of driver data are most relevant and how they should be systematically incorporated into the personalization of DAS. In particular, ACC has been extensively studied as a representative application, as it provides a well-defined longitudinal control task for personalization. In ACC, personalization is commonly achieved by estimating a driver's preferred car-following behavior from observed driving data and adapting control strategies accordingly [19, 20]. Through such behavior- and style-based profiles, ACC systems adjust longitudinal control parameters, including time gap selection and acceleration profiles, to individual drivers.

However, these approaches also have several limitations. Because they are typically designed and validated for a specific DAS, the resulting driver profiles are tightly coupled to a particular function and control objective. As a result, the knowledge obtained from one assistance system cannot be readily transferred to other ADAS with different functionalities, such as warning systems or lateral control assistance. With the increasing number of ADAS implemented in production vehicles, independently personalizing each system becomes impractical and may lead to inconsistent system behavior and increased complexity in system design and integration. These limitations highlight the need for a more comprehensive and unified personalization concept that can be shared across multiple DAS components [16].

In contrast, driver characteristics represent fundamental, DAS-independent properties, making them a promising basis for consistent personalization across multiple assistance systems. Such characteristics capture enduring individual differences that remain relatively stable across driving situations

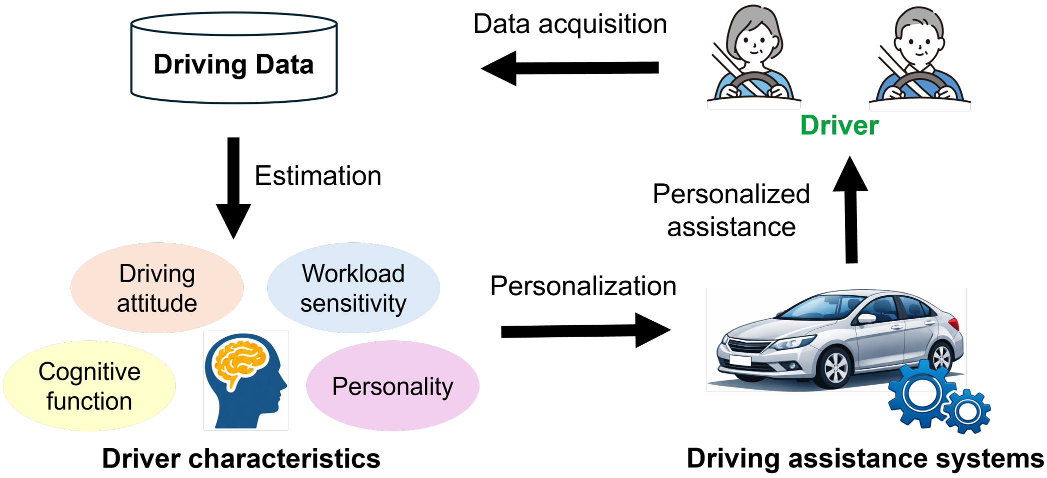


Figure 1.1: Conceptual framework of personalized driver assistance systems.

and over time, although they are not strictly static and may change gradually. Thus, continuous estimation and monitoring of these characteristics are required for effective personalization. Trait-based personalization offers several advantages. First, driver characteristics provide a consistent reference for personalization, reducing sensitivity to short-term fluctuations caused by transient factors such as traffic conditions, fatigue, or emotional state. Second, trait-based approaches improve interpretability, as system adaptations can be explicitly linked to understandable driver characteristics. This facilitates safety assurance, simplifies system validation and deployment, and enhances user trust and acceptance. Finally, driver characteristics enable personalization even in the early stages of system use, thereby alleviating cold-start issues that arise when relying solely on accumulated driving behavior.

However, reliable and practical methods for estimating such driver characteristics have not yet been established. A particular challenge lies in the fact that data collected under diverse driving situations inherently reflect not only driver characteristics but also various confounding factors, such as driving routes, traffic conditions, and transient driver states. Disentangling driver characteristics from these situation-dependent factors, and estimating them in a manner robust to such variations, remains a difficult task.

1.3 Research Objectives

This doctoral thesis aims to establish the technical foundations and insights necessary for realizing a DAS that personalizes assistance strategies to individual driver characteristics. As discussed in the previous section, driver characteristics represent relatively stable, DAS-independent properties that provide a promising basis for consistent personalization across multiple assistance functions. If such characteristics can be automatically estimated from naturalistic driving data, personalization can be achieved implicitly, without imposing burdensome procedures on drivers, such as extensive questionnaires or cognitive tests. Therefore, the ability to reliably estimate driver characteristics from daily driving data is a key prerequisite for the practical realization of personalized DAS. From this perspective, this thesis focuses on the design of robust methods for estimating driver characteristics across diverse driving environments, which form the core of a personalized DAS. In addition, this thesis analyzes how the effectiveness of assistance differs across driver characteristics, thereby providing essential insights into the design of personalized assistance strategies.

An overview of this system concept is illustrated in Figure 1.1. In this system, driving data are continuously acquired during vehicle operation, driver characteristics are estimated from the collected data, and driving assistance strategies are adapted according to the estimated characteristics.

The challenges addressed, and the corresponding solutions, are summarized as follows:

1. **Driver Characteristics Estimation**

   Problem: It remains unclear whether driver characteristics can be reliably estimated from naturalistic on-road driving data, as driving behavior varies significantly depending on road type, driving conditions, and situational context.

   Solution: To address this challenge, road types and driving situations are explicitly incorporated into the feature extraction process for machine learning models. This enables the development of estimation models that are robust to variations in driving routes and situations, allowing driver characteristics to be estimated from naturalistic driving data (Chapters 3 and 4).

2. **Exploring Individual Differences in the Effect of Driving Assistance**

   Problem: The extent to which drivers accept DAS and modify their driving behavior varies from driver to driver. Although driver charac-

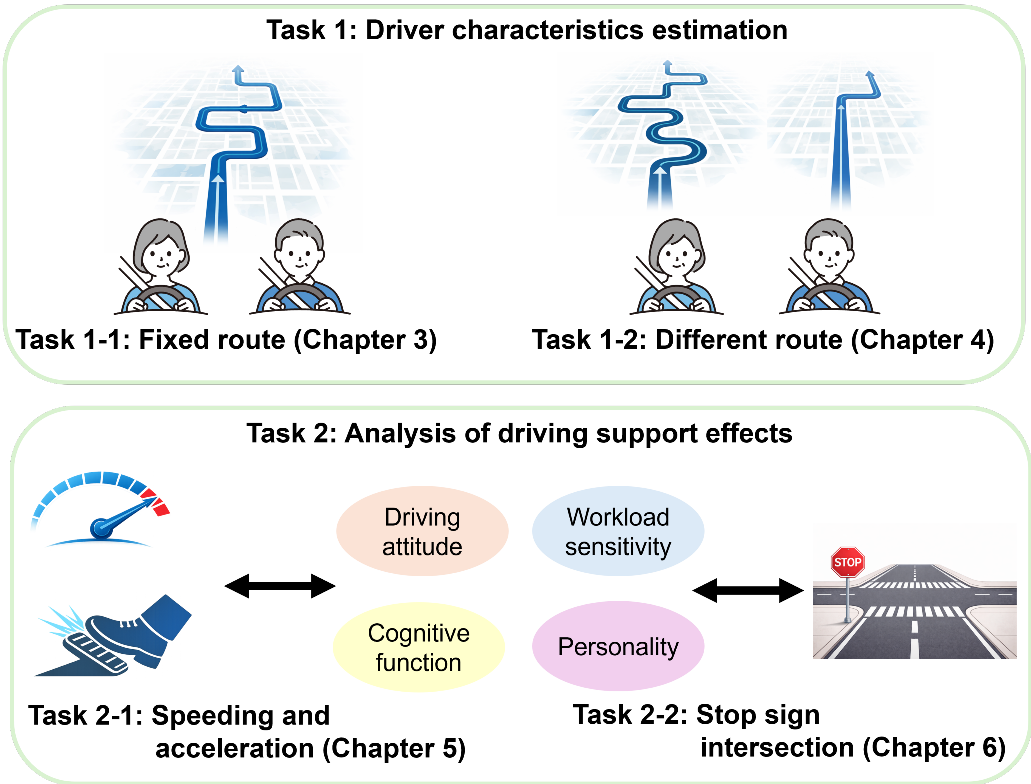


Figure 1.2: Summary of this thesis.

teristics can be estimated from driving data, it remains unclear how these characteristics influence drivers' acceptance of DAS and the resulting behavioral changes, and how such estimations can be effectively linked to the design of driving assistance.

Solution: Driving behavior data were collected during the use of DAS, and changes in driving behavior were systematically analyzed in relation to individual driver characteristics. This analysis identifies driver characteristics that are particularly relevant for the realization of effective personalized DAS (Chapters 5 and 6). Furthermore, in Chapter 6, a model is developed to select optimal driving assistance based on driver characteristics. Based on this, a computational framework is proposed that covers the entire process from driver characteristics estimation to assistance selection and presentation.

1.4 Organization of the Thesis

A summary of this doctoral thesis is depicted in Figure 1.2. The tasks are broadly divided into driver characteristics estimation (Task 1) and analysis of the relationship between driver characteristics and the effects of driving assistance (Task 2). Task 1-1 is a pilot study that estimates driver characteristics on the basis of driving data collected on a fixed route (Chapter 3). Task 1-2 further investigates driver characteristics estimation in a more practical scenario, where driving data are collected from drivers traveling on different routes (Chapter 4). Tasks 2-1 and 2-2 validate the practical relevance of driver characteristics for personalized assistance and provide insights into how the estimated driver characteristics should be utilized in personalized DAS. These analyses connect driver characteristics estimation and how DAS should be personalized based on driver characteristics. These analyses enable the linkage between driver characteristics estimation and the personalization of DAS to individual drivers. Then, a computational model is proposed to select optimal driving assistance based on the estimated driver characteristics, thereby establishing an integrated framework from driver characteristics estimation to assistance selection based on driving data. Task 2-1 focuses on speeding and acceleration behaviors and analyzes the relationships between improvements in these behaviors resulting from driving assistance and driver characteristics (Chapter 5). Task 2-2 focuses on driving behavior at stop-sign intersections and analyzes the relationships between the effects of DAS and driver characteristics (Chapter 6). Furthermore, a model is developed to select driving assistance that each driver perform the safest driving behavior based on driver characteristics. Chapter 2 describes related research surrounding this thesis, Chapters 3 through 6 discuss each issue. Chapter 7 summarizes the insight of these chapters and presents design implications toward personalized DAS based on driver characteristics, and Chapter 8 concludes this thesis.

Chapter 2

Related Works

This chapter provides a brief overview of the current state of personalized DAS and the technologies that enable their implementation. Section 2.1 summarizes existing personalized DAS. Section 2.2 summarizes existing methods for estimating driver characteristics required for the realization of personalized DAS. Section 2.3 reviews driver characteristics that have been identified in previous studies as being relevant to the personalization of DAS. Finally, Chapter 2.4 summarizes the position of this thesis within the existing literature and highlights its main contributions.

2.1 Personalized Driver Assistance System

Drivers continuously process information while driving, integrating perception, decision making, and vehicle control [21]. Because these processes are complex and operate at multiple levels, DAS can support drivers by presenting relevant information and substituting control actions, which helps drivers cope with uncertainty and reduce cognitive demands. While DAS contribute to accident prevention, personalization of DAS is required to meet the diverse needs of drivers. A one-size-fits-all approach may result in limited performance of DAS and reduced satisfaction for individual drivers [22].

Personalization approaches for DAS can be broadly classified into two categories: explicit personalization and implicit personalization [15, 16]. Explicit personalization refers to methods in which drivers manually determine DAS settings according to their preferences. This approach requires drivers to understand system functionality and to actively configure parameters, which may impose additional cognitive and operational burden. In contrast, implicit personalization adapts DAS behavior based on driver data, such as driving behavior and vehicle operation history, without requiring explicit user intervention.

In research settings, methods of implicit personalization have been more frequently investigated than explicit personalization. The earliest studies on personalization in DAS were conducted in the 1990s, focusing on Forward Collision Warning (FCW) systems [23]. In these studies, a combination of rule-based and data-driven approaches was employed to present warnings using driver-specific criteria, allowing the warning thresholds to differ among individual drivers. Subsequently, in the 2000s, research on personalization expanded to ACC systems. In the 2010s, the scope of personalization further broadened to include Lane Keeping Assist (LKA) and Lane Change Assistance (LCA) systems [16]. Currently, ACC represents the most advanced and extensively investigated domain of implicit personalized DAS, with many studies proposing various ACC personalization methods [22, 15, 16]. In [19, 20], personalized car following models are proposed on the basis of driving behaviors. In [24, 25], gap values selected by drivers are predicted using machine learning models that combine vehicle sensor data with driver demographic information. These methods aimed to imitate the following behaviors of drivers. However, a discrepancy between drivers' preferred automated driving style and their own manual driving style has been reported [26, 27], suggesting that drivers do not necessarily prefer driver assistance systems that replicate their own driving behavior [16].

Most existing personalization approaches in commercially available DAS are based on explicit user configuration, where drivers manually adjust system parameters according to their preferences. Although detailed implementations are often not publicly disclosed, personalized DAS have already been implemented in many commercially available vehicles. DAS developed by Hyundai provide several explicit personalization options [28]. For example, drivers can manually configure parameters such as warning timing, warning volume, the presence of haptic alerts, and the maximum desired vehicle speed for systems including Collision-Avoidance Assist (FCA), LKA, Blind-Spot Collision-Avoidance Assist (BCA), Intelligent Speed Limit Assist (ISLA), Smart Cruise Control (SCC), Highway Driving Assist (HDA), and Safe Exit Warning (SEW). Toyota's DAS also offers explicit personalization. Drivers can manually configure parameters such as warning timing, warning sensitivity, and warning methods (audible, visual, or haptic alerts) [29].

However, as the number of DAS implemented increases, independently personalizing each system becomes impractical and may lead to inconsistent system behavior across different DAS. This motivates the need for a unified personalization concept applicable to multiple DAS components [16]. In contrast, DAS that personalize assistance based on driver characteristics can adapt implicitly to individual drivers. By continuously estimating driver characteristics from driving behavior and vehicle operation data, such systems can adjust assistance strategies without requiring explicit user configuration. Furthermore, it facilitates interpretable, unified personalization, which can be consistently shared across multiple DAS components.

2.2 Methodologies for Driver Characteristics Estimation

Driver characteristics estimation is a fundamental component for enabling implicit and unified personalization of DAS. By estimating driver characteristics from observable driving behavior, such as vehicle control, DAS can adapt assistance strategies without imposing additional burden on the user.

Much previous research has focused on driving style recognition from driving data [14] for personalized DAS. However, the definition of driving style varies widely across studies, and many approaches primarily focus on how drivers operate the vehicle, such as acceleration patterns and car-following tendencies. In addition to driving style, several studies have investigated the estimation of driving maneuver skill [30] for DAS personalization, aiming to adapt assistance based on a driver's technical proficiency in vehicle control. While these behavior-centric driver profiles are useful, driving behavior alone is not sufficient to fully explain whether drivers accept or reject assistance provided by DAS, as they lack a psychological perspective on drivers. In this thesis, we focus on driver characteristics that extend beyond observable driving behavior, including personality traits, psychological driving styles, sensitivity to cognitive load, and cognitive ability. These psychological characteristics reflect how drivers approach driving and process information, rather than how they physically execute driving maneuvers. By incorporating such higher-level driver characteristics, DAS may better adapt their assistance strategies to individual drivers, potentially improving perceived comfort, acceptance, and overall effectiveness of driver assistance systems.

Personality represents a general human characteristic that has been widely studied across domains and is considered a promising factor for personalization of DAS. Wang et al. [31] estimated drivers' Big Five personality traits using real driving data. Evin et al. [32] estimated drivers' Big Five personality traits using simulated driving data and physiological data. Ishikawa et al. [33] used naturalistic driving data to estimate drivers' Big Five personality traits. While personality is an important factor for understanding individual differences among drivers, it is not specific to the driving task. As a result, relying solely on personality traits may overlook driving-specific characteristics that are directly relevant to how drivers interact with DAS. In particular, personality alone may be insufficient to capture differences in how drivers perceive driving situations, experience workload, and respond to assistance. Therefore, this thesis focuses on driver characteristics that are more specific to the driving context, namely, psychological driving styles and sensitivity to cognitive workload. These characteristics are closely related to drivers' attitudes toward driving and their perception of workload, and are expected to provide more direct insights for the personalization of DAS than general personality traits.

Cognitive ability is another important factor for DAS personalization, as drivers differ in their ability to perceive, process, and respond to information while driving. Differences in cognitive ability can lead to variability in situations that drivers find challenging, as well as in how they perceive, utilize, and accept assistance provided by DAS [34, 35]. Therefore, considering cognitive ability is essential for understanding individual differences in driver needs and for designing assistance strategies that are appropriately supportive without being intrusive.

Several studies have estimated driver characteristics related to cognitive ability from driving data. Wallace et al. [36] classified drivers as those with Lewy body dementia, Alzheimer's type dementia, and healthy controls. Li et al. [37] estimated driving-related cognitive abilities using driving data and physiological signal data. These studies are primarily based on simulated driving data, and a gap remains in understanding how such cognitive characteristics can be reliably estimated in real-world driving environments, where driving behavior is influenced by uncontrolled and diverse events. Di et al. [38, 39] classified drivers as those with cognitive impairment using naturalistic driving data. Also, Danda et al. [40] estimated Alzheimer's disease on the basis of naturalistic driving data. While these studies are practical in that they used naturalistic driving data, they primarily focused on classification using clinical labels such as dementia or Alzheimer's disease. As a result, their emphasis is placed more on detecting cognitive impairment rather than on leveraging estimated cognitive characteristics for personalization of DAS. To address this gap, this thesis aims to estimate driving-related cognitive abilities from naturalistic driving data. In particular, this work investigates which driving scenes should be focused on to improve the accuracy of cognitive ability estimation when using driving data collected under diverse real-world conditions, such as urban roads and residential areas.

It is worth noting that temporal driver states are also important factors for personalizing DAS. Previous studies have investigated the estimation of transient driver states, such as anger [41], stress [42], workload [43], and drowsiness [44], using physiological signals and driving behavior. In this thesis, the driver characteristics considered represent relatively stable traits and should be addressed in parallel with such temporal driver states when designing personalized DAS.

This thesis establishes the technical foundation for estimating diverse psychological driver characteristics from on-road naturalistic driving data. Furthermore, this thesis proposes a method that enables robust estimation without requiring fixed driving routes, thereby allowing driver characteristics to be estimated under diverse real-world driving conditions. By enabling the estimation of driver-specific information without imposing additional burden, such as questionnaires, this approach provides a practical pathway toward real-world deployment of personalized DAS.

2.3 Integrating Driver Profiles into Driver Assistance System

Although the need to personalize DAS according to individual drivers has been argued [16], and driver characteristic estimation is expected to play a key role in personalizing DAS, the relationship between these estimated characteristics and the effectiveness or acceptance of DAS is still not fully understood. This lack of understanding represents a gap in realizing personalized DAS that adapt to individual driver characteristics. By addressing this gap, it becomes possible to develop a framework for personalized DAS that leverages estimated driver characteristics to adapt and deliver appropriate driving assistance to individual drivers.

To better understand this relationship, several studies have investigated driver characteristics that influence acceptance and preference for assistance systems. Cramer et al. [45] showed that drivers who scored high on locus of control tended to report that the driver should follow the robot's instructions more than those who scored low on locus of control. Li et al. [46] showed that drivers have different preferences regarding and attitudes toward in-vehicle anger intervention systems depending on their driving anger traits. Miyamoto et al. [47] found a relevant connection between users' level of conscientiousness and their evaluation of the utterances of a driving support robot. These studies indicate that diverse driver characteristics are related to the acceptance of and preference for assistance systems; however, their influence on changes in driving behavior has not yet been investigated.

In this thesis, a broad range of psychological driver characteristics is considered to analyze the relationship between driver characteristics and the effectiveness of DAS. Furthermore, beyond subjective driver evaluations, this thesis emphasizes analyzing how actual driving behavior changes, which has been overlooked in existing studies. In particular, this work focuses on driving assistance targeting high-risk behaviors and situations associated with traffic accidents, such as speeding, sudden acceleration, and stop-sign intersections. This analysis provides insights into how driver characteristics estimation can be linked to actual behavioral changes, thereby contributing to the development of effective personalized DAS.

2.4 Research Positioning and Contribution

This thesis addresses two fundamental challenges toward the realization of implicit personalized DAS based on driver characteristics: (1) estimating driver characteristics from naturalistic driving data, and (2) understanding how these characteristics influence the effectiveness of driving assistance. To clarify the novelty of this work, we compare existing studies on both driver characteristic estimation and the integration of driver profiles into DAS.

Table 2.1 summarizes existing studies on driver characteristic estimation from driving data. Previous research has primarily focused on estimating general personality traits or detecting clinical cognitive impairments. While some studies have utilized naturalistic driving data, many were conducted in simulated environments or relied on clinical diagnostic labels. Moreover, few studies have investigated estimation under diverse real-world route conditions. In contrast, this thesis proposes methods for estimating multiple psychological driver characteristics, including cognitive ability, psychological driving styles, and sensitivity to cognitive load, from naturalistic driving data. Furthermore, Task 1-2 extends the framework to enable route-independent estimation, which is essential for real-world deployment of personalized DAS. By addressing both psychological depth and practical applicability, this work establishes a technical foundation for robust driver characteristic estimation in real-world environments.

Table 2.2 summarizes prior studies examining the relationship between driver characteristics and DAS. Existing work has primarily focused on subjective evaluations, such as acceptance, preference, or perceived usefulness of assistance systems. However, the extent to which driver characteristics influence actual behavioral changes induced by DAS has not been sufficiently investigated. To fulfill this gap, this thesis analyzes driving behavior changes resulting from interactions with DAS. Task 2-1 examines how psychological driving styles affect behavioral changes in response to assistance targeting speeding and sudden acceleration and deceleration. Task 2-2 further extends the analysis to cognitively demanding stop-sign intersection scenarios, considering a broader range of driver characteristics, including cognitive ability, personality traits, and workload sensitivity. Through analyses of driver characteristics and driving behaviors, this thesis demonstrates that the effectiveness of driving assistance depends on individual driver characteristics, highlighting the necessity of personalized support strategies. While some driver assistance systems are designed to improve driving skills or reduce fuel consumption, the driving assistance considered in this thesis is designed to facilitate safer driving behavior.

Taken together, this thesis contributes to the field in three main aspects. First, it expands driver characteristic estimation beyond traditional driving-style recognition by incorporating psychological and cognitive traits. Second, it proposes estimation methods applicable to naturalistic and route-independent driving conditions, enhancing practical feasibility. Third, it establishes a systematic link between estimated driver characteristics and objective behavioral effects of DAS, providing empirical evidence for the design of personalized DAS. Finally, by integrating estimation methodologies with behavioral validation, this work presents a unified framework for realizing implicit, interpretable, and scalable personalization across multiple DAS components.

Table 2.1: Comparison of studies on driver characteristics estimation from driving data.

Study	Target Characteristics	Naturalistic Data	Route-Independent
Wang et al. [31]	Big Five personality traits	✓	–
Evin et al. [32]	Big Five personality traits State-Trait Anxiety Inventory	–	–
Ishikawa et al. [33]	Big Five personality traits	✓	✓
Wallace et al. [36]	Dementia	–	–
Li et al. [37]	Driving-related cognitive abilities	–	–
Di et al. [38, 39]	Cognitive impairment	✓	✓
Danda et al. [40]	Alzheimer's disease	✓	✓
This thesis (Task 1-1)	Cognitive ability Psychological driving styles Sensitivity to cognitive load	✓	–
This thesis (Task 1-2)	Cognitive ability	✓	✓

Table 2.2: Comparison of studies investigating the relationship between driver characteristics and DAS.

Study	Target Characteristics	DAS Context	Behavioral Change Analysis
Cramer et al. [45]	Locus of control	Highway entry	–
Li et al. [46]	Driving Anger Scale Driving anger expression	Anger situation	–
Miyamoto et al. [47]	Big Five personality traits	Speeding warning	–
This thesis (Task 2-1)	Psychological driving styles	Speeding Acceleration and deceleration	✓
This thesis (Task 2-2)	Cognitive ability Big Five personality traits Psychological driving styles Sensitivity to cognitive load Self-Awareness changes in cognitive and physical functions	Stop-sign intersection	✓

Chapter 3

Driver Characteristic Estimation: Fixed-Route On-Road Data

3.1 Introduction

To develop personalized and acceptable DAS, automatically monitoring individual characteristics using daily driving data to obtain driver characteristic information is an effective approach. Automatically estimating these characteristics from driving data can provide useful information for DAS without requiring burdensome cognitive tests or questionnaires.

