UNDERSTANDING THE INFLUENCE OF FAMILIARITY ON ROUTE CHOICE AMONG OLDER DRIVERS

By

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ABSTRACT

A number of studies have established the role of familiarity as an important factor of driving for older drivers. Familiarity is known to govern route choice, and there is a need for familiarity to be included in choice models. But very limited work has been conducted in quantifying the degree to which familiarity influences route choice, under what conditions, and how robustly models can approximate familiarity. This dissertation attempts to answer the first 2 knowledge gaps in Chapter 3, where analyses conducted on the factors that influence route choice among older adults showed that a) familiar routes were preferred as they were perceived to be shorter, direct, and had minimal traffic; b) different factors of familiarity were involved in choosing a route; and c) familiarity was the most important factor in explaining route choice after baseline route choice behavior, accounting for 26 percent of the explained variance. Additionally, extensive literature review revealed that current models of route choice that included familiarity failed to capture the multi-criteria nature of familiarity. In Chapter 4, this dissertation attempts to develop an abstraction hierarchy framework for describing the multi-criteria nature of route familiarity, and establishing a mathematical framework that can be used to calculate a new measure of familiarity – *estimated route familiarity*. The final chapter discusses the applications of the *estimated route familiarity* measure and abstraction hierarchy framework for the personalization of driver support systems and vehicle algorithm design.

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As I graduate from one of the best research academies, having learnt all I can, the exploration continues…

Thrusters on full.
Space, the final frontier.
These are the voyages of the Starship Enterprise.
Its continuing mission to explore strange new worlds, to seek out new life and new civilization, to boldly go where no one has gone before.
Engage.

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CHAPTER 1: INTRODUCTION

For older adults, driving is central and plays an important role in prolonging their mobility, independence, autonomy, and ability to age in place. But age-related physical, cognitive, and functional declines make older adults vulnerable to traffic injuries and motor vehicle crashes (MVC). According to the Center for Disease Control and Prevention, one-third of adults 80 years and older are hospitalized due to MVCs, and incur at least $57,000 in hospitalization costs – higher than other age groups. For older adults, MVCs not only incur high financial costs compared to younger adults, but also result in reduced driving and driving cessation. Reduced driving and driving cessation has been shown to affect the overall mobility and independence of older adults, and result in adverse long-term consequences such as higher levels of depressive symptoms, general health decline, decreased life satisfaction, fewer social and recreational trips, and reduced participation in social activities. To address these concerns and take preventative measures, the aim of this dissertation is to explore opportunities for enhancing the mobility and safety of older drivers.

1.1 Older drivers

From 2003 to 2013, the number of adults 65 and older in the U.S. increased from 35.9 million to 44.7 million, and is projected to more than double to 98 million by 2060 (Administration on Aging, 2014). This increase has led to a rise in the number of licensed older drivers, from 14 percent in 2000 to 16 percent in 2012 (TRIP, 2012). Along with this increase, the mobility patterns of older drivers are also shifting. From 1990 to 2009, older drivers spent more time driving, made longer trips, and made more trips (Rosenbloom & Santos, 2014). This shift in driving patterns has been attributed to a number of factors such as older adults leading a more active lifestyle, improved health care, education, and higher income (TRIP, 2012), and an increasing number of older adults remaining in the work force well after retirement age (Rosenbloom & Santos, 2014). Ninety percent of trips taken by adults 65 and older, and 80 percent of trips taken by adults 85 and older are taken in a private vehicle (Rosenbloom, 2003). Hence driving continues to play an important role in maintaining the mobility and independence of older adults.

Older adults are generally safe drivers. But driving maneuvers such as left turns and intersection negotiations can become more challenging with age (Cooper, 1990; Evans, 1991). When driving conditions become challenging – especially due to declining health, it can affect driving ability. Under such conditions, older drivers often limit their driving through self-regulation. Older drivers self-regulate by avoiding difficult driving situations such as rush hours, intersections, nighttime driving, unfamiliar areas, and bad weather (Planek & Fowler, 1971). Experiencing an MVC also prompts self-regulation, such that drivers avoid driving in the rain, making left turns, and driving in rush hours (Ball et al., 1998). Such self-regulation, although important for prolonging driving safety and mobility, can often cause older drivers to cease driving.

Driving cessation, an extreme form of self-regulation, avoids driving-related risk but also reduces participation in social and leisure activities, and can affect overall quality of life and well-being (Herzog, Ofstedal, & Wheeler, 2002). To avoid the costs associated with driving cessation, various interventions have been developed to help drivers adapt to their limits in a way that enhances safety without compromising mobility. These include the use of driver support systems (DSS) such as collision warning systems (CWS), lane departure warnings (LDW), and lane keeping assistance (LKA) that can guide drivers' attention to hazards (Dingus et al., 1997).

The safety benefits analysis of these DSS technologies have shown promising results, with intelligent braking and lateral driver support systems having the potential to avoid many crashes. Most notably, 40.8 percent of all car accidents might be avoided with Collision Mitigation Braking Systems (CMBS), 16.8 percent for Lane Keeping Assist Systems, 1.4 percent for Blind Spot Detection systems, and 24.7 percent for Lane Change Assist systems (Kuehn, Hummel, & Bende, 2009).

Training can also target functional requirements for driving such as physical status, visual functioning, and cognition (Marmeleira, Godinho, & Fernandes, 2009). Speed-of-processing and spatial attention training – a task relevant to driving – has been shown to improve UFOV among older drivers. A study on the effects of speed-of-processing and driver simulator training on driving performance among older drivers revealed training was effective in reducing the degree of UFOV reduction by 38% versus 13% (Roenker, Cissell, Ball, Wadley, & Edwards, 2003). Educational programs have also been suggested as useful in providing remediation for driving skills. Owsley et al. (2004) assessed the Knowledge Enhances Your Safety (KEYS) education program among visually impaired older drivers at high risk for crash involvement. Older drivers who received the KEYS intervention were more likely to acknowledge that they had poor eyesight, admit to experiencing more difficulty with visually challenging situations, were more likely to engage in self-regulatory practices, avoid hazardous driving, and reduce overall driving exposure. Thus training and education interventions offer promise in improving driving safety as they can help maintain safe driving among older drivers in the years following their training (Owsley, Stalvey, & Phillips, 2003).

But older drivers are already known to choose routes that help them avoid challenging driving situations (Kua, Korner-Bitensky, & Desrosiers, 2007). Avoiding challenging driving situations, such as left turns, has emerged as an effective response for 8 out of the 14 age-related conditions facing older drivers (Staplin, Lococo, Martell, & Stutts, 2012). However, little is known regarding the type of routes older drivers choose, factors that influence their route choice, and their route choice behavior.

1.2 Route choice and the role of familiarity

Understanding the *type of route* is complex because each origin-destination pair can have a number of routes that vary in travel time, distance, road characteristics, traffic conditions, etc. Whereas the *factors that influence route choice* is also complex, involving various driver preferences and knowledge about the route such as landmarks, shortest distance, fewer turns, less traffic, etc. (Bovy, 2009). And *choice behavior* along a route may consists of different choice processes such as sequential (decision making along the route), simultaneous (decision made in advance on which route to take), or strategic (adapting to new or unexpected situations along a route) (Gao & Chabini, 2006; Marzano, Papola, & Simonelli, 2009).

To understand the type of routes driven, factors influencing route choice, and choice behvior of older drivers, three studies were conducted. In study I, an in-vehicle instrumentation suite consisting of a two-way facing camera, audio and video recorders, and an on-board diagnostic device were used to record driving behavior, driver state, and driving environment of older drivers for two weeks. Results of the study showed that older drivers planned trips in advance, preferred routes that had fewer turns, construction zones, and traffic incidents (Payyanadan, Gibson, Chiou, Ghazizadeh, & Lee, 2016). A route selection algorithm that implemented older driver route preferences, while considering older driver safety, was developed in study II using the General Estimates System crash statistics (Payyanadan, Sanchez, et al., 2016). Results from the study showed that for the trips driven, there was opportunity to reduce the number of left turns and U-turns by 1.50 and 0.23, and reduce the distance travelled by 0.44 miles per trip.

In study III, the route selection algorithm was implemented in web-based Trip Diaries to provide older adults retrospective feedback of their routes driven and risky driving behavior, with alternate route suggestions based on their preferences and designed to lower route risk (Payyanadan, Maus, et al., 2016). Results from the study showed that although feedback could lower older drivers' route risk by 2.9% per week and speeding behavior by 0.9% per week; the low-risk route alternatives were not always adopted by the drivers. Further analysis indicated that familiarity with the route played an important role in route choice for older drives.

Limited research concerning the influence of familiarity on route choice has shown that compared to younger drivers, older drivers prefer routes with similar trip attributes such as travel time, distance, traffic delays, and speed limits for commuting to events and visiting friends and family, but not for shopping and recreational trips (Zhang & Levinson, 2008). And compared to younger drivers, across trip purposes, older drivers prefer routes that are familiar, as familiarity with the route has been shown to increase recall of the environment and its objects (Peron, Baroni, Job, & Salmaso, 1990), and reduce the likelihood of getting lost (Uc, Rizzo, Anderson, Shi, & Dawson, 2004).

While older drivers prefer familiar routes, few navigation systems consider familiarity. Current navigation systems implement route choice algorithms only for shortest route (Ruan, Luo, & Wu, 2014), routes with less navigational complexity at intersections (Haque, Kulik, & Klippel, 2006), simplest route (Duckham & Kulik, 2003), scenic routes (Zheng et al., 2013), regionalized path planning (Richter, 2009), landmarks (Klippel & Winter, 2005), and traffic congestion (Gehrke & Wojtusiak, 2008). More recent navigational systems have implemented multi-criteria route selection based on driver preferences (Sadeghi, 2008), but fall short as they are primarily concerned with minimizing costs such as time and distance, rather than balancing factors such as familiarity, fewer turns, and stop lights (Jozefowiez, Semet, & Talbi, 2008). Thus, considering familiarity as part of a multi-criteria route selection algorithm could benefit the wayfinding and route planning needs of older drivers.

But modelling route choice as a function of familiarity is complex as it involves a number of factors based on the driver's preference, their cognitive map, and characteristics of the driving environment (Prato, 2009). Given the limited understanding on the influence of familiarity on route choice, the goal of this dissertation is two-fold: a) To determine how familiarity influences route choice, and b) To develop a framework for measuring route familiarity.

1.3 Representing familiarity using Abstraction Hierarchies

Early work on understanding the influence of familiarity on route choice has shown that familiarity with the route is influenced by levels of dynamic and static knowledge about the route and the route network such as type of roads, infrastructure, traffic conditions, and travel speed; spatial and temporal factors such a travel time and distance; type of trip such as purpose of travel; and external factors related to weather, time of departure, etc. (Lotan, 1997; O'Neill, 1992). These knowledge representations have been used to model the decisison process, attitudes, and perceptions involved in route choice using fuzzy set theory, approximate reasoning, fuzzy control, and "*if then*" rules (Lotan & Koutsopoulos, 1993). But modelling these decision processes has been limited due to the complexity in generating the associated membership functions, rule calibrations, and data collection. As a result, only one or two membership functions and rules have been used to model the influence of familiarity on route choice (Prato, Bekhor, & Pronello, 2012); with model testing primarily conducted using data from simulator and survey studies (Prato, 2009). Thus, current route choice models that include familiarty often do not appropriately reflect real-world route choice behavior.

Bovy and Stern (1990; 2012) suggested that models representing real-world route choice behavior should include: distinct mental processes that follow different rules governing route choice; decision-making processes based on constraints, compensatory strategies, and preferences; trial-and-error of route use; information acquistion processes; and account for rule differences between individual drivers even under the same travel conditions. To develop such a complex route choice model, the conceptual framework by Bovy and Stern (1990; 2012) suggests using *factor-importance hierarchy*. *Factor-importance hierarchy* refers to the hierarchical ordering of factors relevant for selecting a satisfactory route. For example, if for any given origin and destination a driver prefers to take a familiar route, then factors such as familiarity with the road network would be at the top of the hierarchy to eliminate route alternatives not within the network; and then be followed by other factors such as trade-offs between familiar routes within the network based on time and distance – often referred to as the *utility function* in route choice models (Ben-Akiva, Bergman, Daly, & Ramaswamy, 1984). Similar hierarchical approaches have been implemented in cognitive, neuropsychological, and neuroimaging studies, where familiarity is represented as hierarchical levels of knowledge (Yonelinas, Kroll, Dobbins, & Soltani, 1999; Yonelinas, 1994, 2002).

Early work in developing a framework to represent different levels of a hierarchy originated from Hierarchy Theory – an analytical approach for understanding complexity (Ahl & Allen, 1999). But with the need to understand complex non-biological systems, hierarchical structures became more widely used in Systems Theory to describe complex dynamic systems such as the organizational structure of steel and petrochemical industries (Mesarovic, Macko, & Takahara, 2000). In Cognitive Engineering, similar hierarchical frameworks have been used to represent complex systems of human problem solving and reasoning, especially for driver behavior such as Michon's Hierarchical Control Model consisting of three hierarchically ordered levels combining driving task and information processing (Michon, 1985); the GADGET-Matrix motivational model of driver behavior – representing a compensatory mechanism for drivers to self-regulate (Christ et al., 2000); and the Drivability Model that considers driving behavior as dynamic and context-dependent (Bekiaris, Amditis, & Panou, 2003). Rasmussen's abstraction hierarchy presents a complementary perspective, which focusses on describing the hierarchical structure of the environment in which the person acts (Rasmussen, 1986).

Among these models, Rasmussen's Abstraction Hierarchy (AH) is the preferred theoretical framework for representing the levels of familiarity influencing route choice because it provides a mechanism for uncovering and representing both the physical and social constraints of a complex system (Roth & Bisantz, 2013). Uncovering and representing these constraints provides a basis for developing better models and designs of support that are robust, and foster flexible and adaptive performance.

1.4 Research objectives

For this dissertation, the vehicle of 29 drivers 65 years and older were instrumented with an on-board diagnostic device (OBII) for a period of 4 months to record their driving behavior, route choice, and trip characteristics. Customized web-based Trip Diaries were used to provide retrospective feedback of their trips. Retrospective feedback included information about routes driven, low-risk route alternatives, risky driving behavior, and a questionnaire on the factors that influence choice of route, familiarity with the route driven, and familiarity with the alternate low-risk route suggested. As such, this dissertation has two measures of drivers' familiarity. *Stated familiarity* taken directly from the Trip Diary feedback responses, will refer to the self-reported responses on familiarity with the driven and alternate low-risk suggested route. This familiarity value is measured in a binary fashion: 1 (yes) and 0 (no). *Estimated route familiarity* is a new measure of familiarity proposed in this dissertation, and determined by mapping the OBDII data recorded from older drivers trips to the results of the content analysis conducted on the Trip Diary feedback responses. This dissertation will address the following questions:

a) *What is the influence of familiarity on route choice for older drivers? Stated familiarity* responses with the route driven and alternate low-risk suggested route from the Trip Diary were used to conduct a mixed-effects model to test the influence of their stated familiarity on route choice. Additionally, Content Analyses – a qualitative approach for analyzing text data, and identifying themes and patterns within the text data (Hsieh & Shannon, 2005) – was conducted on the feedback responses from older drivers on the reasons for choosing a certain route. Results of the content analysis were used to determine the range of factors that affect route choice for older drivers; where route choice is *the selection of a path from origin to destination*.

b) *Can features defined by an abstraction hierarchy representation of routes estimate familiarity?* Results from the Content Analysis were used to develop a hierarchical framework of route familiarity using the levels of Abstraction Hierarchy by Rasmussen (1986). The abstraction hierarchy framework was used to develop a measure of route familiarity – *estimated route familiarity*. To assess the accuracy of *estimated route familiarity*, it is important to understand *How well do the levels of the AH explain the differences in the participants stated familiarity?*

and *How well does the estimated familiarity predict stated familiarity on a test data set?* To answer these questions, the accuracy of the *estimated familiarity* was tested using a logistic regression where *estimated familiarity* predicted *stated familiarity* responses from the participants on the route driven and alternative low-risk routes suggested.

1.5 Contributions

The motivation for this dissertation lies in the evidence pertaining to the multi-criteria nature of route familiarity that influences route choice, the lack of a current approach for assessing route familiarity, and the opportunity for using such an approach to help better predict route choice for route planning and navigation systems that can better match the needs and preferences of select cohort of drivers. This dissertation makes a number of theoretical and practical contributions to understanding the influences of familiarity on route choice.

Theoretical contributions: This is the first framework of familiarity that is based on a hierarchy of whole-part, means-end features of route choice. This representation of familiarity gives the necessary levels of granularity for modelling and better interpretation of spatial and contextual route choice decisions (Matyas & Schlieder, 2009). Secondly, work on assessing the role of familiarity on route choice especially among older drivers has been limited. By showing how strongly familiarity influences route choice can help establish route familiarity as an important measure for future route choice models. Thirdly, the proposed mathematical and theoretical framework for describing route familiarity can be extended to include factors such as memory decay, satisficing behavior, and habit, which have also been shown to influence route choice.

Practical contributions: An important application of the proposed framework of familiarity for predicting route choice is the potential benefits to travel demand, crash risk predictions, and navigation system applications. The emergence of GPS technologies that can capture location, travel behavior, and driver behavior at the individual level can provide valuable insights into the decision-making process, route choice, preferences, and driving safety needs of drivers.

CHAPTER 2: REVIEW OF THE INFLUENCE OF FAMILIARITY ON THE ROUTE CHOICE OF OLDER DRIVERS

Familiarity with the road network condition and layout has been shown to aid drivers in efficiently assessing traffic delays, congestion, predicting diversions (Adler & McNally, 1994; Dia, 2002), and reducing perceived risk and uncertainty associated with route diversions (Bonsall, Firmin, Anderson, Palmer, & Balmforth, 1997). A study on the driving safety errors of stroke patients reported that drivers with stroke made fewer at-fault safety errors, and were less likely to get lost when they were driving a familiar versus an unfamiliar route (Uc, Rizzo, Anderson, Shi, & Dawson, 2004). Although familiarity with the route can enhance safety, it can also result in willingness to engage in risky driving behavior (Maples & Tiefenbacher, 2009). Familiarity has been shown to result in shorter fixations on objects in the driving environment (such as traffic signs), and decrease attention needed to actively encode the environment (Martens & Fox, 2003; Martens, 2004). Yanko and Spalek (2013) found that drivers reduced their headway distance with the lead vehicle, had slower reaction time to lead vehicle braking, and engaged in mind-wandering, when driving familiar routes. Increasing familiarity with the route can also reduce glance durations and attention to environmental changes; as well as reduce attention to peripheral items (Martens & Fox, 2007; Mourant & Rockwell, 1970). Thus, familiarity can have both positive and negative effects on driving safety.

A limited number of studies on the effects of route familiarity on the driving safety outcomes of older drivers have reported similar results. A report on the intersection negotiation problems found that drivers 61 years and older conducted fewer unsafe lane change maneuvers, left-turns errors, and hard braking events before lane change, on familiar versus unfamiliar routes (Staplin, Gish, Decina, Lococo, & McKnight, 1998). Older drivers with Parkinson's disease had fewer safety errors for turn taking and speed control on familiar routes (Uc et al., 2009). Read et al. (2011) found that older drivers were less likely to make navigational errors and get lost during wayfinding on familiar versus unfamiliar routes. Whereas other studies have shown that familiarity with the route did not improve the driving performance of older drivers with cognitive decline (Aksan et al., 2013), increased the number of unsafe driving behavior events among older drivers, and prevented older adults from taking low-risk route alternatives (Payyanadan & Lee, 2017; Peeta & Ramos, 2006). Among older drivers, familiarity with the route has also been associated with reducing attention when driving; negatively influencing driving behavior such as maintaining proper speed and lane position; impairing navigation maneuvers such as turning, following a sequence of turns, and wayfinding; and decreasing visual search that requires attention sharing (McKnight & McKnight, 1999).

Cognitive, neuropsychological, and neuroimaging studies have highlighted a number of reasons why familiarity has both a positive and negative effect on performance. Familiarity and recollection are the two main types of memory processes in the dual-process theory of recognition memory, and commonly measured by recognition and recall tests (Yonelinas, 2002). Compared to recollection, familiar items are recognized more quickly (Hintzman, Caulton, & Levitin, 1998; Hintzman & Caulton, 1997), is automatic (Kelley & Jacoby, 2000), and associated with fluent processing of an item based on past experience; allowing the item to be more easily identified (Jacoby & Dallas, 1981). Whereas recollection is a consciously controlled process, involves active encoding of the object or environment, and supports learning of novel associations (Yonelinas et al., 1999). Studies that have assessed the effect of cognitive behavior such as divided attention on recall and recognition have shown that when subjects conducted concurrent tasks, divided attention had a more disruptive effect on recall than on recognition (Craik, Govoni, & Naveh-Benjamin, M. Anderson, 1996; Troyer, Winocur, Craik, & Moscovitch, 1999). Thus, recollection is more attention-demanding than recognition. Additionally, recognition tests to assess accuracy and response time have shown that the fast recognition process can result in incorrect selections, but additional retrieval time allowed subjects to use the recollection process to reject incorrect selections (Dosher, 1984; Gronlund & Ratcliff, 1989; Rotello & Heit, 2000). Thus familiarity contributes to performance earlier in the decision process than recollection; and under conditions that require quick response or when recollection is impaired, familiarity-based memory can undermine decision-making performance.

Research on the effects of aging on recognition memory have shown that healthy aging, mild cognitive impairment, and Alzheimer's disease impairs recollection-based memory processes, leaving familiarity-based memory processes intact (Koen & Yonelinas, 2014). Similar research has been conducted on pattern completion processes. Pattern completion process – also called hippocampal computation – involves the successful retrieval of memories from degraded or partial cues, and is affected by aging (Vieweg, Stangl, Howard, & Wolbers, 2015). Older adults are reported to have lower recognition accuracy with decreasing pattern completeness, and a tendency to incorrectly select the familiar item as a response, compared to younger adults (Vieweg et al., 2015). Thus older adults in particular, rely more on their recognition processes for quick response and performance behavior, and have a positive response bias toward familiar stimuli.

The positive bias toward familiarity tends to increase perceived safety among older drivers. Studies on the self-regulation strategies of older drivers have reported that they consider familiar roads to be safe (Sullivan, Smith, Horswill, & Lurie-Beck, 2011). Drivers tend to take familiar routes (Payyanadan & Lee, 2017), even if the routes have features that are risky for older drivers, such as left turns, U-turns, traffic incidents, and construction zones (NHTSA, 2014). But research by Uc et al. (2009) and Read et al. (2011) show that there are safety benefits to driving familiar routes for older drivers, because they have fewer errors on familiar routes. Yet very limited work has considered the true influence of familiarity on driving behavior and safety, especially among older drivers.

These studies suggest that familiarity has multiple effects on driving behavior: familiarity can decrease attention demand and workload, and increase risky driving behavior; but from the perspective of the driver, familiarity with the route may allow drivers to select routes, adjust their driving behavior, and possibly drive more safely (Intini, 2016). Current driving behavior and route choice models have focused on safety, but do not consider how route familiarity affects safety. There is also a lack of comprehensive analysis on the combined effect of driving behavior, route choice, and familiarity parameters on driving safety. Given that driving is a complex task, and involves a number of tasks and subtasks – understanding the influence of familiarity on driving behavior, route choice, and safety is still largely incomplete.

The limited research on route familiarity has raised a number of questions such as, a) How do we measure route familiarity? and b) Can route familiarity be used to predict route choice? To answer these questions and determine the current gaps and challenges, a literature review is conducted on the current measures of route familiarity, route choice models that consider route familiarity, and how route choice models can help older drivers.

2.1 Measures of route familiarity

Familiarity has been highlighted as a necessary factor for assessing route quality and generating routes that better reflect preferences (McGinty & Smyth, 2000). Familiarity is either defined by *the frequency of exposure to an item*, or by the *opportunity to learn about the item* determined through characteristics of the item and frequency of exposure to the item (Boster, 1988). In the driving domain, familiarity has been defined in multiple studies by either the expectancy of the driver (travel time, travel distance, traffic conditions, weather), prior driving experience with the route (knowledge of the route attributes, road characteristics, driving environment), personal characteristics of the driver (socioeconomic, choice preference), trip characteristics (purpose, time of day), or the referent frequencies of the route learnt by driving the same routes. While not exhaustive, Table 1 represents common approaches used to measure route familiarity.