Much previous research has focused on driving style recognition from driving data [14] for personalized DAS. However, although psychological driver characteristics such as cognitive ability [48, 49], psychological driving style [50], and workload sensitivity [51], are related to driving behaviors, researchers have not focused on recognizing these characteristics. Thus, it is not clear whether the recognition of these driver psychological characteristics is possible. As a first step toward implementing adaptive assistance systems, the aim of this research is to develop a regression model to estimate a driver's psychological characteristics, such as cognitive function, psychological driving style, and workload sensitivity, from on-road driving behavioral data using machine learning and deep learning techniques. Several studies have shown the relationship between driving performance and cognitive function [48, 49], personality [52, 53], and stress [54, 55]. Based on these results, we posit that psychological driver characteristics can be estimated from driving data.

These characteristics are invariant over a short period, such as a single drive; driving data obtained on public roads contain various kinds of driving behaviors observed in diverse situations. Driving behaviors on public roads vary with road type, driving conditions, and situation. Thus, estimating drivers' psychological characteristics on public roads is a difficult and challenging task, and we do not know in which part of driving data the differences in characteristics will appear. To address this problem, our proposed method segments driving data based on road types and divides them into small sequences to compare driving behaviors under similar conditions. We evaluate the proposed method and investigate the effectiveness of the segmentation. Furthermore, we assessed the use of important in-vehicle sensors for estimation and analyze which characteristics that can be estimated for each road type.

We use the dataset in [56], which includes time-series driving data collected from in-vehicle sensors, for example, acceleration, brake, and steering angle sensors. The subjects are older drivers who drive on public roads. In terms of metrics from driver psychological characteristics, we use the Driving Style Questionnaire (DSQ) [50], Workload Sensitivity Questionnaire (WSQ) [51], and several neuropsychology tests, including the Trail Making Test (TMT) [57], Maze test [58], and Useful Field of View test (UFOV) [59].

The main contributions of this chapter are as follows.

1. **Estimation of drivers' psychological characteristics considering road types:** The proposed method uses road type information to estimate drivers' psychological characteristics. Road type information is informative for the estimation of drivers' psychological characteristics because the ability to drive safely differs across different road types [60]. We introduce the method in Section 3.4 and present the evaluation of the performance in Section 3.6.

2. **Analysis of effective in-vehicle sensors for estimating drivers' psychological characteristics:** The Effectiveness of in-vehicle sensors for estimating psychological driver characteristics from driving data is still unknown. We assess the effectiveness of in-vehicle sensors using various types of sensors in Section 3.7.

3. **Analysis of the effective duration of driving behavior for the estimation of drivers' psychological characteristics:** We reveal how the duration of behavior contains important information about drivers' psychological characteristics in Sections 3.6 and 3.7. This knowledge is useful for feature extraction or estimation models that achieve high accuracy.

3.2 Related Works

This chapter focuses on estimating drivers' psychological characteristics from driving data. No previous study has addressed this estimation, but several studies have analyzed the relationship between driving and psychological characteristics. We hypothesize that psychological characteristics can be estimated from driving data based on previous studies.

3.2.1 Relationship between driving and personality

Some studies have revealed that driving performance is related to personality. Adrian et al. [52] investigated the relationship between driving performance and personality traits among older drivers. It was reported that personality (extraversion) was negatively related to driving performance. In [61], aggressive driving, crashes, and moving violations were estimated from the driver's personality. Guo et al. [62] found that drivers' personality traits affect accident involvement and risky driving behavior. Additionally, an association between driving stress and personality was identified in [54].

3.2.2 Relationship between driving and cognitive function

Cognitive function can be measured by several neuropsychology tests, such as the Mini-Mental State Examination (MMSE) [63], TMT [57], Maze test [64], UFOV [59]. These scores are used in this chapter, and details are described in Section 3.3. The relationship between driving and the scores of these tests has been well studied. Piersma et al. [65] assessed fitness to drive in patients with Alzheimer's disease using clinical interviews, neuropsychological assessments, and driving simulator rides. These three types of assessments are valid for assessing fitness to drive. Baines et al. [66] showed that the patterns of driving cessation differ depending on the sex of participants with dementia. The results of these works show that a correlation exists between cognitive function and driving behavior.

3.3 Dataset

In this chapter, we use the dataset provided by the Institutes of Innovation for Future Society of Nagoya University [56]. The dataset was collected from 24 elderly people (12 males and 12 females) aged 50 to 79 years (average 66 years). They drove on public roads two times each, and a total of 48

Table 3.1: In-vehicle sensors.

	Sensor	Unit
1	Steering angle	deg
2	EPS torque	N m
3	Forward acceleration	$\mathrm{m\,s^{-2}}$
4	Lateral acceleration	$\mathrm{m\,s^{-2}}$
5	Yaw rate	$\mathrm{deg\,s^{-1}}$
6	Speed	$\mathrm{km\,h^{-1}}$
7	Accelerator position	%
8	Brake pressure	MPa
9	Fuel consumption	mL

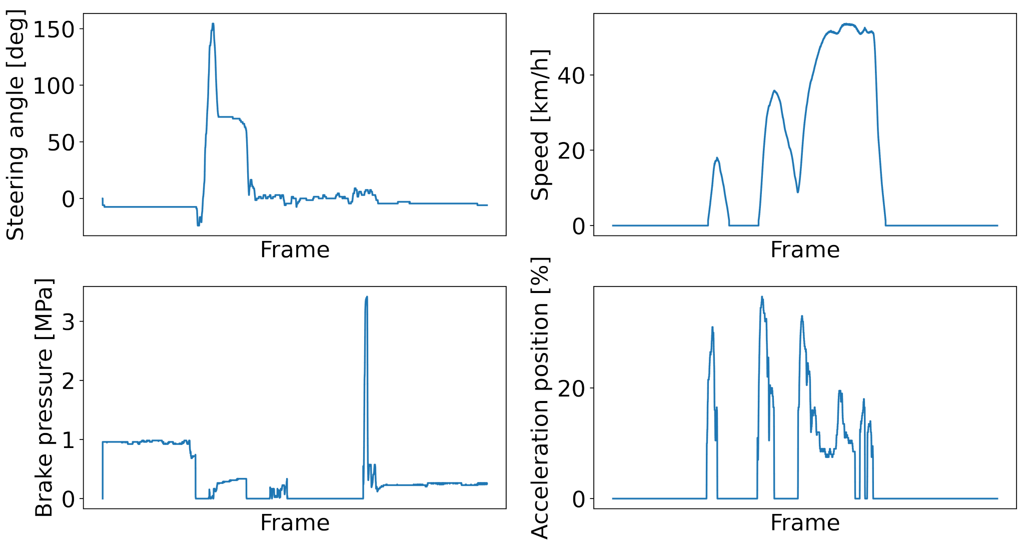


Figure 3.1: Examples of time-series data from in-vehicle sensors.

Table 3.2: Descriptive statistics, and Pearson correlations among cognitive function tests.

	TMT (A)	TMT (B)	MAZE	UFOV	Mean	SD
TMT (A)	–	0.65	0.57	0.23	34.1	10.2
TMT (B)		–	0.51	0.53	94.9	36.3
Maze			–	0.08	26.3	16.9
UFOV				–	151.4	100.1

driving session data were collected. After removing incomplete data, we retained 38 driving session data from 23 drivers. Hence, for some drivers, one driving session data is utilized. All procedures described in this chapter were approved by the Ethical Committee of Nagoya University. Informed consent was obtained from all drivers before conducting the experiments.

The driving tests were performed on public roads. In the tests, all participants drove on an arterial road first and then circumnavigated a residential area. The total mileage and the total driving time were different for each participant. The driving duration ranged from 2245 s to 4762 s, with an average of 2885 s. The mileage ranged from 10079 m to 14810 m, with an average of 12109 m. In addition to the driving tests, the drivers took cognitive function tests and answered questions about their driving style and workload.

3.3.1 In-vehicle sensor data

The car used in the driving tests was equipped with several sensors. We use time-series data from 9 sensors and GPS sensor data. The GPS sensor data are used only for the preprocessing of driving data. Table 3.1 details the in-vehicle sensors. Moreover, we calculate first-order differences in the steering angle, forward acceleration, lateral acceleration, and accelerator position and use them as the velocity of the steering angle, forward jerk, lateral jerk, and rate of change of the accelerator position. From these sensors, we estimate the results of cognitive function tests, the DSQ, and the WSQ. Figure 3.1 shows examples of time-series data of the steering angle, speed, brake pressure, and acceleration position sensors.

3.3.2 Cognitive function data

The dataset also includes scores on neuropsychological tests that measure cognitive function. The details of the tests used in this chapter are as follows.

Trail Making Test (TMT): There are two types of TMT [57]. TMT (A) measures the execution time of a test in which subjects connect numbers writ-

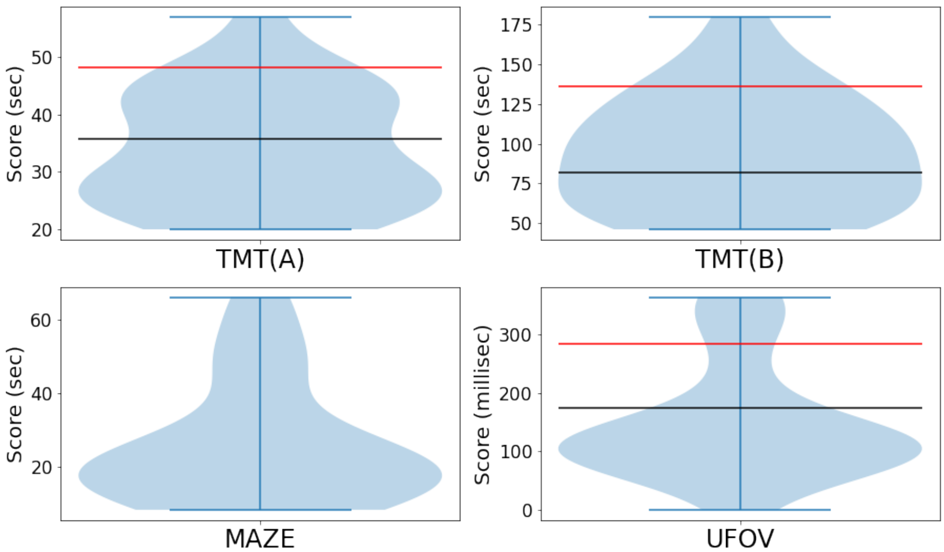


Figure 3.2: Violin plots of the cognitive function scores. The TMT and MAZE scores are expressed in seconds, and the UFOV test scores are expressed in milliseconds. The red and black lines indicate the mild cognitive impairment (MCI) and cognitively normal standards in [1] or passing the driving test in [2]. The average TMT (A), TMT (B), MAZE, and UFOV scores of the subjects were 34.1, 94.9, 26.3, and 151.4, respectively.

ten on a piece of paper in sequence. In TMT (B), subjects connect numbers and letters; thus, cognitive alteration is needed. It has been shown that certain TMT results are correlated with impaired driving in older drivers [67] and that these tests are useful as a screening tool [68].

Maze Test: Subjects execute the Maze test [58], and the time to finish the test is measured. In [58], the correlation between the results of the Maze test and driving performance was verified. There are five types of maze tests, and subjects randomly solve two types of tests. We use the total score from the two types of tests.

Useful Field of View (UFOV) test: The UFOV test [59] measures the visual field area, where information can be extracted without eye or head movements. The time to finish the UFOV test is measured. The results of the UFOV test generally decrease with age [69] and correlate with vehicle accidents [70, 71]. Therefore, the UFOV test is considered an important estimator of the behavior of older drivers.

Descriptive statistics and the Pearson correlations among cognitive function tests of 23 drivers are provided in Table 3.2. Some studies investigated the standard scores of cognitive function tests. Ashendorf et al. [1] investigated the average TMT scores among cognitively normal older adults and adults with MCI. In [2], patients with cognitive dysfunction took a driving test; their UFOV test scores were examined in the passing and failing groups. Figure 3.2 shows violin plots of the test scores. These scores are plotted in Figure 3.2, from which we can confirm that the scores of each test are widely distributed.

In addition to these tests, drivers took the MMSE [63], which is a screening test for dementia estimation. In this test, subjects answer some questions. Subjects who score less than 23 out of 30 are suspected to have dementia, and those who score less than 28 are suspected to have MCI. All drivers included in this dataset had MMSE scores in the range of 28 to 30. Thus, no driver was suspected of having dementia. The MMSE score is not incorporated in the subsequent analysis.

3.3.3 Driving Style Questionnaire and Workload Sensitivity Questionnaire

The DSQ and WSQ, which are based on a self-reported questionnaire, were introduced by [50, 51] for characterizing drivers from a psychological aspect. In [51], the relationship between car-following behavior and DSQ was validated. Table 3.3 details the items in the DSQ and WSQ. The DSQ includes eight items measured on a scale from 1 to 4, and the WSQ includes 10 items

Table 3.3: DSQ and WSQ items.

	DSQ Item
1	Confidence in driving skill
2	Hesitation for driving
3	Impatience in driving
4	Methodical driving
5	Preparatory maneuvers at traffic signals
6	Importance of automobile for self-expression
7	Moodiness in driving
8	Anxiety about traffic accidents
	WSQ Item
1	Understanding of traffic conditions
2	Understanding of road conditions
3	Interference with concentration
4	Decline in physical activity
5	Disturbance on the pace of driving
6	Physical pain
7	Path understanding and search
8	In-vehicle environment
9	Control operation
10	Driving posture

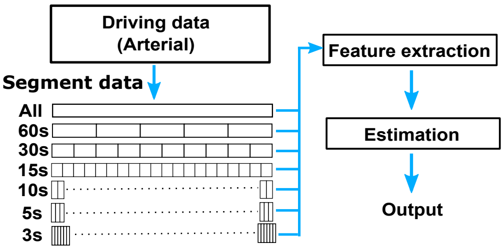
measured on a scale from 1 to 5. We classify drivers with high and low scores on the DSQ and WSQ.

3.4 Method

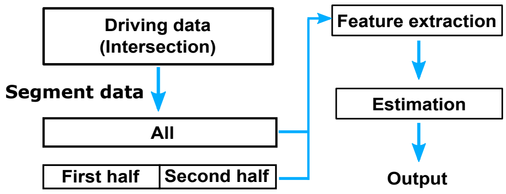
In this section, we present the method for estimating driver characteristics from in-vehicle sensors. An overview of the proposed method is shown in Figure 3.3. We make two hypotheses for the estimation as follows (in Section 3.4.1 and 3.4.2).

3.4.1 Segmentation using road types

First, we hypothesize that driver characteristics, which can be estimated are dependent on the road type. Since driving behavior is strongly related to road type, several studies on driving style recognition from driving data have used road type information [72, 73]. In addition, older drivers tend to be



(a) Overview of the proposed model in arterial roads.



(b) Overview of the proposed model in intersections.

Figure 3.3: Overview of the proposed model.

involved in traffic accidents at intersections [34]. Additionally, the mental workload in driving depends on road context [74] and visibility [75]. Thus, it is natural that features calculated from different road type data elicit different driver characteristics. Moreover, segmenting driving time-series data based on road types makes capturing diverse driving behaviors easier. Based on this hypothesis, we segment time-series driving data into two types, namely, arterial roads and intersections, to consider driving situations. The detailed method of road type segmentation is described in Section 3.4.3.

3.4.2 Segmentation with various durations

Second, we hypothesize that differences in drivers' characteristics are exhibited not only in whole driving but also in partial driving. However, we have no a priori knowledge about when or where the differences in drivers' characteristics are exhibited. Therefore, we segment arterial road and intersection data further with various durations and extract features from each segmented road.

We segment arterial data so that the average number of seconds for each segment is [All, 60, 30, 15, 10, 5, 3]. "All" means no division, i.e., whole arterial road (with an average of 355 s). On the other hand, at intersections, it is difficult to segment driving data based on the average number of seconds, such as arterial road data, because the number of seconds to pass through the intersection is small compared with the arterial road data and varies according to the situation. Thus, we segment the data at the intersection into the first half and the second half.

Long-term driving behavior is captured from features from long-term driving data (segment), while short-term driving behavior is captured from features from short-term driving data (segment). This second hypothesis is similar to the hypothesis in [76] in that only a few subintervals of time-series

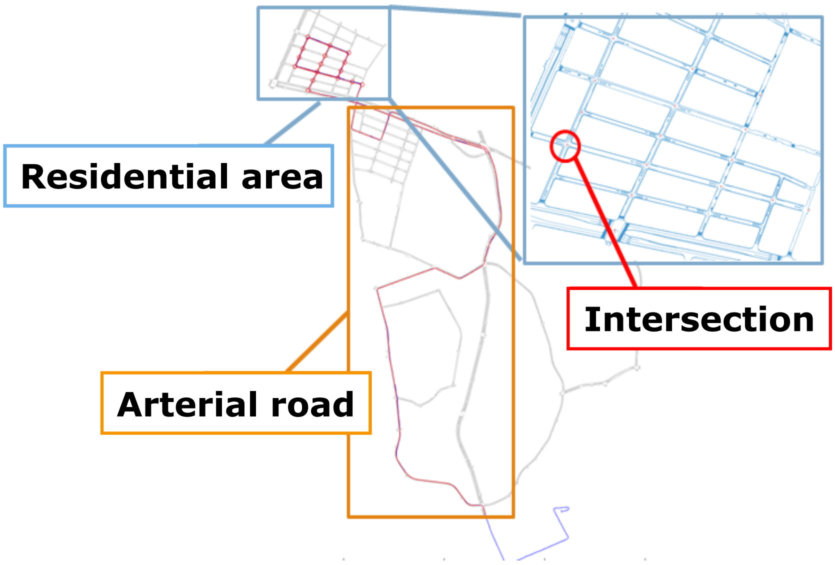


Figure 3.4: Driving test route (red line). Time-series driving data are segmented into arterial roads and intersections. The intersections are located in a residential area.

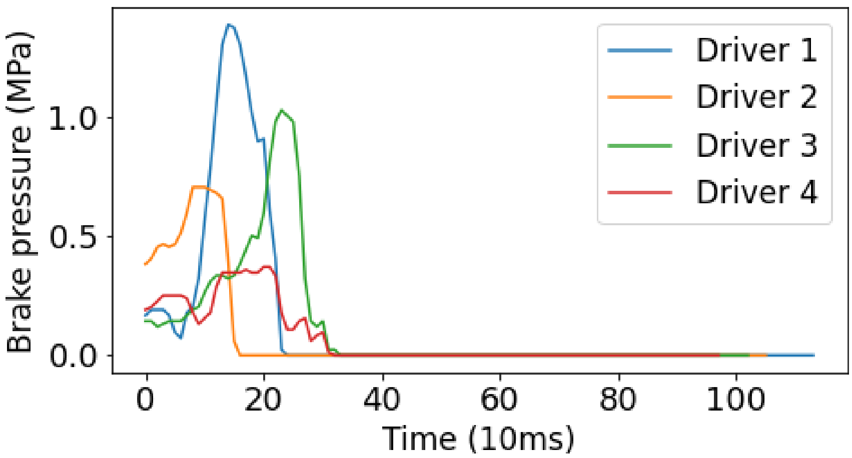


Figure 3.5: Examples of the brake pressure behavior of four drivers. The drivers press the brake pedal when entering an intersection.

driving data are indicative of the class of drivers with ADHD. The detailed method of various durations segmentation is described in Section 3.4.3.

3.4.3 Preprocessing

To segment driving data using road types, we use the car's position obtained through a GPS sensor. The route of the driving test is shown in Figure 3.4. The intersections are located in a residential area. We use four intersections where all drivers' data are recorded accurately. We treat these four intersections as the same road types, but features are extracted from each intersection separately because the visibility and ease of driving are not the same. The time-series driving data collected on the arterial road and at selected intersections are segmented into arterial road data and intersection data.

Furthermore, we segment time-series data on the arterial road. We position segment points so that the average number of seconds for each segment is [ALL (355), 60, 30, 15, 10, 5, 3]. Then, each frame of time-series data is assigned to the nearest segment points, and the arterial road data are segmented into several intervals.

For intersection data, we use brake sensor data to segment the data. When entering an intersection, almost all drivers press the brake pedal, step off the brake, and then step on the accelerator. Figure 3.5 shows the braking behaviors of some drivers at an intersection. Since it is assumed that driving behavior changes before and after stepping off the brake, we segment intersection data into before and after stepping off the brake. We found that small parts of the driving behaviors of some drivers at intersections do not follow this pattern. We exclude these driving data and extract intersection features (the sample size used in the experiment remains the same).

3.4.4 Feature extraction

For each road type and segment in Section 3.4, statistics (mean, median, variance, maximum, kurtosis, and skewness) of each sensor in Table 3.1 are calculated and used as features for estimation models. In total, the numbers of features are 17051 for the arterial road and 905 for the intersection data (missing features are removed). The differences in the features for the arterial road and the intersections are the location and intervals, where driving data are collected.

We estimate cognitive function, DSQ, and WSQ using driving sensors. Regression is performed for cognitive function, and classification is performed for DSQ and WSQ because the scores of cognitive function are continuous values and the scores of DSQ and WSQ are discrete values. The input features are the same for estimation models of cognitive function, DSQ, and WSQ.

3.4.5 Machine learning algorithm

For both regression and classification, we separately estimate the characteristics of drivers on arterial roads and at intersections and compare the estimation results based on two types of roads. To estimate the scores of cognitive function tests, we use linear regression models: lasso regression, ridge regression, and nonlinear regression models: random forest and long short-term memory (LSTM). To estimate the DSQ and WSQ scores, we use linear classification models, i.e., logistic regression with L2 regularization and linear support vector, and nonlinear classification models: random forest and LSTM. We use an LSTM model as a deep learning method that can capture complex time-series relationships between the sensors and cognitive function. An LSTM model is also used in [77] to estimate drivers with ADHD.

The models other than LSTM use the statistical features extracted in Section 3.4.4. The estimation models based on arterial road data use 17051 features, and the estimation models based on intersection data use 905 features. In contrast, LSTM uses the time series signal features of sensors in Table 3.1. The input signals of the LSTM are sampled at 1 Hz. LSTM is used to test the first hypothesis in Section 3.4.1, but it cannot be used for the second hypothesis explicitly because LSTM uses only time-series signals. From intersection data, the LSTM model makes estimations for each intersection because time-series data are directly input, and features extracted from several intersections cannot be utilized. All models output estimated scores of each cognitive function test or class categories of DSQ and WSQ.

3.5 Experimental Settings

3.5.1 Experimental settings for cognitive function estimation

The regularization parameter values of lasso and ridge regression are selected from [0.001, 0.01, 0.1, 1, 10, 100]. The maximum depth of a tree of random forest is selected from [3, 5, 7, 9, 11]. To align the lengths of all time-series signals, the first part of the time-series data is filled with zeros. The LSTM architecture is composed of one hidden layer with 50 units. The mean squared error (MSE) loss is used as the loss function for the LSTM. The number of epochs is 5000 in all models, but the learning is terminated when the value of the loss function does not decrease 10 times in a row. Optimization is performed using the ADAM optimizer with a learning rate of 0.001. As evaluation criteria of estimation models for cognitive function, the Pearson correlation coefficient (r) and root-mean-square-error (RMSE) are used.

3.5.2 Experimental settings for DSQ and WSQ estimation

The regularization parameter values of the logistic regression and linear support vector machine are selected from [0.001, 0.01, 0.1, 1, 10, 100]. The maximum depth of a tree of the random forest is selected from [3, 5, 7, 9, 11]. The architecture of the LSTM models is almost the same as that of regression in Section 3.5.1, but the binary cross entropy loss is used as the loss function. Model training proceeds in the same manner as regression. As an evaluation criterion of classification models, we report the macro F1-score. The scales of DSQ and WSQ are different; we split these scores based on the median value to create binary classification labels and then, conduct binary classification.

For both regression and classification, we use leave-one-person-out cross-validation to evaluate the estimation models. For drivers whose two driving data are used, two estimated scores are aggregated using mean values and are regarded as the final estimated score of drivers to balance a driver's contribution to accuracy. For models other than LSTM, for each fold, we use only features that have a correlation with true scores with $|r| > 0.1$ to avoid overfitting. The hyperparameters are tuned in the training set.

3.6 Results

Table 3.4: Regression accuracy of the model with two types of segmentation.

Road type	Model	r				RMSE			
		TMT (A)	TMT (B)	MAZE	UFOV	TMT (A)	TMT (B)	MAZE	UFOV
Arterial	Lasso	0.213	0.532	**0.334**	-0.150	10.963	31.794	**15.939**	146.331
	Ridge	**0.416***	**0.579***	0.281	-0.149	**9.477**	**29.234**	16.279	130.413
	RF	0.102	-0.403	-0.164	-0.189	10.282	39.618	17.389	106.429
Intersection	Lasso	-0.340	-0.008	-0.282	0.080	12.072	44.755	20.535	121.543
	Ridge	-0.188	0.066	-0.415	0.186	14.813	47.959	28.415	114.376
	RF	-0.298	-0.077	-0.391	**0.559***	11.560	39.049	19.061	**86.287**

Table 3.5: Regression accuracy of the model without various duration segmentation.