Table 1: Review on the measures of route familiarity

Author	Study goal	Study setting	Familiarity operationalized as
Mourant & Rockwell, 1970	Effect of route familiarity on driver search and scan behavior	Simulator	Training drivers on a preset route
Allen et al., 1991	Effect of navigation system characteristics on driver route diversion behavior	Simulator	Recruiting drivers with knowledge of the road network
Kantowitz, Hanowski, & Kantowitz, 1997	Effect of familiarity on the use and acceptance of ATIS	Simulator	Recruiting drivers with knowledge of the road network
Lotan, 1997	Effects of network familiarity on route choice behavior	Simulator	Using travel behavior surveys and interviewing drivers with knowledge of the road network
Beijer, Smiley, & Eizenman, 2004	Effect of route familiarity on glance behavior	On-road	Frequency of travel along a 6 km stretch of an expressway
Srinivas & Hirtle, 2006	Preferences of schematized direction for familiar and unfamiliar routes	-	Training on set routes
Martens & Fox, 2007	Effect of route familiarity on eye fixation changes	Simulator	Repeated exposure to the simulated driving scenarios
Uc et al., 2007	Effect of route familiarity on navigation and safety errors	On-road	Asking drivers of their knowledge of the road network
Mader et al., 2009	Effect of route familiarity on attention and perception processes	Simulator	Repeated exposure to the simulated driving scenarios
Yanko & Spalek, 2013	Effect of route familiarity on hazard avoidance	Simulator	Training drivers on a preset route
Li, Miwa, & Morikawa, 2013	Effect of familiarity to O-D pairs	On-road	Frequency of trips for the same O-D pair
Ramachandran, Karpov, Gupta, & Raux, 2013	Modelling familiarity for navigation	On-road	Categorizing a route as familiar if the driver can complete a route from A to B with minimal map/device assistance
Marquez et al., 2015	Effect of route familiarity on wayfinding	-	Interviews of drivers with knowledge of the road network

Payyanadan & Lee, 2016	Effect of route familiarity on driving behavior and risk	On-road	Route familiarity questions of trips driven
Intini, 2016	Effect of route familiarity on driving behavior	On-road	Recruiting drivers with knowledge of the set route

Current challenges in measuring route familiarity (Table 1) is that familiarity is measured based on knowledge about the route or route network, which may or may not involve knowledge of the type of roads, infrastructure, traffic conditions, and travel speed; spatial and temporal knowledge such as travel time and distance; or knowledge related to weather, time of departure, etc. Additionally, these studies mainly use simulated environments and measure familiarity through ratings. Although simulator studies use measurement validity – defined by indicators that measure the concept of interest to determine whether inferences about real driving behaviors can be made from driving simulator data (Reimer, D'Ambrosio, Coughlin, Kafrissen, & Biederman, 2006); these simulator studies may not necessarily capture the concept of route familiarity. This is because current approaches for measuring route familiarity in simulator settings involve training drivers on preset routes, and using questionnaires and retrieval cues to determine route familiarity. But extensive work by Yonelinas (1994, 2002) has provided empirical evidence to suggest that while recollection is associated with learning novel associations, familiarity only supports novel learning under very limited conditions. Thus studies that train drivers over a short period of time on preset routes, often capture responses that mainly reflect recollection – conscious experience of *remembering* associated with *when* or *where* an item was studied, versus familiarity – conscious experience of *knowing*, which cannot discriminate *when* or *where* an item was studied (Jacoby, 1991; Yonelinas, 2002).

2.2 Route choice models that include route familiarity

Despite the challenges with measuring route familiarity, models have been developed to assess how familiarity influences drivers' route choice. These models have implemented different approaches to representing familiarity. For example, Ramachandran et al. (2013) used GPS traces of drivers recorded over a two-month period to develop familiarity prediction models representing different aspects of route familiarity such as landmarks, segments, and turns. Table 2 highlights some of the models and the representations of route familiarity to predict route choice.

Table 2: Route choice models optimized for route familiarity

Author	Study goal	System/ algorithm/ model	Familiarity represented as	Route choice model optimization criterion
Bonsall et al., 1997	Determine the ability of a route choice simulation to reflect driver's route choice outcomes based on network familiarity	VLADIMIR – route choice model	Subject rating of familiarity with the road network	Familiarity with the road network
McGinty & Smyth, 2000	Develop a case-based route planning system that generates routes based on implicit user preferences	Case-based route planning algorithm	Degree of overlap between route segments	Process complexity, route similarity, familiarity
Hamed & Abdul-Hussain, 2001	Develop a method to quantify driver's familiarity with the route network	Driver's familiarity estimation using maximum likelihood	Subject rating of familiarity on routes driven	Route familiarity, traffic, socioeconomic, familiarity with alternate route, time of travel
Dia, 2002	Determine the influence of route choice feedback in real-time	Agent-based approach	familiarity with network conditions	Travel patterns, traffic, route preferences, willingness to divert, familiarity

Patel, Chen, Smith, & Landay, 2006	Develop a *MyRoute* navigation system to provide users with alternate shorter familiar routes	Personalized routing system using familiar landmarks	Subject familiarity of landmarks	Landmark familiarity, distance, time
Zhang & Levinson, 2008	Develop a calibration framework for calibrating parameters of a driver behavior model	Genetic algorithm	Subject rating on familiarity on travelled and alternate routes	Road geometry, traffic, vehicle controls, OD demands, car-following, lane change, route choice parameters, familiarity
Lin & Chou, 2008	Develop a route guidance system that can adapt to different driving behaviors	Adaptive-network-based fuzzy inference system	Frequency of travel along a route segment	Driver attributes (socio-economic, network familiarity, confidence, sensitivity to delay, personal preferences), route characteristics (travel time, distance, toll, route complexity, location type), situational factors (weather, time-of-day, trip purpose)
Li, Miwa, & Morikawa, 2013	Determine whether route choice behavior is influenced by heterogeneity in the familiarity with O-D pairs	Random utility framework Expanding-path size logit model with a sampling of alternatives	Frequency of travel between an origin-destination pair	Familiarity, O-D pairs

Major gaps with the current route choice models (Table 2) result from their focus on traffic assignment problems, and on enhancing path generation techniques (Prato et al., 2012), rather than understanding the influence of familiarity on driving safety outcomes. The route choice models assume that drivers mainly prefer to maximize their utility based on travel time, distance, and en-route diversion (Lotan, 1997; Prato et al., 2012), and have all the information needed to make an informed decision about a route (Prato, 2009). Additionally, current route choice models that consider familiarity do not consider the context and situational aspects that influence driving behavior such as trip purpose and motivation (Payyanadan et al., 2016). Thus the role of familiarity in these models has been to inform trip planning and real-time route diversion algorithms, rather than model and predict route choice based on driver preferences (Papinski, Scott, & Doherty, 2009).

2.3 Why we need customized route choice models for older drivers

The number of licensed older drivers is growing – increasing by 21 percent from 2002 to 2011, and accounting for 16 percent of all licensed drivers in the U.S. (NHTSA, 2014). This shift towards more older drivers on the road has brought about a need to reassess their driving challenges, and concerns related to their mobility and driving safety outcomes, such as their risk of crash, age-related decline, and driving cessation (Hakamies-Blomqvist & Wahlstrom, 1998; Hakamies-Blomqvist, 2004; Lundberg, Hakamies-Blomqvist, Almkvist, & Johansson, 1998). Understanding these challenges and concerns can help better define the support structure and technology needed to prolong the driving safety, mobility, and independence of older drivers.

2.3.1 Crash risk

In 2011, 5,401 adults age 65 and older were killed, and 185,000 injured in traffic crashes. These older adults made up for 17 percent of all traffic fatalities, and 8 percent of the total population injured in traffic crashes (NHTSA, 2014). In 2012, NHTSA reported that for two-vehicle crashes, older drivers were 75 percent more likely to be involved in a crash between 2 pm and 6 pm, and during daylight – attributed to their increased driving exposure during the day. Older drivers are also involved in greater number of intersection and crossing-related crashes (Hakamies-Blomqvist, 1993) as a result of their increased exposure to intersections due to choice of road type, such as the preference to avoid highways (Langford & Koppel, 2006). The 2012 NHTSA report also showed that left-turn crashes were particularly frequent for older drivers, with 20 percent of drivers 70-79 years, and 25 percent of drivers 80 years and older involved in a left-turn crash. These results suggest that the risk of crash among older drivers under certain driving situations is influenced by their driving exposure patterns and is a major safety concern, as older adults are more vulnerable to crash-related injuries and death.

The increased vulnerability of older drivers to crash-related injuries and death can be attributed to their increased fragility, frailty, and age-related decline. Fragility is commonly defined as the probability of an injury occurring, and frailty is the conditional probability of death given a certain injury (Kent, Trowbridge, Lopez-Valdes, Ordoyo, & Segui-Gomez, 2009). A study on the impact of frontal and side crashes on injury outcomes showed that older drivers sustained higher rates of AIS2+ (Abbreviated Injury Scale) organ injuries (lung, heart and myocardium), as well as more rib and sternum fractures compared to younger drivers 17-39 years old (Morris, Welsh, Frampton, Charlton, & Fildes, 2002). Li, Braver, and Chen (2003) reported that 60-95 percent of the increase in death rates per vehicle mile travelled among older drivers is due to their increased fragility. Analysis of the FARS (Fatality Analysis Reporting System) and NASS-CDS (National Automotive Sampling System Crashworthiness Data System) datasets have shown that the relative mortality rate for frontal and left side crashes is three times greater for older adults than younger adults (Kent, Henary, & Matsuoka, 2005). In the study, despite lower speed and increased seatbelt use, older drivers had significantly greater injury and mortality rates due to their frailty. Studies on chest deflection to assess risk of an injury during a crash showed that regardless of injury onset or injury severity, chest deflection injury strongly depends on age – decreasing to 13 percent for 70 year olds’ compared to 30 year olds’ with deflection level of 35 percent (Kent & Patrie, 2005). Thus, aging inevitably leads to greater fragility and frailty, which are major risk factors for crashes. But while fragility increases by a factor of 8 from ages 20-80, frailty only increases by a factor of less than two over the same range.

2.3.2 Age-related declines

Numerous studies have highlighted the risk factors for increased motor vehicle crashes among older drivers due to age-related decline. These risk factors include cognitive impairments (Lundberg et al., 1998), reduced visual and motor function (Rubin et al., 2007), and decline in physical functioning (Marottoli, Cooney, Wagner, Doucette, & Tinetti, 1994). These age-related factors can degrade driving skills over time.

Cognitive factors that affect driving performance include perceptual and visuo-spatial abilities, processing speed and reaction time, memory, executive function, and mental status. Visuo-perceptual tests such as movement perception have been shown to have moderate association with driving performance. De Raedt and Ponjaert-Kristoffersen (2000) used neuropsychological tests that were relevant to safe driving and sensitive to aging to evaluate response to complex traffic situations among older drivers. Their results showed that movement perception was strongly correlated to driving performance. Reaction time was also shown to have moderate correlations with on-road driving performance, but more so for complex reaction than simple reaction time (McKnight & McKnight, 1999). Additionally, work by Carr and Ott (2010) showed that cognitive impairments such as dementia in older drivers led to a two-fold increase in crash risk.

Driving is a highly visual task and many aspects of visual functioning decline past age 50 (Johnson & Choy, 1987). For older drivers, the primary cause of driving difficulty is the high incidence of visual problems and eye disease (Leibowitz et al., 1979). Hence identifying decline in visual function has been suggested as an indicator of crash risk. Older drivers with acuities in the range of 20/40 to 20/50 are shown to have a greater risk of crashing than other older drivers with better acuity (Gresset & Meyer, 1994). For older drivers, strong association between visual impairment and driving performance has also been reported especially under low luminance conditions (West, Gildengorin, Haegerstrom-Portnoy, Lott, Schneck, & Brabyn, 2003).

Decline of motor functions also affects driving performance of older drivers by restricting their ability to perform certain driving tasks. These include tasks such as entering and exiting a vehicle, depressing the brakes, and gripping the steering wheel; which can lead to difficulty parking, reversing into a parking lot, and checking blind spots. Decline of physical motor functions has been shown to affect the ability of older drivers to control movement with speed and accuracy (Larsson, Grimby, & Karlsson, 1979), impair tracking ability (Jagacinski, Liao, & Fayyad, 1995), and increase the reaction time for carrying out complex driving motor control tasks (Gisolfi, 1995). Marottoli et al., (1998) reported poor neck rotation to be associated with twice the risk of crashing.

2.3.3 Driving cessation and self-regulation

For older adults, crashes not only produces more injury and deaths compared to younger adults (Committee on Trauma, 2003), but also result in reduced driving, which can lead to driving cessation (Oxley & Charlton, 2009). Driving cessation occurs when *one or more mobility options such as driving a personal vehicle becomes unsafe, impractical or impossible due to changing health, function, and/or other circumstances of life* (Meuser, Berg-Weger, Chibnall, Harmon, & Stowe, 2013). Driving cessation has been shown to affect the overall mobility and independence of older adults (Burkhardt, 1999), and results in adverse long-term consequences. Ross, et al. (2009) reported that the odds ratio of not driving for older adults to be 1.11 for each additional year of age and 1.15 for each additional medical condition. In a nine year study Brayne et al. (2000) found that common reasons for driving cessation among drivers 80 years and older were health problems (28.6%), and loss of confidence (17.9%); while one third reported giving up driving on advice from family, friends, or a medical specialist (Gilhotra et al., 2001). A recent study on the potential predictors for driving cessation among older drivers reported similar results, with 35 percent of older adults reporting vision and health as the main reason for driving cessation, while only 7 percent reporting failure of license renewal test as the reason (Choi, Adams, & Kahana, 2012).

Social activity is a strong correlate of life satisfaction and health. Banister and Bowling (2004) reported that having access to a car was associated with greater social activities among older adults. Whereras reduced driving exposure or driving cessation reduced social engagement activities from 13 to 5 percent (Taylor & Tripodes, 2001), and decreased overall out-of-home activities (Siren & Hakamies-Blomqvist, 2004). Reduced activity also increases burden and reliance on family and friends. Fifty-six percent of older adults who stopped driving depended solely on their spouses for medical trips, whereas 24 percent relied on their adult children (Taylor & Tripodes, 2001). Reduced out-of-home activity has been associated with poor health status, well-being, and survival in old age. Edwards et al. (2009) reported the hazard ratio of mortality for nondrivers to be 6.11 times greater than that for current drivers. Thus for older adults, driving cessation reduces participation in social and leisure activities, which in turn can affect quality of life and overall well-being.

To address the challenges associated with crash risk, age-related decline, and driving cessation, older drivers practice self-regulation by avoiding unfamiliar routes; routes with a history of crashes or near misses; roads with traffic, construction, and detours; and avoid driving during poor weather and on roads with poor infrastructure (Payyanadan, Gibson, et al., 2016; Payyanadan, Lee, & Greppo, 2018). These studies have shown that the primary self-regulation strategy among older drivers involves making route-selection decisions based on the familiarity and preferences with the road environment and driving task (Walker, Fain, Fisk, & McGuire, 1997).

2.4 Use of navigation system for route choice assistance

Navigation systems have been shown to improve mobility and safety by providing drivers with information on traffic and road conditions, vehicle location and navigation, and safety warnings (Dingus et al., 1997). Such driver support systems are useful for older drivers – helping make decisions about a preferred route, mode, and departure time against a set of alternative choices (Adler & Blue, 1998), providing route descriptions as well as important sequential traffic information while driving (Entenmann & Küting, 2000), and serving as companions to assist in coping with increasingly complex road networks (Emmerson, Guo, Blythe, Namdeo, & Edwards, 2013).

NHTSA and FHWA reports on early adopters and safety-related driving with advanced technologies found a rise in the use of navigation systems among drivers 60 and older to help with route-selection decisions and driving tasks (Band & Perel, 2007). These reports found that 73 percent of older drivers were willing to drive in unfamiliar areas when using navigation systems, and 98 percent of all drivers preferred using navigation systems to a paper map. The use of navigation systems increased confidence among older drivers when travelling in unfamiliar and congested areas (Emmerson et al., 2013).

But current navigation systems focus primarily on trip optimization strategies, such as avoiding congestion and poor road conditions, and provide only positioning capabilities (Brandt, 2013). Additionally, alternate route suggestion algorithms in navigation systems use traditional trip-based models and activity-based models. Trip-based approaches are part of the four-stage traffic model – trip generation, trip distribution, modal split, and assignment; and is commonly used for traffic planning (Ortúzar & Willumsen, 2001). Although trip-based approaches have helped better understand travel demand and network performance such as traffic flow and equilibrium, they are a simplified way of understanding travel behavior, and do not consider context (Ortuzar & Willumsen, 2011). Context provides important behavioral information needed to understand the safety and mobility needs of a driver, decision-making process for a trip, social and motivational aspects of a trip, and information needs, perspectives, preferences, and priorities of the driver (Federal Highway Administration, 2010). Thus, to better understand how drivers organize their trips and driving behaviors associated with these trips requires an understanding of context, which can provide a better basis for travel demand modelling.

In contrast, activity-based models focus on reproducing the actual travel decision-making of drivers by not only capturing trip information such as locations, successful trips, and travel time and distance; but also driver activities such as type of trip (work, social), time and monetary constraints, coordinated trips with members of their social network, availability and accessibility to resources and services, time and location constraints such as avoiding rush hours, and individual constraints due to prior commitments (to a friend or family member), or health-related issues (Ortuzar & Willumsen, 2011). Despite the focus on context, current activity-based models remain experimental. This is because the two promising approaches to activity-based models – econometric methods and computational process models have a number of limitations. While the models using econometric methods only focus on the optimization of driver's choice by assessing the cost of information acquisition, information representation, information processing, decision making, and choosing the best among alternatives; the computational process models employ 'if-then' rules rather than utility-maximization decision criteria. Thus, despite the numerous applications of activity-based models, they have not yet been adopted for transport modelling and policy development. And both trip-based and activity-based approaches model route choice based on travel and traffic demand rather than preferences, safety, or familiarity.

Other route choice modelling approaches used in navigation systems use a form of the classic path-based and link-based approach (Fosgerau, Frejinger, & Karlstrom, 2013). The path-based approach uses discrete choice sets among paths, which combine the observed paths and paths sampled from a path generation algorithm. Whereas for link-based approach, the choices are modeled as a sequence of link choices. While these route choice model approaches are very useful, they have mainly used simulated data for parameter estimation, raising issues of generalizability and biases. Additionally, these modelling approaches have not been able to successfully capture trade-offs between trip attributes such as travel time versus distance, as they require the use of survey data, and observations of routes driven, which are often not recorded. Lastly, these models continue to focus mainly on dynamic traffic assignment problems for estimating equilibrium traffic flow, rather than driver preference and safety.

Thus, navigation systems and route guidance technologies focus primarily on optimizing route attributes based on travel time, distance, traffic delays, and speed limits, and providing feedback of alternate route options based on routes with fewer traffic incidents and delays. While these factors have been able to provide drivers with the fastest and shortest routes to their destination, and prevent them from getting lost or taking a wrong turn; these technologies are unable to provide route guidance based on the underlying needs, behaviors, challenges, and route preferences specific to the driver (Leshed, Velden, Rieger, Kot, & Sengers, 2008). Currently, the *Intelligent Learning Navigation* (ILENA) by BMW, which is in the developmental stages; and the Volkswagen *Regular Routes* navigation system, are the only known examples of navigation systems providing route options based on route familiarity. ILENA records driving patterns and road conditions to predict route choice, destinations, and driving behavior (Autocar, 2017). And the Volkswagen system records regularly driven routes, and provides alternate familiar route options to avoid traffic congestion based on the three frequently driven routes (Volkswagen, 2016).

2.5 Addressing the gap

With the continued advances in driver support systems, there are opportunities to customize navigation systems with route choice models that can support the delivery of relevant routing options, driving safety, and behavioral feedback to meet the specific driving challenges, safety needs, and driving preferences of older drivers. From the literature reviewed, a number of gaps and approaches to address these challenges have been highlighted below:

a) Influence of familiarity on route choice among older drivers. To understand how familiarity influences route choice, in Chapter 3, the driving behaviors, trip characteristics, route familiarity, and route choice data recorded by OBDII devices and Trip Diary feedback responses of 29 adults 65 years and older were analyzed. Content analyses was conducted on the feedback responses from older drivers to determine the reasons for choosing a familiar route. A mixed-effects model using the OBDII data was used to assess the relationship between stated familiarity and route choice.

b) *A multi-criteria measure of route familiarity*. To develop a measure of route familiarity, results from the content analysis suggesting the multi-criteria nature of familiarity was used in Chapter 4 to develop a hierarchical framework representing route familiarity. Representation of familiarity within each level of the hierarchy framework was guided by the Abstraction Hierarchy framework by Rasmussen (1986). The hierarchical framework was used to propose a theoretical measure of route familiarity – *estimated route familiarity*.

c) *Predict familiarity*. To predict stated familiarity using the proposed *estimated route familiarity*, the abstraction hierarchy framework for describing route familiarity was fit to the OBDII data. Parameter estimation was then conducted using logistic regression models to test the relationship between drivers' stated familiarity and familiarity estimated using the abstraction hierarchy framework.

CHAPTER 3: ASSESSING THE ROLE OF FAMILIARITY ON THE DRIVING BEHAVIOR AND ROUTE CHOICE OF OLDER DRIVERS

3.1 Introduction

For older drivers, limited research on the effect of route familiarity on route choice, driving behavior, and safety have reported mainly positive outcomes. But to determine the true influence of route familiarity on route choice and driving behavior is complex. Complexity arises because route choice and driving behavior are also influenced by the driver's personal characteristics such as age, health, task complexity, stress, and time-pressure (Brunyé, Wood, Houck, & Taylor, 2016; Taylor & Brunyé, 2013), and trip attributes such as travel time, distance, and traffic (Bonsall, 1992). A number of studies have assessed the effect of familiarity on search and scanning behavior (Mourant & Rockwell, 1970), driving performance (Yanko & Spalek, 2013), ATIS use and acceptance (Hanowski, Kantowitz, & Kantowitz, 1994), route choice behavior (Lotan, 1997), driving challenges and intersection errors (Staplin et al., 1998), and glance behavior (Beijer et al., 2004). While these studies have made significant contributions to understanding the influence of familiarity on driving behaviors, few have attempted to assess the effect of route familiarity on route choice and the challenging situational factors governing route choice.

In this Chapter we attempt to assess the influence of familiarity on driving behaviors, route choice, and challenging situational factors that influence route choice. The vehicles of older drivers were instrumented with OBDII devices for a period of 4 months to record their driving behaviors and choice of route. For each trip driven, older drivers were given access to customized web-based Trip Diaries with feedback of their risky driving behaviors and alternate low-risk routes (Payyanadan, Maus, et al., 2016). Risky driving behaviors were driving behaviors such as hard accelerations, hard braking, and hard cornering that are related to the immediate risk of an injury or crash (Blows, Ameratunga, Ivers, Lo, & Norton, 2005); and low-risk routes were suggested using a route risk measure that determined the probability of a crash for any given route based on the route characteristics, such as left turns and U-turns (Payyanadan, Sanchez, & Lee, 2016). Along with the feedback, older drivers were also asked three questions for each trip driven: a) their familiarity with the route driven, b) familiarity with the alternate low-risk suggested route, and reasons or challenging situational factors when choosing a familiar versus unfamiliar route. Challenging situational factors such as traffic incidents, visibility, other drivers, and near misses are associated with greater crash involvement or pose an increased risk of crash to older drivers (Chang, Matz, & Chang, 2013).

3.2 Method

The vehicles of 29 older drivers were instrumented with OBDII devices to collect GPS data, and driving behaviors such as speeding, acceleration, hard braking, and harsh cornering events. The OBDII devices were installed in their cars, and data collected for four months. Reports of each trip, driving behaviors, and feedback questions were made available for the older drivers on a personal Trip Diary page.

3.2.1 Participants

A total of 29 drivers 65 and older were recruited from a Midwestern state in the U.S. Participant’s age ranged from 65 to 82 years. To participate in the study, older adults were required to hold a valid driver’s license, have internet access, and drive at least twice a week.

The demographic data along with the trip details of the participants in the study are shown in Table 3.

Table 3: Mean ages of the older drivers in the study, and driving data of their baseline and treatment periods, grouped by gender.

			Baseline period (1 month)		Treatment period (3 months)	
Gender	Total	Age	Distance (miles)	Time (minutes)	Distance (miles)	Time (minutes)
Males	14	73	7.0	12.6	7.9	13.6
Females	15	70	7.2	13.5	7.0	13.2

3.2.2 OBDII devices

Geotab GO6 OBDII devices were installed in the vehicles of older drivers to collect trip information using GPS data, and risky driving behavior such as speeding, hard braking, accelerating, and cornering events (Table 4). Baseline data were collected from participants for one month, with no access to their trips driven and risky driving behavior events. After the baseline period, participants were given access to a personal web-based Trip Diary page for three months. During the treatment period, the Trip Diary page provided information about their trips driven and risky driving behavior events, along with alternate low-risk route options. The suggested low-risk route is a route with the least number left turns, U-turns, traffic incidents, and lane closures from a subset of routes for any given origin and destination, with minimal increase of trip distance and travel time (Payyanadan, Sanchez, & Lee, 2016).

Table 4: Geotab GO6 OBDII device settings and sensitivity metrics to record participant trip information and risky driving behavior events

Geotab GO6 OBDII data	Definition	Measure and sensitivity settings for passenger vehicle
GPS coordinates	Latitude and longitude data for location retrieval	Event-based
Trip start/stop	A trip starts when the vehicle starts moving. A stop is recorded when the vehicle ignition is turned off, or when the vehicle has a speed of less than 1 km/h for more than 200 seconds.	
Distance	Distance travelled for each trip from origin to destination	Miles
Time	Time taken to travel for each trip from origin to destination	Seconds
Speed	Records changes in speed during a trip	m/s^2, Event-based
Acceleration	3-axis accelerometer recordings to determine vehicle acceleration	Threshold change of 300 milli-G in any direction
Speed violation	Speed is monitored against the posted road speed. If there was no data on the posted speed limit for a section of a trip, no speed violation was recorded.	5 mph over the posted speed limit
Hard braking	A hard braking incident is recorded when it caused a force of 1/2 G to be exerted on the vehicle.	G-force exertion set at – 0.58
Hard cornering	A hard cornering incident is recorded when a hard or aggressive turn causes a force greater than 2/5 G to be exerted on the vehicle.	G-force exertion set at > 0.47 and < - 0.47
Hard acceleration	A hard acceleration incident is recorded when it causes a force of 1/3 G to be exerted on the vehicle.	G-force exertion set at 0.4
Seatbelt violation	A seatbelt violation is recorded when the driver is not wearing a seatbelt while the vehicle is moving faster than 6.21 mph. This information is communicated through the ECM (electronic control unit) of the vehicle. But not all vehicles transmit information about the seatbelt, hence reporting depended on the type of vehicle driven.	
Engine light	Identifies vehicles driven with the ‘Check Engine’ light on.	
Possible accident	A possible accident event is recorded when the accelerometer detects a change in speed of more than 15 mph in 1 second in any direction.	

3.2.3 Trip Diary page and feedback questions

The Trip Diary reports and feedback questions were provided for a period of three months. Trips driven and risky driving behavior events recorded by the OBDII devices were logged on the Trip Diary page. Participants were requested to access their personal Trip Diary page two to three times a week, review each of their trips driven, risky driving behavior events, alternate low-risk route suggestions, and provide responses to the feedback questions for each trip driven. Three feedback questions: familiarity with the route driven, familiarity with the suggested low-risk route, and reasons for choosing the driven route, were asked on each trip report (Figure 1).

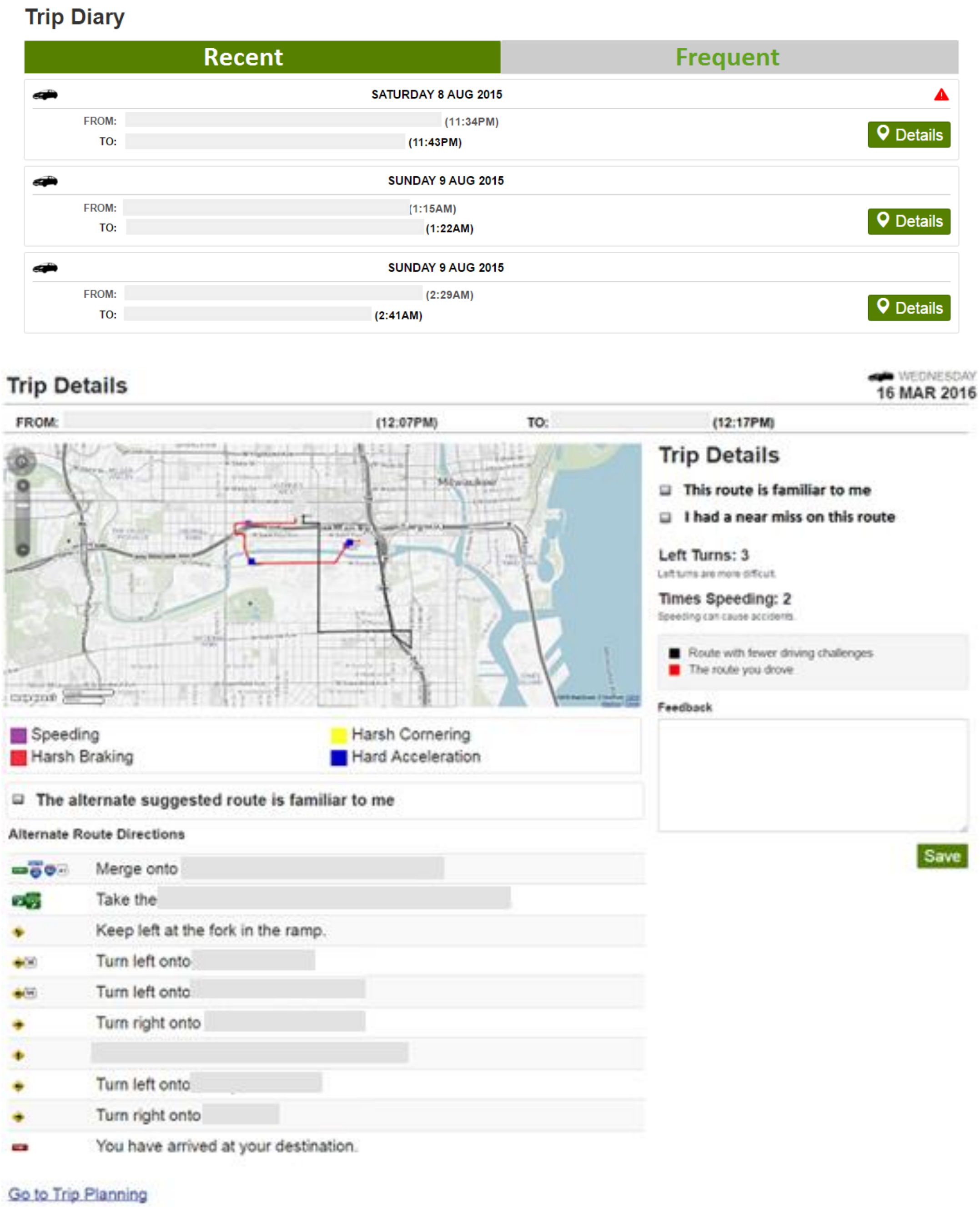


Figure 1: Trip Diary page of a participant with list of trips and trip details with feedback questions from participant drives.

The two familiarity questions: familiarity with the route driven and familiarity with the alternate suggested route, were yes/no questions because the pilot study showed that older adults found the five-point Likert scale for familiarity to be confusing. The third question on reasons for choosing a route was an open-ended question where participants could state the decisions and challenges that influenced their route choice.

3.2.4 Models, assumptions, and analysis

OBDII devices recorded GPS data and risky driving behaviors such as hard braking, hard cornering, speeding, and hard acceleration events. From the GPS data, the *route risk* – a measure developed to quantify the crash risk based on the route's physical characteristics, such as distance, number of left and right turns, and portion under construction, was determined (Payyanadan, Sanchez, et al., 2016). This crash risk measure of a route was used to estimate risk associated with a participant's route choice by comparing the risk of the route they chose to drive against alternative low-risk routes – *route choice risk*. In this study, time under treatment is the amount of time passed since the participants were given access to the Trip Diary. To understand the true effect of route familiarity on route choice risk and risky driving behavior events, we control for the effect of the treatment—Trip Diary feedback. To determine the influence of familiarity on the route choice risk and risky driving behavior events, the following assumptions were made:

- Older drivers' route choice risk is a function of their route choice, route familiarity, and the amount of time under treatment.
- Older drivers' risky driving behavior events are a function of their route choice, route familiarity, and the amount of time under treatment.
- The older driver population has a mean route choice risk and response to treatment, but individuals within the population may differ.

Influence of familiarity on risky driving behavior events: Analysis was conducted at two levels – at the route level and at the participant level. At the route level, a paired sample t-test was conducted on the difference in risky driving behavior events between familiar and unfamiliar routes. At the route level, we tested the hypothesis that there was no difference in risky driving behavior events between familiar and unfamiliar routes, with the expectation that participants would exhibit more frequent risky driving behavior events on familiar routes. At the participant level, we tested the hypothesis that there is a non-zero relationship between familiarity with driven routes and risky driving behavior events, with the expectation that participants would have more frequent risky driving events on familiar routes.

Influence of familiarity on route choice risk: For analyzing the influence of familiarity on route choice risk, a mixed-effects regression with identity link was used. The model assumptions are,

a) An older driver's route choice risk is a linear function of the chosen route's risk *X*, and the amount of time under treatment X_t (Equation 2). In equation 2, *T* is the effect of time under treatment, *BR* is the effect of baseline route choice risk, *FD* is the effect of familiarity with driven routes, *FA* is the effect of familiarity with alternate low-risk routes, *TBR* is the effect of the interaction between time under treatment and baseline route choice risk, *TFD* and *TFA* are the effect of the interaction between time under treatment and familiarity. The Z_i represent randomness from the participants and are hence random effects (both slope and intercept), where $\mathrm{Z_i} \sim \mathrm{N}(0, \sigma_i^2)$, $\mathrm{i} \in \{\mathrm{T}, \mathrm{BR}\}$ and $\varepsilon_j \sim \mathrm{N}(0, \sigma^2)$.

$$\text{Route Choice Risk Ratio}_j \sim \beta_0 + Z_0 + T \cdot X_t + Z_t \cdot X_t + BR \cdot X_{BR} + Z_{BR} \cdot X_{BR} + TBR \cdot X_t \cdot X_{BR} + FD \cdot X_{FD} + TFD \cdot X_t \cdot X_{FD} + FA \cdot X_{FA} + TFA \cdot X_t \cdot X_{FA} + \varepsilon_j \qquad (2)$$

b) There is a mean population route choice risk and effect of time under treatment, but drivers in the population vary around each mean with constant variance.

c) The effect of treatment time depends on the baseline route choice risk, i.e. *TBR ≠ 0.*

d) For any two routes *k* and *j* in the network of routes driven by a participant, $\varepsilon_k \perp \varepsilon_j$ for all *k≠j*.

Using the generalized linear mixed-effects regression model, two hypotheses were considered to determine the influence of familiarity on route choice risk (Table 5).

Table 5: Hypotheses to determine the interaction between familiarity and route choice risk

Claims	Hypothesis – Influence of familiarity on route choice risk	
H_C	There is an interaction between familiarity with driven route and treatment time	H_{C0}: $TFD = 0$, H_{C1}: $TFD \neq 0$
H_D	There is an interaction between familiarity with alternative low-risk suggested route and treatment time	H_{D0}: $TFA = 0$, H_{D1}: $TFA \neq 0$

Factors influencing route choice: A total of 612 feedback responses were collected during the three-month treatment period. Fifty-eight percent of the responses were written responses that reflected the reasons governing route choice, 80 percent of the responses were yes/no responses to familiarity with the route driven, and 27 percent of the responses were yes/no responses to familiarity with the suggested alternate low-risk route. To assess the factors influencing route choice among older drivers, and its relation to route familiarity, the written feedback responses were analyzed using Content Analysis.

Content analysis is a research method used for analyzing text data, identifying themes and patterns within text data, coding through a systematic classification process, interpreting content and concepts, and assessing contextual meaning of the identified concepts (Hsieh & Shannon, 2005). Two types of content analysis were used to assess the feedback responses from older drivers: conceptual analysis and relational analysis. Conceptual analysis was used to establish the existence and frequency of the concepts, and relational analysis was used to examine the relationship between the concepts (Busch et al., 2012). Steps for assessing the feedback responses using content analysis are shown in Figure 2.

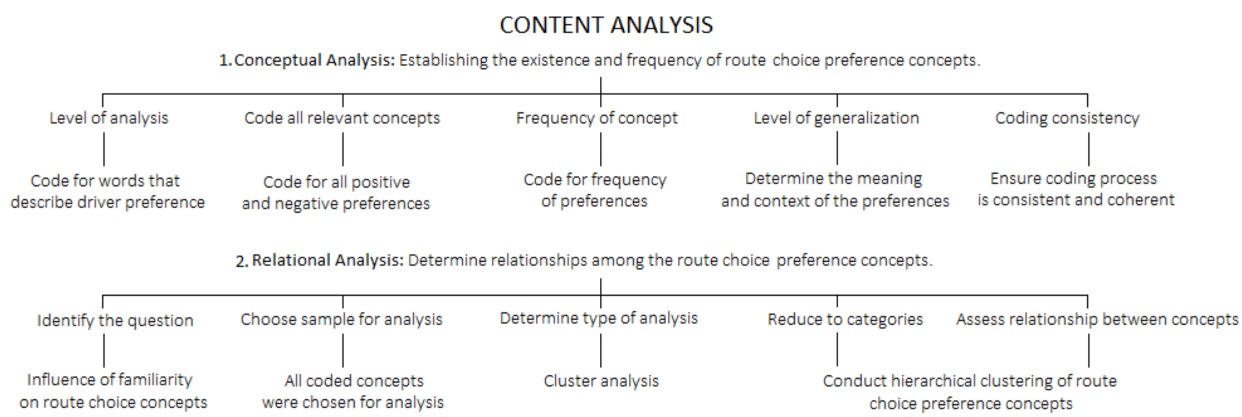


Figure 2: Steps to conduct content analysis on the feedback responses from older drivers

3.3 Results

The results are organized into five sections. The first and second section provide a summary of the trip details, route choice risk, risky driving behavior events, and familiarity responses of older drivers in the study. The third and fourth section shows the influence of familiarity on the risky driving behavior events and route choice risk of older drivers. The final section describes the situational factors, derived from the content analysis that influences the decision to choose a route.

3.3.1 Risky driving behavior events and route choice risk of older drivers

Older drivers' trips had a mean length of 7.1 miles, a mean trip time of 13.2 minutes, and mean speed of 23.4 miles/hr. A total of 5,365 trips were completed during the treatment period, and familiarity responses were received for 5.3% of the trips driven. Based on the trips with familiarity responses, 78% of the driven routes were familiar (CI = (74.9, 82.1)), 14% unfamiliar (CI = (10.3, 17.5)), and the remaining 8% had no responses (CI = (4.3, 11.6)). Summary statistics of the routes driven and risky driving behavior events are shown in Table 6. From the list of OBDII data recorded (Table 4), driving with the engine light on was not recorded for all vehicles, and only one participant had a crash event recorded. For the baseline period of the study, the mean route choice risk was 1.56 (SE of 0.03). This can be interpreted as the average route chosen was 1.56 times the risk of the safest suggested alternative. For the treatment period of the study, the mean route choice risk ratio was 1.59 (SE of 0.02), which establishes whether meaningfully safer choices exist.

Table 6: Summary of the risky driving behavior events of older drivers for baseline and treatment periods

			Percent of trips with				
	Total trips	Average speed	Speed violations	Hard braking	Hard cornering	Harsh acceleration	Seatbelt violation
Baseline (1 month)	2450	23.44	47	0.52	3	88	0.7
Treatment (3 months)	5365	23.34	44	0.49	5	91	0.4

Estimated odds ratio [95% CI]	0.80 [0.70, 0.92]	1.32 [0.63, 2.74]	0.90 [0.64, 1.26]	1.85 [0.84, 4.07]	0.56 [0.37, 0.83]

3.3.2 Route familiarity of older drivers

A total of 612 familiarity feedback responses were recorded from older drivers during the treatment period. The quartiles of the baseline route choice risk were used to group the familiarity responses of older drivers for the driven and alternate low-risk suggested route. Table 7 shows the relationship between route choice risk, and familiarity with the driven routes and alternate low-risk suggested routes. In Table 7, older drivers with a greater familiarity with the alternative routes had lower baseline route choice risk than those who did not; as each 10% increase in familiarity with the alternate low-risk route was associated with a 5.5% (CI = (1.6%, 9.2%)) decrease in baseline route choice risk.

Table 7: Summary of the responses for familiarity with routes driven and alternate low-risk suggested routes for each baseline route choice risk group

Baseline route choice risk	Range of baseline route choice risk	Percentage of driven routes that a driver was familiar with	Percentage of low-risk alternate routes that a driver was familiar with
Low	[0.69, 1.03]	79.6%	71.0%
Medium	(1.03, 1.41]	75.0%	60.5%
High	(1.41, 1.81]	86.2%	59.6%
Very high	(1.81, 2.45]	93.6%	82.8%
All	[0.69, 2.45]	85.3%	67.0%

3.3.3 Influence of familiarity on risky driving behavior events of older drivers

The effect of familiarity on risky driving behavior events is reflected in the data in two ways – through the frequency that the risky driving behavior event is observed per mile, and the frequency that the behavior is observed per trip. Both possibilities were tested using paired samples t-tests ($\alpha = 0.05$), with participant's risky driving behavior event per mile and per trip on familiar and unfamiliar routes comprising the paired samples. Table 8 shows the results for the per mile t-tests. Risky driving behavior events measured on a per mile driven basis was done to control for the difference in length between routes.

Table 8: Paired sample t-test results of the risky driving behavior events per mile driven

Risky driving behavior events per mile	For familiar routes (mean)	For unfamiliar routes (mean)	Estimated difference of familiar and unfamiliar routes	P-value	95% CI
Harsh cornering	0.005	0.001	0.004	0.41	[-0.005, 0.013]
Hard braking	0.00	0.00	0.00	0.33	[0.000, 0.001]
Hard acceleration	2.10	3.91	-1.90	0.12	[-3.94, 0.14]
Speeding	0.87	0.78	0.09	0.74	[-0.37, 0.54]
Overall events	2.89	4.69	-1.81	0.13	[-3.76, 0.15]

For routes where risky driving behavior events occurred, there might be a difference in their frequency of occurrence on familiar and unfamiliar routes (Table 9). Results showed that on a per trip basis, there was no significant difference in the risky driving behavior events of older drivers across familiar and unfamiliar routes. Together, these tests imply there is no evidence to suggest that driving familiar routes have higher frequencies of risky driving behavior events compared to unfamiliar routes.

Table 9: Paired sample t-test results of the driving behavior events per trip.

Risky driving behavior events per trip	Proportion of familiar routes with	Proportion of unfamiliar routes with	Estimated difference in proportions between familiar and unfamiliar routes	P-value	95% CI
Harsh cornering	0.01	0.01	0.004	0.79	[-0.02, 0.03]
Hard braking	0.004	0.00	0.004	0.33	[-0.003, 0.01]
Hard acceleration	0.82	0.81	0.01	0.94	[-0.12, 0.13]
Speeding	0.46	0.47	-0.01	0.890	[-0.18, 0.15]
Overall events	0.86	0.85	0.02	0.83	[-0.11, 0.14]

Although the results of the paired t-tests (Table 8, Table 9) provide little evidence for differences in risky driving behavior events between familiar and unfamiliar routes; they do not address the difference in risky driving behavior events between participants who are more (or less) familiar with the routes they drove. To test this difference, a linear regression was used to assess how the frequency of risky driving behavior events depended on their familiarity with routes driven. To do so, the frequency of risky driving behavior events per mile, and proportion of familiar routes driven were aggregated and used as inputs for the regression analysis. Results from the linear regression showed that for every 10 percent increase in proportion of familiar routes driven, there is an estimated 0.70 (CI[0.19,1.23]) increase in risky driving behavior events per mile. Thus older drivers with a higher proportion of familiarity with the driven routes had more risky driving behavior events per mile.

3.3.4 Influence of familiarity on the route choice risk of older drivers

A generalized mixed-effects regression model with an identity link was used to analyze the influence of familiarity on the route choice risk of older drivers. Table 10 shows the combined effect of treatment and familiarity on the participant's route choice risk. The interaction between treatment time and familiarity with driven routes was not significantly different from zero, providing insufficient evidence to support the hypothesis that familiarity with driven routes affects participant's response to the Trip Diary feedback. The interaction between treatment time and proportion of familiarity with alternate low-risk route was significant, supporting the claim that familiarity with suggested low-risk alternative routes affects participant's response to the Trip Diary feedback. The positive slope implies that the more familiar a participant is with the suggested low-risk alternatives, the longer they are in the study, the less likely they are to choose low-risk routes.

Table 10: Estimated effects on the route choice risk of older drivers

	Estimated effect	Std. error	t-value	95% CI
(Intercept)	-0.31	0.23	-1.37	[-0.76, 0.13]
Treatment time	0.07	0.07	0.83	[-0.08, 0.20]
Baseline risk choice ratio	0.61	0.12	5.02*	[0.37, 0.85]
Familiarity with driven routes	0.25	0.23	1.08	[-0.20, 0.70]
Familiarity with suggested low-risk routes	-0.56	0.20	-2.75*	[-0.96, -0.16]
Treatment time X baseline choice risk ratio	-0.10	0.04	-2.26*	[-0.18, -0.01]
Treatment time X Familiarity with driven routes	-0.04	0.08	-0.49	[-0.19, 0.11]
Treatment time X Familiarity with suggested low-risk routes	0.21	0.07	3.18*	[0.08, 0.34]

The results in Table 10 suggests that familiarity influences route choice risk and route choice interventions. Prior to incorporating familiarity into the analysis (see Payyanadan, Maus, et al., 2016), the most important factor affecting route choice risk was how risky an individual's baseline route choices were – those with high baseline route choice risk showed the most improvement. When familiarity was included in the model, the most important factor became familiarity with the alternative low-risk routes (Figure 3).

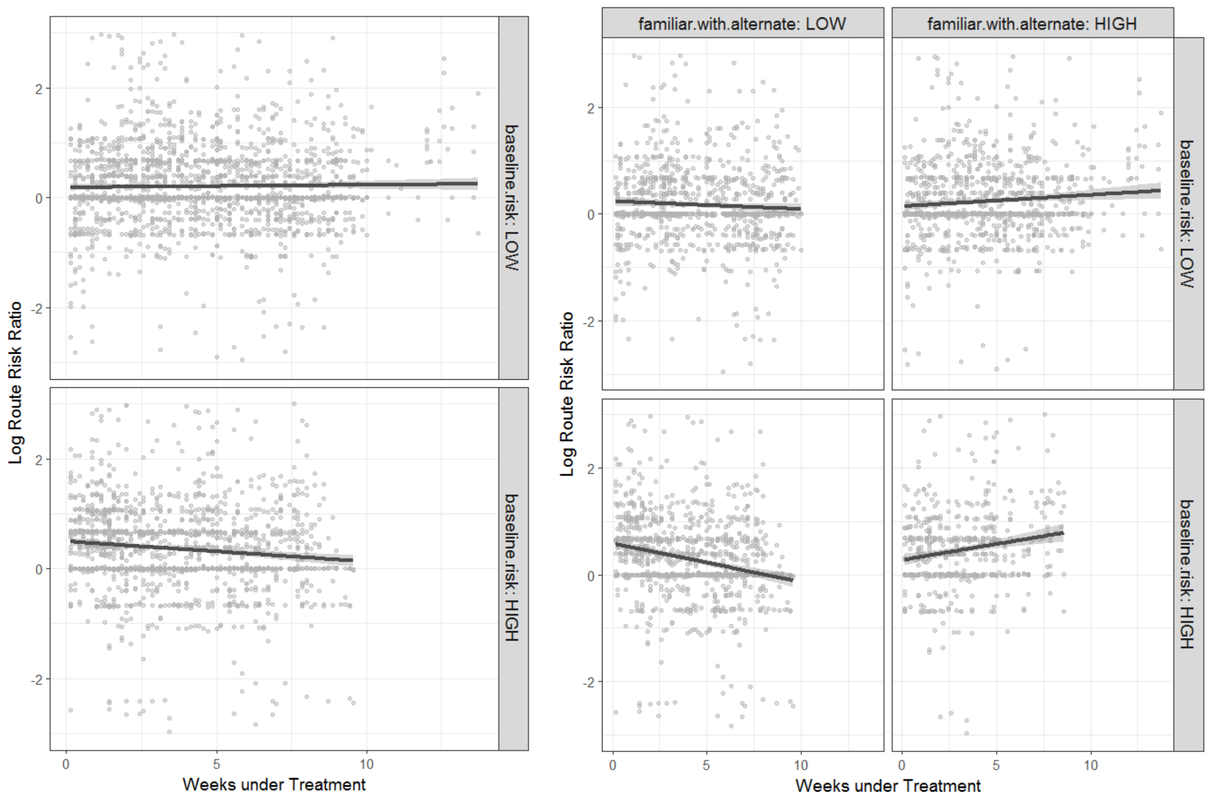


Figure 3: The y-axis is the route choice risk of the driven route compared to that of the suggested low-risk alternative route. The set of plots on the left show the importance of baseline route choice risk when familiarity is ignored. The strong downward slope of the high baseline route choice risk group highlights the effectiveness of the treatment for that group. The plot on the right shows the effect of familiarity. The columns differentiating high and low familiarity indicate that drivers take the suggested low-risk alternatives if they are unfamiliar with the route.