Road type	Model	r				RMSE			
		TMT (A)	TMT (B)	MAZE	UFOV	TMT (A)	TMT (B)	MAZE	UFOV
Arterial	Lasso	0.073	0.313	0.244	0.055	10.691	35.603	16.178	107.376
	Ridge	0.400	0.224	**0.411***	-0.134	9.838	37.893	**15.085**	123.433
	RF	0.207	-0.062	0.068	-0.111	10.226	38.816	17.420	108.093
Intersections	Lasso	-0.353	0.214	-0.120	0.439*	11.606	36.655	18.526	90.759
	Ridge	0.213	0.284	-0.025	0.316	10.804	38.722	20.639	114.131
	RF	0.128	0.055	-0.273	**0.708***	10.307	38.026	18.794	**81.564**

Table 3.6: Regression accuracy of the model without any segmentation.

Model	r				RMSE			
	TMT (A)	TMT (B)	MAZE	UFOV	TMT (A)	TMT (B)	MAZE	UFOV
Lasso	-0.226	0.205	-0.124	-0.345	12.237	37.883	19.314	129.162
Ridge	0.279	0.403	0.094	-0.320	10.497	33.721	18.342	150.510
RF	-0.087	0.362	0.091	0.426	11.688	33.784	17.101	91.490

In this section, we evaluate the proposed model and confirm the efficacy of two types of segmentation. We compare the estimation accuracies of three models, namely, (i) a model with both road type and various duration segmentation, (ii) a model with only road type segmentation, and (iii) a model without any segmentation. The features used in model (ii) are extracted from each road type without various duration segmentation. The features used in model (iii) are extracted from whole driving data without any segmentation. The accuracy of the LSTM model is low for cognitive function, DSQ, and WSQ. The estimation results of the LSTM are detailed in Appendix A.

3.6.1 Regression accuracy for cognitive function

Table 3.4 shows the regression accuracy of model (i) for the arterial road and intersection data. The first column shows the road types that are used for feature extraction. Lasso regression, ridge regression, and random forest are denoted as Lasso, Ridge, and RF, respectively, in the second column. The bold values indicate the highest accuracy among each cognitive function test. We performed t-tests to validate the null hypothesis of no correlation between estimated values and labels. Correlation coefficients with p-values smaller than 0.05 are marked with * in Table s3.4.

Using ridge regression for the arterial road data, TMT (A) and TMT (B) were estimated, with r values of 0.416 and 0.579, respectively. These r values indicate a moderate correlation between estimated scores and true scores, namely, the estimation worked well for TMT (A) and TMT (B). However, the accuracies for these tests were not high in the intersection models. MAZE was best estimated with lasso regression for the arterial road, and the r value was 0.334. Using a random forest for the intersection data, UFOV had an r value of 0.559. In [78], correlations between 0.1 and 0.5 are interpreted as weak correlations, those between 0.5 and 0.7 as moderate correlations, and those between 0.7 and 0.9 as strong correlations. Thus, the highest estimation accuracies of model (i) for TMT (A) and MAZE were weak correlations, and those for TMT (B) and UFOV were moderate. The estimation models that achieved the best RMSE for each cognitive function test were not always the same as the estimation models that achieved the best r. The best RMSE values of all tests were smaller than the standard deviation (in Figure 3.2). Hence, we find that the estimation by our models was better than the estimation by mean values.

In Table 3.4, the estimations for TMT (A), TMT (B), and MAZE were better for the arterial roads than those at the intersections. On the other hand, the results of UFOV were worse for the arterial roads. These results confirm that cognitive functions, which can be estimated depend on the road type. As [70] reported that older drivers with a useful-field-of-view disorder had 15 times more intersection accidents, and it is assumed that the difference in the UFOV results of drivers is likely to be apparent at an intersection.

All computations were carried out on an Intel Core i7-12700K CPU with 12 cores and 32 GB RAM. Preprocessing and feature extraction took a total of 55.7 seconds per driver for the arterial road data, and 40.0 seconds per driver for the intersection data. We also measured the time spent during CV to train and test the models. Ridge regression for the arterial road was the best model to estimate TMT (B), and it took an average of 1.33 seconds to learn the driving data of 22 drivers and an average of 0.02 seconds to estimate the driving data of one driver.

Effectiveness of various duration segmentation

Next, to confirm the effectiveness of various duration segmentation, we compare the accuracies of the models with road type and various duration segmentation (i) and the models only with road type segmentation (ii). Table 3.5 shows the regression accuracies of model (ii). The bold values indicate the accuracies that were higher than the best accuracies of model (i).

For model (ii), the accuracies of MAZE and UFOV were high in comparison with model (i). For intersections in particular, improvements in UFOV were significant. Model (ii) achieved a moderate r value in MAZE (0.411) and a strong r value in UFOV (0.708). These results illustrate that the various duration segmentation worked well for TMT (A) and TMT (B) on arterial roads but did not work well for the intersections.

Effectiveness of road type segmentation

As described in Section 3.4, we hypothesized that road types are informative for the estimation of the driver's cognitive function. To test this hypothesis, we compare the accuracies of the models with road type segmentation (i) and (ii) and the models without road type segmentation (iii). Table 3.6 shows the regression accuracies of model (iii). None of the tests were estimated more accurately than models with road type segmentation. Therefore, it is important to consider the road type when estimating the cognitive functions of drivers.

3.6.2 Classification accuracy for DSQ and WSQ

Table 3.7: Classification accuracy (F1-score) for DSQ.

DSQ item	Model (i)			Model (ii)			Model (iii)		
	LR	SVM	RF	LR	SVM	RF	LR	SVM	RF
Arterial							Whole		
Confidence in driving skill	0.356	0.387	0.415	0.415	0.360	0.406	0.415	0.315	0.387
Hesitation for driving	0.321	0.296	0.387	0.387	0.512	0.345	0.296	**0.649**	0.432
Impatience in driving	0.397	0.397	0.415	0.460	0.389	0.406	0.415	0.333	0.367
Methodical driving	0.356	0.377	0.387	0.360	0.374	0.367	0.424	0.415	0.360
Preparatory maneuvers at traffic signals	0.308	0.378	0.378	0.526	0.472	0.482	0.568	0.603	0.526
Importance of automobile for self-expression	0.333	0.333	0.333	0.255	0.415	0.374	0.470	0.550	0.506
Moodiness in driving	0.507	0.432	0.356	0.552	0.491	0.544	0.404	0.491	0.525
Anxiety about traffic accidents	0.424	0.424	0.424	0.507	0.513	0.475	0.562	**0.683**	0.424
Intersection									
Confidence in driving skill	0.377	0.309	0.397	0.406	0.408	0.387			
Hesitation for driving	0.616	0.591	0.418	0.389	0.391	0.356			
Impatience in driving	0.367	0.404	0.397	0.432	**0.525**	0.397			
Methodical driving	0.321	0.359	0.356	0.345	0.434	0.432			
Preparatory maneuvers at traffic signals	0.591	0.670	0.470	0.755	**0.784**	0.582			
Importance of automobile for self-expression	0.582	**0.661**	0.424	0.397	0.482	0.415			
Moodiness in driving	**0.553**	0.512	0.474	0.513	0.491	0.457			
Anxiety about traffic accidents	0.415	0.406	0.424	0.424	0.415	0.424			

Table 3.8: Classification accuracy (F1-score) for WSQ.

WSQ item	Model (i)			Model (ii)			Model (iii)		
	LR	SVM	RF	LR	SVM	RF	LR	SVM	RF
Arterial							Whole		
Understanding of traffic conditions	0.449	0.513	0.360	0.330	0.232	0.454	0.391	0.352	0.454
Understanding of road conditions	0.548	0.493	0.345	0.491	0.482	0.468	0.548	0.574	**0.627**
Interference with concentration	0.232	0.265	0.269	0.375	0.444	0.438	0.394	**0.550**	0.298
Decline in physical activity	0.277	0.331	0.352	0.282	0.391	0.308	0.191	0.421	0.338
Disturbance on the pace of driving	0.472	**0.514**	0.434	0.265	0.391	0.406	0.359	0.391	0.384
Physical pain	0.255	0.284	0.247	0.415	**0.681**	0.338	0.391	0.444	0.361
Path understanding and search	0.247	0.170	0.103	0.472	0.500	0.289	0.419	0.521	0.394
In-vehicle environment	0.223	0.339	0.330	0.526	0.591	0.391	0.622	0.598	0.373
Control operation	**0.578**	0.491	0.391	0.368	0.419	0.500	0.472	0.419	0.472
Driving posture	0.404	0.309	0.367	0.356	0.415	0.309	0.321	0.454	0.345
Intersection									
Understanding of traffic conditions	0.512	**0.582**	0.391	0.435	0.460	0.391			
Understanding of road conditions	0.545	0.574	0.438	0.591	0.574	0.545			
Interference with concentration	0.482	**0.550**	0.394	0.428	**0.550**	0.308			
Decline in physical activity	0.579	**0.631**	0.521	0.525	0.552	0.521			
Disturbance on the pace of driving	0.339	0.406	0.449	0.454	0.438	0.449			
Physical pain	0.265	0.438	0.223	0.359	0.391	0.373			
Path understanding and search	0.579	0.552	0.419	**0.632**	0.578	0.550			
In-vehicle environment	**0.725**	0.683	0.491	0.622	0.709	0.460			
Control operation	0.521	0.438	0.521	0.552	0.474	0.521			
Driving posture	0.321	0.449	0.321	0.309	0.491	0.333			

Tables 3.7 and 3.8 show the classification results of DSQ and WSQ of model (i), model(ii), and model (iii), respectively. LR, SVM, and RF denote logistic regression, support vector machine, and random forest. The bold values indicate the highest accuracy among each item with values exceeding 0.5.

The DSQ items with the highest accuracy greater than 0.5 were hesitation for driving, impatience in driving, preparatory maneuvers at traffic signals, importance of automobile for self-expression, moodiness in driving, and anxiety about traffic accidents. In particular, the macro F1-score of preparatory maneuvers at traffic signals was high (0.784) at intersections. The highest accuracy of two out of eight DSQ items did not exceed 0.5 with all models. Other than driving posture, all WSQ items were estimated with the highest accuracy greater than 0.5. In particular, the macro F1-score of in-vehicle environment was high (0.725) at intersections. Concerning DSQ, none of the models using arterial data achieved the highest accuracy using model (i) or model (ii). Concerning WSQ, the model using arterial data achieved the highest accuracy on three items, while the model using intersection data achieved the highest accuracy on six items.

Model (i) achieved the highest accuracies for two DSQ items and six WSQ items, while model (ii) achieved the highest accuracies for two DSQ items and three WSQ items. Thus, segmentation with various durations worked well for some items of the psychological characteristics but did not work for other items. For both DSQ and WSQ, estimation at intersections tends to be more accurate than on arterial roads. With model (iii), two DSQ items and two WSQ items are estimated with the highest accuracy. Based on these results, for some DSQ and WSQ items, segmentation based on road type was not effective for estimation.

3.7 Discussion

In this section, we further investigated the efficacy of two types of segmentation. We focused on the results of the estimation of cognitive function and analyzed why the segmentation improved the accuracies using feature importance.

3.7.1 Contribution of sensors

We investigate which sensors contributed to the estimation. We focus on the results of TMT (B) with model (i) using ridge regression for the arterial roads and those of UFOV with model (ii) using random forest for the intersections.

Table 3.9: The three most important sensors for TMT (B) and UFOV estimation.

	TMT (B) (arterial)	
1	Rate of change of the accelerator position	75.0%
2	Steering angle	21.7%
3	Lateral jerk	1.7%
	UFOV (Intersection)	
1	Rate of change of the accelerator position	84.6%
2	Accelerator position	9.81%
3	Steering angle	3.11%

Table 3.10: Relative proportion of importance of each segment duration.

Duration of segment	Unnormalized	Normalized
All	0.1%	1.9%
$60s$	9.3%	30.3%
$30s$	18.1%	29.7%
$15s$	17.6%	16.2%
$10s$	19.4%	12.2%
$5s$	17.0%	5.7%
$3s$	18.6%	3.9%

We regard the absolute values of the standardized regression coefficient of ridge and the mean of accumulation of the impurity decrease within each tree of random forest as the contribution of each feature. The absolute values are summed for each sensor. Then, we compare the relative proportions of the three most important sensors.

Table 3.9 shows the relative proportions of the three most important sensors. For the arterial roads, the three most important sensors and their relative proportions were the rate of change of the accelerator position (75.0%), steering angle (21.7%), and lateral jerk (1.7%), while for the intersections, the three most important sensors and their relative proportions were the rate of change of the accelerator position (84.6%), accelerator position (9.81%), and steering angle (3.11%). The rate of change of the accelerator position and steering angle are commonly important sensors for both arterial roads and intersections. At intersections, the accelerator position was a unique effective sensor, and furthermore, the rate of change of the accelerator position was more important. These important sensor differences between road types were also observed in other tests. Thus, these differences were caused by the differences among road types rather than those among cognitive function tests. Moreover, we assume that these differences occurred because driving behavior depends on the road type or driving scene and road type segmentation could capture these differences.

3.7.2 Contribution of segmentation

We analyze which segments worked well for the estimation in the same way as in the previous subsection. We focus on the results of TMT (B) of model (i) using ridge regression for the arterial roads and then aggregate feature importance for each segment duration.

Table 3.10 shows the relative proportions of the importance of each duration of the segment. We compare duration importance which was normalized by the number of segments or not normalized because the number of segments was different depending on the duration of segments. The left side of Table 3.10 shows the relative proportion without normalization, and the right side shows that with normalization. The unnormalized importance of segments [All, 60, 30, 15, 10, 5,] were [0.1%, 9.3%, 18.1%, 17.6%, 19.4%, 17.0%, 18.6%], respectively, while the normalized importance of segments [All, 60, 30, 15, 10, 5,] were [1.9%, 30.3%, 29.7%, 16.2%, 12.2%, 5.7%, 3.9%], respectively. Unnormalized proportions demonstrate that every duration, except for "All" of the segment, contributed to the estimation to some extent. On the other hand, the normalized proportion implies that many segments with short durations were not used much. This is because important driving behaviors appear not in whole driving but in partial driving. Moreover, segments with a short duration are noisier than segments with a long duration.

3.8 Conclusion

In this chapter, we addressed a challenging task, estimating the psychological characteristics of drivers, such as cognitive function, psychological driving style, and workload sensitivity, from on-road driving data. Our proposed model uses two types of segmentation, namely, road type segmentation and various duration segmentation, to capture driving behavior. For cognitive function items, capturing road type information and various durations of driving behavior made the estimation accuracy high. The best r values of the TMT and UFOV tests were 0.579 and 0.708, respectively. The experimental results demonstrated that considering the road type improved the accuracy of estimation. Both long-term and short-term driving behaviors contributed to the estimation on arterial roads and improved the regression accuracy. Additionally, we confirmed that the rate of change of the accelerator position and steering angle were effective for estimation on arterial roads and at intersections. For psychological driving style and workload sensitivity, the two types of segmentation improved the accuracy for some items, but they were less effective compared to cognitive function and their effectiveness depended on the items. These results indicate that psychological driver characteristics can be estimated from on-road driving data, providing a foundation for the realization of driver assistance systems tailored to individual driver characteristics.

Our proposed method can be used in situations where all drivers drive the same route because driving data segmentation requires GPS data. However, in real-world driving environments, drivers typically follow different routes, and the proposed method cannot be directly applied. To address this limitation, it is necessary to focus on particular driving behaviors such as lane changing, overtaking, and curve negotiation without relying on GPS data, and to extract effective features from such behaviors. Additionally, camera sensors can be used to capture driver behaviors, such as eye movements and head direction, which are easily obtainable and impose little burden on the driver. This direction is explored in Chapter 4, where driver characteristics are estimated under more practical driving conditions.

Chapter 4

Driver Characteristic Estimation: Different Routes On-Road Data

4.1 Introduction

In Chapter 3, driver characteristics were estimated under a fixed driving route, where driving conditions were partially controlled. Although this setting allowed for detailed analysis, real-world deployment of driver characteristic estimation requires the ability to estimate driver characteristics while drivers travel along different and changing routes in daily life. For practical personalization of DAS, estimation models must work robustly under diverse road environments rather than relying on a specific predefined route. Accordingly, we aim to estimate drivers' cognitive function from daily driving data collected across different routes using machine learning models. This approach makes driver characteristics estimation more practical for the personalization of DAS.

However, this estimation task is difficult, and there are several related challenges. First, there are no established methods for estimating cognitive function based on driving behavior on different routes since no study has yet addressed this problem. Second, a vast amount of driving data can be collected from daily driving, and it is not clear which of these data best represent distinctive driving behaviors that are useful for estimation. Since a cognitive function is invariant for a short time, we can obtain only one cognitive function label data toward a vast amount of driving data. Therefore, it is important to select distinctive parts of driving data to estimate drivers' cognitive function accurately.

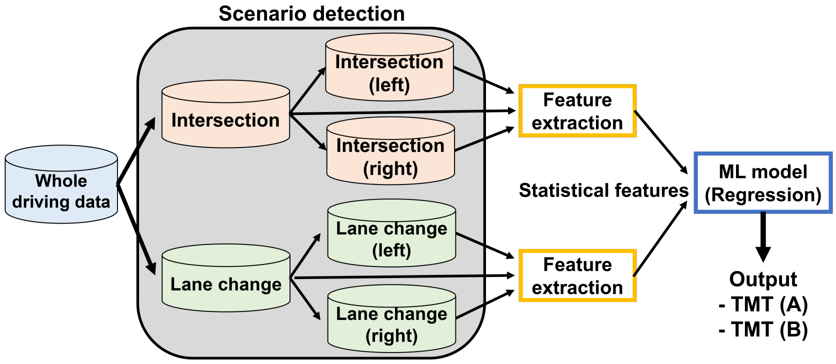


Figure 4.1: Overview of the proposed method. First, whole driving data is segmented into some driving scenarios, and then features are extracted from each scenario data. Finally, a cognitive function is estimated by machine learning models.

Accordingly, we use a dataset from drivers traveling along different routes, and this chapter proposes a method of estimating cognitive function in such a situation. The dataset includes signals from various in-vehicle sensors, such as speed, braking, steering angle, and gaze position. Using these time-series sensor data, we estimate drivers' cognitive function. In Chapter 3, not only cognitive function but also DSQ and WSQ were estimated. However, due to data availability constraints in the present chapter, we focus exclusively on cognitive function.

We hypothesize that it is possible to estimate cognitive function by focusing on particular driving scenarios that are common across different routes. Since older drivers with low cognitive function are especially prone to accidents at intersections [34] and during lane changes [35], we hypothesize that differences in cognitive function may be relatively strongly expressed in driving behaviors found in these driving scenarios. Based on this hypothesis, we segment the driving data based on such driving scenarios and perform cognitive function estimation for each segmented driving scenario. This segmentation helps us analyze the relationships between cognitive function and driving behaviors.

4.2 Method

The statistics of overall driving data provide simple information about driving behaviors, but daily driving data include a wide range of driving behaviors that occur in diverse situations. Such simple statistical features lose detailed information that is important for driver characteristic estimation. Consequently, it is difficult to capture the intuitive relationship between driving behavior and cognitive function using such features. Instead, in this chapter, we focus on particular driving scenarios, namely, intersections and lane changes. The overview of our proposed method is shown in Figure 4.1.

4.2.1 Dataset

In this chapter, we use a dataset shared by Toyota Motor Corporation for our research purposes. The dataset includes 412 driving sessions obtained from 35 professional drivers driving on public roads in Japan. Note that in Japan, drivers drive on the left side of the road. The total time of driving data is approximately 7839 hours, and the average driving time for each driver is approximately 224 hours. The driving data consist of time-series signals obtained from 119 in-vehicle sensors. We use 19 of these sensors, as listed in Table 4.1, and extract features for cognitive function estimation. Since the equipment used for data collection differs from that used in Chapter 3, additional sensors such as the turn lamp and camera-based measurements of gaze position and head rotation are included. Vehicle movements are reflected in sensors such as speed and steering angle, and driver behaviors such as gaze position and face angle are captured directly by a camera. Each signal is sampled at 10 Hz.

The dataset also includes the results of cognitive function tests. TMT [57], which was also used in Chapter 3, is adopted as a measure of cognitive function in this chapter. The drivers took two types of TMTs, namely, TMT (A) ($M = 35.0,\ std = 11.9$) and TMT (B) ($M = 67.1, std = 25.5$). Figure 4.2 shows the scores of TMT tests of the subjects. Compared with the subjects in Chapter 3, the TMT (A) scores are at a similar level, whereas the TMT (B) scores show a slightly lower tendency. However, these differences are not considered to indicate any substantial difference in cognitive function, suggesting that the sample includes drivers with both lower and higher levels of cognitive function. In this chapter, we estimate the TMT results from daily driving data.

4.2.2 Driving scenario detection method

We use sensor data and rule-based methods to detect intersections and lane changes. Intersection events are classified into left turns at intersections and right turns at intersections, and lane changes are similarly classified into lane changes to the left and lane changes to the right.

Table 4.1: In-vehicle sensors used for the estimation.

	Sensor
1	Stop lamp state
2	Brake pressure
3	Brake pressure velocity
4	Accelerator position
5	Speed
6	Forward acceleration
7	Forward jerk
8	Steering angle
9	Steering angular velocity
10	Turn lamp state (right)
11	Turn lamp state (left)
12	Yaw angle
13	Yaw rate
14	Fuel consumption
15	Gaze position (horizontal)
16	Gaze position (vertical)
17	Face angle (pitch)
18	Face angle (yaw)
19	Face angle (roll)

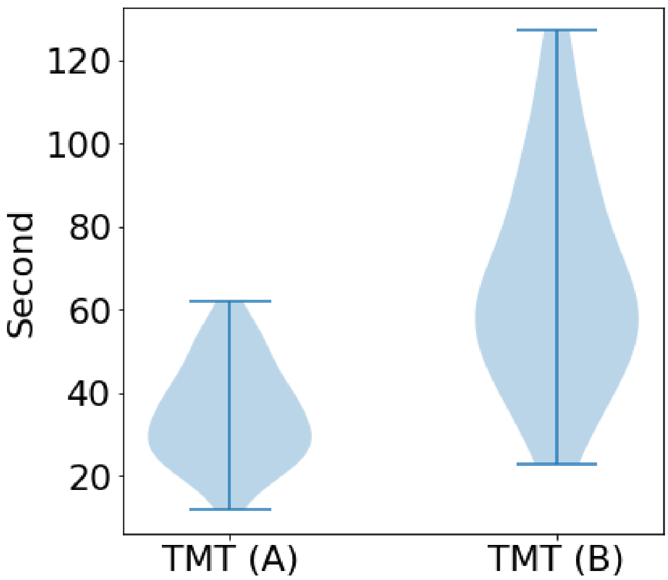


Figure 4.2: Violin plots of the cognitive function scores.

For the detection of intersections, we first detect intervals that satisfy both a yaw rate of 3.0 deg/sec or higher and a change in yaw angle of 20 degrees or higher. Then, the detected intervals and the five seconds before and after each detected interval are extracted as intersection events. As exceptions, we exclude such events for which the change in yaw angle is smaller than 60 degrees and the minimum speed is 60 km/h or higher. Furthermore, the steering angle is used to classify the intersection events into left turns and right turns at intersections.

For the detection of lane changes, we consider the intervals that are five seconds before and after a time when the absolute value of the yaw rate exceeds 0.8 deg/sec to be lane change events. As exceptions, we exclude such events for which the average speed is less than 20 km/h or the turn lamp does not light. Similar to the intersection events, based on steering angle information, the intervals corresponding to lane changes are classified as lane changes to the left and lane changes to the right.

4.2.3 Machine learning models and feature extraction

We use the lasso regression, ridge regression, random forest, and long short-term memory (LSTM) models for estimation. The lasso regression, ridge regression, and random forest models use statistical features, while the LSTM model uses time-series signals of sensors.

With respect to statistical features, we extract features from each of the six scenarios detected in Section 4.2.2 separately (intersection, intersection (left), intersection (right), lane change, lane change (left), and lane change (right)). For each scenario, the extracted intervals are concatenated, and then the statistics are calculated from concatenated signals. Finally, one feature sample is obtained per driver. The statistical features considered are the mean, median, standard deviation, maximum, minimum, skewness, and kurtosis of the sensor values (Table 4.1). Finally, 133 (19 sensors $\times$ six statistics) features are extracted and standardized for each scenario.

For time-series signal features, we resample the raw time-series signals of the sensors in Table 4.1 at 1 Hz, and they are input to the LSTM. To align the lengths of all time series signals, the first part of the time-series data was filled with zeros.

4.2.4 Experimental settings

For all models, the root mean square error (RMSE) is used as a measure of accuracy. Leave-one-out cross-validation is used to evaluate the accuracy of the models. We remove drivers whose TMT scores fall outside the range of $\mu \pm 2\sigma$ (where μ is the mean and σ is the standard deviation of the scores). The hyperparameters of the lasso regression, ridge regression, and random forest models are obtained through a grid search. Only features with a correlation of 0.1 or greater with the training labels are used for model training to avoid overfitting. The LSTM architecture is composed of one hidden layer with 20 units. The mean squared error (MSE) loss is used as the loss function. The number of epochs is 100, and optimization is performed with the ADAM optimizer. The initial learning rate is 0.1, and a learning rate of 0.05 is used after 30 epochs.