In Figure 3, values above 0 imply that the driven route had higher crash risk versus the alternative low-risk suggested routes. These results also showed that older drivers with no familiarity with the alternative low-risk routes were expected to lower their route choice risk by 3.9 percent per week, whereas a 50 percent familiarity with the alternative route showed an expected increase in route choice risk by 1 percent per week. This suggest that older drivers with a higher proportion of familiarity with alternative low-risk suggested routes are likely to show no change or increase their route choice risk when provided with feedback. This may indicate a type of *digging in your heels* affect – where when a driver is confident in their familiarity with the alternative route, dismisses the lower risk associated with the alternate route, and affirm their conviction that they are already making safe route choices.

3.3.5 Understanding the influence of familiarity on route choice among older drivers

Trip Diaries were used to provide reports of routes driven, alternate low-risk routes, risky driving behavior events along the route driven, and three feedback questions to determine: driver's familiarity with the route driven, familiarity with the alternate low-risk route suggested, and reasons for choosing the route driven and not considering the alternate low-risk suggested route. To assess the reasons for choosing a route by older drivers, the feedback questions were analyzed using content analysis.

A total of 612 feedback responses were recorded. Content analysis was conducted on the responses from older drivers. Conceptual analysis was first used to develop codes from the written responses for all the reasons that governed route choice, and record their frequency of occurrence. Conceptual analysis revealed a total of 18 concepts that reflected the reasons for choosing a route. The 18 concepts, concept frequency, and examples of the driving situations reported by older drivers are shown in Table 11.

Table 11: Reasons for route choice along with the corresponding driving context and situations

Reasons for route choice	Frequency of occurrence	Driving context and examples of route choice reasons
Less traffic	25	Route chosen based on traffic conditions – where *less traffic* conditions were preferred, *traffic* referred to medium traffic, which was also acceptable and driven if necessary. But *heavy traffic* was almost always avoided. *E.g. Certain routes will have heavy traffic at different times of the day. Routes are chosen keeping the varying traffic along different route segments in mind.*
Traffic	84	
Heavy traffic	25	
Construction	46	Avoiding construction zones. *E.g. Construction zones involved detours, lane changes and merging were avoided even if the alternate route was longer.*
Habitual	41	No particular reason for choosing a route. *E.g. Used to taking the same route every day.*
Travel time	24	A route was chosen based on minimal delays to travel time. *E.g. Depending on the intent of the trip, shortest route was chosen to a particular destination due to time constraints, and to reduce time in traffic. Else the most scenic route with no traffic was chosen.*
Road type	20	Route chosen based on the type of road characteristics. *E.g. Roads that involve crossing 4 lanes, roundabouts, and quick merging were avoided. Roads that were scenic and along familiar residential areas were preferred.*
Errands	18	Make multiple stops along a trip. *E.g. Trips such as visiting the bank, dropping off mail, grocery shopping are conducted as a single trip with multiple stops for efficiency.*
Not interested	16	Not inclined to alter current route choices or driving behavior. *E.g. Did not consider their route choice or driving behavior needed any feedback.*
Stop signs and traffic lights	15	Route chosen based on the preference for traffic lights and avoidance of stop signs. *E.g. Stop signs cause drivers to often miss their turn, hence traffic lights are preferred.*
Time of day	13	Driving during the day versus night, and during low traffic conditions. *E.g. Choice of route and departure time depended on the level of traffic along certain routes and daylight for ease of visibility.*

Unfamiliar streets	12	Route avoided due to lack of knowledge of the street and neighborhood. *E.g. Preferred to avoid unfamiliar streets and neighborhoods as it was difficult to pay attention to both driving and the new routes. Driving unfamiliar routes also increased fear of getting lost.*
Direct route	11	Route chosen based on the directness of the route. *E.g. If the route has no turns and is the shortest route to the destination, it is preferred even if there is traffic.*
Driving maneuvers	10	Route chosen based on the comfort with driving maneuvers. *E.g. Routes that require driving on a roundabout involve driving maneuvers that are new and hence avoided.*
Controlled left turns	7	Choosing routes with controlled versus uncontrolled left turns. *E.g. Controlled left turns were preferred and considered safest.*
Safety concern	7	Routes avoided based on past history of near misses or crashes. *E.g. Due to driver inattention such as merging without checking their blind spot resulted in a near miss. Hence such routes with a history of crashing or near misses was avoided.*
Complicated route	6	Route avoided if it had too many direction changes. *E.g. Older drivers defined routes with too many turns and merging to be complicated.*
Speed limit	5	Avoiding routes with varying speed limits. *E.g. Changes in speed limits was difficult to always keep track off when paying attention to the road. Hence routes with fewer speed limit variations were preferred.*

Based on the frequency of concepts, the conceptual analysis revealed that traffic, construction, and habit dominated the reasons for choosing a route, accounting for 47 percent of the total written responses. To determine which of the concepts were associated with familiarity, the 18 concepts were clustered based on the familiarity responses to the route driven and alternate low-risk suggested route, as shown in Figure 4.

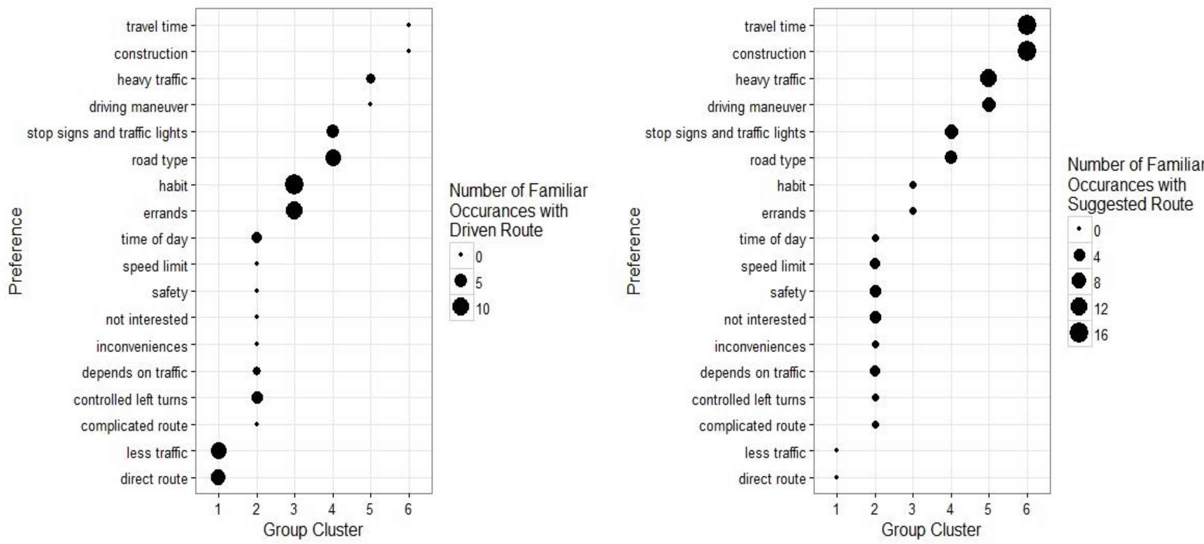


Figure 4: Route choice concepts associated with preferring a) familiar route and b) familiar alternate low-risk routes suggested.

Conceptual analysis revealed that the reasons for choosing a familiar route was governed by four main concepts – the route being direct, less traffic, the sequence of errands, and habitual route. Habitual routes were defined by older drivers as a route that they were familiar with, drove frequently, and were considered reliable. Road type, the number of stop signs, and traffic lights further influenced the choice of route. For the alternate low-risk suggested routes that older drivers were familiar with but chose not to drive; drivers' reasons included construction, more traffic, increased travel time, and involved more complex driving maneuvers.

Relational analysis was conducted to determine the relationship between the 18 route choice concepts for four situations – when the driver was familiar and unfamiliar with the route driven, and familiar and unfamiliar with the low-risk suggested route.

Familiar with the route driven – Seventy-six percent of the older drivers preferred the driven route versus the alternate route, irrespective of fewer number of left turns, U-turns, travel time and distance. Responses from older drivers showed that apart from general preference to drive a route that was familiar, route characteristics such as short and direct, minimal traffic, and time of day contributed to the overall route choice. Driving familiar routes versus alternate unfamiliar low-risk routes was also preferred when running errands. Route choice was also influenced by route characteristics such as road type, number of stop signs, and number and length of traffic light stops. Road types such as freeways, poor road conditions, winding roads, roads with a lot of pedestrian crossings, roundabouts, and roads with parked vehicles that obstructed view of traffic were avoided. Older drivers also avoided driving in areas such as school zones in the morning, and downtown areas in the evening. Driving on main roads, along scenic routes, and in familiar residential areas were preferred. Older drivers preferred to avoid stop signs because waiting their turn often resulted in them losing their chance to turn due to late reaction. On the other hand, they preferred traffic lights to stop signs, as it gave them time to complete their driving maneuver.

Unfamiliar with the route driven – Older adults drove unfamiliar routes for 15 percent of the trips. Reasons for choosing the unfamiliar route was if they were touring or running errands that required deviating from a familiar route, detour due to construction zones or lane closures, drop-off their spouse or friend at a particular location.

Familiar with the suggested low-risk route alternative – Twenty-nine percent of the responses showed familiarity with the alternate low-risk suggested route. Older drivers stated construction and travel time to be the main factors for avoiding the suggested low-risk route. The 511 DOT data used to retrieve construction information as part of the low-risk measure for suggesting alternate routes were not always updated, accurate, or current; hence the suggested route alternatives were not always void of construction. Travel time was considered a major factor for avoiding the alternative route, because even though distance and turns were fewer, traffic was not considered as part of the determining factor for the suggested alternative low-risk route. Older drivers preferred to avoid any type of traffic condition, with time of departure to destination governed by the current and projected traffic along the route. Additionally, the alternative low-risk route was not driven because of the driving maneuvers involved. Older drivers reported that although the alternative routes had fewer left turns and U-turns, it required other driving maneuvers such as crossing a four-lane road in traffic, turn taking across a wide intersection, required a lot of merging, and conducting unprotected left turn maneuvers.

Unfamiliar with the suggested low-risk route alternative – In 6% of the responses, older drivers considered taking the suggested unfamiliar route. Older drivers reported avoiding the alternative unfamiliar route when they were concerned with following the directions while driving – especially if the directions were confusing or the route was long, and driving on routes with too many turns that would increase the number of maneuvers.

3.4 Discussion

This study showed that route familiarity influences the risky driving behavior events and route choice risk of older drivers. This is especially true for the proportion of familiar routes older drivers chose to drive, and their familiarity with the alternative low-risk routes they could have driven instead. Older drivers who were familiar with the low-risk alternative routes had an increase in the rate of risky driving behavior rate of 5 percent for every 10 percent more familiarity they had with the routes. Results also showed that as older drivers gained familiarity with the route, they increased their route choice risk by 2 percent for every 10 percent gain in familiarity with the alternative low-risk suggested route. Even though these results show the effect of familiarity with the routes driven and alternate low-risk suggested route, it is important to note that the influence of familiarity on a more granular level of individual routes was not found to be significant in this study.

For alternate low-risk route options that had fewer left turns, U-turns, and traffic incidents – only 6 percent of the older drivers considered driving the alternate route. Reasons for preferring the driven route included shorter distance, direct route, and minimal traffic. Previous studies have shown that route familiarity can lead to inefficient route choice (Ardeshiri, Jeihani, & Peeta, 2015), and perception bias between actual and perceived travel distance (Zhang & Levinson, 2008). The content analysis conducted on the feedback responses from older drivers in this study showed that habitual route choice behavior was also a reason for preferring the driven route despite being familiar with the low-risk route option. Habitual route choice behavior can deter drivers from switching to a new route of comparable or better efficiency because of the costs of information acquisition and processing, and risk aversion (Zhang & Levinson, 2008).

Drivers have been reported to make trade-offs between risk and travel time by increasing their speed on familiar roads (Intini, Colonna, Berloco, & Ranieri, 2017). Ciscal-Terry et al., (2016) quantified the deviation of an observed route from its optimal alternative and reported that there are a number of reasons drivers might choose riskier routes – a) to avoid traffic by opting for faster roads even if they are twice the length of the shortest route, b) habitual driving, c) to avoid driving through the city even if it is shorter, and d) opting for routes with deviations that allow for driving on alternate routes with higher speeds. For older drivers, content analysis of the familiarity feedback responses showed similar reasons for not driving the low-risk alternative – route familiarity, avoiding heavy traffic, number of stop signs, and number and length of traffic light stops.

For older drivers, much of the decision-making governing route choice occur before departure (Payyanadan et al., 2016, 2017). Thus the opportunity to incorporate familiarity with the route as part of the user preference in trip planning and route guidance systems could produce useful route choice models that may better reflect real-world route choice behavior. Future work will involve developing a route choice model that incorporates user preferences such as route familiarity in generating alternate routes.

The study has a number of limitations that need to be addressed. Due to limited sample size, especially with the number of unfamiliar driven routes, the number of unfamiliar driven routes would often be 0 or 1, even if the participant provided feedback on 20 or more routes. Trip distance and time were not included as independent variables in the linear mixed-effects model due to the incorporation of these variables in the route choice risk measure. Although the suggested low-risk routes were developed to provide drivers with fewer left turns, U-turns, traffic incidents, and construction zones; written responses from older drivers revealed that some of the low-risk route alternatives had construction. Further investigation revealed that the 511 Department of Transportation source used to provide the information was not always updated. Traffic as a factor of risk was not part of the low-risk algorithm for suggesting alternative route options. Lastly, it was not always possible to accurately assess whether the alternate low-risk suggested route was driven because of the limited number of GPS points recorded per trip by the Geotab GO6 device.

3.5 Chapter summary

In this chapter we investigated the influence of familiarity on driving behavior and route choice among older drivers. Findings suggest that older drivers’ route choice risk depended primarily on familiarity with the route and traffic conditions, which also influenced their willingness to change routes. Including factors such as familiarity in modelling route choice behavior for older drivers can have important implications for the development of driver support systems such as advanced travel information systems and navigation systems, which can increase willingness of older drivers to switch to safer route alternatives.

CHAPTER 4: A THEORETICAL AND MATHEMATICAL FRAMEWORK FOR MEASURING ROUTE FAMILIARITY

Older drivers prefer avoiding risky driving situations, and are known to choose routes based on their preferences, and dynamic and static knowledge about the route and route network such as time of day, traffic conditions, weather, etc. (Lotan, 1997; O'Neill, 1992; Payyanadan & Lee, 2017). But ICT (information and communication technology) based decision-support systems, navigational tools, and route guidance systems developed to provide alternate route options based on the preferences and driving safety needs of the driver have reported low adherence especially among older adults to divert from their route compared to younger drivers (Abdel-Aty, Vaughn, Kitamura, Jovanis, & Mannering, 1993; Payyanadan, Maus, et al., 2016). The unwillingness to divert among older drivers has been attributed to preference for routes that are primarily familiar, which can involves multiple factors such as knowledge of estimated trip time and distance, traffic conditions, road type, direction of travel, road and weather conditions, etc. (Abdel-Aty & Huang, 2004; Mannering, Kim, Barfield, & Ng, 1994; Payyanadan & Lee, 2017; Zhang & Levinson, 2008).

Preliminary work conducted in Chapter 3 found similar results, where stated familiarity responses from 29 older drivers collected over a six month period was used to determine the factors of route familiarity that influenced choice of route among older drivers. Results from the study showed that while older drivers preferred to drive familiar routes, where familiarity was influenced by their prior knowledge about route characteristics (direct route, less traffic, road type), and preferences such as trip purpose; they were willing to divert to the alternate low-risk suggested route if they were not familiar with the suggested route. But current interventions aimed at providing smarter route alternatives face challenges incorporating features such as route familiarity into their route choice models due to the complexity involved in generating route alternatives based on the multi-criteria nature of familiarity (Prato, 2009), lack of understanding about the reasons for choosing a familiar versus unfamiliar route (Payyanadan & Lee, 2017), and in identifying the factors of familiarity within a framework (Bovy & Stern, 2012).

To address these challenges, the goal of this dissertation is two-fold: a) to develop a theoretical and mathematical representation of route familiarity that captures the multi-faceted nature of route familiarity; and b) to develop a model of route choice governed by route familiarity (Figure 5). This Chapter will focus on developing a theoretical and mathematical representation of route familiarity. Stated familiarity feedback responses collected from 29 drivers 65 years and older representing the factors of familiarity that influenced their choice of route were mapped onto levels of an abstraction hierarchy framework (Figure 5A). The abstraction hierarchy framework was then used to conceptualize a mathematical representation of route familiarity (Figure 5B). Operationalizing the mathematical representation of route familiarity using naturalistic driving data from the 29 older drivers recorded for a period of four months was then used to develop a new measure of route familiarity – *estimated route familiarity* (Figure 5C).

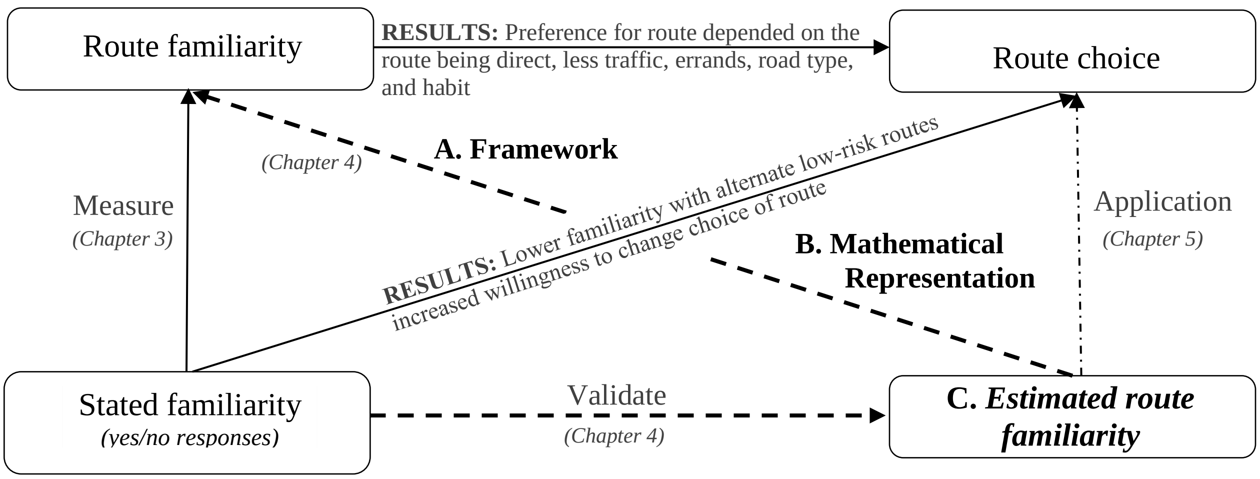


Figure 5: Steps for developing a measure of route familiarity – *estimated route familiarity*, to predict route choice

This Chapter is organized into three sections. The first section provides an overview of the theoretical abstraction hierarchy (AH) framework – *Rasmussen's Abstraction Hierarchy* (Rasmussen, 1983) used to represent the multi-faceted nature of route familiarity. In this section, prompts and keywords provided by Naikar (2013) are applied to the 612 feedback responses from older drivers to extract the multiple factors of route familiarity, and mapped to the specific levels of the AH framework. In the second section, the AH framework describing the factors of route familiarity is formalized into a mathematical representation. The goal of the mathematical representation is to establish a method for quantifying each of the AH levels, establish a measure of familiarity – *estimated route familiarity*, and illustrate how to incorporate different types of driving data structures (Mesarovic & Takahara, 1975). In the final section, naturalistic driving data from 29 older drivers are used to validate the *estimated route familiarity* measure.

4.1 Framework for describing the factors of route familiarity that influence route choice

Cognitive and computational models of geographic information and the effect of this information on orientation and navigation have considered the environment in terms of a space consisting of different dimensions representing external objects, representation of self, embodiment of value, and arena for action (Ittelson, 1973). Within this environmental model, the information selection of a set of attributes, objects, or actions required for the goal or task creates levels of abstraction, defined as *the ordering imposed on the environmental model depending on the goal or task* (Timpf, 1999). When the selection is repeated several times, hierarchies are created by abstracting information. Research on mental map models have shown that humans cluster spatial and non-spatial information as abstraction hierarchies even when there are no predetermined hierarchies (Hirtle & Jonides, 1985). Thus abstraction hierarchies play an important role in human cognition.

Abstraction hierarchy models have been used to represent categories of mental representations of object or events abstracted from observations of the environment (Smith & Medin, 1989). But not all categories observed in the environment can be structured into hierarchies. For example, Rosch et al. (1976) showed that while for some concepts such as *concreteness* or *imagability*, there does not exist a preference for basic, subordinate, and superordinate levels of categorization; other studies have shown that only the basic levels are representational of concepts (Tversky & Hemenway, 1984). For understanding familiarity, early work using abstraction hierarchy models have shown that familiarity was strongly associated with categorization of features to describe an item or event as familiar (Goldberg, 1986). Thus abstraction hierarchies serve as a suitable framework for describing the features of familiarity that influence route choice.

4.1.1 Overview of Rasmussen's abstraction hierarchy (AH) framework

In Cognitive Engineering, Rasmussen's AH framework is used to represent systems in a way that reflects human memory and problem solving characteristics, but is also event independent, allowing for a wide range of situations and unforeseen events (Vicente & Wang, 1998). Such a framework offers an opportunity to model the functional structure of the physical, social, and cultural environments of actors in the system; which enables a) identifying constraints on actors, b) revealing possibilities of actions available, c) determining rationale for actor's behavior, d) applicable across a range of situations, and e) result in designs that can support the actor in dealing with a variety of events (Hajdukiewicz, Burns, Vicente, & Eggleston, 1999; Naikar, 2013). Thus Rasmussen's AH framework is the preferred theoretical framework for representing the multi-faceted nature of route familiarity because it provides a systematic description of the system in engineering terms that is compatible with the psychological representation people use to deal with complex systems (Vicente & Wang, 1998).

Rasmussen's AH framework commonly used for modelling the functional structure of the environment, is also referred to as the *abstraction-decomposition space*, and is represented as a matrix (Figure 6). In the *abstraction-decomposition space*, the vertical axis comprises of the *means-ends relations* of the *abstraction dimension*, and the horizontal axis comprises of the *part-whole relations* of the *decomposition dimension* (Naikar, 2013). The cells of the matrix are populated with representations of the functional structure of the environment, and is specific to the particular level of abstraction and decomposition. While the *abstraction dimension* is typically described by five levels, there are no set levels for the *decomposition dimension*.