4.3 Results

To assess the effectiveness of a proposed method focusing on particular driving scenarios, we evaluate the regression accuracy of the proposed model. We compare the accuracy of the proposed model against the accuracy of a model using features extracted from all driving data as a whole. Since the size of all driving data is too large to train an LSTM model, LSTM experiments are not conducted with all driving data.

Table 4.2 shows the estimation accuracy. The bold values indicate the highest accuracy among the estimates for each cognitive function test. The TMT (A) score is estimated with the highest accuracy (lowest error) based on the lane change scenario by the random forest model, with an RMSE value of 10.27. The TMT (B) score is estimated with the highest accuracy (lowest error) based on the lane change (right) scenario by the random forest model, with an RMSE value of 21.55. Also, the RMSE value of the ridge regression based on the intersection (left) scenario is low, with an RMSE value of 21.79. The model using features extracted from all driving data does not achieve the highest accuracy. These results indicate that focusing on particular driving scenarios across different routes helps improve estimation accuracy and enables the estimation of cognitive functions using daily driving data. Additionally, the accuracies of the LSTM model do not high.

We summarize the top two results with the best RMSE value for TMT (A) and TMT (B) in Table 4.3 and calculate the Spearman rank correlation coefficients (r). Correlation coefficients with p-values smaller than 0.05 are marked with *, and correlation coefficient values less than 0 are reported as 0. The highest r values are 0.34 and 0.48 for TMT (A) and TMT (B), respectively. We confirm that the highest correlation coefficients have p-values below 0.05. The scenarios with the highest r and RMSE are the same for TMT (A), while they are different for TMT (B). Based on these results, we find that the driving scenarios from which the TMT (A) and TMT (B) scores can be successfully estimated are not the same.

4.4 Discussion

To reveal the relationship between driving behaviors and cognitive function, we analyze the effective features for estimating the TMT (B) score, which is estimated with the highest r value in Section 4.3. We regard the absolute values of the standardized regression coefficients of ridge regression based on the intersection (left) scenario as the contribution of each feature. The average of these coefficients for a feature among the learned models is treated as its importance.

The three most important features for the estimation of TMT (B) are shown in Table 4.4. Drivers with low cognitive function (a high TMT score) tend to have higher values for the features with positive coefficients, while drivers with high cognitive function (a low TMT score) tend to have higher values for the features with negative coefficients in the regression models.

The skewness of the distribution of the steering angle velocity at intersections is the most important feature, with a positive coefficient value. Since positive skewness of a distribution means that the right tail is longer, the results indicate that the steering angle velocity of drivers with a high TMT (B) score is less likely to be high. Figure 4.3 shows examples of the distribution of the steering angle velocity at intersections for a driver with a high TMT (B) score and a driver with a low TMT (B) score, and the skewness of these distributions are 0.13 and -0.21, respectively. Regarding the yaw rate, distributions of drivers with a high TMT (B) score tend to have high kurtosis. Drivers with low kurtosis often perform left turns at a large yaw rate because kurtosis is a measure of whether the data are heavy-tailed. In addition, the coefficient of the median of the forward jerk is negative. Based on these analyses, drivers with a high TMT (B) score and low cognitive function tend not to perform quick left turns. Arakawa et al. [79] presented a similar analysis and found that elderly drivers tend to have a lower rate of speeding, sudden braking, and sudden handling.

In [80], it was shown that at intersections, older drivers with worse TMT results were associated with low performance of visual-motor coordination, which refers to how well visual perception and fine motor skills are coordinated. Therefore, it is possible that drivers with low cognitive function take longer to process information and tend not to perform quick left turns at intersections, where complicated processing is required. These analyses explained which features are important to estimate the TMT scores by visualizing the weight of the model, and the results show the importance of the

Table 4.2: The regression accuracy for TMT (A) and TMT (B).

Driving scene	Model	TMT (A)	TMT (B)
Intersection	lasso	19.74	48.38
	ridge	19.4	43.88
	RF	12.31	25.58
	LSTM	13.671	28.36
Intersection (left)	lasso	18.41	24.69
	ridge	18.45	21.79
	RF	12.9	25.52
	LSTM	12.07	24.55
Intersection (right)	lasso	16.52	40.34
	ridge	14.6	39.92
	RF	11.09	25.07
	LSTM	11.23	22.84
Lane change	lasso	15.03	34.47
	ridge	14.16	36.55
	RF	**10.27**	25.27
	LSTM	13.82	25.98
Lane change (left)	lasso	14.76	35.21
	ridge	15.57	29.5
	RF	12.09	24.72
	LSTM	15.09	28.25
Lane change (right)	lasso	18.34	33.09
	ridge	17.75	29.71
	RF	11.9	**21.55**
	LSTM	12.03	23.03
All driving	lasso	18.52	36.78
	ridge	16.96	35.8
	RF	11.77	25.17

Table 4.3: The top two results with the best RMSE value for TMT (A) and TMT (B).

Driving scenario	Model	TMT (A)		TMT (B)	
		r	RMSE	r	RMSE
Lane change (right)	RF	0	11.9	0.33	**21.55**
Intersection (left)	Ridge	0	18.45	**0.48***	21.79
Lane change	RF	**0.34***	**10.27**	0	25.27
Intersection (right)	RF	0.15	11.09	0	25.07

Table 4.4: Three most effective features for estimation of TMT (B) score based on the scenario of intersection (left).

Feature	Mean coefficient value
Steering angle velocity (skewness)	215.01
Yaw rate (kurtosis)	193.88
Forward jerk (median)	−192.97

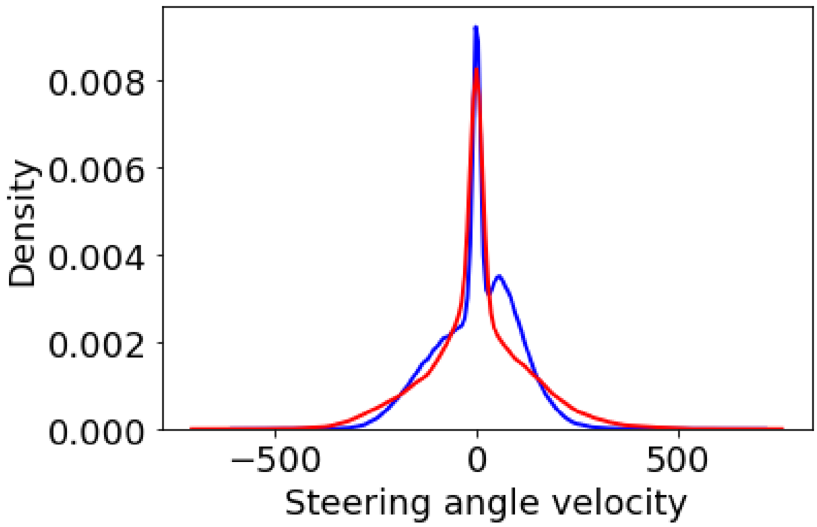


Figure 4.3: Examples of the distribution of the steering angle velocity at intersections for a driver with a high TMT (B) score (red line) and a driver with a low TMT (B) score (blue line).

method focusing on particular driving scenarios. They provide motivation to search for other distinctive driving scenarios where drivers are required complicated processing for estimation.

As described in Chapter 4.2.1, the drivers in this chapter and Chapter 3 show similar TMT (A) scores, suggesting that there is no substantial difference in cognitive function between the two groups. Although further investigation is required to clarify the extent to which professional drivers differ from general drivers, the feature extraction results in this chapter indicate that drivers with reduced cognitive function did not perform rapid left turns. This finding is also consistent with previous studies on general drivers, suggesting that it is not a behavior unique to professional drivers. Therefore, the results presented in this chapter are considered to have general applicability to the broader driver population.

4.5 Conclusion

In this chapter, we proposed a model for estimating a driver's cognitive function from daily driving data collected from drivers traveling along different routes. We showed that focusing on particular driving scenarios that are common across different routes improves the estimation accuracy, and the highest estimation accuracies achieved for TMT (A) and TMT (B) scores were $r = 0.34$ and 0.48, respectively. These results demonstrate that driver characteristics can be estimated under more realistic driving conditions, enhancing the practicality of such estimation for personalized DAS.

Furthermore, the proposed model enables us to capture the relationships between driving behaviors and cognitive function. It was found that drivers with low cognitive function tend not to make quick left turns at intersections as often as drivers with high cognitive function. These findings are consistent with previous studies, supporting the validity of the proposed approach and demonstrating the generalizability of both the estimation accuracy and the interpretability of the results.

As a next step toward the realization of personalized DAS, it is necessary to investigate how driving assistance should be provided based on the psychological driver characteristics that have been shown to be estimable. The following chapter addresses this issue by analyzing how driver characteristics influence the effects of driving assistance.

Chapter 5

Driver Assistance Systems and Driver Characteristics: Effects on Speeding, Acceleration, and Deceleration

5.1 Introduction

In Chapters 3 and 4, the technical foundation for estimating driver characteristics from naturalistic driving data was established. Building upon this foundation, the present chapter investigates how such estimated characteristics can be utilized to design effective personalized driving assistance. Specifically, this chapter examines how driver characteristics influence the behavioral effects of driving assistance targeting speeding and sudden acceleration and deceleration. By analyzing driving data collected after drivers received support from a DAS, we aim to clarify how individual differences influence the effectiveness of assistance. This analysis provides a link between driver characteristics estimation and personalized driving assistance. Understanding these interactions is essential for realizing personalized DAS that adapt feedback strategies according to driver characteristics.

Speeding and sudden acceleration or deceleration were selected as target behaviors for two main reasons. First, these behaviors are widely recognized as high-risk driving actions that are closely associated with traffic accidents and near-miss events [81, 82]. Second, they can be detected relatively easily and reliably using commonly available in-vehicle sensors, such as acceleration sensors and vehicle speed data, in combination with digital map information (e.g., speed limits).

We are developing a DAS that involves a compact communication robot providing feedback based on the driver's driving evaluation in situations that lead to accidents (e.g., excessive speed). The DAS system is designed to prioritize driver safety and to provide feedback to the driver through the robot's utterance in a manner that does not interfere with the driver's driving. In [83], the agent provides attention awakenings and revision suggestions with regard to driving operation to ensure drivers stop at stop signs or avoid pedestrians and parked cars. However, existing systems provide feedback to all drivers in the same manner, and differences in feedback effects resulting from differences in driver characteristics are unclear.

To advance the development of personalized DAS that can provide efficient feedback in line with specific driver characteristics, the purpose of this chapter is to analyze the improvements in driving behavior resulting from interactions between drivers and DAS. Due to data availability constraints in this experiment, the analysis focuses primarily on DSQ.

As introduced in Chapter 2.3, some studies have found relationships between drivers' characteristics and their preferences regarding or acceptance of DAS. Cramer et al. showed that drivers who scored high on locus of control tended to report that the driver should follow the robot's instructions more than those who scored low on locus of control [45]. Li et al. showed that drivers have different preferences regarding and attitudes toward in-vehicle anger intervention systems depending on their driving anger traits [46]. Miyamoto et al. found a relevant connection between users' level of conscientiousness and their evaluation of the utterances of a DAS [47]. These previous studies have identified differences in the outcomes of interaction between humans and DAS depending on driver characteristics.

With regard to driver characteristics, this chapter uses the DSQ [50] to characterize drivers in a psychological context. The ways in which humans interact with DAS may also be related to demographic attributes, such as gender or age. However, even if drivers are of the same gender and age, they nevertheless have different attitudes toward driving [50]. Therefore, we assume that the DSQ is more suitable for analyzing such interaction.

The preferences and acceptability demonstrated in the research mentioned above were based on the subject's responses to the questions. Certainly, acceptance of the assistance provided by a robot may improve driving, but it does not necessarily lead to actual improvement. This chapter analyzes the improvement of driving behavior by reference to driving data collected in the context of daily driving.

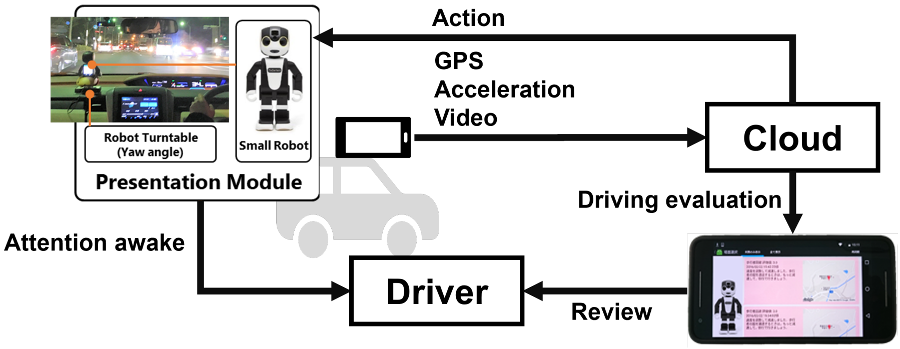


Figure 5.1: Overview of the driver assistance system.

5.2 Dataset and Drier Assistance System

5.2.1 Dataset

In this chapter, we use a dataset shared by the Institutes of Innovation for Future Society of Nagoya University. The dataset includes 5578 driving sessions obtained from 50 drivers who drive regularly and range in age from their twenties to sixties. Driving data were collected in the context of daily driving, and the driving environment, such as route, time, and frequency of driving was different for each driver. The DAS detailed in Section 5.2.2 was attached to the front of the driver during driving. Global positioning system (GPS) data, acceleration, and video of the front of the car were recorded using a smartphone (AQUOS sense2 SH-M08). We excluded data for cases in which the driving distance was less than 1 km, the driving time was less than 3 minutes, or some parts were missing. After this preprocessing, 4087 driving data remained. Nagoya University's ethics committee approved the experimental plan for collecting the driving data with support from the DAS after making a judgment regarding driver safety. All participants with a Japanese driving license agreed to provide informed consent regarding their participation in the experiments.

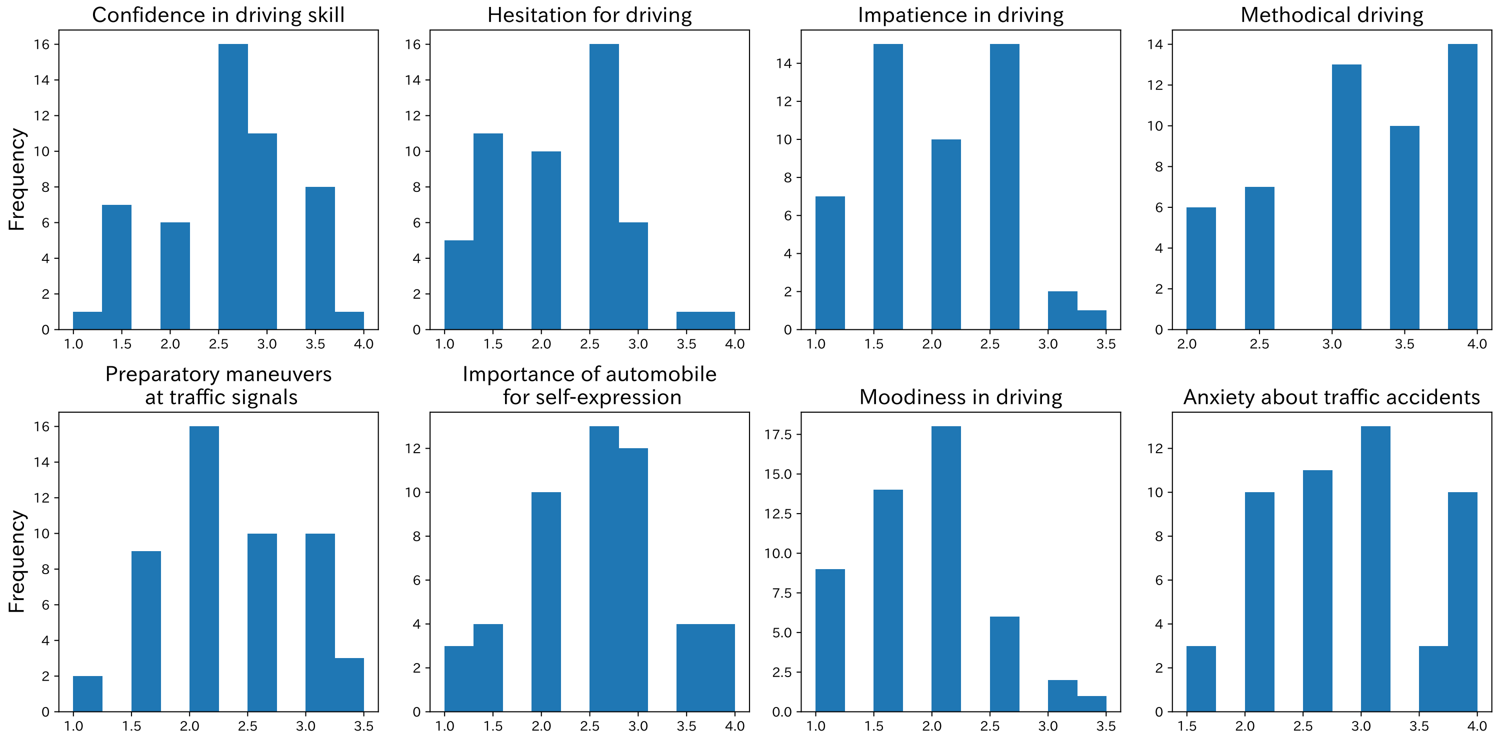


Figure 5.2: Histgrams of DSQ scores of the subjects.

5.2.2 Driving support robots

This chapter uses a compact communication robot (RoBoHoN, Sharp Co., Ltd) as a DAS. Figure 5.1 shows an overview of this DAS system. The robot provides two types of support, namely, an attention awakening and a review of driving.

The former type of support is provided during driving and aims to revise dangerous driving behaviors. The content of this support aims to promote exact stopping at stop signs and to prevent sudden acceleration/deceleration and speeding.

These types of support were generated based on an instruction set developed by professional driving instructors. This chapter focuses on the effect of support on the prevention of non-safe driving behavior, such as sudden acceleration/deceleration and speeding. Sudden acceleration/deceleration is detected based on acceleration data. When the acceleration or deceleration exceeds 1.3G, the robots notify of drivers of the sudden acceleration/deceleration by saying "Wow. Oops." and making a motion. Speeding is detected using the speed of a car and the legal speed limit on roads obtained based on GPS data. Additionally, the robot suggests speed reduction via both voice and motion in cases in which the speed exceeds the legal speed limit by 15 km/h. After expressing a warning, the robot does not issue another warning regarding sudden acceleration/deceleration for approximately five minutes to avoid bothering the driver.

The latter type of support is provided to drivers after each driving session via a smartphone. The application evaluates the driver's driving and offers reviews of good and bad scenes to the driver. The feedback consists of an evaluation value, advice comments, a map based on GPS data, and a recorded movie. The details of this review are described in [83].

5.2.3 Driving Style Questionnaire

To investigate the effect of support by DAS (Section 5.2.2) in accordance with each driver's characteristics, we asked drivers to answer the DSQ questionnaire to characterize their attitudes toward driving. The DSQ includes eight items scored on a scale ranging from 1 to 4. Each item is associated with two questions, and their mean value represents the score for the item. Scores for negative-form questions are reversed to calculate the item scores. Since, the DSQ focuses on the attitudes, orientations, and ways of thinking associated with daily driving [50], we assume that the DSQ is related to the acceptability of the support provided by the driver robot. Moreover, in Chapter 3, it is indicated that the most DSQ score can be automatically estimated based on driving data. Such automatic estimation of driver characteristics facilitates personalization without the administration of requiring burdensome questionnaires to drivers.

Figure 5.2 shows a Histgrams of DSQ scores of the subjects. The DSQ item scores are widely distributed across the subjects.

DSQ item	Speeding					Sudden acc/dec				
	High		Low		Diff	High		Low		Diff
	r	p	r	p	p	r	p	r	p	p
Confidence in driving skill	0.027	0.374	-0.029	0.814	0.980	-0.133	0.014	-0.124	0.068	0.910
Hesitation for driving	0.096	0.003	-0.160	0.064	0.003	-0.092	0.052	-0.207	0.008	0.434
Impatience in driving	-0.039	0.627	0.079	0.020	0.115	-0.128	0.016	-0.134	0.073	0.991
Methodical driving	0.004	0.538	0.031	0.575	0.731	-0.180	0.001	0.021	0.831	0.122
Preparatory maneuvers at traffic signals	-0.007	0.751	0.082	0.176	0.639	-0.121	0.010	-0.167	0.074	0.702
Importance of automobile for self-expression	0.021	0.501	-0.007	0.507	0.849	-0.070	0.096	-0.241	0.005	0.132
Moodiness in driving	0.032	0.260	-0.016	0.756	0.140	-0.134	0.017	-0.125	0.083	1.000
Anxiety about traffic accidents	0.035	0.106	-0.017	0.744	0.274	-0.207	0.004	-0.043	0.179	0.104

Table 5.1: Wilcoxon one-sample signed-rank test's p-values for each group and Mann-Whitney U test's p-values for comparing groups.

5.3 Analysis and Results

We analyze the effect of supportive feedback from the DAS for each DSQ characteristic. For this purpose, we focus on whether drivers changed (revised) their driving behavior after they received feedback from the DAS.

5.3.1 Long-term improvement in driving behavior

We evaluate the long-term improvement in driving behaviors. As the performance indexes of each session of driving, we count the number of speeding or sudden acceleration/deceleration events per mile. Then, we sort these indices by date of driving and calculate the Pearson correlation coefficient (r) between the sorted indices and the number of sessions of driving for each driver. If this r value is small (negative), the number of speeding or sudden acceleration/deceleration events per mile tends to decrease, and driving behavior is regarded as having improved. Finally, we compare the results between the high DSQ groups, in which drivers scored greater than or equal to the median score, and the low DSQ groups, in which drivers scored less than the median score. We conducted the Wilcoxon one-sample signed rank test for r values for each group and the Mann-Whitney U test for the comparison of r values among groups. Table 5.1 shows these tests' p-values. The underlined p-values are less than 0.05.

As a result of the analysis, for speeding, in the high group for "hesitation for driving" and the low group for "impatience in driving", the mean values of r are significantly different from zero. Moreover, we found a significant difference in the mean values of r between the high and low groups for "hesitation for driving". Figure 5.3 shows the boxplots of r values for the high and low groups for "hesitation for driving". We found that the high groups do not tend to decrease their speeding, while the low groups do tend to decrease their speeding.

With regard to sudden acceleration/deceleration, in the eight high groups and the two low groups, a significant difference from zero was found. However, we could not find DSQ items that exhibited significant differences between the mean values of r of high and low groups. Most r values were smaller than those for speeding, and their signs were negative with the exception of the low group for "methodical driving".

5.3.2 Temporal improvement in driving behavior

Changes in driving behavior immediately after receiving support from the DAS indicate that temporal improvement in driving behavior is caused by

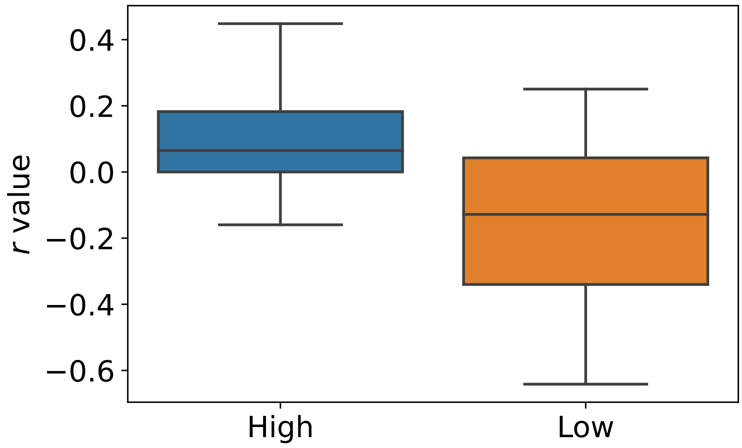


Figure 5.3: Boxplots of r values of the speeding performance for the high and low groups of "hesitation for driving".

the DAS, and the interaction between the DAS and the driver is successful. Hence, we focus on the temporal improvement in driving behavior, which refers to the duration of speeding after receiving support. If drivers accept the warning regarding their speeding, they attempt to reduce their speed to comply with the speed limit. As described in Section 5.2.2, the DAS does not warn drivers again for five minutes after conveying the warning on detection of speeding. Thus, we use the first speeding data regarding each driving session for which a warning must be provided.

We performed the Mann-Whitney U test for the comparison between the mean duration of speeding after receiving support across groups. Table 5.2 shows the mean duration of speeding after receiving support for the high and low DSQ groups and the tests' p-values. The underlined p-values are less than 0.05. We found significant differences only in the comparison of the high and low groups for "confidence in driving skill". Figure 5.4 shows the boxplots of the mean values of the duration of speeding in the high and low groups for "confidence in driving skill". The mean value associated with the high groups for "confidence in driving skill" was smaller than the mean value associated with the low groups.