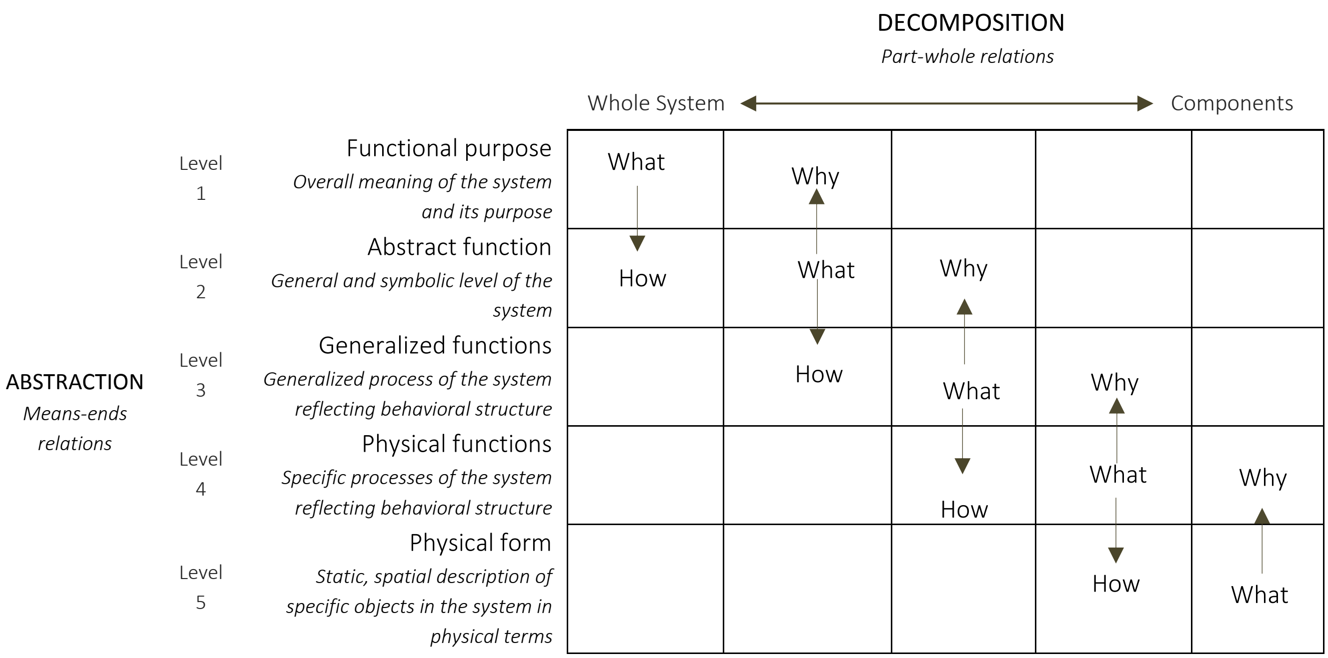


Figure 6: The abstraction-decomposition space

The *abstraction dimension* describes the properties of the environment used for achieving an end, and is comprised of five levels reflecting distinct concepts – functional purpose, abstract function, generalized functions, physical functions, and physical form. Functional purpose represents the primary purpose of the system; abstract function represents the intentions or the intended operational state of the system; and generalized functions represent the functional relationships in the system independent of physical manifestation. Lastly, physical function level represents the mechanical, electrical, or chemical processes of the system or its parts; and the physical form represents the appearance or configuration of the systems and its parts. Moving up or down the levels of abstraction represents the *means-ends relations*. The *abstraction dimension* allows both a bottoms-up approach for describing the use of the system components and functions for serving the purpose or goal; and a top-down approach of how the purpose or goal can be implemented by the functions and components of the system. Although each cell can be populated with specific constraints or means, it is not considered efficient (Miller & Vicente, 1998). Instead, it is recommended that only the constraints or means that provide meaningful or useful information about the environment be incorporated into the abstraction-decomposition matrix – represented along the diagonal of the matrix (Naikar, 2013).

Each level of the *abstraction dimension* describes a different set of constraints or means associated with the activities in a system. For example, to drive to the hospital for a doctor's appointment, a driver may choose a route that has less traffic, fewer stop lights, and park in a spot that is easy to access (Payyanadan et al., 2016). Here the route chosen and parking spot are the means for getting to the doctor's appointment on time, and the traffic and stop lights are the constraints of the driving environment on the driver. These *means-end relations* are determined as a *how*-*what*-*why* triad, representing the demands on the actor and the context of the situation for the actor (Hajdukiewicz et al., 1999; Naikar, 2013; Rasmussen, 1986).

The *decomposition dimension* consists of few or many levels representing details of the functional environment as its *parts* and *wholes*. Thus, the levels of decomposition are connected by *part-whole relations*, where the lower levels are the functional parts of the higher levels, and the higher levels are the wholes of the lower levels – representing different levels of the same system. For most applications of the framework, specifying the *decomposition dimension* of the model is important for providing a complete and accurate representation of the system, but a methodological analysis of the *decomposition dimension* is not essential, and hence will not be explored in this dissertation.

4.1.2 Levels of the abstraction hierarchy

The *abstraction dimension* is made up of five qualitatively distinct concepts used for modeling the structural properties of the environment, and is characterized by the *means-ends* relations. The labels ascribed to each level and the constraints or means represented within each level by Rasmussen (1986) along with examples from the driving domain are defined below:

Functional purpose level – The function purpose level represents the overall goals and purpose of the system, objectives, and the external limits on the system due to the environment. The system's purpose remains relatively constant, while the objectives and external limits of a system are dynamic – changing with respect to the situation (Burns & Vicente, 2001). The system can have multiple objectives. The external limits refer to the properties of the environment that impose on the system's purpose (Naikar, 2013). For example, the purpose of a trip is to reach the destination. Whereas there might be multiple objectives for the trip – primary objective to arrive for dinner on time; and the secondary objective is to stop and pick up dessert before dinner. External limits by the driving environment on the trip could include traffic regulations. Thus at the functional purpose level, purpose, objectives, and external limits govern the interaction between the system and the environment.

Abstract function level – The abstract function level represents the values and priority measures needed to fulfill the purpose of the system (Naikar, 2013). For example, for the trip where the purpose is the reason for making the trip such as going out for dinner, with the primary objective to arrive on time for dinner, and secondary objective to stop and pick up dessert; several criteria can be employed for evaluating how the purpose is fulfilled. Criteria such as selecting the shortest, selecting the fastest route, etc., can allow the driver to compare, prioritize, and allocate resources to achieve the trip purpose. Assessing these criteria can help evaluate whether the purpose is fulfilled.

Generalized function level – The generalized functions level represents the functions that must be supported to fulfill the system's purpose, independent of the underlying physical objects or object-related processes needed to implement them (Naikar, 2013). For example, for the trip where the primary objective is to arrive on time for dinner, the secondary objective to stop and pick up dessert, and criteria such as time of departure is used to evaluate fulfillment of the trip purpose; requires a number of purpose-related functions that need to be supported. These include challenges such as maintaining a certain speed and acceleration with other drivers on the road, overtake vehicles if they are driving to slow, etc. (Kesting, Treiber, & Helbing, 2010). While there are no reported variations on how factors at this level are characterized, these functions need to be represented in general terms using terminology common to the field, such that the functions indicate the type of system but not the specific system (Naikar, 2013; Rasmussen, 1994).

Physical function level – The physical functions level represents the object-related processes or parts of the system that are used to characterize the functional states (Rasmussen, 1986). The object-related processes or parts are tightly related to the physical objects, and represented by their reason for use, or by their limiting properties. The resolution of the details represented in this level depends on the specific task or interaction with the system. For a trip, the number of stop signs, street parking, etc. (*at the physical properties level*), influences the purpose-related functions such as speed maintenance, start-stop events, etc. (*at the driving challenges level*), affecting the evaluation criteria such as duration of travel (*at the travel conditions level*), and the goals and objectives of the trip such as reaching on time at the destination (*at the trip purpose level*). The physical representation is tightly coupled with the functional states, where changes at the physical functional level propagate up the hierarchy, and influence the higher levels (Rasmussen, 1986).

Physical form level – The bottommost level represents the physical appearance and configuration of the system and its parts (Rasmussen, 1986). Representation of the system and its parts at this level reflects what parts are vital for interaction with, and manipulation of the system to achieve the purpose-related functions of the system. For example, for the trip where the primary objective is to arrive on time for dinner, and the secondary objective to stop and pick up dessert, based on the route chosen – trip features of the route can include information about the name and type of road, appearance of the road (winding, curvy), location or position (cardinal points, origin, destination), and physical distribution and connections (GPS trace, proximity, overlap) (Naikar, 2013). Thus, this level is represented by names or attributes that can help identify and distinguish objects and their properties for navigating the system (Rasmussen, 1986).

4.1.3 Mapping the factors of route familiarity into levels of abstraction

For specifying levels of the abstraction hierarchy to describe the factors of route familiarity that influence route choice; Trip Diary feedback responses from older drivers collected for a period of four months were used. A total of 612 feedback responses representing reasons for choosing a familiar route were first transcribed. Concepts were then extracted from the transcriptions using the prompts and keywords provided by Naikar (2013) to determine the constraints and means specific to each level of the abstraction hierarchy as shown in Table 12.

Table 12: Examples showing the extraction of the means and constraints for each level of the abstraction dimension from the Trip Diary feedback responses from older drivers, using the prompts and keywords

Examples of Trip Diary feedback responses	Prompts *(Naikar, 2013)*	Keywords *(Naikar, 2013)*	AH Levels *(Rasmussen, 1986)*
Had to visit the bank, then drop off some mail, get my groceries	Why does the system exist? Why is the system necessary? What objectives is the system designed to achieve? What external constraints is the system designed to fulfill?	Reasons, purpose, goals, aims, objectives, intentions, outputs	LEVEL 1 Functional purpose
There was construction there…had detours, needed a lot lane changes, and merging with traffic	What purpose-related criteria must be met to achieve the functional purpose? What criteria can be used for comparing, prioritizing, and allocating resources to the purpose-related functions of the system?	Criteria, measures of success, effectiveness, performance	LEVEL 2 Values and priority measures
Higher speed limit on this route	What functions must the system be capable of support to achieve its functional purpose? What functions are afforded by the systems object-related processes?	Processes, activities, roles, responsibilities, positions	LEVEL 3 Purpose-related functions
Prefer to avoid that route because of the roundabout	What functional capabilities or limitations of physical objects are of relevance to the system?	Limitations, capacity, applications	LEVEL 4 Object-related processes
Needed to leave from my friend's place at 6PM and take the highway	What physical objects are necessary to enable the system's object-related process?	Geographical features, infrastructure, tools	LEVEL 5 Physical objects

Each level of the *abstraction-dimension space* was then populated along the diagonal and labelled to represent the AH levels describing route familiarity within the framework. The factors of familiarity that influenced route choice for older drivers was shown to depend on the purpose of the trip (grocery shopping, bank work), preferred driving conditions (less traffic, fewer pedestrians, shortest distance), avoidance of certain situational challenges (construction zones, lane change), knowledge of the physical properties of the driving environment (posted road speed, landmarks), and the cardinal direction for the trip (origin and destination). In Table 13, the abstraction hierarchy describes the driver's familiarity through the five levels of abstraction: trip purpose, travel conditions, driving challenges, properties of the driving environment, and trip features. And the part-whole abstraction aggregates each level of the means-end abstraction by representing a trip as a sequence of segments, series of maneuvers, micro adjustments of lateral and longitudinal control, and cardinality. The constraints and means identified from the feedback responses for familiar and unfamiliar routes were populated along the diagonal.

Table 13: Levels of the abstraction hierarchy applied to describe familiarity

ABSTRACTION DIMENSION	DECOMPOSITION DIMENSION				
	Type of trip	Sequence of segments of a trip	Series of maneuvers along a trip	Micro adjustments of lateral and longitudinal control	Cardinality
constraint prompts	*Reasons, goals, aims, objectives*	*Criteria, measures, effectiveness*	*Activities, processes*	*Limitations, capabilities*	*Geographical features*
Trip Purpose LEVEL 1	Grocery shopping Church Touring Multiple errands Visiting family and friends Volunteer work Rides for family and friends Bank work				

Travel conditions LEVEL 2	Safety Travel time Less pedestrians Less traffic Direct route Time of day Access to parking
Driving Challenges LEVEL 3	Speeding to keep with flow of the traffic Crossing a number of wide intersections Multiple lane changes on 4-lane, high traffic roads Hard braking for quick turns Speeding on turns to merge with speeding traffic Construction zones
Physical properties of the environment LEVEL 4	Onramp Complex navigation Wide intersections High speed limit Crossing 4-lane in traffic Long traffic lights Multiple stop signs Narrow routes Landmarks
Trip features LEVEL 5	Direction of travel Origin and destination

The levels of the abstraction hierarchy in Table 13, applied to describe familiarity, show that familiarity depends not only on the higher levels of trip purpose and travel conditions, but also on the lower levels of situational challenges, properties of the driving environment, and trip features. Previous research on understanding the driving challenges of older drivers have reported similar results, where familiarity with the road network, neighborhood, traffic conditions, traffic lights, stop signs, and signals along a route, controlled turn intersections, types of driving maneuvers along a route, time of day, travel time, alternate routes, weather conditions, road conditions, construction zones, traffic incidents, and rush hours, influenced route choice (Dickerson et al., 2007; Molnar & Eby, 2008; Payyanadan et al., 2017; Payyanadan, Maus, et al., 2016). Thus such a framework can be used to understand and guide the development of a familiarity measure to help determine the influence of familiarity on a driver's decision to choose a route, predict the willingness to deviate from a route, and develop better models of route choice.

4.2 Mathematical representation of the AH framework describing route familiarity

The AH framework describing familiarity was constructed by abstracting information about a driver's familiarity with the route to form abstraction levels representing ordered classes of information. But drivers can have different contexts and definitions that represent their conceptualization of familiarity of objects or events. To develop a mathematical structure that represents each of the AH levels, the following sections provides a review of the common approaches for measuring familiarity; and using these approaches to guide the formalization of a mathematical framework for route familiarity.

4.2.1 Similarity, recency, and frequency as measures of route familiarity

Current hierarchy models have used similarity, recency, and frequency functions to facilitate the comparison among objects or events, take meaning into account, and obtain better matches between user-expected and system-retrieved information (Lee, Kim, & Lee, 1993; Richardson, Smeaton, & Murphy, 1994). In the driving domain, similar parallels have been made to understand wayfinding on familiar and unfamiliar routes, where similarity measures are used to assess differences in the routes driven (Bryden, Charlton, Oxley, & Lowndes, 2013) based on four types of information – geometric (position, shape), features (landmarks), attributes (characteristics of the features such as number of lanes, etc.), and topology (Olteanu-Raimond, Mustiere, & Ruas, 2015); and recency and frequency measures to assess driving activities (Trick, 2004).

But route choice studies often use similarity, and frequency and recency separately to assess route familiarity measures (Froehlich & Krumm, 2008). For example, cognitive models using computational representation of human behavior have commonly used only recency and frequency measures to understand decision-making behaviors such as travelling patterns (Richard, Zito, & Paterson, 2016). This is because studies have shown that the recency and frequency of a trip increased the likelihood of the same trip recurring (Barbosa, de Lima-Neto, Evsukoff, & Menezes, 2015), and also due to limitations in the modelling approach, technology, and tools available to appropriately capture and compare GPS trace data to asses similarity.

Due to the limited work in using recency, frequency, and similarity measures in assessing familiarity in the driving domain; we draw from experimental psychology research on learning, memory, and cognition, where models of recency, frequency, and similarity, and their relationship for assessing familiarity have been studied (Hintzman, 2001; Kelley & Jacoby, 2000; Mickes, Johnson, & Wixted, 2010; Wixted, 2007). Past studies in experimental psychology have shown that similarity, recency, and frequency are considered as independent and orthogonal dimensions for measuring familiarity (Helgoe, 1976; Hintzman, 2001; Zhang & Ghorbani, 2004); where similarity is determined by the relatedness between the characterizing attributes of two or more events (Vrotsou & Forsell, 2011); recency by the distribution of occurrences across time of the event; and frequency by the rate of occurrences of the event (Wixted, 2007).

4.2.2 Visualization and hypotheses of the proposed relationship between similarity, recency, and frequency, and route familiarity

In the proposed AH framework describing route familiarity, the lower levels represent the physical features, processes, and attributes of the route, and the higher levels represent the trip purpose and driving functions. We assume that similarity, recency, and frequency dimensions across the levels of the abstraction hierarchy will determine familiarity. Then, familiarity can be formally defined as *a function of the degree of similarity between routes, and the frequency and recency with which the routes are travelled*; where frequency and recency are represented in the structure of the five levels of the similarity measure and the reference set upon which they are defined. The space on which familiarity lives as a function of similarity, recency, and frequency can be represented by a unit cube (Figure 7).

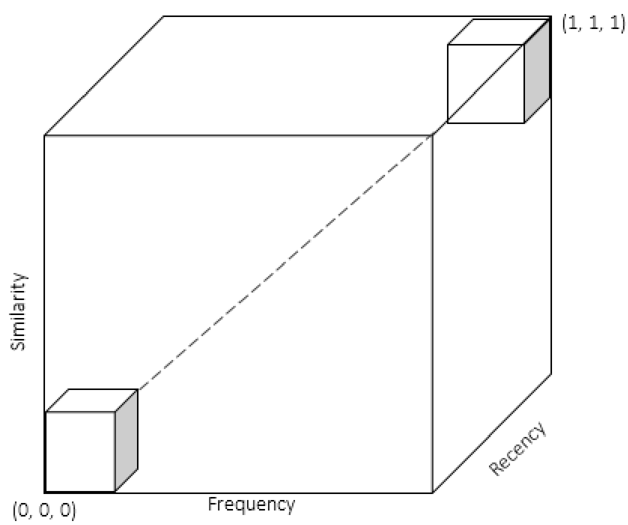


Figure 7: Proposed relationship between familiarity, similarity, recency, and frequency dimensions.

We hypothesize that *as recency, frequency, and similarity increases, the degree of familiarity also increases* (Figure 7). We also hypothesize that *the degree of familiarity within the unit cube is not fixed across the population of drivers* – i.e. each driver can have their own unit cube, and the strength of familiarity will depend on how receptive the driver is to each of the inputs of the proposed familiarity model. Route familiarity and the way we propose to estimate it is an attempt to determine if there is a common distribution for familiarity within the unit cube. Lastly, it is important to note that although similarity, frequency, and recency are proposed to be the primary dimensions that influence familiarity in this dissertation, there is evidence to suggest that other dimensions such as memory strength, knowledge, and decision-making attributes also influence familiarity (Wixted, 2007).

4.2.3 A measure of route familiarity - Estimated *route familiarity*

For the proposed AH framework for describing and developing a measure of route familiarity, some trips are closer than others because they share *similar* trip attributes (distance, time, direction of travel etc.), are *frequently* driven, or have been driven *recently*. To conceptualize a mathematical representation of route familiarity using the AH framework, *similarity* between trips will be determined by the relatedness between the characterizing attributes of two or more trips such as distance, time, and direction of travel (Vrotsou & Forsell, 2011), *recency* by the distribution of trip occurrences across time; and *frequency* by the rate of occurrences of the trip (Wixted, 2007). Thus, repeating the same trip many times and having done so recently makes the trip familiar. And a trip that has never been taken might be considered familiar if it is very similar to another trip that has been taken many times.

To mathematically represent each of the AH levels describing route familiarity, we first define trips for all origin O and destination D pairs. For each *O-D* pair, there are N possible route choices to get from O to D, and the route associated with an *O-D* pair is the route driven. Then each individual will have a set of all routes driven to create their own *route reference set* R^I, where R^I is the set of routes ordered by when they were driven, and I is a distinct individual in the population.

We assume that, R^I is not a set of distinct routes, i.e., any route can occur multiple times in R^I. And the ordering of R^I is based on the absolute point in time that each route was driven. In the route reference set, the ordering of the routes captures *recency*, and the aggregation of routes driven captures the *frequency* of the routes driven. For each level of the AH framework describing route familiarity, *familiarity* is determined by *the degree of similarity between routes, and the recency and frequency with which the routes are driven*; where *similarity* is characterized by *the degree of relatedness between shared features of two or more routes*, and *relatedness* is the measure of overlap or distance between the two features. The mathematical representation for each of the AH levels describing route familiarity is shown in Table 14. Appendix A provides details of the underlying assumptions and the formulation of the mathematical structure to aid further understanding of the proposed theory, modelling approach, and results.

Table 14: Mathematical representation of each of the AH levels describing route familiarity

Description of the AH Levels by Rasmussen (1983)	AH Levels (and examples) describing familiarity	Mathematical representation of the AH Levels describing familiarity	Similarity measure for each of the AH Levels describing familiarity
Overall *Purpose* of the system, *Objectives*, and the *External Constraints* on the	Trip Purpose LEVEL 1 *(e.g. grocery shopping, running errands)*	*Similarity* (S_F) of the trip **Purpose** $(\mathbf{S_p})$, **Objectives** $(\mathbf{S_o})$, and **External**	$S_F(R_j) = f(S_p, S_o, S_e)$

system due to the environment		**Constraints (S_e)** between two or more trips	
Values and *Priority* measures needed to fulfill the functional purpose of the system	Travel Conditions LEVEL 2 *(e.g. shortest route, fastest route)*	*Similarity (S_A)* in the **Overlap (O)** between the travel conditions **Criteria (C)** between two or more routes	$S_A(R_j) = f(O(C))$
Functions and *Processes* that must be supported to fulfill the system's functional purpose, independent of the underlying physical objects or object-related processes needed to implement them	Driving Challenges LEVEL 3 *(e.g. braking, accelerating)*	*Similarity (S_G)* in the overlap of driving challenges **Criteria (G)** between two or more routes	$S_G(R_j) = f(O(G))$
Object-related Processes or *Parts* of the system that are used to characterize the functional states	Physical properties of the environment LEVEL 4 *(e.g. speed bumps, U-turns)*	*Similarity ($S_{Pfunction}$)* in the **Overlap (M)** of sequence of the **object-related processes or parts (N)** between two or more routes	$S_{Pfunction}(R_j) = f(N, M)$
Physical Appearance and *Configuration* of the system and its parts	Trip features LEVEL 5 *(e.g. home to grocery store)*	*Similarity (S_{Pform})* in the **Overlap (O)** of **Physical location (A)**, and **spatial distribution (Pr)** between two or more routes	$S_{Pform}(R_j) = f(O(A, Pr))$

In Table 14, the mathematical structure establishes how similarity can be represented at each of the AH levels to describe familiarity, and generalized such that the mathematical structures can incorporate a wide range of situations and unforeseen factors in the driving domain (Rasmussen, 1986). Since recency and frequency depend on the set of routes driven by an individual and contribute to a driver's familiarity with the route; they are represented in the driver's route reference set R^I where *recency* is captured in R^I by the ordering of each trip, and *frequency* by how many times a distinct route is in R^I. Then, the *estimated route familiarity* can be mathematically represented as a function of the similarity in the travel conditions, driving challenges, properties of the driving environment, and trip features, between the target route (route driven) and the routes in the *route reference set* R^I (Eq. 1). For Eq. 1, we assume that route familiarity is a continuous, bounded variable defined on a subset of the unit interval.

$$Estimated\ \text{Route Familiarity} = f\left(S_F, S_A, S_G, S_{Pfunction}, S_{Pform}, R^I\right) \in [0,1] \qquad (1)$$

4.3 Using naturalistic driving data to operationalize *estimated* route familiarity measure

The proposed *estimated route familiarity* is represented as a linear combination of the similarity, recency, and frequency between trip purposes, travel conditions, driving challenges, properties of the driving environment, and trip features. To operationalize the *estimated route familiarity*, naturalistic driving data was collected from 32 drivers 65 years and older for a period of 6 months.

4.3.1 Method

On-board diagnostic devices (OBDII) were installed in the vehicles of 32 drivers 65 years and older. Participants had the devices installed for a period of six months. Participants were also given access to personalized web-based Trip Diaries to provide them with feedback of their driving behaviors, routes driven, alternate routes; and a questionnaire of their route familiarity.

4.3.2 Participants

A total of 32 adults 65 years and older were recruited from a larger study conducted in a Midwestern State, USA, focused on understanding the needs of older adults at risk of entering nursing care (see Gustafson et al., 2015). Eligibility criteria for this study required that participants hold a valid driver's license, own their own vehicle, and drive at least twice a week. Demographic data of the participants are shown in Table 15.

Table 15: Demographic data and trip characteristics of older drivers in the study

Gender	Total	Mean age	Total trips	Distance (miles)	Time (minutes)	Speed (miles/hr)
Males	14	73	27,348	7.0	12.6	44
Females	15	70	17,468	7.2	13.5	42

Although data was collected from the 32 participants, only 29 participants provided at least one familiarity response, and 14 (of the 29) provided both *yes* and *no* responses to familiarity. Thus analyses using stated familiarity was conducted using only data from the 14 participants.

4.3.3 Tools and technology

Geotab GO6 OBDII devices from Sprint were installed in the vehicles of 32 older drivers for six months to collect trip information using GPS data, and risky driving behaviors such as speeding, hard braking, accelerating, and cornering events. Personalized web-based Trip Diaries were used to provide information about their trips driven and risky driving behavior events, along with alternate low-risk route options (see Payyanadan, Sanchez, & Lee, 2016). The web-based Trip Diaries were also used to collect feedback on participants' familiarity with the route driven (yes/no responses), familiarity with the alternate low-risk route suggested (yes/no responses), and reasons for choosing the driven route (open ended response).

4.3.4 Data structure and transformation for analyzing each of the AH levels

The OBDII devices had pre-defined measure and sensitivity settings that were set based on the recommended specifications for a passenger vehicle. This data was used to build the *route reference set* R^I for each participant. R^I was then used to calculate the route similarity, recency, and frequency for each of the AH levels. Due to the limitations of the device, the physical properties of the environment (pedestrian crossing, stop signs) representing AH level 4 could not be captured. Additionally, the recorded GPS coordinates were event-based (see Chapter 3, Table 4), where GPS data was recorded by events (start, stop, hard braking, harsh cornering, etc.), and not just by time; where event-based measures reflect the frequency of the behavior, and time-based measures show how long it took for a behavior to begin, and an estimate of event duration. This can potentially result in incorrect estimation in travel distance due to missing GPS coordinates (Battelle Institute, 1995). To accurately fill in the missing GPS coordinates, a match-and-fill algorithm was used to fill in the missing GPS points (see Payyanadan, Sanchez, et al., 2016).