5.4 Discussion

The results of the experiment showed that, depending on the DSQ items, the degree of improvement in driving behavior due to the DAS varies.

With regard to long-term improvement in speeding, the difference in im-

DSQ item	μ_{high}	μ_{low}	Diff (p)
Confidence in driving skill	7.200	13.152	<u>0.004</u>
Hesitation for driving	8.068	10.752	0.213
Impatience in driving	8.910	9.225	0.573
Methodical driving	9.230	8.457	0.618
Preparatory maneuvers at traffic signals	8.795	10.114	1.000
Importance of automobile for self-expression	9.145	8.804	0.732
Moodiness in driving	9.710	8.057	0.875
Anxiety about traffic accidents	9.861	8.064	0.390

Table 5.2: Mean duration of speeding after receiving support and Mann-Whitney U test's p-values for the comparison across groups.

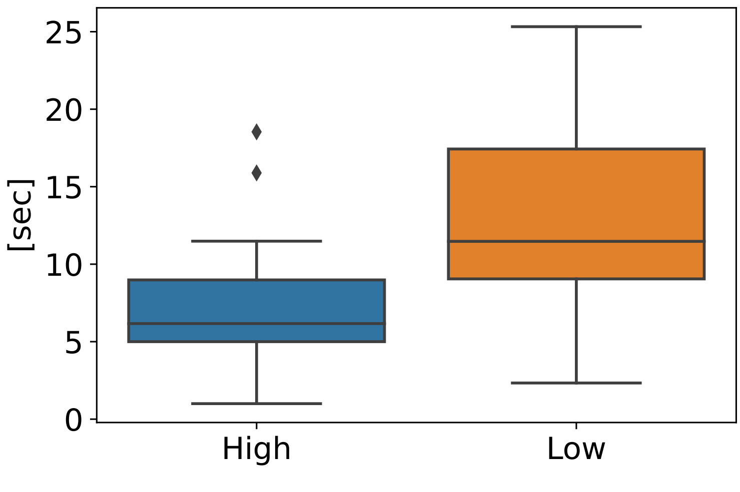


Figure 5.4: Boxplots of the mean duration of speeding after receiving support for the high and low groups for "confidence in driving skill".

provement between the high and low groups for “hesitation for driving” was most significant in the results. The mean r value for the low group for “hesitation for driving” was negative, while that of the high group for “hesitation for driving” was positive; that is, their driving behavior did not improve. Thus, there is room for improvement in the driving behavior of the high group for “hesitation for driving”, and adapting the support provided based on the driver’s level of “hesitation for driving” seems to be effective. One possible reason for this result is that drivers who exhibit a high level of “hesitation for driving” tend to hesitate not only to drive but also to use the DAS.

With regard to long-term improvement in sudden acceleration/ deceleration, no significant differences were observed between the groups with high and low DSQ scores. This result can be interpreted as occurring because the support was effective for most of the groups. On the other hand, the mean r value of the low group for “methodical driving” was positive; that is, their driving behavior did not improve. Drivers in the low group for “methodical driving” might not have paid attention to the robot’s support or might have ignored the support provided by the smartphone. How to improve the driving behavior of drivers who ignore support is a difficult problem. Increasing the frequency of support is a simple solution to this problem, but if drivers feel uncomfortable with the robot, they will stop using it. The group associated with the lowest r value was the group of drivers who exhibited high levels of “anxiety about traffic accidents”. Since their driving behavior is influenced by their moods and is prone to fluctuations, support from the robot or smartphone may have helped them become aware of their unconscious driving behavior resulting from their moods.

With regard to temporal improvement in speeding, and the duration of speeding after receiving support from the robot, the difference between the high and low groups for “confidence in driving skill” was most significant. Hence, specific support is needed for drivers who exhibit a low level of “confidence in driving skill” to improve their driving behavior. It is possible that one’s driving skills lead to a margin of acceptance of the support.

Furthermore, based on the result of the analysis of long-term improvement, the support for sudden acceleration/deceleration is more effective than the support for speeding. While speeding can easily be confirmed by looking at the speedometer, it is more difficult to be aware of sudden acceleration/deceleration. In other words, the driver may consciously cause speeding and unconsciously cause sudden acceleration/ deceleration. We predict that support from the robot or a smartphone is more likely to improve unconscious driving behavior by making drivers aware of it.

5.5 Conclusion

In this chapter, we investigated the varying effects of the support provided by DAS depending on driver characteristics. We analyzed long-term and temporal improvements in driving behavior associated with speeding and sudden acceleration/deceleration. The results revealed that the effect of support depends on drivers' scores on the DSQ scale, highlighting the importance of providing personalized support to change driving behavior more effectively. These findings support the importance of personalizing driving assistance based on driver characteristics and provide insights that bridge the method for driver characteristics estimation in Chapters 3 and 4 and the design of personalized driving assistance.

Several limitations remain in this chapter. First, due to dataset constraints, the analysis was limited to DSQ. Second, because the support was provided via a smartphone, it was not possible to capture and analyze detailed driving behavior or drivers' internal states. Furthermore, although insights into the personalization of driving assistance were obtained, a method for determining how to select and present appropriate support has not yet been established. Chapter 6 addresses these limitations by utilizing a driving simulator to collect a wider range of driver characteristics.

Chapter 6

Driver Variability and the Effectiveness of Stop-Sign Driving Assistance

6.1 Introduction

Following Chapter 5, which revealed that the effectiveness of personalized driving assistance depends on driver characteristics, this chapter further investigates how such driver characteristics can be used to design personalized driving assistance. To examine interactions between drivers and DAS in detail, new experimental data were collected using a driving simulator. This enables a fine-grained analysis of driving behaviors, including speed, braking patterns, and head movement, and allows investigation of their relationships with a broad range of driver characteristics. In contrast to Chapter 5, where the analysis was limited to DSQ due to data constraints, this chapter considers a wider range of driver characteristics. By analyzing both support types and driver-specific factors, this chapter aims to clarify how personalized assistance strategies can be designed.

While Chapter 5 did not focus on intersection scenarios, this chapter specifically examines driving behavior at stop-sign intersections, where the accident risk and cognitive load are high for older drivers [84]. Some types of driving support provided at a stop sign intersection differ in terms of the amount of information and the content of the support. To examine which type of support promotes safe driving for different types of drivers, we use a driving simulator to collect driving data such as speed, braking, and head pose data (Section 6.3). We then build regression models to explain driving behaviors on the basis of driver characteristics, support types, and their interactions (Section 6.4). In this model, we reveal the effectiveness of interaction terms between driver characteristics and support types, reflecting the extent of the importance of personalized support. Our regression analysis revealed that the effectiveness of driving support to change driving behavior depends on individual driver characteristics.

Finally, we develop a model that selects optimal support based on driver characteristics and present findings regarding which types of drivers are influenced by specific types of support (Section 6.5). We use a machine learning algorithm to explore the complex and interpretable relationships between driver characteristics and the effectiveness of the support. These results provide a basis for determining how to select and present appropriate support based on driver characteristics, thereby establishing a framework that spans from driver characteristics estimation to personalized driving assistance.

6.2 Related Works

6.2.1 Older drivers' behaviors at stop sign intersections

At stop sign intersections, older drivers often exhibit risky driving behaviors; thus, driving support is required to promote safe driving for such drivers. Yonekawa et al. [85] reported that older drivers tended to enter stop sign intersections at high speeds and performed insufficient left and right checks. Similarly, drivers with impaired cognitive function performed fewer left and right checks, and their checking time tended to be shorter [86]. Yoshihara et al. [87] analyzed driving behaviors and reported that older drivers passing through stop sign intersections tended to make narrower and slower head movements and to drive faster than middle-aged drivers while checking left and right. Dukic and Broberg [88] investigated visual search behaviors, revealing that older drivers look less at dynamic objects such as other cars, which are possible threats at intersections. Liu et al. [89] reported that older and younger drivers tended not to pause adequately at intersections. These risky behavioral tendencies increase the likelihood of drivers under 18 years of age or over 65 years of age being at fault in accidents at stop-and-go intersections in the U.S. [84]. DAS that help modify these behaviors are expected to significantly reduce the accident risk at intersections.

For these reasons, this chapter focuses on driving support at stop sign intersections, and driving behavior data at stop sign intersections with driving support systems are collected. At intersections with stop signs, drivers must stop at the stop line, check for crossing objects, and ensure that no vehicles or pedestrians are passing before proceeding into the intersection. The desired system should encourage drivers to perform these behaviors. Yonekawa et al. [85] argued for the importance of support systems that not only urge drivers to stop but also to check for crossing objects, prepare for evasive maneuvers, and warn drivers if a vehicle is present. The usefulness of support systems that encourage older drivers to check left and right more often and for longer periods has also been noted in [86, 87]. No prior work has evaluated such instructive assistance at stop sign intersections, and available datasets lack the required intersection context and driving assistance exposure; therefore, we collected a purpose-built dataset. This chapter confirms whether such instructive support is valid for older drivers at intersections.

6.2.2 Driving assistance for older drivers

Some studies have investigated effective driving assistance for older drivers. However, to our knowledge, the suitable amount of information and content of the support tailored to each driver's cognitive ability and personality remains unexplored. Sumner et al. [90] used cognitive profiles to personalize the safety interface of an assistance system to reduce the inclination to run through yellow light zones. Ge et al. [91] investigated the effectiveness of different types of driver assistance messages across various driving scenarios. They compared three types of messages: event notifications (e.g., "You are getting too close to the lead vehicle"), prescription support (e.g., "Please increase the distance from the lead vehicle"), and a combination of event notification and prescription support. The results of a questionnaire revealed that the combination of both event notification and prescription messages comparably increased drivers' willingness to drive safely in a questionnaire. Conversely, DAS that provide instructions for multiple driving behaviors while driving can impose a significant cognitive load on drivers, especially those with impaired cognitive functions. Since driving is a cognitively demanding behavior, especially for older drivers, it is not clear whether they can understand support messages that include both event notifications and instructions and then change their driving behavior accordingly. Souders et al. [92] suggested that the concurrent use of forward collision warnings and lane departure warning systems did not adversely affect older drivers' driving performance and subjective workload. Wang [93] conducted a questionnaire on older drivers and compared the perceived importance of three types of warning systems, namely, external environment, car status, and driver condition warnings. They indicated that the perceived importance of external environment warnings is greater than that of car status warnings and driver condition warnings to older adults and that their perceived importance is related to driving experience. In this chapter, actual driving behavior is evaluated rather than relying on subjective impressions captured through questionnaires.

While no studies have explicitly examined the relationship between the amount of driving assistance and behavioral changes, several papers have explored how the amount of information on road signs affects drivers' cognitive loads and reactions. Fu et al. [94] analyzed the relationship between the amount of information on traffic signs and drivers' reaction times. They reported that an increase in information led to slower reaction times. Han et al. [95] indicated that the amount of information on traffic signs influences the driver's visual workload. Similar to the amount of information on traffic signs, the relationship between the amount of information provided by a support while driving and the driver's acceptance of and response to support is an important factor, and the corresponding effect on driver support remains unclear. In this chapter, we aim to address this gap by evaluating driving assistance at intersections with stop signs. Our approach involves presenting drivers with notifications about the presence of stop signs and providing behavioral instructions designed to encourage safer driving behaviors. By examining how the amount and content of information impact drivers' acceptance of and responses to support, effective strategies for delivering driving assistance tailored to older drivers are identified.

In the design of personalized DAS for older drivers, in addition to the content and amount of information, modality (e.g., audio, visual, or tactile) and timing are key personalization factors. With respect to modality, Xu et al. [96] explored hazard warning modalities and timing thresholds for older drivers with and without impaired vision. Their findings revealed that tactile warnings resulted in slightly longer fixation times on hazards than auditory warnings did. Rukonić et al [97] reported that speech messages effectively convey the warning information to older drivers and that visual warnings can distract drivers and increase their workload. Adell et al. [98] compared abstract and language (semantic) warnings across audio, visual, and tactile modalities. In noncritical situations, abstract visual warnings led to quicker recognition of warning urgency, whereas audio warnings were more effective in critical situations. Additionally, Adell et al. [99] found that although haptic warnings, such as those delivered through the accelerator pedal, were more effective than auditory beep signals, more drivers expressed a preference for the auditory system. Regarding both the effectiveness for older drivers and the ease of implementation, this chapter uses an audio assistance system. Older drivers generally require more time to process information and make decisions [100]. In Xu et al. [96], older drivers prefer early timing of hazard warnings, and their performance was better with them. Based on these findings, the assistance timing in this chapter is early so that older drivers have sufficient time to interpret the information on assistance and react properly.

6.2.3 Key contributions

Based on the prior studies described above, several research gaps can be identified. First, no prior study has focused on actual driving behavior to examine how the effectiveness of driving support varies depending on driver characteristics. Some studies evaluated driving support through questionnaire-based impressions [45, 47, 91], but in real-time driving under cognitive load, analyzing how driver characteristics relate to changes in driving behavior remains an essential open problem. Second, although prior work has pointed out the importance of providing instructive support at stop-sign intersections for older drivers [86, 87], it remains unclear whether such instructive support is actually effective for older drivers, and how the content and amount of such assistance should be personalized to individual drivers. Third, although personalization has been widely recognized as an important direction for driver assistance systems, there is still no established framework or method for personalizing support based on driver characteristics. If the most effective support could be selected in advance according to a driver's characteristics, DAS could adaptively provide the most effective support before the driver reaches an intersection. To fill these gaps, this chapter conducts data collection, analysis, and experiment, providing essential findings for establishing a personalized assistance system.

The main contributions of this chapter are as follows:

- We analyze changes in driving behavior in response to instructive support at stop sign intersections for older drivers, rather than relying on answers to questionnaires.
- We focus on the amount and content of support information and clarify effective support strategies tailored to driver characteristics.
- We present a machine learning model to predict the most effective support before a driver reaches an intersection based on driver characteristics.

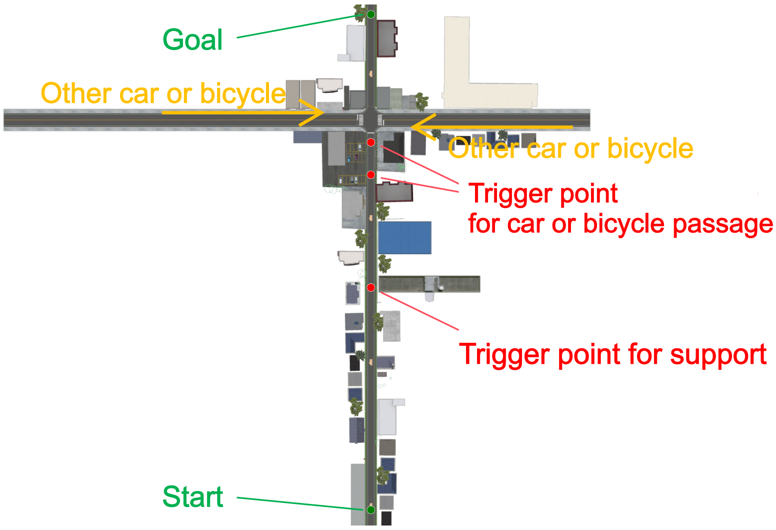


Figure 6.1: Driving course with a stop sign intersection. The drivers pass straight through the intersection. The drivers are presented with driving support when they pass the trigger point for support. The car-passing scenario or bicycle-passing scenario starts when the driver passes the trigger point near the intersection.

6.3 Materials and Method

6.3.1 Participants

Forty drivers, mainly older individuals who drove regularly, were recruited for the experiment. Since two subjects stopped the experiments because of motion sickness, we analyzed data collected from 38 subjects (24 females and 14 males). The subjects' ages ranged from 19 to 83 years, with a mean age of 59.3 years and a standard deviation of 15.1 years. Although the main target population of this chapter is older adults, we recruited participants from a wide range of age groups to avoid bias in the distribution of cognitive test scores. Participant recruitment was outsourced to an external company. Among individuals who expressed interest in participating, candidates were selected to ensure a broad distribution of scores on cognitive function tests. As shown in Section 6.3.4, this approach was successful, and we were able to recruit drivers with a wide range of cognitive function levels as intended. The frequency of driving per week was 6.0 ± 1.7 (mean $\pm$ SD) days, and the amount of driving experience was 36.9 ± 15.4 years.

Figure 6.2: The view ahead when entering an intersection. A stop sign is located on the left side, and the views to the left and right are blocked by buildings.

6.3.2 Procedures

An experiment consists of explaining and obtaining consent for the experiment, adjusting equipment, practicing driving with the simulator, performing 10 alternating runs, completing a questionnaire survey about the subjective evaluation of the support system, completing questionnaire surveys about driver characteristics, and performing cognitive function tests. First, all the subjects provided informed consent before the experiment. Then, we adjusted the seat in the driving simulator to make it easier to step on the accelerator and brake pedals, and a wristband-type device was attached to the subject's arm. Next, each subject practiced driving with the simulator to get accustomed to driving on the practice course. After the practice period, a subject received several types of driving support in driving sessions and answered questionnaires about their subjective impressions of the driving support. Then, to assess driver characteristics, they completed multiple questionnaires and cognitive function tests. This experiment was conducted with the approval of the Life Science Committee of the Japan Advanced Institute of Science and Technology.

6.3.3 Driving course and support

In the driving sessions, all the participants drove on a simulated one-way residential street and proceeded straight to an intersection. The course was revised from the one used by [87], where the driving behaviors were related

Figure 6.3: Driving simulator. The side displays offered peripheral views, and the subjects could check for oncoming cars or bicycles at the intersection.

to the driver's cognitive functions. A stop sign was present at the simulated intersection, and the speed limit for the course was set to 40 km/h When the driving session began, the subjects were guided by an audio announcement instructing them to "Please go straight through the next intersection." Each subject participated in 10 driving sessions and experienced various scenarios and types of driving support.

Two types of scenarios were used in the driving sessions: a car-passing scenario and a bicycle-passing scenario at the intersection. The timing of a car or bicycle passing was set so that a collision would occur if the subject entered the intersection without decelerating or if the subject entered the intersection after briefly stopping without checking left and right. Furthermore, buildings were placed around the intersection to reduce visibility to the left and right. Thus, to avoid a collision with a car or bicycle, the subject needed to sufficiently pause before entering the intersection, check left and right to ensure that no car or bicycle was passing the intersection, and then travel straight ahead. Figure 6.1 shows the driving route, and Figure 6.2 shows the view ahead at the intersection. The driving simulator used in this chapter was equipped with three computer displays. The central display provided a forward view, and the side displays offered peripheral views, enabling the subjects to observe oncoming cars or bicycles at the intersection. These setups supported the realistic simulation of driving conditions, replicating common challenges faced by older drivers at intersections. Figure 6.3 shows the driving simulator used in this chapter.

During the driving sessions with the aforementioned scenarios, the subjects were provided with one of four types of driving support or no support at all, depending on the session. All driving support was delivered through audio announcements. The content of the announcements for the four types of support was as follows:

Support 1: ”You are approaching a stop sign.”

Support 2: ”You are approaching a stop sign. Stop completely.”

Support 3: ”You are approaching a stop sign. Check the left and right sides.”

Support 4: ”You are approaching a stop sign. Stop completely and check the left and right sides.”

For support 1, the announcement simply informed the subject that a stop was present at the intersection. For support 2, the announcement, ”Stop completely” was added, an instruction for a specific driving behavior. For support 3, the announcement, ”Check the left and right sides” was added, prompting another specific driving action. For support 4, both additional announcements were given. The supports were triggered when the subject passed a designated reference point, which was consistent across all sessions. The timing of providing the support set so that the subject had enough time to hear and understand the support, press the brake, and make a full stop at the intersection. Drivers experienced 10 sessions with different scenarios and support (two scenarios × (four support types and no support)) in random order. Between driving sessions, the drivers completed a questionnaire about their experience with support and took breaks freely.

6.3.4 Data acquisition

Video data

Video data for the subjects’ upper bodies was recorded using a webcam mounted on top of the front screen of the driving simulator. These data were used to analyze gaze direction and face angle, enabling the detection of drivers’ left-right checks and fixations during the driving sessions.

Biological signal data

During the experiment, biological signals, such as electrodermal activity (EDA), heart rate, and body temperature, were measured using the Empatica EmbracePlus wristband. In addition to these signals, the wristband also captured acceleration and angular velocity.

Driving log data

The driving simulation software, UC-win/Road, recorded detailed driving log data. This included information on the vehicle speed, vehicle acceleration, opening degree of the brake and accelerator pedals, degree of the steering angle, positions of other vehicles and bicycles, and collisions with vehicles and bicycles. These driving log data were used to quantify driving behaviors, as described in Section 6.4.1.

Driver characteristics questionnaire

To assess driver characteristics, we administered four types of questionnaires: the Driving Style Questionnaire (DSQ) [50], the Workload Sensitivity Questionnaire (WSQ) [51], the Questionnaire on Self-Awareness changes in cognitive and physical functions while driving (QSA) [101], and the Japanese version of the Ten-Item Personality Inventory (TIPI-J) [102]. The specific characteristics measured by these questionnaires are detailed in Table 6.1. In this chapter, instead of the original WSQ, we used the short-form WSQ [103], which was designed specifically for older drivers to reduce the burden of responding. The short-form WSQ consists of 10 questions, each rated on a 5-point Likert scale, for 10 specific workload-related factors. The QSA was designed to assess self-perceived changes in cognitive and physical abilities while driving. Seven factors are measured using 18 questions, each rated on a 4-point Likert scale. The TIPI-J is a measure of the Big Five personality dimensions assessed through 10 questions on a 7-point Likert scale. Although the Big Five personality dimensions were not specifically developed to assess driver characteristics, their associations with driving behavior have been demonstrated in various studies. For example, a meta-analysis by Luo et al. [104] showed that conscientiousness, agreeableness, and openness were negatively associated with risky and aggressive driving behavior.

Cognitive function test

To evaluate the cognitive abilities of drivers, we conducted two cognitive function tests: the Trail Making Test (TMT) [105] and the Useful Field Of View (UFOV) [71] to measure drivers' cognitive ability.

Figure 6.4 shows the TMT and UFOV subtest 2 scores of the subjects and reference scores. While both TMT and UFOV are related to driving ability, cutoff points to determine dangerous drivers or criteria for cessation of driving have not been defined. For the TMT subtests, scores of older adults with mild cognitive impairment and Alzheimer's disease were reported in [106, 107]. For UFOV, cutoff points to predict the on-road performance

Table 6.1: Driver characteristics obtained via the questionnaires.

Questionnaire	Characteristics name
DSQ	Confidence in driving skill Hesitation for driving Impatience in driving Methodical driving Preparatory maneuvers at traffic signals Importance of automobile for self-expression Moodiness in driving Anxiety about traffic accidents
WSQ	Driving at midnight Irregular day-night rhythm Roads with complex lane configurations Poor physical condition Inability to get a sense of the vehicle and its width Driving while looking for routes and destinations Fine steering wheel operation and speed adjustment Frequent fine steering wheel operation Driving with a load of care Roads whose shape changes from one to the other
QSA	Change in visual function Change in precision operations Change in ability to execute driving operations Change in ability to assess traffic conditions Change in ability to keep up with traffic flow Change in workload sensitivity Change in motion control function
TIPI-J	Extraversion Agreeableness Conscientiousness Neuroticism Openness

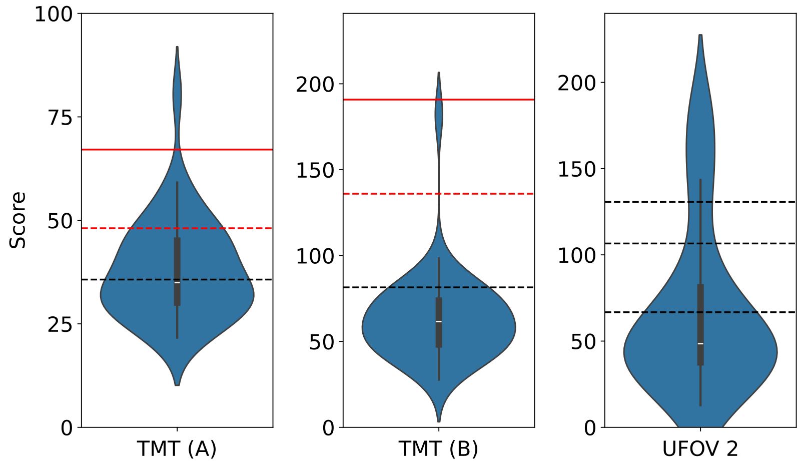


Figure 6.4: TMT and UFOV subtest 2 scores for the subjects. For the TMT, the top, middle, and bottom horizontal lines indicate normal standards for the older adults in normal control, those with mild cognitive impairment, and those with Alzheimer's disease, respectively [1]. For UFOV, the top, middle, and bottom horizontal lines indicate cutoff points to predict performance in the on-road driving test [3].

of older drivers were reported in [3]. Based on these scores, we could recruit drivers with a wide range of levels of cognitive ability.

Subjective impression questionnaire

We asked for subjective evaluations of the driving support after each driving session with the driving support. The questionnaire included seven questions designed to capture multifaceted evaluations of the system, with responses recorded on a 5-point Likert scale. The questions addressed the following aspects of the driving support system: (1) the support was easy to understand, (2) the amount of information was just right, (3) the timing of the support was just right, (4) the driving support promoted safe driving, (5) the support distracted me from driving, (6) I would like to use this driver support system on a daily basis, and (7) I would purchase this system if it were available at an affordable price.

6.4 Analysis of the Relationship among Driving Behavior, Driver Characteristics, and Support Type

In this section, we analyze the effect of each type of driving support on driving behavior and explore the relationship between the effectiveness of the support and driver characteristics. As detailed in Section 6.3.3, the subjects provided four types of support, which differ in their content and amount in driving. Specifically, the four types of support included: (1) a simple stop sign reminder, (2) a simple stop sign reminder and stop instruction, (3) a simple stop sign reminder and left-right check instruction, and (4) a simple stop sign reminder and stop and left-right check instruction. Our analysis reveals the effectiveness of the content and the amount of support for each driver. First, we define the measures of driving behavior, which are derived from the driving logs and video data. Second, we build hierarchical regression models to explain driving behaviors using the types of support and driver characteristics. This regression analysis investigates the direct impacts of the supports for driving behaviors and how these impacts vary depending on individual driver characteristics. In this analysis, we hypothesize that drivers with different characteristics respond differently to supports. This difference in response due to driver characteristics is expressed through a regression analysis of driving behaviors using interaction terms between driver characteristics and support types.

6.4.1 Measures of driving behavior

To evaluate the effectiveness of the driving support types, several measures of safe driving behavior were calculated using the driving and video data. These measures include the Time To Collision (TTC), stop duration, the number of left-right checks, and vehicle speed. These measures are related to the content of the presented supports and are those that are expected to change as a result of the driving support provided. Except for stop duration, these measures were also used in a previous study [87]. We calculated these measures for each driving session.

TTC

TTC is the time before a collision happens between two objects if their speeds do not change. A session with small TTC values indicates risky driving with a higher collision probability. In the experimental setting, as a subject's car entered the intersection, other cars or bicycles approached from the left and right. First, to calculate the TTC, we identified the crossing point of the trajectory of the subject's car and other cars or bicycles. Then, we calculated the differences in time for the subject's car and other cars or bicycles to reach the crossing point. Finally, the TTC for each session was determined as the minimum time difference among all the objects.

Stop duration

In each session, the stop duration was calculated as the total number of seconds the subject spent near the intersection speed below 0.15 km/h during each session. Short stop durations indicate inadequate stops and insufficient caution at intersections.

The number of left-right checks

The number of left-right checks was derived from video data by analyzing the subject's face angle. Using the open-source software OpenFace [108], the pitch, yaw, and roll of the subject's face angle were captured at a frequency of 30 Hz. The resulting time series data were smoothed using a moving average with a window width of 15 frames. Frames where the absolute yaw angle of the face direction exceeded a threshold of $\theta = 0.17$ rad were classified as frames where left-right checks occurred. This threshold is the same as that used in [87], and we were also able to successfully detect left-right checking behavior in our dataset with this threshold value. Consecutive frames of left-right checks were grouped into left-right checking phases, and the total number of these phases was counted for each session. A lower count of left-right checks indicates inadequate safety confirmation. Figure 6.5 provides an example of the horizontal face angle data near an intersection, with the left-right checking phases highlighted.

Vehicle speed

Vehicle speed is defined as the average of the subject's vehicle speeds during all left-right checking phases within a driving session. Left-right checking at high speed is a dangerous driving behavior, and the vehicle speed evaluates this driving behavior.

Table 6.2 shows the correlations among the driving behavior measures. The TTC is positively correlated with the stop duration and the number of left-right checks, and negatively correlated with the vehicle speed during a left-right check. Thus, a short stop duration, few left-right checks, and a fast vehicle speed lead to a small TTC. The TTC may increase depending on

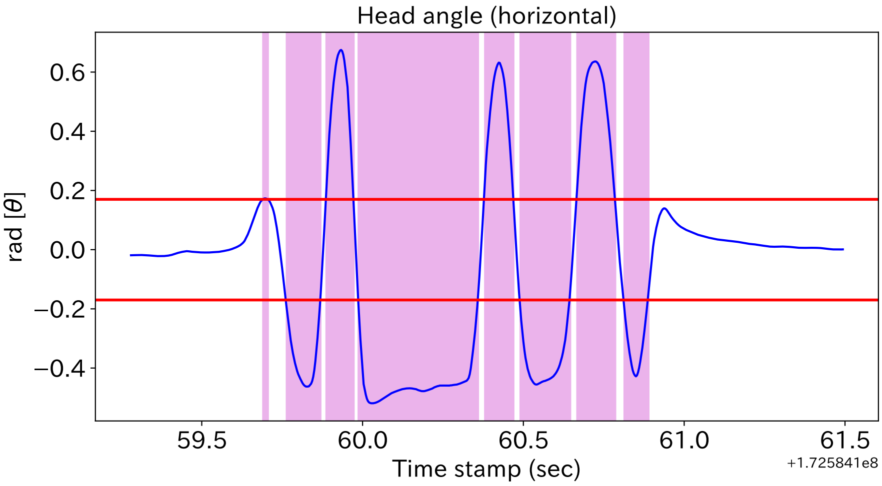


Figure 6.5: An example of a horizontal face angle near an intersection. The red horizontal lines indicate the threshold values ($|\theta| = 0.17$) used to identify left-right checking behavior. Frames with color highlights represent left-right checking phases, where the absolute yaw angle of the face direction exceeds the threshold.

Table 6.2: Correlation among driving behavior measures.

	1	2	3	4
1. TTC	–			
2. Stop duration	0.20*	–		
3. Left-right checks	0.18*	0.28*	–	
4. Vehicle speed	-0.12*	-0.11*	0.07	–

*. Correlation is significant at the 0.05 level ($p < 0.05$).

the timing of the intersection passage, even if safe driving behaviors are not performed. Additionally, the correlation coefficients between these measures are not high. Therefore, we evaluate safe driving behaviors using all these measures rather than just one.

6.4.2 Hierarchical regression analysis

The goal of this analysis is to evaluate the effectiveness of the driving support types using hierarchical regression models. This regression analysis investigates how different types of support, driver characteristics, and their interactions influence driving behavior. The analysis consists of three steps. The first step of the analysis is to build regression models that explain the

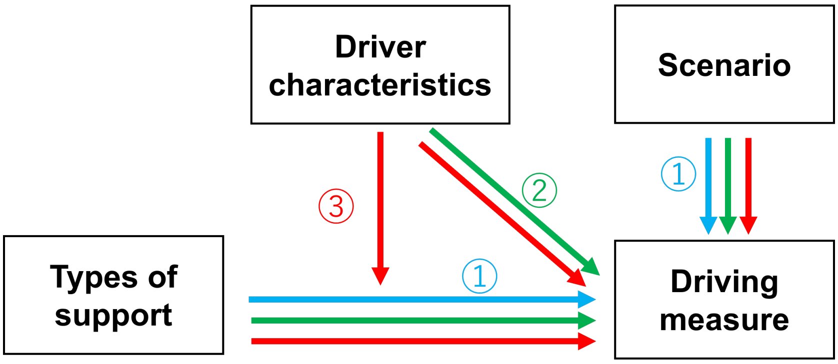


Figure 6.6: Overview of the hierarchical regression analysis. The variables used in each step are added as 1, 2, and 3 to construct a regression model of driving behavior.

measures of driving behavior using the variables of types of support. In the second step, driver characteristic variables are added to the models. This step evaluates the extent to which driving behaviors are influenced by driver characteristics, which are independent of driving support. Finally, in the third step, interaction terms between the types of support and driver characteristics are incorporated into the models. These terms capture how the effectiveness of the supports varies depending on driver characteristics. Our hypothesis is verified based on the contribution of interaction terms to the regression model in the third step. An overview of these analyses is shown in Figure 6.6.

Table 6.3: Results of the hierarchical analyses.

Measure	Model	R^2_{adj}	F (p)	Result
TTC	Step 1	0.12	10.79*	Not explained by support variables.
	Step 2	0.23	7.31*	Modest contribution of driver characteristics.
	Step 3	0.40	4.54*	Additional contribution of interaction terms.
Stop duration	Step 1	0.00	0.72	Not explained by support variables.
	Step 2	0.09	3.72*	Slight contribution of driver characteristics.
	Step 3	0.41	5.23*	Large additional contribution of interaction terms.
Left-right checks	Step 1	0.01	2.11	Not explained by support variables.
	Step 2	0.54	15.89*	Significant contribution of driver characteristics.
	Step 3	0.66	9.90*	Additional contribution of interaction terms.
Vehicle speed	Step 1	0.00	0.53	Not explained by support variables.
	Step 2	0.55	13.02*	Significant contribution of driver characteristics.
	Step 3	0.65	9.38*	Additional contribution of interaction terms.

Table 6.4: Regression coefficient of the support type and scenario variable in Step 1.

Measure	β_{s_0}	β_{s_1}	β_{s_2}	β_{s_3}	β_{s_4}	$\beta_{\text{car\_scenario}}$
TTC	0.06	0.05	0.11	0.11	−0.04	−0.70*
Stop duration	−0.12	0.17	−0.05	−0.03	0.03	−0.02
Left-right checks	−0.10	−0.08	0.01	0.10	−0.06	0.30*
Vehicle speed	0.07	−0.09	−0.11	0.09	0.02	0.04

Step 1: Effectiveness of the support

To assess the influence of different types of support on driving behavior, regression analyses were performed using the measures of driving behavior as dependent variables. Additional control variables, such as scenario information from the driving course, were included to account for external factors. The regression models were based on the following equation:

$$
\begin{aligned}
y = \beta_0 &+ \beta_{s_0} D_{s_0} + \beta_{s_1} D_{s_1} + \beta_{s_2} D_{s_2} \\
&+ \beta_{s_3} D_{s_3} + \beta_{s_4} D_{s_4} + \beta_{\text{car\_scenario}} D_{\text{car\_scenario}},
\end{aligned}
$$

where D_{s_0} is a dummy variable set to 1 in sessions without any support, and D_{s_1}, D_{s_2}, D_{s_3}, and D_{s_4} are dummy variables for the respective types of support (as described in Section 6.3.3). For example, a D_{s_1} value of 1 indicates the session in which support type 1 was provided. $D_{\text{car\_scenario}}$ is a dummy variable equal to 1 for the car-passing scenario sessions and 0 for the bicycle-passing scenario sessions. The dependent variable y represents a specific measure of driving behavior. Separate regression models were built for each measure.

Table 6.3 presents the results of hierarchical analyses, including the adjusted coefficient of determination R^2_{adj} and the F values of the model. The F values with an asterisk (*) indicate the values with statistical significance at the 5% significance level. In step 1, the R^2_{adj} values were low, and only the F value for the TTC was statistically significant. Table 6.4 shows the regression coefficients with statistically significant values marked with an asterisk (*). Since β_{s_4} was negative for the TTC, support 4 had a negative effect on the TTC. With respect to the stop duration and the number of left-right checks, β_{s_0} was negative and had the lowest coefficient. Thus, the subjects made shorter stops and performed fewer checks when no support was provided. Additionally, β_{s_1} had the largest coefficient for stop duration, indicating that notification support tended to increase stop duration more than instructive support did. It is possible that the subjects paid attention to stopping with only notification-type support, while an instruction, "Stop completely", was redundant. For the number of left-right checks and vehicle speed, β_{s_3} had the largest coefficient. Since support 3 was instruction-type support encouraging left-right checks, the subject appeared to perform these checks when stopped and then accelerated. However, none of the coefficients related to the types of support were statistically significant for any of the driving behavior measures. This suggests that differences in support type did not lead to significant overall changes in driving behavior. The scenario variable $D_{\text{car\_scenario}}$ was significant for the TTC and the number of left-right checks. In the car-passing scenario, the TTC was lower and the number of left-right checks was higher than in the bicycle-passing scenario. This can be attributed to the higher speed of passing cars, which results in small TTC values and prompts subjects to frequently check leading safety.

To further explore the effectiveness of support, a regression analysis was conducted using a simpler model with a dummy variable indicating whether any support was provided. Even with this model, no significant changes in driving behavior were observed due to the provision of support.

Step 2: Effects of driver characteristics

In addition to the variables used in Step 1, driver characteristics were added as independent variables to evaluate their impact on driving behaviors in Step 2. The driver characteristic variables consisted of 30 variables obtained from the questionnaires and six variables obtained from the cognitive function tests. All driver characteristic variables were standardized. Regression models were constructed using sequential variable selection, where variables were added one by one to the existing model based on their contribution to increasing the adjusted coefficient of determination. The regression models after variable selection were based on the following equation:

$$
\begin{aligned}
y = \beta_0 &+ \beta_{s_0} D_{s_0} + \beta_{s_1} D_{s_1} + \beta_{s_2} D_{s_2} + \beta_{s_3} D_{s_3} \\
&+ \beta_{s_4} D_{s_4} + \beta_{\text{car\_scenario}} D_{\text{car\_scenario}} + \sum_{i \in \mathcal{A}} \beta_i X_i,
\end{aligned}
$$

where $\mathcal{A}$ is a set of indexes of selected driver characteristic variables determined through variable selection.

In Step 2, as shown in Table 6.3, the addition of the driver characteristic variables increased the R^2_{adj} for all the driving behavior measures compared with those of the models in Step 1. Significant improvements were observed in the models for the number of left-right checks and vehicle speed, where R^2_{adj} increased from 0.01 and 0.00 in Step 1 to 0.54 and 0.55, respectively. These results suggest that these driving behaviors are strongly influenced by driver characteristics. In contrast, the model for stop duration exhibited a lower R^2_{adj} of 0.09, indicating that this measure of driving behavior could not be adequately explained by either the type of support or the driver characteristics. The selected variables in a set $\mathcal{A}$ by variable selection are listed in Appendix B.

Step 3: Effects of the interaction between driver characteristics and types of support

In this step, we evaluated how the interaction between driver characteristics and the types of support influenced driving behavior. These interaction terms were included in the regression models to capture variations in the effectiveness of support based on individual driver characteristics. Similar to Step 2, regression models were built using incremental sequential variable selection. The regression models after variable selection were based on the following equation:

$$
\begin{aligned}
y = {} & \beta_0 + \beta_{s_0} D_{s_0} + \beta_{s_1} D_{s_1} + \beta_{s_2} D_{s_2} + \beta_{s_3} D_{s_3} \\
& + \beta_{s_4} D_{s_4} + \beta_{\text{car\_scenario}} D_{\text{car\_scenario}} + \sum_{i \in \mathcal{A}} \beta_i X_i + \sum_{(j,k) \in \mathcal{B}} \beta_{jk} X_j D_{s_k},
\end{aligned}
$$

where $\mathcal{B}$ is a set of index pairs of selected interaction terms determined through variable selection.

As shown in Table 6.3, the addition of interaction terms resulted in higher R^2_{adj} values for all driving behavior measures than those for the models in Step 2. This finding demonstrates that interaction terms between driver characteristics and types of support were effective in explaining variations in driving behavior. That is, the effectiveness of specific support types varied depending on individual driver characteristics. In particular, the R^2_{adj} value for the stop duration increased significantly, which indicated that the effectiveness of support types in changing stopping behavior was highly dependent on individual driver characteristics. The increase in the R^2_{adj} value for vehicle speed was relatively small (0.10). Since the provided support did not contain instructions regarding speed while left-right checking, its contribution to explaining driving behaviors was limited. The selected variables in set $\mathcal{A}$ and $\mathcal{B}$ by variable selection are listed in Appendix B

Table 6.5: Significant interaction terms in the regression model for the stop duration.

Interaction term	Coefficient
Support 1 – Driving while looking for routes and destinations (WSQ)	−1.24
Support 1 – Change in ability to keep up with traffic flow (QSQ)	1.23
Support 1 – Change in ability to assess traffic conditions (QSA)	1.12
Support 1 – Hesitation for driving (DSQ)	1.12
Support 1 – UFOV subtest 1 (cognitive function)	−1.12
Support 1 – Methodical driving (DSQ)	0.86
Support 1 – Fine steering wheel operation and speed adjustment (WSQ)	−0.84
Support 1 – TMT (B) (cognitive function)	−0.75
Support 1 – Change in precision operations (QSA)	−0.73
Support 1 – Conscientiousness (TIPI-J)	0.68
Support 1 – Impatience in driving (DSQ)	0.65
Support 1 – Anxiety about traffic accidents (DSQ)	-0.63
Support 1 – Openness (TIPI-J)	−0.53
Support 1 – Neuroticism (TIPI-J)	−0.51
Support 1 – Change in motion control function (QSA)	0.43

6.4.3 Discussion

We summarize the results of the hierarchical regression analysis. In Step 1, we attempted to explain each measure of driving behavior using the support variables. However, none of the support variables showed statistically significant effects in the regression models. In other words, neither the type of support provided (instruction vs. notification) nor the amount of information contained in the support led to consistent changes in driving behavior across drivers. This is likely because, as later revealed in Step 3, the effectiveness of driving support varies across drivers depending on their individual characteristics, making it difficult to observe a consistent support effect when considering all drivers as a single group. In Step 2, driver characteristics variables made a substantial contribution to explaining driving behavior. In particular, the R^2_{adj} value increased notably for left-right checks and vehicle speed. This improvement suggests that these behaviors were strongly influenced by individual differences regardless of the type of support provided. In Step 3, we observed that adding interaction terms between driver characteristics and support variables improved the R^2_{adj} values beyond those in Step 2. Although support variables alone were not effective in Step 1, their effects became explanatory when combined with driver characteristics. This indicates that the behavioral changes produced by driving support differ across individuals depending on their driver characteristics. Based on these results, providing support that is personalized to driver characteristics appears to be more effective in promoting safe driving behaviors than presenting one-size-fits-all support.

Next, we analyze which interaction terms were effective for explaining the stop duration, where the greatest enhancement was observed. Based on the results of Sections 6.4.2 and 6.4.2, stop duration was only slightly explained by driver characteristics, whereas the explanatory power of the regression model increased substantially when the interaction terms between driver characteristics and support variables were included. In contrast, for the other driving-behavior measures, more than half of the variance in Step 3 can be explained by driver characteristics alone in Step 2. This indicates that stop duration has a larger proportion of variance that can be explained through the use of interaction terms compared to the other measures, and therefore, a greater improvement in support effects tailored to driver characteristics can be expected.

Table 6.5 lists the interaction terms in the Step 3 regression model with coefficients with p-values less than 0.01. All the significant interaction terms involved support 1, which only notified drivers of the presence of a stop sign. This result suggests that when support 1 was provided, stop durations were more likely to vary depending on driver characteristics. Notably, support 1 had the largest impact on the stop duration in the analysis of step 1.

Since coefficients related to cognitive function tests, such as TMT and UFOV, were negative, drivers with lower cognitive functions had shorter stop durations when support 1, which was only a situational notification, was presented. These findings suggest that the benefits of instruction-type support for drivers with lower cognitive functions outweigh the impact of the cognitive load associated with understanding the information provided. Additionally, drivers with methodical and hesitant driving tendencies or high conscientiousness exhibited longer stop durations than others, even with support 1. Similarly, drivers who were aware of their declining ability to keep up with traffic flow or assess traffic conditions also tended to stop longer with minimal support. This is likely because they recognize their declining driving abilities and strive for safe driving, thereby enabling safe driving even with minimal informational support. In Popken et al [109], drivers who viewed themselves as anxious, emotional, and nervous drivers trusted a lane-keeping control system, which provides a high level of assistance to a greater extent. In our results, drivers who had higher anxiety about traffic accidents, workload sensitivity, and neuroticism showed shorter stop durations. This tendency may be caused by their high reliability of high-level driving support, which involves both notification and instruction. While these findings reveal the influence of driver characteristics on the effectiveness of support, the diversity of significant interaction terms complicates conclusions based solely on specific traits. Instead, the results indicate that the effectiveness of support varies depending on the wide range of driver characteristics.

6.5 Exploration of Interaction Effects

In the hierarchical regression analysis discussed earlier, we examined interaction terms between a single driver characteristic and a single type of support variable. While these analyses revealed important findings, the effects of driving support may depend not only on a single characteristic but also on combinations of two or more characteristics. To explore these complex and interpretable interactions, we employed the machine learning algorithm RuleFit [110]. Using RuleFit, we identified significant interaction terms involving multiple driver characteristics and types of support. Although both neural network models and RuleFit are capable of capturing nonlinear relationships, they differ in interpretability. RuleFit provides explicit rules that reveal the basis of its predictions, whereas neural networks generally act as black-box models.

Predicting driving behavior based on driver characteristics and types of support enables assistance systems that adaptively provide the most effective support before a driver reaches an intersection. Thus, the performance of this model was evaluated to assess its ability to predict driving behaviors based on driver characteristics and types of support.

6.5.1 RuleFit algorithm and experimental setting

RuleFit is a machine learning algorithm that learns predictive rules from input variables to predict target outcomes. These predictive rules are constructed by combining input variables through decision trees, learned sequentially in an ensemble manner. RuleFit applies L1 regularization, similar to lasso regression [111], to retain only the most important rules. The predictive model is

$$F(\mathbf{x}) = \hat{a}_0 + \sum_{k=1}^{K} \hat{a}_k r_k(\mathbf{x}) + \sum_{j=1}^{n} \hat{b}_j l_j(x_j)$$

with

$$(\{\hat{a}_k\}_0^K, \{\hat{b}_j\}_1^n) = \arg\min_{\{a_k\}_0^K} \sum_{i=1}^{N} L\left(y_i, a_0 + \sum_{k=1}^{K} a_k r_k\left(\mathbf{x}_i\right) + \sum_{j=1}^{n} b_j l_j\left(x_{ij}\right)\right) + \lambda \cdot \left(\sum_{k=1}^{K} |a_k| + \sum_{j=1}^{n} |b_j|\right),$$

where $r_k(x)$ is the k-th conjunctive rule and equals 1 when the input variable x satisfies the rule and $\hat{a}_k$ represents the weight of the k-th rule $r_k(x)$. The term $\sum_{j=1}^{n} \hat{b}_j l_j(x_j)$ captures the linear relationship between features and outcomes and $l_j(x_j)$ are the transformed features of x_j for robust prediction. Here, K is the number of rules, n is the number of features, and N is the number of samples. The term $\lambda \cdot (\sum_{k=1}^{K} |a_k| + \sum_{j=1}^{n} |b_j|)$ is the L1 regularization term, which encourages the selection of only the most important rules and features, and λ is the regularization parameter. The loss function $L(y_i, \cdot)$ was set to be a mean squared error. Large decision trees can capture complex rules, but such rules make interpretation difficult. In contrast, rules extracted by small decision trees are easy to interpret, but they do not tend to be able to predict outcome variables well. To balance interpretability and predictive power, a tree size of four was used in RuleFit for this chapter.

First, we apply RuleFit to the whole dataset to explore predictive rules, and then evaluate the generalization performance of the model via cross-validation. Since the results in Section 6.4.2 showed that the TTC and

Table 6.6: Training accuracy (R^2 and r) of RuleFit.

Metrics	Step	TTC	Stop duration	Left-right checks	Vehicle speed
R^2	1	0.00	0.00	0.00	0.00
	2	0.43	0.19	0.61	0.68
	3	0.55	0.90	0.81	0.99
r	1	0.00	0.08	0.10	0.00
	2	0.66	0.54	0.80	0.83
	3	0.76	0.95	0.91	0.99

Table 6.7: Generalization accuracy (R^2 and r) of RuleFit.

Metrics	Step	TTC	Stop duration	Left-right checks	Vehicle speed
R^2	1	0.00	−0.02	−0.02	−0.02
	2	0.14	0.02	0.48	0.43
	3	0.07	−0.06	0.52	0.36
r	1	−0.14	−0.18	−0.28	−0.24
	2	0.43	0.22	0.70	0.66
	3	0.38	0.24	0.73	0.64

the number of left-right checks were influenced by the scenario, the analysis was focused on driving sessions with the car-passing scenario. Similar to the hierarchical regression analysis, this analysis has three steps in building models to verify the effectiveness of the interaction terms. In Step 1, the models used only the variables related to the type of support. In Step 2, the models used only the variables related to the driver characteristics. In step 3, the models incorporated both support types and driver characteristics, capturing the interaction effects among them. The driver characteristics and outcome variables were standardized before model construction in all steps.

6.5.2 Performance of RuleFit

Table 6.6 shows the model training accuracies, including the coefficient of determination R^2 and Pearson correlation r between the measurements of driving behavior and the predicted values obtained with RuleFit. The models in Step 1 failed to predict driving behaviors even in the training phase. In Step 2, the prediction accuracy improved significantly, and further improvements were observed in Step 3. In particular, the accuracy values for the stop duration are significantly increased from step 2 to step 3. The results from

Step 1 indicate that support type alone was insufficient to predict driving behavior. However, in Step 3, when combined with driver characteristics, the inclusion of support type contributed to improved model accuracy. These findings align with those of the hierarchical regression analysis and emphasize the important role of the interaction effects in explaining variations in driving behavior. Table 6.7 shows the models' generalization accuracy for test data, as evaluated using 10-fold cross-validation. The model in Step 3 achieved the highest R^2 value for the number of left-right checks and the highest r values for the stop duration and the number of left-right checks.