Individual route reference set - $\boldsymbol{R^I}$, recency, and frequency

The R^I for each participant was created as a rolling set of R^I at the weekly level because participants were required to access their Trip Diary page only weekly to provide feedback on their familiarity questionnaire. Every new route driven (here on referred to as the *target route*) was then compared to the *reference routes* (routes in their R^I). It is important to note that participant's familiarity response rate was on average 77 percent for the six month period. But irrespective of whether a response was received or not, R^I was updated every week. This was to ensure that the relative density of the routes driven by each participant was captured for accurate representation of each driver's reference set of routes and their recency.

In the following sections, the R^I for each AH level is created based on the data collected from the OBDII devices. For each of the AH levels, frequency of a route is included in the R^I as the reference set contains all routes driven, regardless of whether it was a previously driven route. Whereas the route recency was assessed based on the *forgetting curve* equation, which defines how information is forgotten over time by the human brain (Ebbinghaus, 1985). Variations of the forgetting curve are commonly implemented in route choice modelling approaches to measure route recency (Tang, Gao, & Ben-Elia, 2015).

Level 1 – Trip purpose - $\boldsymbol{F_p}$

The trip purpose *estimated familiarity* F_p is determined by the *similarity, recency, and frequency of the trip purposes, objectives, and external limits between two or more trips*. In this dissertation, only trip purposes will be used to measure F_p. The R^I for individual trip purposes was populated by using origin, O and destination, D GPS points of a trip (Wolf, Guensler, & Bachman, 2001), and from the feedback responses to determine the trip purpose. Data collected from the study consisted of 18,868 unique $O - D$ pairs. Trip purpose for each O and D were manually identified using Google Maps, and coded for destination type. For example, in response to the reason for choosing a route, a participant stated '*I was driving home from the grocery store and prefer this route for running my errands*'. Thus the O and D were labelled as *home* and *grocery shopping*, respectively. Additionally, using Google Maps, each O and D were labeled using both *specific* and *general* codes defined by the 2009 National Household Travel Survey (Table 16); where *specific* code corresponds to the location address name reported by Google Maps, and *general* code corresponds to the trip purpose categories (Santos, McGuckin, Nakamoto, Gray, & Liss, 2011). For example, if the destination address is East Towne Mall, Madison WI on Google Maps, the specific code would be *East Towne Mall* and the general code would be *shopping*.

Table 16: List of all the general codes by the 2009 National Household Travel Survey used to determine trip purpose

General code	Characteristics of the general code
Home	To or from the driver's primary residence
Residence	To or from a residence
School	To or from a school, school park, school field, school park, school library, school gym, daycare, after school care
Church	To or from a church or religious institution
Medical	To or from a hospital, clinic, health and wellness center, private clinic, health professional service centers, dental, chiropractic care
Errands	To or from shopping, groceries, hardware store, post office, bank, car service, professional services (non-medical), pet care, drop someone
Social/recreational	To or from dining, gym, park, sports field, recreational and sports clubs, entertainment centers, wedding, funeral
Unknown	No clear distinction of the GPS location
NA	When GPS coordinates were in the middle of the road network

Due to the variability in parking, some of the destinations were difficult to characterize, as the driver might park at a residence or near a variety of businesses that serve a range of purposes such as shopping, dining, personal business, etc. In the absence of driver feedback, for the former, a 0.25 mile radius from the destination location were inspected using Google Maps *Streetview* to determine whether the surrounding locations were only residences, or whether there were shops or churches in the area. Unless a shop, senior center, or church was identified within a 0.25 mile radius, these destinations were marked as *residence* – indicating that the driver visited a friend or family. The latter were labelled as *errands*, if the 0.25 mile search revealed no residences. In cases where there was no clear distinction, or where the destination GPS data point was located on or away from the road network versus a property boundary; the destination was labelled as *unknown* and *NA*, respectively.

Thus at the trip purpose *estimated route familiarity*, F_p can be represented by the proportion of times the target route R_j, had the same purpose as the routes in their reference set R^I (Eq. 1). In Equation 1, the numerator denotes the number of times the trip purpose matches the routes in the reference set, and the denominator represents the total number of routes in the reference set.

$$F_p(R_j) = \frac{\sum_{k \neq j}^{|R^I|} W_k * I(P(R_k) = P(R_j))}{\sum_{k \neq j}^{|R^I|} W_k} \quad (1)$$

Where,

k – k^{th} route of the reference set for individual I

W_k – Recency of route k

I – Indicator function, (1 – True, 0 – False)

$P(R_j)$ – Purpose of route j

Level 2 – Travel conditions - $\boldsymbol{F_A}$

The travel conditions *estimated familiarity*, F_A is determined by the *similarity in the overlap of travel conditions for two or more routes, and the recency and frequency with which the route is driven*. In this level, criteria is used to evaluate whether the trip purpose was fulfilled (Naikar, 2013; Rasmussen, 1986). Contextual inquiry used to understand the travel conditions experienced by older drivers revealed that criteria such as choosing routes with fewer turns, shortest distance, and short travel time were important (Payyanadan et al., 2016). Based on these findings, the travel conditions criteria chosen for this dissertation are the *safest route* and *fastest* *route* for a driven $O - D$ pair. If the route driven was both the fastest and the safest, it was given a criteria label – *Other*. Using the list of 3-8 routes available from Google Maps for any driven $O - D$ pair, the reference routes in R^I of each participant were classified based on these criteria – *safest route*, *fastest route*, and *Other*. The classification of the routes driven into *safest*, *fastest,* and *other* followed the approach conducted previously in the work by Payyanadan, Sanchez, and Lee (2016).

There are other criteria such as driver comfort (Blanchard & Myers, 2010), traffic conditions (Charlton et al., 2006), weather conditions (Myers, Trang, & Crizzle, 2011), etc. that are known to influence trip purpose, but were not recorded in this study; and hence not considered. Thus the travel conditions *estimated familiarity*, F_A can be represented by the proportion of times the target route R_j, had the same criteria as the routes in their reference set R^I (Eq. 2).

$$F_A(\mathrm{R_j}) = \sum_{k \neq j}^{|R^I|} \sum_{i}^{N_i} O(T_k(C_i), T_j(C_i)) \qquad (2)$$

Where,

k – k^{th} route of the reference set for individual I

i – i^{th} criterion out of the set of all criteria

N_i – Number of trip criteria

O – Function that measures the overlap of the travel conditions criteria

T_k – Travel conditions for the k^{th} route of criterion i

C_i – Countable set of distinct criteria

$T_k(C_i), T_j(C_i)$ – Measure on criteria i between routes k and j

Level 3 – Driving challenges - $\boldsymbol{F_G}$

Older drivers modify their driving behavior to adapt to the driving challenges, which arise due to complexities in the driving environment, or due to cognitive, functional, and physical declines – increasing their risk of crash. Adapting to driving challenges cause older drivers to self-regulate their driving behavior by driving only at a certain speed, accelerating, braking, steering, lane change, etc. (Smiley, 2004; Vlahodimitrakou et al., 2013). Thus the *estimated familiarity* in driving challenges, F_G involves the driving challenges that need to be overcome to fulfill the trip purpose, and is determined by the *similarity in the overlap of driving challenges between two or more routes, and the recency and frequency with which those driving challenges occurred*.

The reference routes in R^I of each participant were classified based on these driving behaviors (hard braking, harsh cornering, harsh accelerating, and speeding). Magnitude and frequency of each of the driving behaviors measured, for example how often the speeding occurred and how much over the speed limit; were used as proxies for driving challenges. To keep the analysis simple, this dissertation will only consider the point of time and space at which the driving challenges occurred, i.e. the frequency of the driving challenge For this we assume the time and space measure of familiarity to be negligible. Thus the *estimated familiarity* in the driving challenges, F_G can be represented by the overlap of hard braking, hard cornering, harsh acceleration, and speeding events between the target route and the routes in reference set R^I (Eq. 3).

$$F_G\left(\mathrm{R_j}\right) = \sum_{k \neq j}^{|R^I|} \sum_i^G \sum_n^{m_i} O(G^{D \in M}), \text{ and} \tag{3}$$

$$O(G^{D \in M}) = \min(f_k(G_i), f_j(G_i))$$

Where,

G – The number of driving challenges

n – n^{th} dimension of strategy i

m_i – Total number of dimension for strategy i

O – Overlap function measure

$G^{D \in M}$ – Measure on driving challenges i between routes j and k

$f_k(G_i)$ – Proportion of route k where the driving challenge i occurred

Level 4 – Physical properties of the driving environment - $\boldsymbol{F_{pfunction}}$

The *estimated familiarity* in the physical properties of the environment, $F_{pfunction}$ is determined by the *similarity measured by the overlap of objects (stop lights, traffic lights, landmarks, etc.), and the sequence of these objects between the target route and reference route, and the recency and frequency with which the overlap and sequence occurs*. A number of studies have been conducted on assessing the sequence of objects by using longitudinal and lateral acceleration and speed to understand driving patterns when turn taking (Mitrović, 2005), and speed and acceleration behavior to differentiate between healthy drivers and drivers with obstructive sleep apnea (McLaurin et al., 2014). Other studies have studied the sequence of landmarks – especially among older drivers, for navigation support and wayfinding behavior (Goodman, Gray, Khammampad, & Brewster, 2004); and the use of Online Traffic Information System (OTIS), for tracing the sequence of traffic lights, traffic signs, etc. along a route. Then *estimated familiarity* in the physical properties of the environment, $F_{pfunction}$ can be determined by the similarity measured by the overlap and sequence of objects in the driving environment between two or more routes (Eq. 4).

$$F_{Pfunction}(\mathrm{R_j}) = \frac{\sum_{k\neq j}^{|R^I|}\sum_{i}^{|N_k|} I(i^{th}\ element\ in\ N_k = i^{th}\ element\ in\ N_j)}{\sum_{k\neq j}^{|R^I|}\sum_{i}^{|N_k|} 1} \tag{4}$$

Where,

N_k – Set of elements (objects in the driving environment) in the k^{th} route

I – Indicator function

The OBDII data only recorded event-and time-based latitude and longitudinal points along a route. This limited the ability to extrapolate the GPS route traces to include the sequence of traffic lights, traffic signs, etc. Thus, this dissertation will not include level 4. In the following section 4.3.3 on *Model, Analyses, and Assumptions*, we address how this would affect the overall *estimated route familiarity* measure.

Level 5 – Trip features - $\boldsymbol{F_{pfeatures}}$

The *estimated familiarity* at the trip features level, $F_{pfeatures}$ is determined by the *similarity in the appearance, location, and spatial distribution of the physical attributes between two or more routes,* S_{Pform}*, and the recency and frequency with which these features occur*. Similarity between two or more routes at the trip features level involves comparing information about the name and type of road, appearance of the road (winding, curvy), location or position (cardinal points, origin, destination), and physical distribution and connections (GPS trace, proximity, overlap) (Naikar, 2013). Common approaches in measuring similarity at the geographic or topographic level have involved assessing length or proportion of overlap between GPS points (Payyanadan, Sanchez, et al., 2016), sequence of locations using GPS points (Zheng & Xie, 2011), and point-segment distance measures (Froehlich & Krumm, 2008). Since the OBDII data only recorded event-and time-based latitude and longitudinal GPS points along a route, this dissertation will only use the available absolute GPS coordinates in the R^I of each participant. The *estimated route familiarity* at the trip features level can be determined by the similarity measured by the overlap of the probability density function (pdf) for the GPS latitude and longitude points between the target route and reference routes (Eq. 5).

$$F_{Pform}(R_t) = \frac{similarity(R_t)}{\sum_{j\in R^I} similarity(R_j)} \in [0,1] \tag{5}$$

Where,

$similarity(R_t) = \frac{\sum pdf(R_t|R^I)}{|R_t|}$ – average similarity across GPS latitude and longitude points

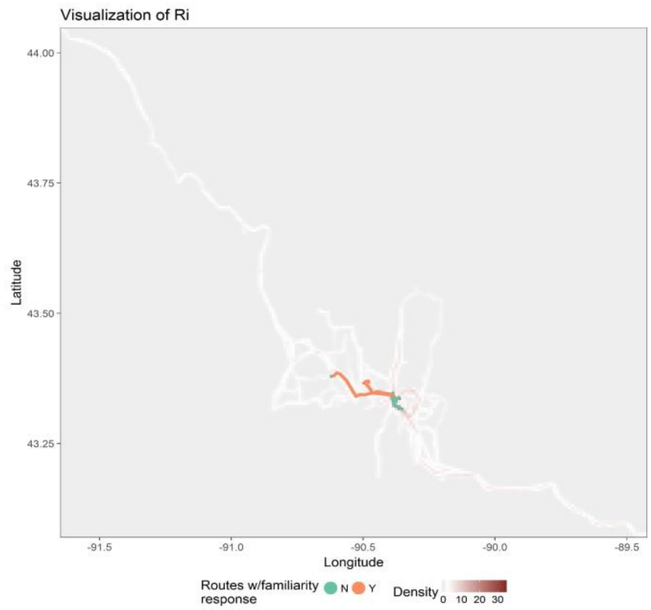
R_t – target route

R_j – route in reference set

Previous studies have mainly focused on matching GPS traces based on the degree of GPS overlap between two or more routes (Payyanadan, Sanchez, et al., 2016). But overlap measures tend to be binary, and does not provide further information on whether the route is close in terms of distance to another route. To account for closeness between routes, a bivariate kernel density estimation (KDE) approach was used (Downs, 2010). KDE quantifies the spatial intensity of each latitude and longitude GPS point using a kernel function, and then weights the contribution of the latitude and longitude points based on their distance from other GPS points (Silverman, 1986). Thus, every latitude and longitude has a density estimate.

The bivariate KDE approach provided a better understanding of whether a route driven was closer to a certain neighborhood or location of another route. Because the GPS traces were sparse and event-dependent; using KDE made the comparison calculation more suitable. Additionally, the KDE could be normalized, allowing it to align with the proposed AH mathematical structure.

And to ensure that the grid representing all the routes was computationally feasible, a fixed kernel bandwidth (Silverman, 1986) of 200 units was found to be the optimal value. Visual representation of the R^I using KDE for level 5 are shown in Figure 8.



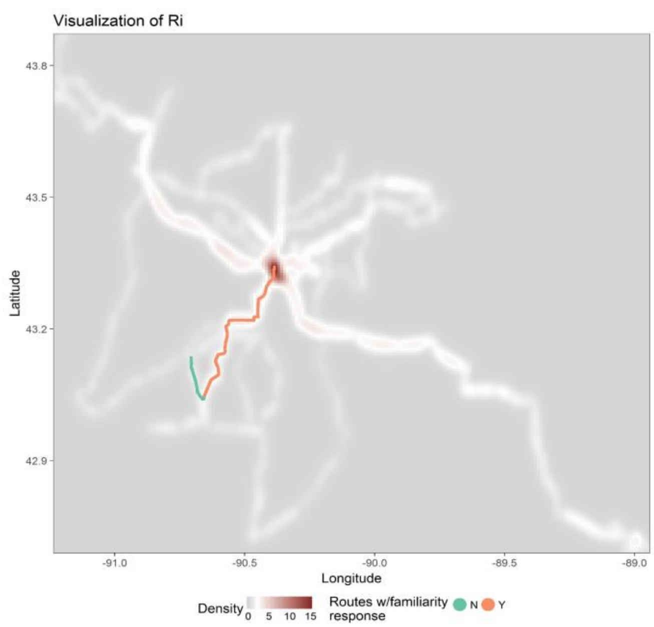


Figure 8: Examples of kernel density estimation to calculate the route density for each R^I

To calculate similarity of a route using KDE, where each latitude and longitude point has a density; similarity of the target route to the reference routes was determined by the mean kernel density of all points in the target route. The mean versus the sum was chosen because the sum would imply that very short routes would be less similar than longer routes. The normalized kernel density of the target route was then calculated by dividing it by the sum of the mean kernel densities of all the routes in the reference set.

4.3.3 Models, Analyses, and Assumptions for calculating and validating estimated route familiarity

The *estimated route familiarity* using the AH framework will be operationalized by measuring the relationship between the probability that a route is familiar and a linear combination of the five AH levels: trip purposes, travel conditions, driving challenges, properties of the driving environment, and trip features similarity; so that the influence of similarity on one level of the hierarchy is independent of the value of similarity at other levels in the abstraction hierarchy.

For this dissertation, there are two values of drivers' familiarity. *Stated familiarity* taken directly from the Trip Diary feedback responses, refers to the self-reported responses on familiarity with the driven and alternate low-risk suggested route. And e*stimated route familiarity* developed by mapping the OBDII data recorded from older drivers trips to the results of the content analysis conducted on the Trip Diary feedback responses. An important motivation for developing the *estimated route familiarity* is that it could help eliminate the need to continuously sample participant familiarity responses.

But it is unknown which levels of the AH are most closely related to stated route familiarity, raising two important questions: *How well do the levels of the AH explain the differences in the participants familiarity responses?* and *How well does the estimated route familiarity perform on a test data set?* To answer these questions, logistic regression is used to a) determine the predictability of the stated familiarity using the levels of the *estimated route familiarity* as inputs; and b) the effect size of the coefficients for each of the levels of AH will be used to determine the relationship with stated familiarity.

Since stated familiarity is binary, the appropriate way to relate the levels of the proposed *estimated route familiarity* to stated familiarity is through the log odds of the probability of a route being familiar based on a the linear combination of the similarity constructs. This relationship can be represented in Eq. 1 as follows,

$$\log\left(\frac{\mathrm{P}(\mathrm{F}(\mathrm{R_j})=1)}{1-\mathrm{P}(\mathrm{F}(\mathrm{R_j})=1)}\right) = \sum_{k=1}^{5} \beta_k S_k(R_j) \tag{1}$$

Where,

k – Index for the 5 similarity constructs

F – Stated familiarity response of route j

β – Coefficient relating the effect of similarity k on stated familiarity

S_k – Value of similarity k

For the analysis, there are a number of model assumptions that need to be specified as the AH framework represents both characteristics of the driver and the driving environment, as well as subjective interpretation of the environment and preferences of the driver. Model assumptions are as follow:

- The effect of the similarity levels on stated familiarity is independent of the value of the other levels
- Stated familiarity is a binary variable
- Estimated familiarity of route i is independent of estimated familiarity of route j once the similarity of all the levels for route i and j are taken into account,

$$f\left(R_i \middle| S_F, S_A, S_G, S_{Pfunction}, S_{Pform}\right) \perp f\left(R_j \middle| S_F, S_A, S_G, S_{Pfunction}, S_{Pform}\right)$$

- There exists a linear relationship between the log odds of stated familiarity and some function of each of the levels of similarity.

The logistic regression results will be supported with sensitivity analyses (cross-validation and ROC curves). Inferences will be conducted on the coefficients to determine the estimated effect of the levels of familiarity on stated familiarity. Coefficients will measure the estimated change in the log odds of stated familiarity based on the unit change of each of the hierarchy levels.

4.4 Results

The results section is divided into five parts. The first section shows the summary of the trips driven, driving behaviors, route choice, and stated familiarity responses of older drivers in the study. The second and third section provides details of the computational checks for calculating the *estimated route familiarity* and predicting stated familiarity at each AH level, and with all the levels. The fourth section explores the ability for *estimated route familiarity* to predict stated familiarity with the presence and absence of driver's identities. And the final section sheds light on the reasons for choosing a mean-centered *estimated route familiarity* measure for our analyses.

4.4.1 Trips driven by older adults and the stated route familiarity

A total of 44,816 trips were driven over a six-month period by 32 drivers 65 years and older, with a total of 25,390 unique trips. Older adults in the study had a mean speed of 45 miles/hr, 0.50 hard braking events, 3.5 hard cornering events, 89 hard acceleration events, and 0.3 seatbelt violations. While all the participants provided *yes* stated familiarity responses, only 14 participants gave a *no* stated familiarity response as well. Thus for the analyses, only data of 14 participants were used.

4.4.2 Predicting stated familiarity using the estimated route familiarity at each AH level

For each of the AH levels, logistic regression was used to predict stated familiarity, using the levels of the *estimated route familiarity* as inputs. The effect size of the coefficients for each of the AH levels were used to determine the relationship with stated familiarity.

At the *trip purpose level 1,* there were 465 unique trip purposes. Based on the trip destination, each unique trip was categorized into one of 8 codes defined by the National Household Travel Survey (Santos et al., 2011): home, residence, school, medical, church, social/recreational, errands, unknown, and NA. Of the 8 coded purposes, travelling home comprised 34% of the total trip purposes, followed by 31% for running errands such as grocery shopping, and 18% for visiting family and friends. Trip were not analyzed for multiple purposes.

Similarity between trip purposes was determined by the percentage of times the target route's trip purpose was in the reference set. Frequency of trip purposes for each participant was calculated, representing the application of the mathematical framework for the trip purpose level on R^I. This results in the *estimated route familiarity* at the purpose level. Results from conducting a logistic regression with logit link using the *estimated route familiarity* at the trip purpose level (Figure 9) revealed that there was no significance on stated familiarity at the 95% confidence level (odds ratio lift per 1 standard deviation change in level 1 estimated route familiarity = 0.97, CI = (0.74, 1.26), SD = 0.16). The lack of significance could be due to the fact that the NHTS survey may not provide enough granularity in assessing the trip purposes; and the trip purposes were only coded based on the destination, rather than using the O-D pair.

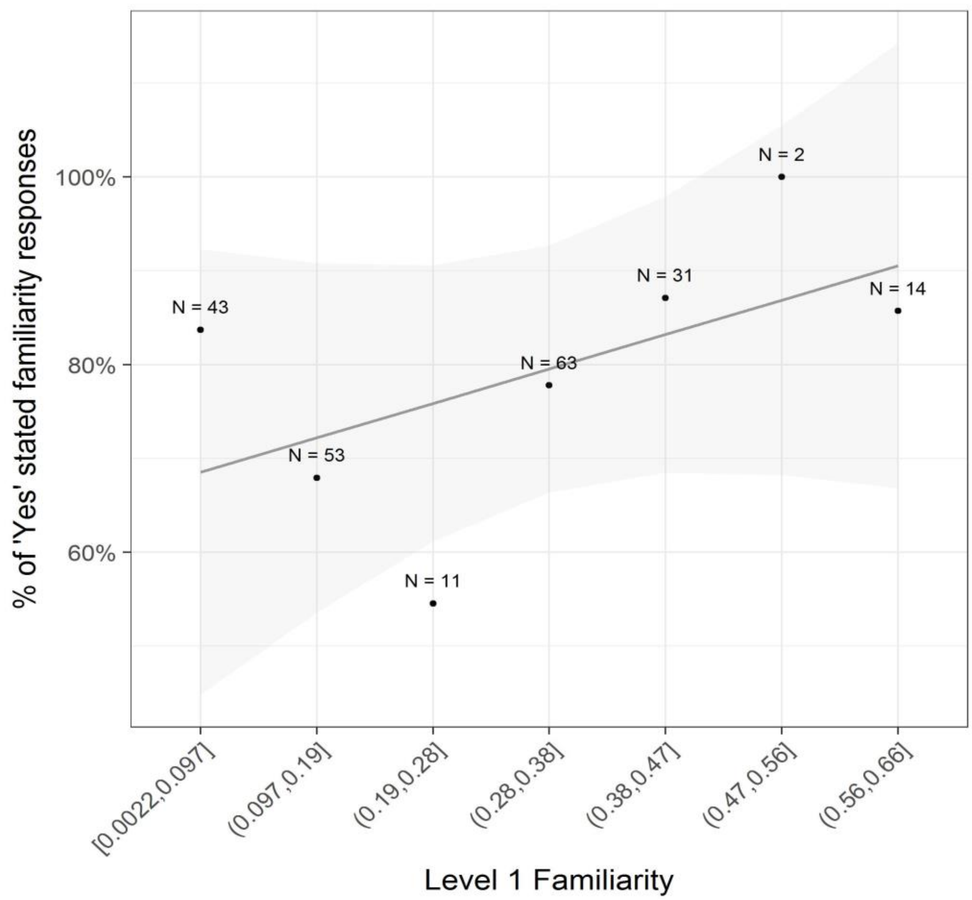


Figure 9: The large confidence interval around the slope shows there is an inconsistent relationship between *estimated route familiarity* at the purpose level and stated familiarity. The *N* labels represent the number of routes that fell into each interval of *estimated route familiarity* at the purpose level.