The success in predicting stop duration and the number of left-right checks based on driver characteristics and support types can contribute to the development of personalized support. When driver characteristics are known, this model can predict the most effective support type, and assistance systems can provide personalized support before drivers reach intersections. However, for other driving behavior measures, the Step 3 model did not achieve the highest accuracy. These limitations in generalization performance may be due to the small sample size. Conjunctive rules tend to overfit when trained on limited data. To address this issue, future research should focus on developing complex and robust rules using a larger sample size. Figure 6.7 shows the predicted values of the TTC and the number of left-right checks for a particular driver. For each support type, the model outputs predicted driving behavior based on driver characteristics. Using this model, we can compare driving behaviors and select the optimal support type. Support 2 was the best support for this example driver to increase the TTC and the number of left-right checks.

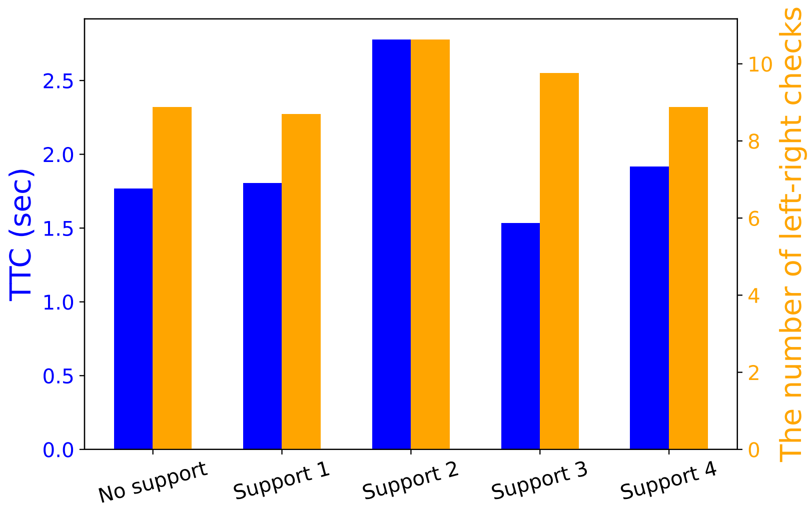


Figure 6.7: Predicted driving behaviors (TTC and the number of left-right checks) for a certain driver with each support type.

Table 6.8: Conjunctive rules explored by RuleFit for predicting the number of left-right checks.

	Rule	Coefficient
Rule 1	Support 4 $= 0$ Openness (TIPI-J) > 0.91 Neuroticism (TIPI-J) > 0.65	0.94
Rule 2	Support 2 $= 1$ Frequent fine steering wheel operation (WSQ) > 0.01 Inability to get a sense of the vehicle and its width (WSQ) ≤ 0.60	0.48
Rule 3	Support 3 $= 0$ Confidence in driving skill (DSQ) ≤ 0.54 Driving at midnight (WSQ) > -0.89	-0.29

6.5.3 Explored rules

For the number of left-right checks, the generalization accuracies were the highest across all steps and were successfully verified. Given this result, we analyze the conjunctive rules identified by the RuleFit algorithm for predicting the number of left-right checks. Table 6.8 provides the top three conjunctive rules with the largest absolute values of coefficients ($\hat{\alpha}$). The magnitude of these coefficient values indicates the importance of each rule in the prediction model. When a rule is satisfied, the corresponding driving behavior is likely to be influenced according to the coefficient's sign and magnitude. All the representative rules included both support type and driver characteristic variables. These rules thus reflect which types of drivers were influenced by specific types of support.

Rule 1 emerged as the most representative rule, indicating that subjects with high levels of openness and neuroticism performed more left-right checks in the absence of Support 4. Several studies have explored the relationships between these personality traits and driving behaviors. For example, a meta-analysis by Luo et al. [104] revealed that risky and aggressive driving behaviors are negatively associated with openness. Austerschmidt et al. [112] reported that older drivers with high openness levels displayed better on-road performance in the dimensions of complex intersections and traffic signs. These findings suggest that drivers with high openness may perform well even without support. Furthermore, interactions with DAS depend on various personality traits, as reported in a previous study. Li et al. [113] found that openness level was negatively associated with trust in a partial driving automation system. They indicated that individuals with high openness levels are inclined to seek intellectually challenging activities, and this tendency may cause low trust in the system. Consistent with our findings, participants with high openness levels may have preferred not to use Support 4, which involved multiple instructions and extensive information. Regarding neuroticism, Luo et al. [104] also reported that risky and aggressive driving behaviors are positively associated with neuroticism. Furthermore, Tement et al. [114] indicated that individuals with high levels of neuroticism were less able to adapt their behavior to increased information processing demands, particularly when such behaviors were difficult to recognize on their own. Our results similarly suggest that neurotic subjects may have faced difficulties processing the multiple instructions provided by Support 4 and modifying their behaviors. Combined with the findings in Section 6.4.3, these findings suggest that neurotic drivers may be highly inclined to rely on driving support. However, compared with nonneurotic subjects, they may have had greater difficulty modifying their behavior in response to the multiple provided instructions. Rule 3 indicates that subjects with low confidence and not high levels of workload sensitivity at midnight driving had fewer checks without support 3, which instructed them to the left and right sides. This may be because they rely on instructions to compensate for their low confidence and reduce their cognitive workload.

6.6 General Discussion

In this chapter, we investigated the relationship between driver characteristics and the effectiveness of driving support. Our analyses in Section 6.4 and 6.5 showed that the wide range of driver characteristics moderates the effect of the driving support, and they have key roles in personalizing assistance systems. For example, the results of the hierarchical regression analysis indicated that drivers with cognitive decline showed short stop durations, whereas drivers with an awareness of their cognitive decline stopped for longer periods when they were provided with simple support (Table 6.5). Therefore, it is important to focus on not only single-driver characteristics but also multifaceted driver characteristics when developing personalized DAS. In addition, to capture such complex mechanisms of driving behavior change moderated by a wide range of driver characteristics and use them in assistance systems, a machine-learning approach is a good choice, as shown in Section 6.5. These findings highlight the importance of personalizing driving support systems based on individual driver traits and contribute to the development of more tailored assistance systems. However, the underlying reasons why these characteristics influence the effectiveness of support remain unclear.

This chapter has several limitations. First, the number of participants was relatively small, and the sample included not only older adults but also younger and middle-aged drivers to avoid recruiting only drivers with declined cognitive function. As a result, the findings may not be specific to older drivers, who are the primary target population for driving-assistance systems. Future studies should increase the sample size and focus more explicitly on older adults to improve the generalizability of our findings. In addition, as discussed in Section 6.5, the predictive performance of the support-effect models was limited. With a larger dataset, it may become possible to develop more accurate models using neural networks to better predict the effects of driving assistance.

Second, the experiment was conducted using a driving simulator. Although simulators allow for controlled and safe examination of driving behavior, the results cannot be perfectly replicated under real world conditions. In particular, participants might drive with increased attention, anticipating that certain events could occur during the experiment. While simulators enable precise control over event occurrences and presentation conditions, fundamental aspects of driving behavior such as attention and hazard perception are likely to be more accurately captured in real world environments. Furthermore, the effectiveness of DAS that provide situational information may differ between simulator conditions and real world conditions, as drivers' baseline awareness and hazard perception can vary depending on the environment. Therefore, field experiments are necessary to verify whether similar effects can be observed in actual driving situations and to support the implementation of personalized DAS in real world environments.

Third, we adopted audio-announcement support due to its effectiveness and the ease of implementation as discussed in Section 6.2.2. To realize more personalized assistance for older drivers with greater hearing impairments, support modalities other than auditory cues, such as visual or haptic feedback, are important. As future work, it will be essential to investigate the relationship between driver characteristics and the types of support that are most effective for these alternative modalities.

Finally, although the analyses in Chapters 5 and 6 connected driver characteristics to personalized driving assistance, a unified analysis that consistently links driver characteristics estimation with support effectiveness has not yet been conducted. The next chapter addresses this issue by integrating driver characteristics estimation and support-effect analysis within a unified framework.

6.7 Conclusion

This chapter investigated the impact of driving support on drivers at stop sign intersections, focusing on how driving behaviors vary based on a wide range of driver characteristics. Several types of driving support were considered in terms of the amount of information and content provided. Using hierarchical regression analyses and the RuleFit machine learning algorithm, we found that the effectiveness of the support types varied significantly depending on a wide range of driver characteristics. These models provide a basis for selecting and presenting appropriate support based on driver characteristics, thereby completing a framework that spans from driver characteristics estimation to personalized driving assistance.

In particular, drivers with cognitive decline tended to perform safe driving behaviors when provided with instructive support. In contrast, neurotic drivers appeared to be more dependent on driving support than other drivers but struggled to process the information it provided. In addition to cognitive functions, characteristics such as self-awareness of cognitive decline, driving style, workload sensitivity, and personality also influence the effectiveness of driving support. These findings emphasize the importance of personalizing DAS based on a wide range of driver characteristics rather than a single characteristic.

Chapter 7

General Discussion

This chapter summarizes insights gained throughout this thesis toward realizing personalized DAS that adapt assistance based on driver characteristics. Subsequently, directions for future work are presented.

7.1 Design Implications for Personalized Driver Assistance Systems

Based on the findings in Chapters 5 and 6 regarding the effects of driving support across different driver characteristics, together with the estimation performance of these characteristics examined in Chapters 3 and 4, the following discussion integrates these results and discusses insights and perspectives toward the realization of personalized DAS. The results in Chapter 6 showed that drivers with worse scores on UFOV and TMT (B), indicating reduced cognitive function, tended to exhibit short stopping behavior at stop sign intersections when provided with simple warning-based support. This suggests that, for drivers with cognitive decline, assistance strategies that provide explicit information and reduce cognitive load during driving are more effective. This interpretation is consistent with previous studies, which have argued that assistance providing explicit behavioral instructions is necessary for older drivers [86, 87]. Accordingly, the amount and content of information provided to drivers with cognitive decline emerge as critical design considerations for personalized DAS. Importantly, the cognitive characteristics relevant to these assistance effects were shown to be reliably estimated from naturalistic driving data in this thesis. In Chapter 3, UFOV and TMT (B) scores were estimated with correlation coefficients of 0.708 and 0.579, respectively, under fixed-route conditions. Furthermore, Chapter 4 demonstrated that TMT (B) could still be estimated with a moderate correlation of 0.48

using driving data collected from different routes. These results indicate that cognitive function measures such as UFOV and TMT (B) are not only influential in determining the effectiveness of driving assistance, but are also practically estimated from on-road driving data. Taken together, these findings suggest that cognitive function represents a driver characteristic that can be reliably estimated from naturalistic driving data and is meaningfully linked to assistance effectiveness. This property makes cognitive function a particularly promising basis for the realization of personalized DAS, in which both the content and amount of support can be adapted according to individual driver characteristics.

In addition to cognitive function, personality traits also played an important role in the effectiveness of driving support. In Chapter 6, the results showed that drivers with high levels of neuroticism and openness in the Big Five personality traits exhibited fewer left−right checking behaviors at stop sign intersections when provided with information-rich support involving multiple instructions. Drivers with high neuroticism were interpreted as having greater difficulty modifying their behavior in response to multiple simultaneous instructions. This suggests that, for drivers with high neuroticism, assistance strategies that avoid presenting excessive information at once and instead provide guidance in a reduced and stepwise manner may be more effective. Similarly, drivers with high openness were considered to have preferred not to use driving support that involved multiple instructions and extensive information. For such drivers, assistance approaches that provide only minimal and essential information may be more suitable. As discussed in Chapter 6, these interpretations are consistent with findings from previous studies, indicating that the observed effects represent robust behavioral tendencies rather than incidental results. Although personality traits were not estimated in this thesis, previous studies have demonstrated that neuroticism and openness are estimable from driving data. For example, a two-class classification approach distinguishing high and low levels of neuroticism and openness achieved ROC−AUC scores of 0.74 and 0.72, respectively [33]. In addition, a regression-based approach reported correlation coefficients of 0.57 for neuroticism and 0.88 for openness [31]. These properties make these personality traits promising candidates for personalization of DAS. While variability in cognitive function is relatively limited among younger drivers, personality traits such as neuroticism and openness exhibit substantial variability even within younger driver populations. Therefore, personality-based personalization has the potential to complement cognitive-function-based approaches and broaden the applicability of personalized DAS across a wider range of drivers.

Chapters 5 and 6 consistently showed that the effectiveness of driving support differed depending on drivers' levels of confidence in driving skill and hesitation for driving as measured by the DSQ. Drivers with high confidence in driving skill exhibited immediate reductions in speeding behavior in response to speeding warnings in Chapter 5. In addition, in Chapter 6, drivers with high confidence in driving skill showed improvements in TTC and vehicle speed at stop sign intersections when provided with information-rich driving support. These results suggest that drivers with high confidence in their driving skill, in contrast to highly neurotic drivers, possess a greater ability to adapt their driving behavior in response to driving assistance. Accordingly, providing richer and more detailed information may be an effective support strategy for drivers with high confidence in driving skill. However, as shown in Chapter 3, confidence in driving skill could not be reliably estimated from driving data using the proposed estimation approach. Therefore, while the importance of confidence in driving skill as a factor for personalization was demonstrated, improving the estimation accuracy of this characteristic remains an important challenge for the realization of personalized DAS. Regarding the DSQ item of hesitation for driving, drivers with high levels of hesitation showed limited behavioral improvement in response to driving support in both Chapter 5 and Chapter 6. In Chapter 5, drivers with high levels of hesitation for driving did not tend to decrease their speeding behavior over the long term. In Chapter 6, drivers with high levels of hesitation showed improvements in stopping duration and left–right checking behavior at stop sign intersections when provided with simple driving support. However, when more information-rich support was provided, TTC deteriorated for drivers with high hesitation for driving. These results suggest that drivers with high hesitation for driving may benefit from simple and focused assistance, whereas providing excessive information can negatively affect their driving performance. At the same time, as shown in Chapter 3, the estimation accuracy for hesitation for driving was relatively limited, with an F1-score of 0.649. Therefore, similar to confidence in driving skill, improving the estimation accuracy of hesitation for driving remains an important challenge for effectively incorporating this characteristic into personalized DAS.

7.2 Limitations and Future Work

While this thesis provides insights into personalized DAS based on driver characteristics, it has several limitations.

7.2.1 Driver Characteristic Estimation Models Considering Traffic Environment

In this thesis, driver characteristic estimation was primarily conducted based on driving behavior features extracted from vehicle sensor data. Although road types and scenarios were considered, dynamic traffic environment factors such as surrounding vehicles, pedestrians, traffic signals, and road markings were not explicitly incorporated into the estimation framework. However, driving behavior is inherently shaped by the surrounding traffic environment. The relationship between traffic situations and drivers' responses is particularly important when estimating cognitive function and other psychological characteristics. For example, cognitive decline has been reported to cause delays in information processing, including understanding traffic situations and translating situational awareness into appropriate driving behavior [115, 116]. Ignoring such contextual factors may limit estimation accuracy and reduce the interpretability of the learned models. Therefore, incorporating traffic environment information into driver characteristic estimation represents an important next research direction. To achieve this, it is necessary to move beyond vehicle sensor data alone and incorporate video-based sensing that captures traffic context and driver gaze behavior, enabling multimodal estimation of driver characteristics. Research toward this goal is currently underway in this thesis, aiming to integrate traffic situation information with driving behavior signals in a unified modeling framework.

7.2.2 Extension of Driver Characteristic Estimation Models to More Complex Models

Driving behavior is inherently sequential, and time-series modeling has the potential to capture fine-grained temporal dynamics, which may contain rich information relevant to driver characteristics. However, as described in Appendix A, attempts to estimate driver characteristics using an LSTM-based time-series model did not yield satisfactory performance in this thesis. One possible reason for this result is the limited size of the available dataset. Deep learning models such as LSTM generally require large amounts of training data to achieve robust performance. Therefore, constructing a large-scale dataset that includes both extensive driving data and reliable measurements of driver characteristics is essential for realizing effective time-series-based estimation. However, collecting substantial amounts of naturalistic driving data together with psychological and cognitive characteristic data is costly and time-consuming. Accordingly, it is also necessary to develop modeling approaches that can learn meaningful relationships between driving signals and driver characteristics even with limited data.

Even if larger datasets become available, simply applying more complex time-series models such as LSTM may not necessarily lead to accurate estimation of driver characteristics. This is because driving behavior is influenced by many contextual factors that are unrelated to intrinsic driver traits, including traffic density, surrounding vehicles, pedestrians, and road infrastructure. If these contextual factors dominate the learned representations, the model may fail to capture intrinsic individual differences. Nevertheless, the findings obtained in this thesis indicate that focusing on specific road environments and driving behaviors, such as arterial roads, turning at intersections, and lane changes, enables accurate estimation. These insights are expected to remain useful even when more complex models are adopted and can serve as important cues for designing future models that aim to extract driver-specific information from large-scale time-series data.

In this regard, the Multiple Instance Learning (MIL) [117] framework represents a promising approach. In the MIL framework, a driving session can be regarded as a bag consisting of multiple driving behavior instances. Rather than assuming that all behavior segments equally reflect driver characteristics, MIL allows the model to identify and focus on informative instances within the bag. By selectively attending to behavior segments that are more indicative of driver-specific traits, MIL may reduce the influence of irrelevant contextual factors and enable more robust estimation from large-scale time-series data.

7.2.3 System-Level Validation and Integration Challenges

From a system-level perspective, several challenges remain before personalized DAS can be fully realized in real-world deployment.

First, this thesis focused on DAS that provide warnings and informational support, such as alerts for speeding, sudden acceleration, and warnings at stop sign intersections. Although the findings are expected to be relevant to DAS with higher levels of automation, such as systems involving partial or conditional vehicle control, further validation is required to confirm their applicability in those contexts.

Second, this thesis primarily addressed relatively stable driver characteristics that do not change significantly over short time scales. In parallel, temporal driver states, including stress, emotions, and momentary workload, are also expected to play an important role in personalizing DAS. How relatively stable driver characteristics and temporal driver states should be combined to achieve effective personalization of DAS remains an important topic for future research.

Finally, in this thesis, the driver characteristics estimation module and the driving assistance module were evaluated separately. While this approach allowed for a detailed analysis of each component, future work should focus on evaluating an integrated system that unifies estimation and assistance. In particular, it is necessary to investigate how estimation accuracy and uncertainty in driver characteristics affect the effectiveness of personalized driving assistance in real-world operation. Addressing these limitations is expected to move toward the realization of robust and scalable personalized DAS.

Chapter 8

Conclusion

This thesis addressed key challenges toward realizing personalized DAS based on driver characteristics. This chapter concludes each chapter and summarizes this thesis. In Chapter 3, psychological characteristics of drivers, such as cognitive function, psychological driving style, and workload sensitivity, were estimated from on-road driving data collected along a fixed driving route. By explicitly considering road types and multiple temporal scales of driving behavior, the proposed method enabled the estimation of these psychological driver characteristics for most of the examined items. In particular, by considering road types, the TMT (B) and the UFOV were estimated with relatively high accuracy, achieving correlation coefficients of 0.579 and 0.708, respectively. In contrast, estimation performance for confidence in driving skill and methodical driving in the DSQ, as well as driving posture in the WSQ, remained low and did not exceed the chance level of 0.5, indicating that these characteristics could not be reliably estimated with the current approach.

In Chapter 4, cognitive function was estimated using on-road driving data collected from different driving routes. By focusing on particular driving scenarios that commonly appear across different routes, this chapter demonstrated that drivers' cognitive function can still be estimated from driving data even under varying route conditions. The highest estimation accuracies achieved for the TMT (A) and TMT (B) scores were correlation coefficients of 0.34 and 0.48, respectively. Although a direct comparison with Chapter 3 is not possible due to differences in participants, the results indicate that estimation accuracy decreased when using data from different routes, but cognitive function could still be estimated with moderate correlation.

In Chapter 5, the effects of driving support related to speeding and sudden acceleration, presented by a driving support robot, were analyzed in relation to individual driver characteristics. The results showed that drivers with high levels of hesitation for driving in the DSQ did not tend to decrease their speeding behavior over the long term, whereas drivers in the low group exhibited a gradual reduction in speeding. In addition, drivers with low confidence in driving skill tended to continue speeding even immediately after receiving speeding warnings, suggesting that the provided assistance was less effective for these drivers. Regarding assistance for sudden acceleration and deceleration, the results indicated that the driving support was effective for drivers with high levels of methodical driving. In contrast, sudden acceleration and deceleration behaviors did not decrease among drivers in the low methodical driving group.

In Chapter 6, the impact of driving support at stop sign intersections was investigated. Multiple types of driving support were examined, differing in both the amount and content of the information provided. In particular, drivers with cognitive decline tended to exhibit safer driving behaviors when provided with instructive support, whereas drivers with high neuroticism appeared to rely more heavily on driving support but had difficulty processing the information it provided. Beyond cognitive function, characteristics such as self-awareness of cognitive decline, driving style, workload sensitivity, and personality were found to influence the effectiveness of driving support. These findings highlight that the impact of driving assistance at stop sign intersections is not uniform across drivers and emphasize the importance of personalizing DAS based on a broad set of driver characteristics rather than a single factor. Furthermore, Chapter 6 provided a basis for selecting and presenting appropriate support based on driver characteristics. These results establish a framework that spans from driver characteristics estimation to personalized driving assistance.

In summary, the findings of this thesis demonstrate that the effectiveness of driving assistance varies depending on individual driver characteristics, and that certain characteristics are both critical determinants of assistance effectiveness and can be reliably estimated from naturalistic driving data. Among the examined characteristics, cognitive function emerged as a particularly promising basis for personalization. It was shown to significantly influence drivers' responses to assistance in cognitively demanding situations, such as stop-sign intersections, while also being reliably estimated with moderate to high accuracy from on-road driving data. The combination of an influence on the effectiveness of personalized assistance and the feasibility of reliable estimation positions cognitive function as a central component for realizing implicit personalized DAS. Personality traits, especially neuroticism and openness, were also shown to meaningfully affect how drivers respond to different types of assistance. Because personality exhibits substantial variability even among younger drivers and has been shown in prior studies to be estimable from driving data, personality-based personalization can complement cognitive-function-based approaches and expand personalization to a broader driver population. At the same time, the results revealed that not all driver characteristics that influence assistance effectiveness can currently be estimated with sufficient accuracy. Characteristics such as confidence in driving skill and hesitation for driving demonstrated clear relationships with behavioral adaptation to assistance, yet their estimation performance remains limited. Taken together, this thesis suggests that effective personalized DAS should be grounded in driver characteristics that satisfy both criteria, namely, meaningful impact on assistance effectiveness and robust estimability from driving data. By integrating psychological and cognitive perspectives into assistance design, this work provides a concrete step toward implicit, interpretable, and scalable personalization of DAS.

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Appendix A: Experimental Results of LSTM Model

Here, we detail the estimation results of the LSTM model in Chapter 3. Table 8.1 shows the regression accuracy of the LSTM model for cognitive function. The LSTM model did not achieve the best accuracy for all cognitive function items. It is thought that the LSTM model could not learn well because the sample size was small. Table 8.2 shows the classification accuracy of the LSTM model for DSQ and WSQ. Similar to the result of the estimation of cognitive function, the LSTM model did not work well for all items and none of the LSTM models achieved an accuracy greater than 0.5. The accuracy of an LSTM model is expected to improve when the amount of training data increases. However, it is difficult to collect considerable driving data and characteristic data. Thus, we need to develop a method that can capture a relationship between driving signals and driver characteristics with few data.

Table 8.1: Regression accuracy of the LSTM model for cognitive function.

Model	Road type	r				RMSE			
		TMT (A)	TMT (B)	MAZE	UFOV	TMT (A)	TMT (B)	MAZE	UFOV
LSTM	Arterial	0.216	0.252	-0.084	-0.022	11.278	35.903	18.419	101.603
LSTM (Int 1)	Intersection	-0.222	-0.156	-0.084	0.113	11.490	34.252	16.035	97.078
LSTM (Int 2)		-0.066	0.109	0.026	-0.110	12.726	35.297	16.653	104.196
LSTM (Int 3)		-0.469	-0.243	-0.013	-0.157	14.191	35.581	16.115	93.642
LSTM (Int 4)		-0.031	-0.054	-0.012	0.183	11.850	34.834	16.404	95.538

Table 8.2: Classification accuracy of the LSTM model for DSQ and WSQ.

	Arterial	Intersection			
DSQ item	LSTM	LSTM (Int 1)	LSTM (Int 2)	LSTM (Int 3)	LSTM (Int 4)
Confidence in driving skill	0.333	0.337	0.352	0.340	0.354
Hesitation for driving	0.387	0.387	0.401	0.404	0.399
Impatience in driving	0.415	0.418	0.425	0.424	0.424
Methodical driving	0.396	0.392	0.399	0.388	0.402
Preparatory maneuvers at traffic signals	0.355	0.359	0.369	0.356	0.371
Importance of automobile for self-expression	0.377	0.374	0.368	0.357	0.363
Moodiness in driving	0.387	0.392	0.391	0.394	0.398
Anxiety about traffic accidents	0.424	0.411	0.416	0.423	0.409
WSQ item	LSTM	LSTM (Int 1)	LSTM (Int 2)	LSTM (Int 3)	LSTM (Int 4)
Understanding of traffic conditions	0.366	0.370	0.375	0.342	0.364
Understanding of road conditions	0.355	0.356	0.367	0.381	0.356
Interference with concentration	0.355	0.338	0.357	0.361	0.340
Decline in physical activity	0.344	0.353	0.374	0.375	0.358
Disturbance on the pace of driving	0.333	0.345	0.368	0.368	0.350
Physical pain	0.355	0.362	0.382	0.383	0.365
Path understanding and search	0.333	0.342	0.364	0.366	0.347
In-vehicle environment	0.355	0.360	0.381	0.378	0.365
Control operation	0.333	0.354	0.350	0.349	0.360
Driving posture	0.387	0.366	0.387	0.385	0.373

Appendix B: Selected Variables in Hierarchical Regression

Here, we present details regarding selected variables used in hierarchical regression in Sections 6.4.2 and 6.4.2. Table 8.3 shows the selected driver characteristic variables for the hierarchical regression in step 2. Table 8.4 shows the selected driver characteristic variables for the hierarchical regression in step 3. Table 8.3 shows the selected interaction terms between the support and the driver characteristic variables for the hierarchical regression in step 3. These variables are listed in the order in which they were added during the selection procedure.

Table 8.3: Selected driver characteristic variables of hierarchical regression in step 2.

Selected variables	Coefficient	p-value
TTC		
Hesitation for driving (DSQ)	−0.21	0.00
Moodiness in driving (DSQ)	0.09	0.15
Change in ability to execute driving operations (QSA)	−0.12	0.05
Fine steering wheel operation and speed adjustment (WSQ)	0.23	0.00
Importance of automobile for self−expression (DSQ)	0.13	0.04
Openness (TIPI)	−0.03	0.59
Preparatory maneuvers at traffic signals (DSQ)	0.06	0.24
Anxiety about traffic accidents (DSQ)	0.01	0.86
Change in workload sensitivity (QSA)	0.29	0.00
UFOV subtest 2 (cognitive function)	−0.15	0.01
Irregular day-night rhythm (WSQ)	−0.13	0.12
Change in visual function (QSA)	−0.14	0.06
Driving with a load of care (WSQ)	−0.09	0.23
Stop duration		
Driving while looking for routes and destinations (WSQ)	−0.31	0.00
Poor physical condition (WSQ)	0.24	0.00
Change in workload sensitivity (QSA)	0.07	0.44
Change in visual function (QSA)	−0.05	0.52
Confidence in driving skill (DSQ)	−0.10	0.15
Agreeableness (TIPI)	−0.10	0.08
UFOV subtest 1 (cognitive function)	0.28	0.01
UFOV subtest 2 (cognitive function)	−0.22	0.03

Table 8.3: Selected driver characteristic variables of hierarchical regression in step 2 (continued).

Selected variables	Coefficient	p-value
Frequent fine steering wheel operation (WSQ)	−0.16	0.06
Driving with a load of care (WSQ)	0.14	0.10
Left-right checks		
Openness (TIPI)	0.33	0.00
Agreeableness (TIPI)	−0.68	0.00
UFOV subtest 1 (cognitive function)	0.48	0.00
TMT (A) (cognitive function)	0.02	0.68
Methodical driving (DSQ)	0.15	0.03
Extraversion (TIPI)	−0.47	0.00
Change in visual function (QSA)	0.24	0.00
Confidence in driving skill (DSQ)	0.73	0.00
Poor physical condition (WSQ)	0.18	0.01
Driving at midnight (WSQ)	−0.21	0.01
Fine steering wheel operation and speed adjustment (WSQ)	0.30	0.00
Importance of automobile for self-expression (DSQ)	0.51	0.00
Preparatory maneuvers at traffic signals (DSQ)	0.22	0.00
Conscientiousness (TIPI)	−0.28	0.00
Driving with a load of care (WSQ)	0.54	0.00
Impatience in driving (DSQ)	−0.35	0.00
Change in ability to keep up with traffic flow (QSA)	−0.27	0.00
Irregular day-night rhythm (WSQ)	−0.46	0.00
Anxiety about traffic accidents (DSQ)	0.23	0.00
Driving while looking for routes and destinations (WSQ)	−0.19	0.01

Table 8.3: Selected driver characteristic variables of hierarchical regression in step 2 (continued).

Selected variables	Coefficient	p-value
Frequent fine steering wheel operation (WSQ)	0.37	0.00
Change in ability to execute driving operations (QSA)	−0.15	0.01
Change in precision operations (QSA)	0.17	0.02
Roads whose shape changes from one to the other (WSQ)	−0.16	0.15
UFOV subtest 2 (cognitive function)	−0.10	0.30
Vehicle speed		
Poor physical condition (WSQ)	1.01	0.00
Extraversion (TIPI)	1.06	0.00
Roads whose shape changes from one to the other (WSQ)	−1.05	0.00
Anxiety about traffic accidents (DSQ)	1.28	0.00
Change in motion control function (QSA)	0.37	0.00
Driving with a load of care (WSQ)	0.12	0.33
Irregular day-night rhythm (WSQ)	−1.24	0.00
Roads with complex lane configurations (WSQ)	1.25	0.00
Preparatory maneuvers at traffic signals (DSQ)	−0.47	0.00
Change in precision operations (QSA)	0.84	0.00
Conscientiousness (TIPI)	0.16	0.13
UFOV subtest 3 (cognitive function)	2.67	0.00
Openness (TIPI)	1.33	0.00
Change in ability to keep up with traffic flow (QSA)	−0.82	0.00
TMT (B) (cognitive function)	0.99	0.00
UFOV subtest 2 (cognitive function)	−4.62	0.00
Importance of automobile for self-expression (DSQ)	−1.72	0.00

Table 8.3: Selected driver characteristic variables of hierarchical regression in step 2 (continued).

Selected variables	Coefficient	p-value
Change in workload sensitivity (QSA)	0.39	0.01
Methodical driving (DSQ)	−0.10	0.29
Neuroticism (TIPI)	0.75	0.00
Moodiness in driving (DSQ)	−1.01	0.00
Driving while looking for routes and destinations (WSQ)	0.32	0.01
Change in ability to execute driving operations (QSA)	0.13	0.17
Confidence in driving skill (DSQ)	−1.41	0.00
Change in visual function (QSA)	−0.79	0.00
UFOV subtest 1 (cognitive function)	2.84	0.00
Inability to get a sense of the vehicle and its width (WSQ)	1.02	0.00
Change in ability to assess traffic conditions (QSA)	−2.51	0.00
Impatience in driving (DSQ)	1.26	0.00
Hesitation for driving (DSQ)	−1.00	0.00
Agreeableness (TIPI)	0.51	0.00
TMT (A) (cognitive function)	−1.12	0.00
Frequent fine steering wheel operation (WSQ)	0.47	0.04
Driving at midnight (WSQ)	−0.18	0.06
UFOV total score (cognitive function)	0.20	0.00

Table 8.4: Selected driver characteristic variables of hierarchical regression in step 3.

Selected variables	Coefficient	p-value
TTC		
Change in ability to execute driving operations (QSA)	-0.11	0.05
Fine steering wheel operation and speed adjustment (WSQ)	0.35	0.00
Importance of automobile for self-expression (DSQ)	0.19	0.02
Irregular day-night rhythm (WSQ)	-0.03	0.80
Change in workload sensitivity (QSA)	0.09	0.33
Conscientiousness (TIPI)	-0.16	0.09
Driving with a load of care (WSQ)	-0.26	0.01
TMT (B) (cognitive function)	-0.25	0.00
UFOV subtest 2 (cognitive function)	0.16	0.08
Frequent fine steering wheel operation (WSQ)	-0.29	0.04
Confidence in driving skill (DSQ)	-0.14	0.17
Poor physical condition (WSQ)	0.16	0.16
Anxiety about traffic accidents (DSQ)	-0.10	0.29
Driving while looking for routes and destinations (WSQ)	-0.24	0.01
Stop duration		
Poor physical condition (WSQ)	0.14	0.06
Agreeableness (TIPI)	-0.18	0.00
Extraversion (TIPI)	-0.32	0.00
Neuroticism (TIPI)	-0.10	0.16
Change in ability to keep up with traffic flow (QSA)	0.08	0.26
Change in ability to execute driving operations (QSA)	-0.16	0.02
Driving with a load of care (WSQ)	0.24	0.01

Table 8.4: Selected driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Roads whose shape changes from one to the other (WSQ)	-0.27	0.01
Driving at midnight (WSQ)	0.15	0.06
Change in ability to assess traffic conditions (QSA)	0.22	0.03
Anxiety about traffic accidents (DSQ)	-0.19	0.05
Left-right checks		
Openness (TIPI)	0.10	0.14
Agreeableness (TIPI)	-0.59	0.00
UFOV subtest 1 (cognitive function)	0.47	0.00
TMT (A) (cognitive function)	0.01	0.92
Methodical driving (DSQ)	0.22	0.00
Extraversion (TIPI)	-0.49	0.00
Change in visual function (QSA)	0.35	0.00
Moodiness in driving (DSQ)	-0.22	0.01
Poor physical condition (WSQ)	0.14	0.07
Confidence in driving skill (DSQ)	0.80	0.00
Driving at midnight (WSQ)	-0.09	0.26
Fine steering wheel operation and speed adjustment (WSQ)	0.36	0.00
Driving with a load of care (WSQ)	0.47	0.00
Preparatory maneuvers at traffic signals (DSQ)	0.16	0.00
Importance of automobile for self-expression (DSQ)	0.59	0.00
Impatience in driving (DSQ)	-0.30	0.00
Conscientiousness (TIPI)	-0.28	0.00
Irregular day-night rhythm (WSQ)	-0.40	0.00

Table 8.4: Selected driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Change in ability to keep up with traffic flow (QSA)	-0.24	0.00
Anxiety about traffic accidents (DSQ)	0.18	0.02
Frequent fine steering wheel operation (WSQ)	0.29	0.03
Change in ability to execute driving operations (QSA)	-0.09	0.17
UFOV subtest 3 (cognitive function)	-0.24	0.03
Roads with complex lane configurations (WSQ)	-0.29	0.01
Inability to get a sense of the vehicle and its width (WSQ)	0.29	0.03
Roads whose shape changes from one to the other (WSQ)	-0.14	0.27
Vehicle speed		
Poor physical condition (WSQ)	0.99	0.00
Extraversion (TIPI)	1.11	0.00
Roads whose shape changes from one to the other (WSQ)	-0.80	0.00
Anxiety about traffic accidents (DSQ)	1.41	0.00
Change in motion control function (QSA)	0.41	0.00
Driving with a load of care (WSQ)	0.07	0.62
Irregular day-night rhythm (WSQ)	-1.29	0.00
Roads with complex lane configurations (WSQ)	1.24	0.00
Preparatory maneuvers at traffic signals (DSQ)	-0.56	0.00
Change in precision operations (QSA)	0.87	0.00
Change in ability to execute driving operations (QSA)	0.23	0.01
Moodiness in driving (DSQ)	-1.02	0.00
Neuroticism (TIPI)	0.77	0.00
Change in visual function (QSA)	-0.83	0.00

Table 8.4: Selected driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	*p*-value
Change in ability to keep up with traffic flow (QSA)	-0.67	0.00
UFOV subtest 1 (cognitive function)	2.82	0.00
Conscientiousness (TIPI)	0.11	0.31
Driving while looking for routes and destinations (WSQ)	0.16	0.31
Openness (TIPI)	1.33	0.00
Impatience in driving (DSQ)	1.27	0.00
Change in workload sensitivity (QSA)	0.43	0.00
Change in ability to assess traffic conditions (QSA)	-2.67	0.00
Inability to get a sense of the vehicle and its width (WSQ)	1.10	0.00
UFOV subtest 2 (cognitive function)	-4.58	0.00
Support 0 – Driving with a load of care (WSQ)	0.17	0.11
Importance of automobile for self-expression (DSQ)	-1.75	0.00
Hesitation for driving (DSQ)	-1.01	0.00
Agreeableness (TIPI)	0.58	0.00
UFOV subtest 3 (cognitive function)	2.77	0.00
Confidence in driving skill (DSQ)	-1.26	0.00
Fine steering wheel operation and speed adjustment (WSQ)	0.11	0.62
Driving at midnight (WSQ)	-0.31	0.00
TMT (A) (cognitive function)	-1.00	0.00
TMT (B) (cognitive function)	0.93	0.01
Methodical driving (DSQ)	-0.10	0.29
Frequent fine steering wheel operation (WSQ)	0.35	0.27

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3.

Selected variables	Coefficient	*p*-value
TTC		
Support 2 – Hesitation for driving (DSQ)	-0.12	0.30
Support 4 – Conscientiousness (TIPI)	0.19	0.15
Support 1 – Change in precision operations (QSA)	-0.19	0.06
Support 2 – Driving at midnight (WSQ)	-0.20	0.07
Support 2 – Importance of automobile for self-expression (DSQ)	-0.29	0.01
Support 1 – Importance of automobile for self-expression (DSQ)	-0.24	0.03
Support 3 – Extraversion (TIPI)	0.03	0.78
Support 0 – Conscientiousness (TIPI)	-0.10	0.35
Support 3 – Change in motion control function (QSA)	0.13	0.21
Support 4 – Poor physical condition (WSQ)	0.46	0.00
Support 4 – Confidence in driving skill (DSQ)	0.34	0.04
Support 4 – Openness (TIPI)	-0.02	0.84
Support 0 – Hesitation for driving (DSQ)	-0.27	0.04
Support 0 – Change in precision operations (QSA)	0.20	0.07
Support 1 – Extraversion (TIPI)	0.28	0.01
Support 2 – Extraversion (TIPI)	0.26	0.01
Support 0 – Change in workload sensitivity (QSA)	-0.23	0.07
Support 3 – Hesitation for driving (DSQ)	0.14	0.22
Support 0 – Impatience in driving (DSQ)	-0.04	0.76
Support 4 – Change in precision operations (QSA)	0.40	0.00
Support 4 – Change in visual function (QSA)	-0.36	0.01

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Support 4 – Change in ability to assess traffic conditions (QSA)	-0.44	0.01
Support 4 – TMT (B) (cognitive function)	0.34	0.02
Support 4 – Hesitation for driving (DSQ)	-0.38	0.02
Support 4 – Driving while looking for routes and destinations (WSQ)	0.34	0.04
Support 4 – Frequent fine steering wheel operation (WSQ)	0.29	0.13
Support 0 – Change in ability to keep up with traffic flow (QSA)	0.18	0.12
Support 0 – TMT (A) (cognitive function)	0.17	0.13
Support 0 – Change in motion control function (QSA)	-0.15	0.17
Support 4 – Methodical driving (DSQ)	-0.18	0.16
Support 4 – Moodiness in driving (DSQ)	-0.13	0.30
Stop duration		
Support 1 – Change in workload sensitivity (QSA)	0.29	0.15
Support 1 – Change in precision operations (QSA)	-0.73	0.00
Support 1 – Change in ability to keep up with traffic flow (QSA)	1.23	0.00
Support 1 – Driving while looking for routes and destinations (WSQ)	-1.24	0.00
Support 1 – UFOV subtest 1 (cognitive function)	-1.12	0.00
Support 1 – Change in ability to assess traffic conditions (QSA)	1.12	0.00
Support 1 – Conscientiousness (TIPI)	0.68	0.00
Support 1 – Driving with a load of care (WSQ)	-0.17	0.39
Support 1 – Frequent fine steering wheel operation (WSQ)	0.60	0.05
Support 1 – TMT (B) (cognitive function)	-0.75	0.00
Support 1 – Hesitation for driving (DSQ)	1.12	0.00

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Support 1 – Anxiety about traffic accidents (DSQ)	-0.63	0.00
Support 3 – Change in ability to assess traffic conditions (QSA)	0.24	0.06
Support 1 – Methodical driving (DSQ)	0.86	0.00
Support 1 – Fine steering wheel operation and speed adjustment (WSQ)	-0.84	0.00
Support 1 – Impatience in driving (DSQ)	0.65	0.00
Support 1 – Neuroticism (TIPI)	-0.51	0.00
Support 1 – Change in motion control function (QSA)	0.43	0.00
Support 1 – Openness (TIPI)	-0.53	0.00
Support 3 – Anxiety about traffic accidents (DSQ)	-0.10	0.44
Support 0 – Irregular day-night rhythm (WSQ)	-0.14	0.18
Support 4 – Openness (TIPI)	-0.15	0.14
Support 4 – Neuroticism (TIPI)	-0.10	0.35
Support 2 – TMT (A) (cognitive function)	0.09	0.31
Support 1 – UFOV subtest 3 (cognitive function)	0.29	0.19
Support 1 – Change in visual function (QSA)	0.46	0.03
Support 1 – Importance of automobile for self-expression (DSQ)	0.38	0.04
Support 3 – Moodiness in driving (DSQ)	-0.12	0.23
Support 2 – Change in workload sensitivity (QSA)	0.13	0.19
Support 4 – Change in motion control function (QSA)	-0.10	0.29
Support 2 – Openness (TIPI)	0.10	0.31
Left-right checks		
Support 2 – UFOV subtest 3 (cognitive function)	0.25	0.03

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Support 2 – Driving while looking for routes and destinations (WSQ)	-0.33	0.00
Support 1 – Driving while looking for routes and destinations (WSQ)	-0.42	0.00
Support 4 – Fine steering wheel operation and speed adjustment (WSQ)	-0.25	0.02
Support 2 – Openness (TIPI)	0.29	0.00
Support 2 – Change in motion control function (QSA)	0.12	0.20
Support 0 – Roads with complex lane configurations (WSQ)	-0.10	0.38
Support 3 – Neuroticism (TIPI)	0.18	0.03
Support 3 – Openness (TIPI)	0.29	0.00
Support 4 – Preparatory maneuvers at traffic signals (DSQ)	0.17	0.06
Support 2 – Roads with complex lane configurations (WSQ)	-0.19	0.09
Support 1 – Moodiness in driving (DSQ)	0.17	0.06
Support 2 – Methodical driving (DSQ)	-0.33	0.00
Support 1 – Hesitation for driving (DSQ)	0.24	0.01
Support 3 – Inability to get a sense of the vehicle and its width (WSQ)	-0.53	0.00
Support 3 – Poor physical condition (WSQ)	0.32	0.02
Support 3 – Roads with complex lane configurations (WSQ)	0.35	0.01
Support 3 – Irregular day-night rhythm (WSQ)	-0.18	0.11
Support 1 – Anxiety about traffic accidents (DSQ)	-0.12	0.21
Support 0 – Change in precision operations (QSA)	0.20	0.03
Support 2 – Fine steering wheel operation and speed adjustment (WSQ)	0.24	0.06
Support 2 – TMT (A) (cognitive function)	0.18	0.10
Support 2 – Conscientiousness (TIPI)	0.16	0.12

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Support 1 – Conscientiousness (TIPI)	0.16	0.09
Support 0 – Poor physical condition (WSQ)	-0.18	0.15
Support 3 – Agreeableness (TIPI)	-0.13	0.12
Support 4 – Change in motion control function (QSA)	-0.12	0.14
Support 4 – Change in visual function (QSA)	-0.18	0.05
Support 4 – Change in ability to keep up with traffic flow (QSA)	0.11	0.26
Support 4 – Methodical driving (DSQ)	-0.14	0.15
Support 4 – Change in precision operations (QSA)	0.16	0.09
Support 3 – Change in precision operations (QSA)	0.16	0.07
Support 0 – Anxiety about traffic accidents (DSQ)	0.22	0.05
Support 1 – Change in ability to execute driving operations (QSA)	0.12	0.22
Support 0 – Extraversion (TIPI)	0.15	0.09
Support 0 – Conscientiousness (TIPI)	-0.11	0.26
Support 0 – Change in ability to assess traffic conditions (QSA)	-0.13	0.25
Support 2 – Preparatory maneuvers at traffic signals (DSQ)	0.10	0.30
Vehicle speed		
Support 4 – Importance of automobile for self-expression (DSQ)	-0.30	0.00
Support 3 – Conscientiousness (TIPI)	-0.11	0.32
Support 2 – Change in visual function (QSA)	-0.29	0.00
Support 0 – Driving with a load of care (WSQ)	0.17	0.11
Support 3 – Confidence in driving skill (DSQ)	-0.32	0.01
Support 4 – Neuroticism (TIPI)	0.12	0.16

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	p-value
Support 1 – Change in ability to keep up with traffic flow (QSA)	0.09	0.33
Support 2 – Driving at midnight (WSQ)	0.27	0.01
Support 4 – Openness (TIPI)	0.14	0.13
Support 3 – Preparatory maneuvers at traffic signals (DSQ)	0.26	0.01
Support 3 – Change in motion control function (QSA)	-0.20	0.04
Support 3 – Agreeableness (TIPI)	-0.17	0.07
Support 2 – Methodical driving (DSQ)	-0.20	0.06
Support 2 – Frequent fine steering wheel operation (WSQ)	-0.34	0.03
Support 2 – Fine steering wheel operation and speed adjustment (WSQ)	0.24	0.12
Support 1 – Extraversion (TIPI)	-0.07	0.36
Support 4 – TMT (B) (cognitive function)	-0.16	0.08
Support 0 – TMT (A) (cognitive function)	-0.09	0.26
Support 3 – Irregular day-night rhythm (WSQ)	-0.30	0.02
Support 3 – Poor physical condition (WSQ)	0.36	0.01
Support 1 – Driving while looking for routes and destinations (WSQ)	0.18	0.09
Support 1 – Inability to get a sense of the vehicle and its width (WSQ)	-0.20	0.09
Support 0 – Roads with complex lane configurations (WSQ)	-0.24	0.03
Support 0 – Driving at midnight (WSQ)	0.20	0.06
Support 4 – Driving with a load of care (WSQ)	-0.30	0.02
Support 4 – Irregular day-night rhythm (WSQ)	0.19	0.11
Support 4 – Driving while looking for routes and destinations (WSQ)	0.16	0.13
Support 4 – UFOV subtest 1 (cognitive function)	0.14	0.14

Table 8.5: Selected interaction terms between support and driver characteristic variables of hierarchical regression in step 3 (continued).

Selected variables	Coefficient	*p*-value
Support 3 – UFOV subtest 1 (cognitive function)	0.23	0.07
Support 3 – Change in ability to keep up with traffic flow (QSA)	-0.13	0.21
Support 1 – Change in precision operations (QSA)	0.13	0.14
Support 0 – Change in ability to assess traffic conditions (QSA)	0.13	0.18
Support 2 – Preparatory maneuvers at traffic signals (DSQ)	0.09	0.28
Support 4 – Agreeableness (TIPI)	0.09	0.30

Publication List

Publications Corresponding to This Thesis

International Journal (Peer-Reviewed)

R. Kimura, T. Tanaka, Y. Yoshihara, K. Fujikake, H. Kanamori, and S. Okada, ”Estimating Driver Personality Traits From On-Road Driving Data”, IEEE Access, 2023. (Corresponds to Chapter 3 in this thesis)

International Conferences (Peer-Reviewed)

R. Kimura, T. Tanaka, Y. Yoshihara, K. Fujikake, H. Kanamori, and S. Okada, ”Psychological Characteristics Estimation from On-Road Driving Data”, International Conference on Human-Computer Interaction 2022, 2022. (Corresponds to Chapter 3 in this thesis)

R. Kimura, T. Tanaka, and S. Okada, ”Driver’s Cognitive Function Estimation Using Daily Driving Data”, 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society, 2023. (Corresponds to Chapter 4 in this thesis)

R. Kimura, H. Horimoto, T. Tanaka, and S. Okada, ”Investigating the Effect of Driving Support Robot Depending on Driver Characteristics”, Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction (Late-Breaking Reports), 2024. (Corresponds to Chapter 5 in this thesis)

International Journal (Under Review)

R. Kimura, T. Tanaka, and S. Okada, ”Towards Personalized Driving Assistance: Exploring Individual Differences in the Effect of Driving Support at Stop Sign Intersections", submitted to User Modeling and User-Adapted Interaction (UMUAI) (Corresponds to Chapter 6 in this thesis)

Other Publications

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T. Hayashi, R. Kimura, R. Ishii, F. Nihei, A. Fukayama, and S. Okada, "Rapport Prediction Using Pairwise Learning in Dyadic Conversations among Strangers and among Friends", International Conference on Human-Computer Interaction 2024, 2024.

H. Horimoto, R. Kimura, T. Tanaka, and S. Okada, "Psychological Driving Style Estimation from GPS Sensor Data Alone", 2024 Asia Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), 2024.

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