For each trip, the alternate routes generated by Google and MapQuest were assessed for the *fastest* or *safest* alternative. At the *travel conditions level 2*, each trip was then classified as being more similar to the *fastest*, *safest*, or *other* route; where a route was classified as *other* when the *safest* and *fastest* route were identical, or when the driven route had zero overlap with either the *safest* or *fastest* route. This classification represented the choice of ordering the travel conditions criteria for level 2.

Similarity between travel conditions was determined by the percentage of times the target route's travel conditions criteria was in the reference set. Frequency of the travel conditions criteria for each participant was calculated, representing the application of the mathematical framework for the travel conditions level on R^I. This results in the *estimated route familiarity* at level 2. Results from conducting the logistic regression with logit link using the *estimated route familiarity* at level 2 (Figure 10) revealed that there was a significant effect on stated familiarity at the 95% confidence level (odds ratio lift per 1 standard deviation change in level 2 estimated route familiarity = 1.46, CI = (1.12, 1.9), SD = 0.12).

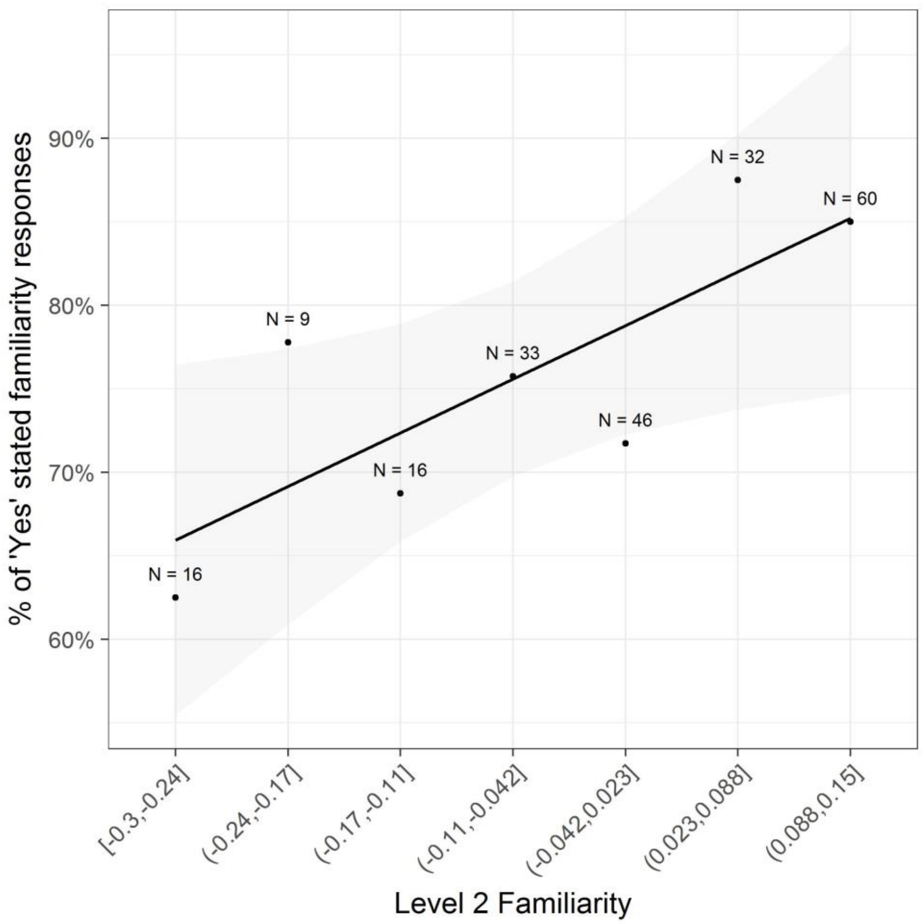


Figure 10: The confidence interval around the slope shows there is a significant relationship between *estimated route familiarity* at the travel conditions level and stated familiarity. The *N* labels represent the number of routes that fell into each interval of *estimated route familiarity* at the travel conditions level.

At the *driving challenges level*, multiple driving behaviors representing driving challenges – hard acceleration, hard braking, harsh cornering, seatbelt violation, and speeding were available. Frequency of each of the driving challenges for each participant was calculated, representing the application of the mathematical framework for the driving challenges level on R^I. This results in the estimated route familiarity at level 3. Only hard acceleration and speeding events were used for the analysis because these were the only driving challenges that had enough variability in driver behavior to warrant estimation. The similarity between hard acceleration and speeding events were determined by the percentage of times these driving challenges in the target route were in the reference set. Fitting the logistic regression with logit link using the *estimated route familiarity* at level 3 (Figure 11) revealed an effect of level 3 familiarity on stated familiarity (odds ratio lift per 1 standard deviation change in level 3 familiarity = 1.46, CI = (1.09, 1.96), SD = 0.11).

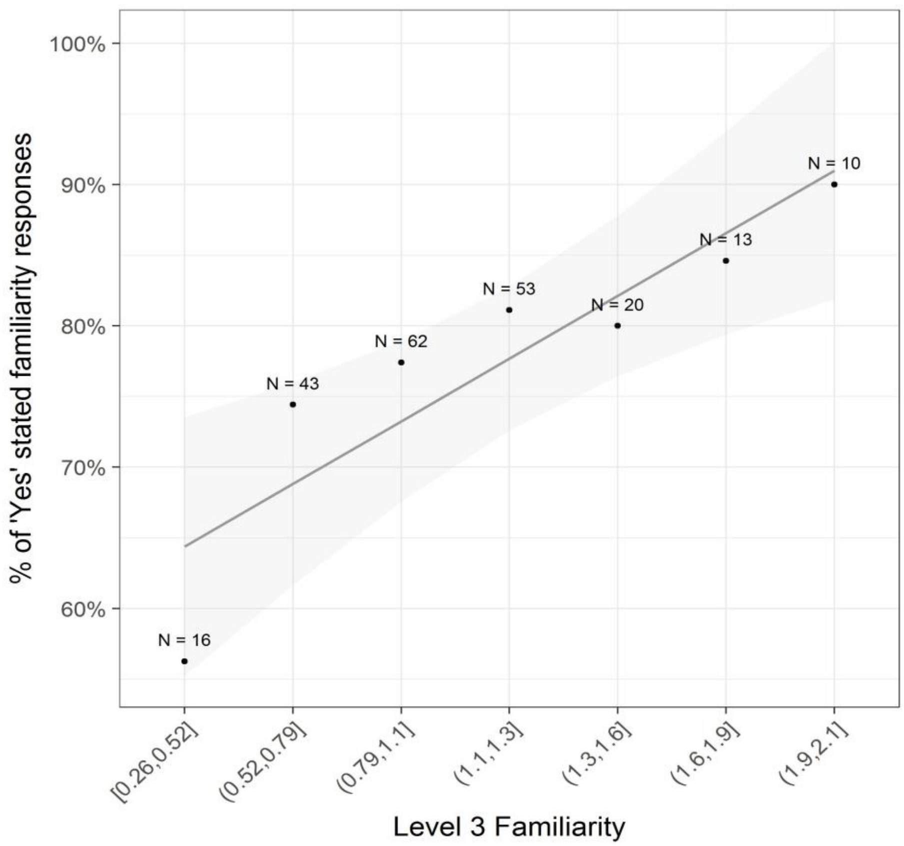


Figure 11: The confidence interval around the slope shows there is a significant relationship between *estimated route familiarity* at the driving challenges level and stated familiarity.

At the *trip features level*, first the density for each GPS point of the participant within a single route was calculated (Figure 12). In Figure 12, the vertical dashed line represents the mean density for a single route. This was followed by calculating the raw mean density for all the routes of each participant and normalizing the mean density. These steps were conducted for all participants for *estimated route familiarity* at level 5.

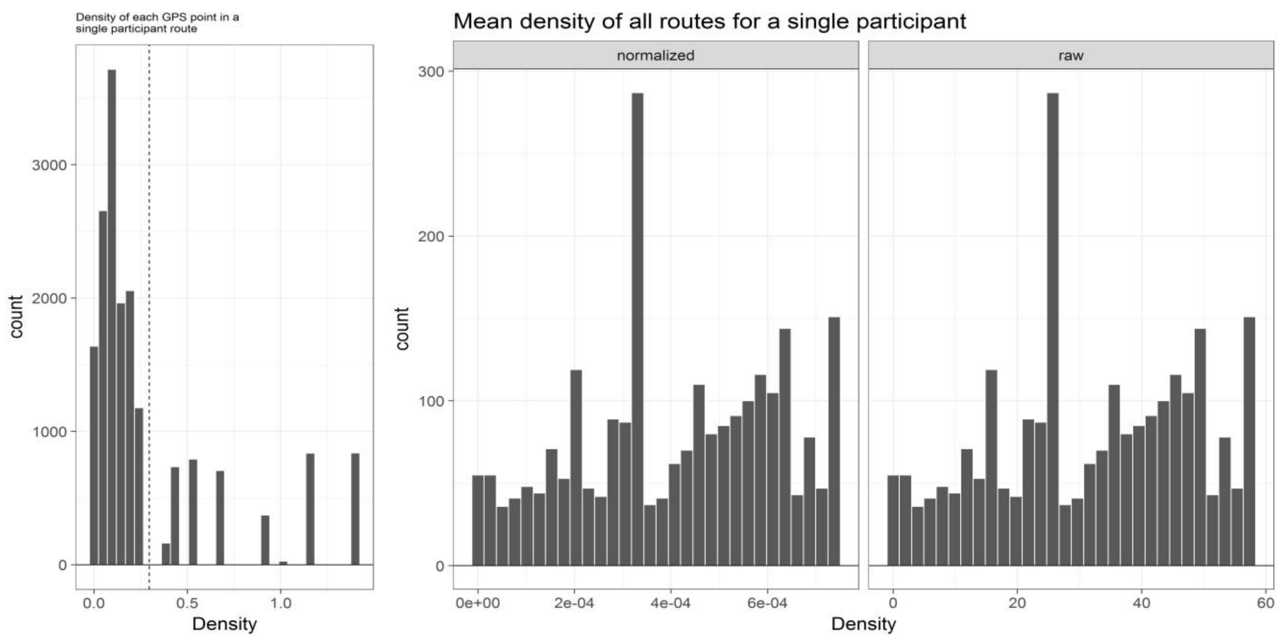


Figure 12: Representation of the computational checks and steps for calculating the *estimated route familiarity* at the trip features level.

The similarity in the trip features were determined by the percentage of times the features in the target route was in the reference set. Results from conducting the logistic regression with logit link using the *estimated route familiarity* at level 5 (Figure 13) revealed that there was a significant effect on stated familiarity at the 90% confidence level (odds ratio lift per 1 standard deviation change in level 5 familiarity = 1.33, CI = (1.01, 1.75), SD = 0.17).

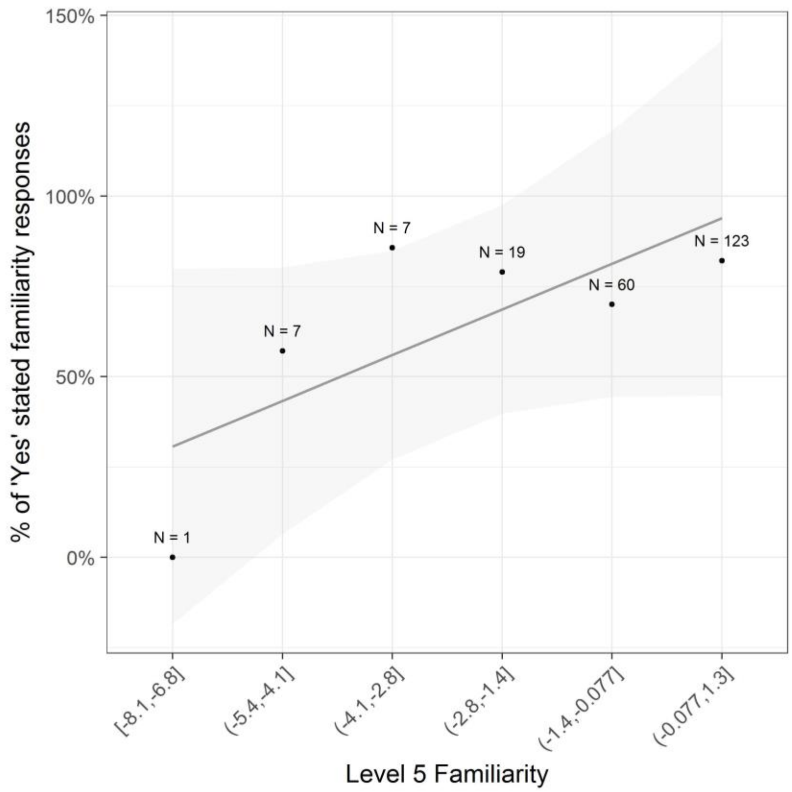


Figure 13: The confidence interval around the slope shows a weak relationship between *estimated route familiarity* at the trip features level and stated familiarity.

4.4.3 Predicting stated familiarity using estimated route familiarity with all AH levels

Before conducting the logistic regression, a test for correlation between the AH levels was conducted. Results are shown in the correlation matrix in Table 17. Only level 5 had a significant correlation with the levels 2 and 3. All other correlations were not significant.

Table 17: Upper diagonal correlation matrix between AH levels

	Level 1	Level 2	Level 3	Level 5
Level 1	1.00	0.09	0.11	-0.05
Level 2		1.00	0.05	**0.26***
Level 3			1.00	**-0.17***
Level 5				1.00

Logistic regression model predicting stated familiarity using all the AH levels as predictors was fit. Compared to the null model, the Chi-squared test conducted for the *estimated route familiarity* model was shown to be significant (p-value < 0.001, 12.59, 4 DOF). Figure 14a shows the regression coefficient and their standard errors, where AH Levels 2 and 3 were significant at the 0.05 and 0.1 levels, respectively. In addition, a Chi-squared test was also conducted to determine if there were interaction between the levels and their association with stated familiarity. Results (Figure 14b) showed that none of the interaction coefficients were significant, and the interaction model failed to reject the Chi-squared test (p-value > 0.10, 2.8, 6 DOF) when compared to the non-interaction model.

A

	Estimate	Std. Error	Z Value	Pr(>|Z|)
(Intercept)	-1.53	0.75	-1.38	**0.06***
Trip purpose level 1 estimated familiarity	0.23	1.10	0.95	0.44
Travel conditions level 2 estimated familiarity	0.98	1.38	1.89	**0.08****
Driving challenges level 3 estimated familiarity	1.10	0.48	2.32	**0.02****
Trip features level 5 estimated familiarity	0.53	0.13	1.63	0.11

B

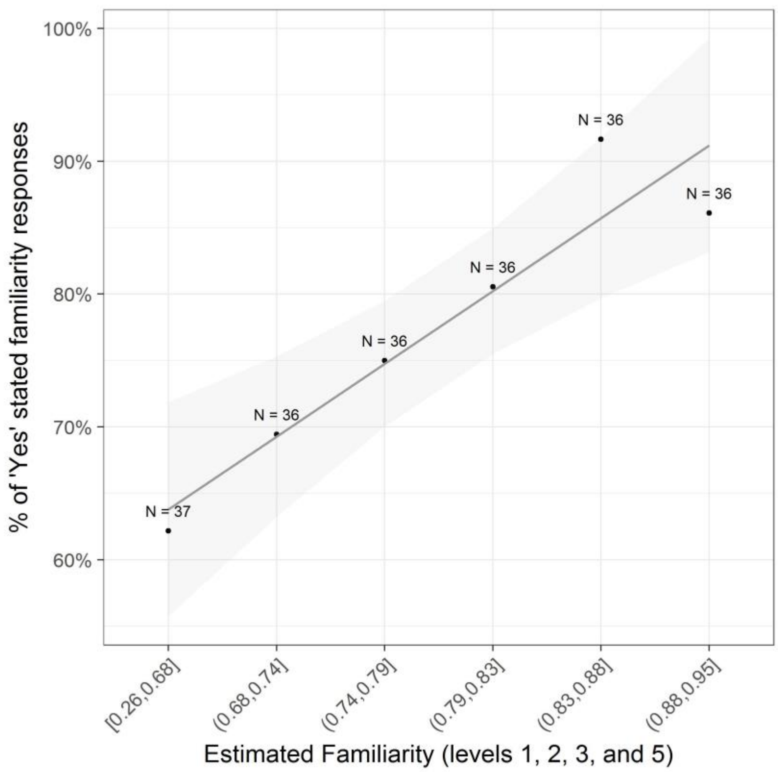


Figure 14: A) Regression coefficients and the standard errors. B) Plot showing the estimated route familiarity using all the AH levels against stated familiarity responses.

To test the ability of the *estimated route familiarity* measure to differentiate between *yes* and *no* stated familiarity responses, a receiver operating characteristics (ROC) analysis was conducted (Figure 15). ROC curve and analysis provides a graphical representation of the relationship between sensitivity and specificity and helps decide the optimal model through determining the best threshold for the diagnostic test (Zhu, Zeng, & Wang, 2010). While sensitivity is the proportion of true positives that are correctly identified by the diagnostic test; specificity is the proportion of true negatives correctly identified by the diagnostic test. The threshold provides a measure of accuracy – how correctly the diagnostic test identifies and excludes a given condition. The ROC analysis resulted in an AUC of 0.67, implying that there are viable trade-offs for predicting unfamiliar routes. Based on the AUC = 0.67, we describe a scenario where a navigational system can provide route options under three settings depending on the trade-off between the rate of identification and degree of accuracy of familiar and unfamiliar routes.

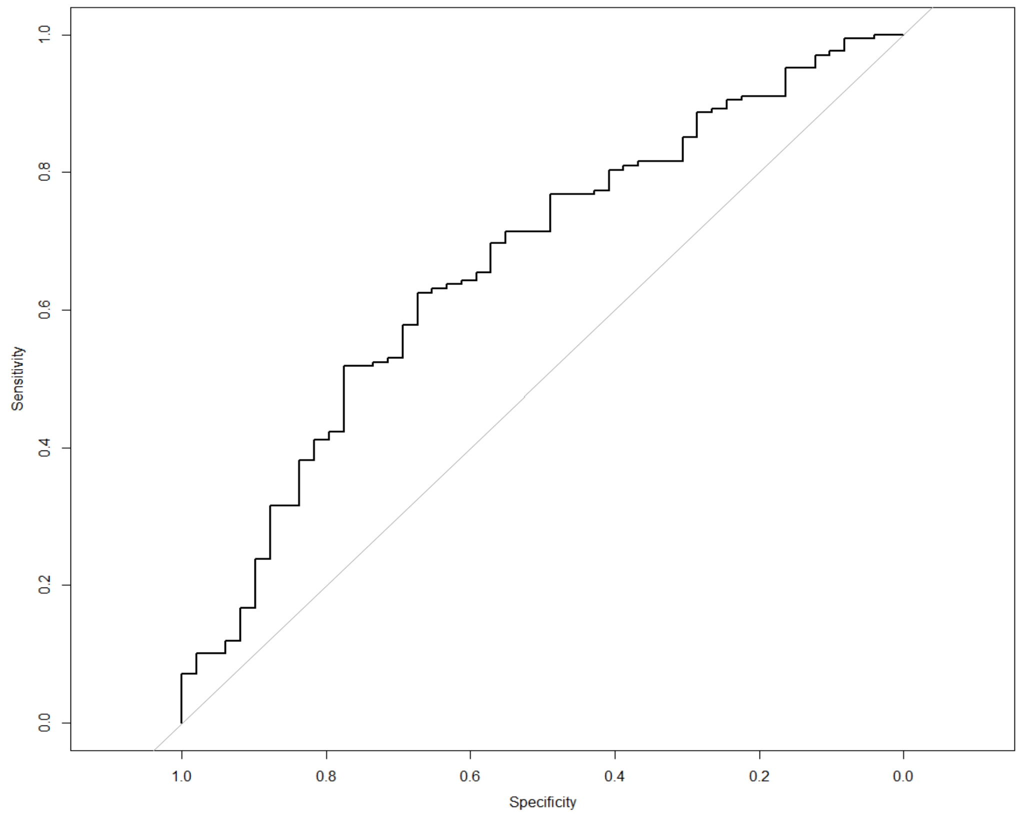


Figure 15: ROC curve for *estimated route familiarity*

Setting 1: Low rate of identification but high degree of accuracy (Table 18)

When the threshold for *estimated route familiarity* is less than 50%, the navigational system will rarely provide a suggestion for unfamiliar routes (< 1%). But when the system provides a suggestion, it is highly likely that the route is truly unfamiliar to the driver. That is, about 4% of unfamiliar routes will be correctly identified by the system.

Setting 2: Medium rate of identification and medium degree of accuracy (Table 18)

When the threshold for *estimated route familiarity* is less than 60%, the navigational system will occasionally provide suggestions for unfamiliar routes (~ 5%). But when the system provides a suggestion, it is 50% likely that the route will be truly unfamiliar to the driver. That is, about 12% of unfamiliar routes will be correctly identified by the system.

Setting 3: High rate of identification, but low degree of accuracy (Table 18)

When the threshold for *estimated route familiarity* is over 77%, the navigational system will be able to regularly provide suggestions for unfamiliar routes (~37%). But when the system provides a suggestion, 35% of the time the route will be truly unfamiliar to the driver. That is, about 57% of unfamiliar routes will be correctly identified.

Table 18: Settings 1, 2 and 3 to differentiate between unfamiliar and familiar routes

SETTING 1		Estimated route familiarity		Estimated route familiarity ability to identify stated familiarity
		No	Yes	
Stated familiarity with driven route	*No*	2	47	0.04
	Yes	0	168	1.00
	% correct	1.00	0.78	

SETTING 2		Estimated route familiarity		Estimated route familiarity ability to identify stated familiarity
		No	Yes	
Stated familiarity with driven route	*No*	6	43	0.12
	Yes	5	163	0.03
	% correct	0.55	0.21	

SETTING 3		Estimated route familiarity		Estimated route familiarity ability to identify stated familiarity
		No	Yes	
Stated familiarity with driven route	*No*	28	21	0.57
	Yes	52	116	0.31
	% correct	0.35	0.15	

The results in sections 4.4.2 and 4.4.3 use only information from the driving data, R^I, where individuals were not identified in the population. It would also be interesting to determine whether the *estimated route familiarity* measure holds under the condition where we use the identity of individuals in the population, along with *estimated route familiarity* to predict stated familiarity.

4.4.4 Prediction of stated familiarity using estimated route familiarity and driver identity

For the condition where the driver's identities were used to determine whether we could improve on the prediction of stated familiarity using *estimated route familiarity*, a model with only the driver's identities was used; resulting in an AUC of 0.75. Then the *estimated route familiarity* was added in with the identities, resulting in an AUC of 0.81. This improvement implies that under the hypothetical scenario, navigational systems could be further improved on their familiar and unfamiliar route identification and accuracy if drivers occasionally provide feedback on their route familiarity.

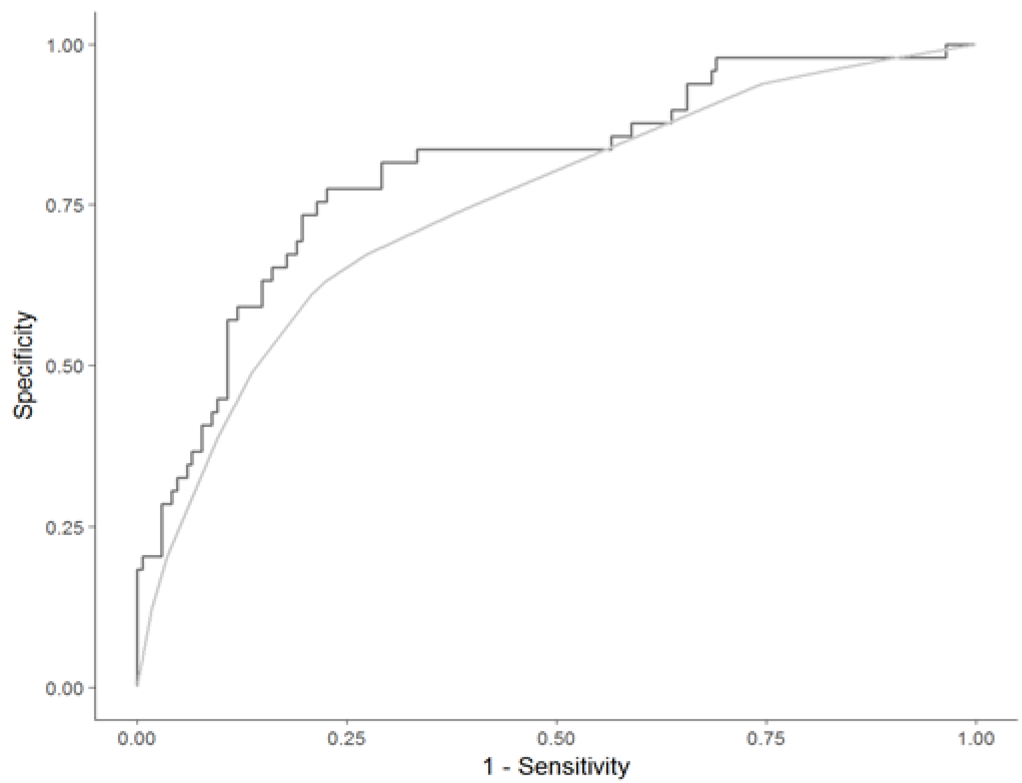


Figure 16: ROC curve for *estimated route familiarity* with drivers identified

4.4.5 Absolute versus relative estimated route familiarity

In the analyses conducted in sections *4.4.3* and *4.4.4*, *estimated route familiarity* for each of the AH levels were mean-centered at the participant level to conduct the logistic regression to predict stated familiarity. Here, mean-centered is simply the difference between a given familiarity and the mean *estimated route familiarity* of a driver. The rationale for using mean-centered *estimated route familiarity* is due to the possibility that familiarity is a *relative* judgment rather than an *absolute* judgment (Fox & Levav, 2000). For example, *absolute judgement* is when a driver who is 70% familiar with their reference routes will have a higher rate of *yes* stated familiarity responses than a driver who is 25% familiar with their reference routes. Whereas *relative judgment* is when in the same situation, the drivers will have an equal proportion of *yes* stated familiarity responses. In this case, the driver with a 70% average familiarity is more likely to mark a route with 40% familiarity as ‘unfamiliar’. Whereas a driver with a 25% average familiarity is likely to mark a route with 40% familiarity as ‘familiar’. Figure 17 shows a histogram of the absolute and relative judgement of participants in the study, where relative is the mean-centered *estimated route familiarity*. Results in Table 19 and Figure 18 showed that for all the AH levels, relative judgment is best supported by the data.

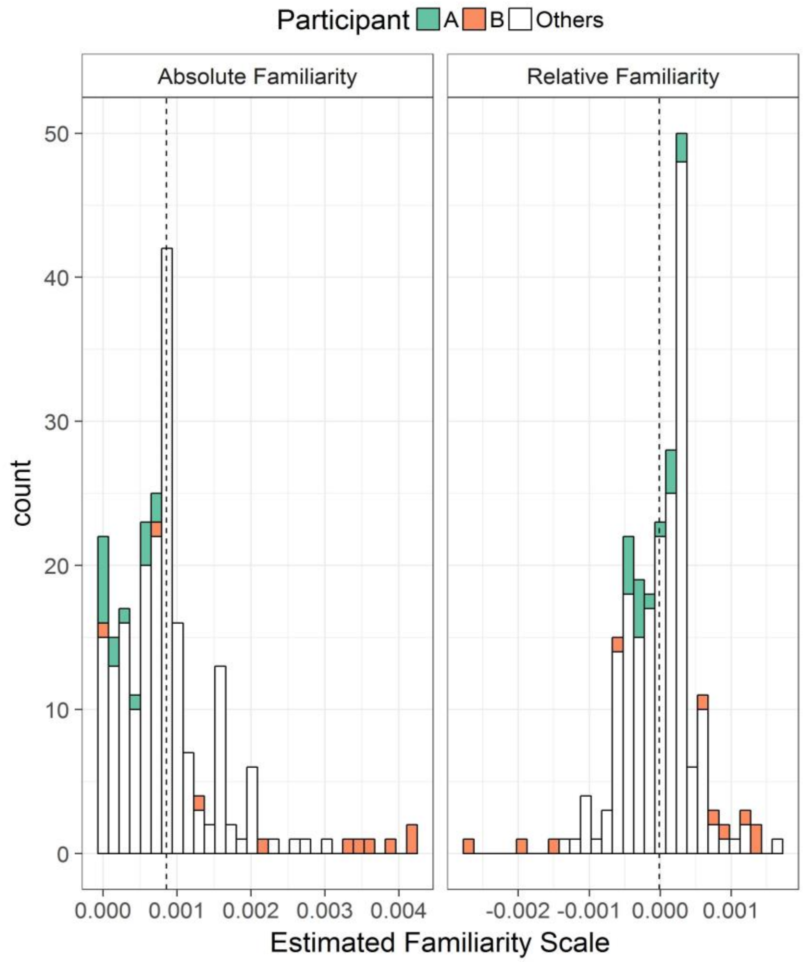


Figure 17: For absolute judgement, the participants *estimated route familiarity* were congregated to the right or left of the center. For relative judgement, mean-centering allowed each participant to be centered in the histogram.

Table 19: logistic regression to test which judgement best supported the data

	Absolute judgment		Relative judgment	
	Logit(stated familiarity) ~ L1.abs + L2.abs + L3.abs + L5.abs		Logit(stated familiarity) ~ L1.rel + L2.rel + L3.rel + L5.rel	
Coefficient	Estimated Value	P-value	Estimated Value	P-value
Intercept	-0.24	0.73	-1.53	**0.06***

Level 1	1.18	0.27	0.23	0.44
Level 2	3.55	**0.009*****	0.98	**0.08***
Level 3	0.24	0.85	1.10	**0.02****
Level 5	-1.09	0.21	0.53	0.11

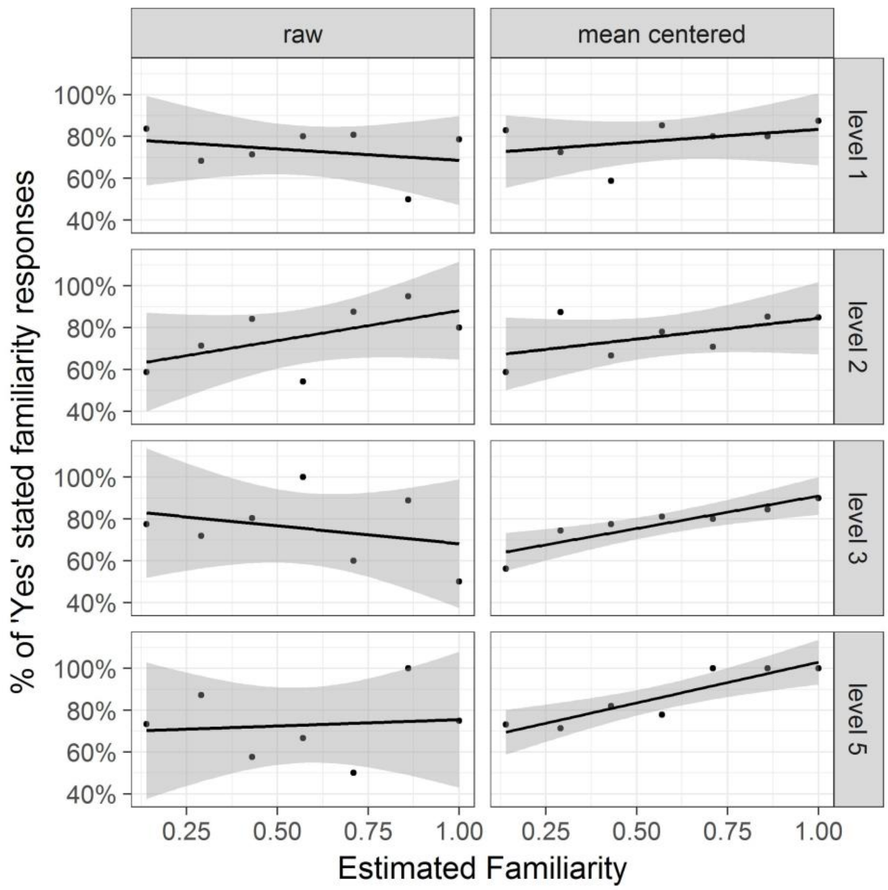


Figure 18: Mean-centered *estimated route familiarity*

4.5 Discussion

By introducing a theoretical and mathematical framework for describing route familiarity, this dissertation addresses an important question: *Can a measure of familiarity, defined by features of trips considered at five levels of abstraction, be used to predict a driver's familiarity* *with a route?* To address this question, in the following sections we attempt to highlight the importance and limitations of the framework proposed for describing route familiarity, and the implications of our analyses conducted to establish *estimated route familiarity*.

4.5.1 The theoretical and mathematical framework for describing route familiarity

The AH framework is a useful representation for route familiarity as it provides both a static and scalable view of the dynamic processes involved in understanding familiarity and its influence on route choice behavior (Jones, 2016). To determine the usefulness of the proposed AH framework describing route familiarity and the attempt to operationalize *estimated route familiarity*, we first address the utility and limitations of the framework. The following discussion reflects some of the uses and challenges of the theoretical AH framework, and grounds for future work.

Levels of the abstraction hierarchy: The framework uses a complex approach that attempts to reflect the influence of familiarity on route choice using the driving activities and stated preferences of the driver. In the framework, assumptions are made about the stated familiarity, and observed (route driven, direction of travel, sequence of events) and unobserved (purpose, constraints) activities of the driver – represented as features within levels of the AH framework. An important challenge for such a framework is that the probability of a feature being a member of a particular AH level to describe familiarity is mainly judged on the basis of how representative the feature is of the level (Lind, 1999). For example, features such as *fastest* and *safest* route, although not directly associated with route familiarity, represented criteria chosen by older adults (see Payyanadan et al., 2016) as reasons for preferring a familiar route. Thus the framework does not require that every input into each of the AH levels be a direct feature of route familiarity, rather it has a less restrictive requirement in that the inputs at each level simply be associated with familiarity. Additionally, the goal of the AH framework is to estimate route familiarity using naturalistic driving data. This can place a high demand on data validation, and may bias the base rate probabilities of the representations within a familiarity level (Jacko, 2012). Lastly, the abstraction hierarchy levels are *fixed* – creating a stable environment for parameter estimation and implementing value learning algorithms; but suffers from increased computational complexity. Whereas *adaptive* abstractions can enable algorithms to find abstraction levels that can adapt to the current state, or by aggregating parts of the model by grouping levels – allowing model minimization (Van Otterlo, 2009).

Representations within the levels of the abstraction hierarchy: There are a number of limitations that arise from the availability or lack of information. Information needed for developing such multi-level models can be greatly limited by the sensor technology suite, affecting the reliability, usability, and integrity of the information needed for capturing the different feature representations within the AH levels (Vicente & Rasmussen, 1992). But there are also concerns that arise as more information is added to the representations, and as they become more specific within each of the AH levels. Firstly, it can produce high specificity among the features that might be unrelated to the baseline preference of the user, decrease the meaningfulness of the feature, and result in choices that are inconsistent with user preferences (Laran & Wilcox, 2011). Secondly, increased representations and feature complexity can bias analyses measuring the strength of similarity on the familiarity levels. Thirdly, greater representations can lead to shared attributes resulting in cross-correlation. This in turn can lead to erratic coefficient estimation, and dilute the robustness of estimating the effect of individual features of the model on familiarity. Additionally, recent work has highlighted the limited understanding of whether the source of the variances from individual-specific constructs such as familiarity and route choice are from *preference heterogeneity* and/or *process heterogeneity*. Where *preference heterogeneity* refers to the different preferences based on the context, situation, or experience; and *process heterogeneity* refers to the different decision rules used to implement the preference attributes (Johnson, Hardie, Meyer, & Walsh, 2006). Future work could shed light on how often these challenges may occur in practice.

Values and membership of the features: A number of features are incorporated within the levels of the AH framework such as directionality of the trip, purpose, etc. But there is no clear understanding of the order or ranking of these criteria within each of the AH levels, and whether order is important. While the proposed AH mathematical framework provides structure for incorporating ranking of criteria and estimating its importance; determining ranking or ordering is needed, and future work could address the importance of ranking, and under what driving context and conditions. Studies conducted on ranking features or categories within AH levels has suggested increased dependency of the representations on the geographic context, thereby reducing the significance of the user's overall ranking and context (Zheng & Xie, 2011). Additionally, the representations captured from the feedback and preferences of older drivers are of varying generality – *safe, interesting*, which could be split into several lower-level attributes as well. Future work can explore better ways to characterize user feedback and description of preferences.

4.5.2 Estimated route familiarity

The formulation and quantifications that have been developed as theoretical and methodological contributions for assessing an estimate of route familiarity are preliminary, and require further refinement as highlighted in the limitations in this Chapter and future work in Chapter 5. Preliminary results showed that when only information from the driving data, R^I was used, and when individuals were not identified in the population, the *estimated route familiarity* was able to predict driver's familiarity with the route. This has important implications for the customization of route choice models for navigational systems, as it provides drivers with the opportunity to set their own thresholds for receiving important notifications along a route based on their familiarity with the route. For example, older drivers in general prefer avoiding unfamiliar routes (Payyanadan et al., 2016). Incorporating their relative *estimated route familiarity* measure in route choice models can help navigational systems provide a more customized, safer, alternate route suggestion that matches their route choice and driving preferences. Additionally, the ability to use the *estimated route familiarity* measure to determine whether a route is familiar or not can also be used to customize driver feedback by providing additional safety-related route information when driving routes that are unfamiliar.

Similar applications can be implemented for older drivers with mild to medium cognitive decline. Research has shown that older adults with Alzheimer's, Parkinson's, and dementia make fewer driving and navigation errors on familiar routes (Uc et al., 2009, 2004). The ability to use only driving data and individual R^Is to capture route familiarity provides a first step towards incorporating measures such as *estimated route familiarity* in route choice models and navigational systems for such drivers; and an opportunity to prolong their driving safety, mobility, and independence. From a design and information theory perspective, the opportunity to use different familiarity thresholds in recommending route alternatives can be used by navigational systems to reduce mind wandering and inattention often caused due to the monotonic nature of driving long and familiar routes (Martens & Fox, 2007; McKnight & McKnight, 1999), by providing alternate routes that are less familiar.

The goal of this chapter was to focus on developing a framework for describing and operationalizing a measure of route familiarity. The following Chapter focuses on some of the theoretical and practical applications of the proposed abstraction hierarchy theoretical and mathematical framework; and opportunities for using the *estimated route familiarity* as a measure of route choice behavior.

4.5.3 Study limitations

Older drivers were recruited for the study through a larger study (see Gustafson et al., 2015). But the sample of older drivers who volunteered for the study may not be representative of the older driver population, as the participants could be considered active drivers, interested in understanding their driving behavior, and already avoid risky driving situations. Additionally, the driving strategies and behavior recorded by the OBDII devices may not be representative of the driving behavior due to the Hawthorne effect from the devices in the vehicle.

There are a number of challenges and limitations with the analytical approach that need to be addressed due to the nature of the data recorded. A major limitation in the analyses was the constraint on the number of representations that could be used for measuring similarity within each of the abstraction levels. For example, at the trip purpose level, only trip purpose similarities were considered, as trip objectives and external limitations were not recorded. Each trip was recorded and analyzed only as a single, independent trip. It is possible to consider multiple-stop trips by assessing the number of trips taken in a day, and creating a time window of 30-40 minutes between O-D pairs to assume a multi-purpose trip.

At the travel conditions level, criteria was determined through analyses of open-ended feedback questions. Future work could develop better approaches for capturing and ranking the criteria of preferences. At the driving challenges level, due to the complexity involved in implementing the point of time at which the driving strategies occurred along a route, only the frequency of occurrence of the driving challenges were considered. Lastly, at the physical properties of the driving environment and trip features levels, the OBDII devices only captured GPS points based on events, limiting the availability of road and infrastructure data that could be obtained from whole GPS traces to develop additional representations within the hierarchy such as landmarks.

For each the AH levels, it could be argued that further data transformation could be done to extract information. For level 2, *fastest* and *safest* routes were selected as criteria important for fulfilling the trip purpose for older drivers. Based on different driver cohorts, these criteria could vary. For example, teenage and middle-aged drivers are known to prefer the shortest route, and willing to divert from their current route irrespective of their route familiarity. Similarly, for level 4, which was not included in the *estimated route familiarity* calculation; overlap in the sequence of turns could be extracted from the GPS traces, and used as a proxy for assessing level 4 *estimated route familiarity*. For level 1, trip purpose was determined by manual coding of the O-D pairs by the research team and assigning the destination as the trip purpose. Future work could include a questionnaire where drivers provide feedback of their trip purpose. And for level 5, only the densities of GPS traces were used, but other trip features such as scenery, etc. could be further investigated as separate elements within level 5.

4.6 Chapter summary

The proposed theoretical and mathematical AH framework describing route familiarity provides a useful first step towards an *estimated route familiarity* measure, which could help guide the development of better route choice models that can be customized to meet the specific route choice and safety needs of drivers. The implementation of such route choice models in driver support systems can have multiple benefits, such as the ability to include familiarity in the cost function for selecting routes so that the resulting routes are more likely to be accepted; used to update membership functions and ‘if-then’ rules in different scenarios based on the driver’s route familiarity; and to assist in both pre-trip planning and dynamic route choice feedback.

CHAPTER 5: FUTURE WORK

A driver's route choice behavior depends on their individual experience which has been accumulated through daily driving (Tanaka, Uno, Shiomi, & Ahn, 2014). For older drivers in particular, studies conducted to understand the factors that influence route choice behavior have shown that they tend to be risk averse. They prefer certain routes such as freeways (Madanat & Jain, 1997), driving during specific times of the day (Payyanadan et al., 2016), and driving familiar routes. Chapter 3 showed that route choice also depended on older driver's familiarity with the available alternate routes; where those more familiar with the alternate routes were less likely to change their route choice to a low-risk route. Additionally, limited work on route familiarity has suggested that habit, attention, and automation also interact with familiarity. Although not exhaustive, the following sections below provide insights on how the body of work presented in this dissertation can be further expanded to other research areas in Human Factors.

5.1 Assessing the role of recency and frequency on route familiarity

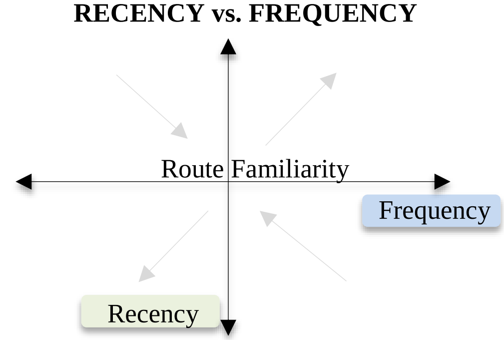
Most route choice models have used some measure of recency, frequency, or both to understand and predict route choice behavior. But recent work in route choice modelling has revealed that there are interactions between recency and frequency with other behavioral factors such as memory and information. Work by Ben-Elia and Shiftan (2010) showed that when drivers had route information, they were more likely to choose a route based on both the recency of route driven and long-run (memory) learning. Whereas in the absence of information, the decision to choose a route was based on the most recent route driven. Additionally, other studies in cognitive behavior have shown that there is interaction between recency and frequency, where the temporal order of frequency learning is positively biased towards the recency of the learning (Zhang, Johnson, & Wang, 1998).

Results from Chapter 4 showed that frequency and not recency influenced route familiarity. Using the AH framework for describing route familiarity, the relationship between recency and frequency can be further explored as shown in Figure 19. From Figure 19 we can hypothesize whether a) Recency, frequency, or both have a global effect on familiarity; and b) Recency, frequency, or both have a local effect on familiarity, where at each of the AH levels, a combination of recency and frequency has a different effect on familiarity.

ABSTRACTION HIERARCHY FRAMEWORK
For describing route familiarity

AH levels	Factors of route familiarity
Trip purpose	Purpose, objectives, external limits
Travel conditions	Safest, shortest, fastest
Driving challenges	Hard braking, accelerating, speeding
Physical properties of the driving environment	Turns, traffic lights, roundabouts
Trip features	Location, direction, origin, destination

RECENCY vs. FREQUENCY



INFLEUNCE OF RECENCY, FREQUENCY

AH levels	Familiarity	Recency	Frequency
Individual	Increase	Increase	Increase
Within	Decrease	Increase	Decrease
Combination	Increase	Decrease	Increase
All	Decrease	Decrease	Decrease

Figure 19: Hypotheses and relationships for testing the local and global effect of recency and frequency on familiarity to understand route choice behavior

5.2 Route choice and habit

Habit is commonly defined as *learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end states*

(Verplanken & Aarts, 1999). In the driving domain, a number of studies have observed the relationship between route familiarity and habit. Recent work by Vacca, Prato, and Meloni (2017) showed that the greater the habit of travelling along a certain route, the less likely drivers were willing to switch their route. Results from the content analysis conducted in Chapter 3 showed that despite providing older adults with shorter routes with fewer turns, *habit* was a reason for driving the preferred route; even though the preferred route had more turns, travel time, and distance. In economics, *habit* is distinguished from *choice*, where *habit* is a behavior that is performed repetitively and is considered automatic with conscious thought. Whereas *choice* is a behavior selected from a range of alternatives, and involves conscious deliberation.

Work by Duhigg (2013) in the *Power of Habit* reported that habit formation is influenced by a cycle of *reminder*, *routine*, and *reward*. *Reminder* is a cue or trigger that starts the habit; *routine* refers to the action taken in response to the reminder; and *reward* is the benefit from doing the habit. By using the feedback responses from older drivers who responded to a route being habitual, it is possible to focus on only routes labelled *habit* by participants and determine which of the AH levels might be triggered by the habit cycle.

5.3 Customizing driver support systems based on the driver's *estimated route familiarity*

Enabling driver support systems to adapt to the driver's specific needs, expertise, and knowledge of the road and road network can reduce burden on drivers by delivering only useful information about the route, and instructions for staying on the intended route. Having an estimate measure of a driver's familiarity with the route or road network can help determine the extent of a driver's familiarity with the route, and in turn help develop customizable driver support systems (DSS) such as navigational aids to not only provide better route alternatives, but also improve the delivery of route information by adapting the *information content* and *information presentation* of navigational systems to match the drivers' performance.

The categories of driving performance can be distinguished as three levels: *S*kill-, *R*ule-, and *K*nowledge-based performance (Rasmussen, 1983) for different levels of route familiarity. This *SRK Model* has been used extensively for describing the various mechanisms of driver's processing information, where *knowledge-based performance* involves analytical problem solving (slow, laborious, serial), and *skill-based performance* and *rule-based performance* involves perceptual processing (fast, effortless, parallel), and action, respectively (Wang, Hou, Tan, & Bubb, 2010). When considering different driving situations, it is important to determine how DSS technologies can enhance driving performance through efficient function modification and allocation.

5.4 Using estimated route familiar as a marker for assessing driver's situation awareness

Situation awareness (SA) is a *state of knowledge pertaining to the state of the dynamic environment*; and *situation assessment* is the process of *achieving, acquiring, or maintaining SA* (Endsley, 1995). Individual factors such as goals, preconceptions, knowledge, experience, training, abilities, and environmental factors are used to develop and maintain SA (Endsley, 1995). When SA is incomplete or inaccurate, research has shown that it is linked to poor driving performance; but can be addressed if drivers are aware of their lack of SA.

Current approaches to measuring SA have been through different task performances such as real-time probes, SAGAT – *situation awareness global assessment technique*, and *WOMBAT situational awareness and stress tolerance test* (Jones & Endsley, 2000; Strater, Endsley, Pleban, & Matthews, 2001). Despite the usefulness and broad application of SA in error analysis, safety, design, prediction, teamwork, and automation and workload; there have been concerns over the measurement approaches (Durso, Rawson, & Girotto, 2007), and the need for more naturalistic techniques to measure SA (Wickens, 2008).

Past research has shown that older drivers in particular prefer to drive familiar routes, but driving familiar routes can increase the number of risky driving behavior events among older drivers. This has been attributed to reduced attention and mind wandering when encoding a familiar driving environment (Martens & Fox, 2003, 2007; McKnight & McKnight, 1999).

Based on the work in this dissertation, it may be theoretically possible to assess whether a driver's SA can be determined through naturalistic driving data used to measure their *estimated route familiarity*. Figure 20 proposes an approach to mapping levels of *estimated route familiarity* to a driver's SA levels. We assume that there is an *ideal* one-to-one relationship between a driver's *estimated route familiarity* and SA levels. But due to *factors that limit SA*, a driver's *estimated route familiarity* might fall to the lower level – *observed* relationship. To establish the one-to-one relationship, We propose two hypotheses: a) Under SA that do not limit SA, high, medium, and low *estimated route familiarity* is correlated with SA level 3, 2, and 1 – *ideal relationship*; and b) Under situations that limit SA, *the estimated route familiarity* will be correlated with the immediate lower level of SA – *observed relationship*. The difference between the ideal and observed relationship can then be *bridged* by identifying and developing the factors that limit SA.

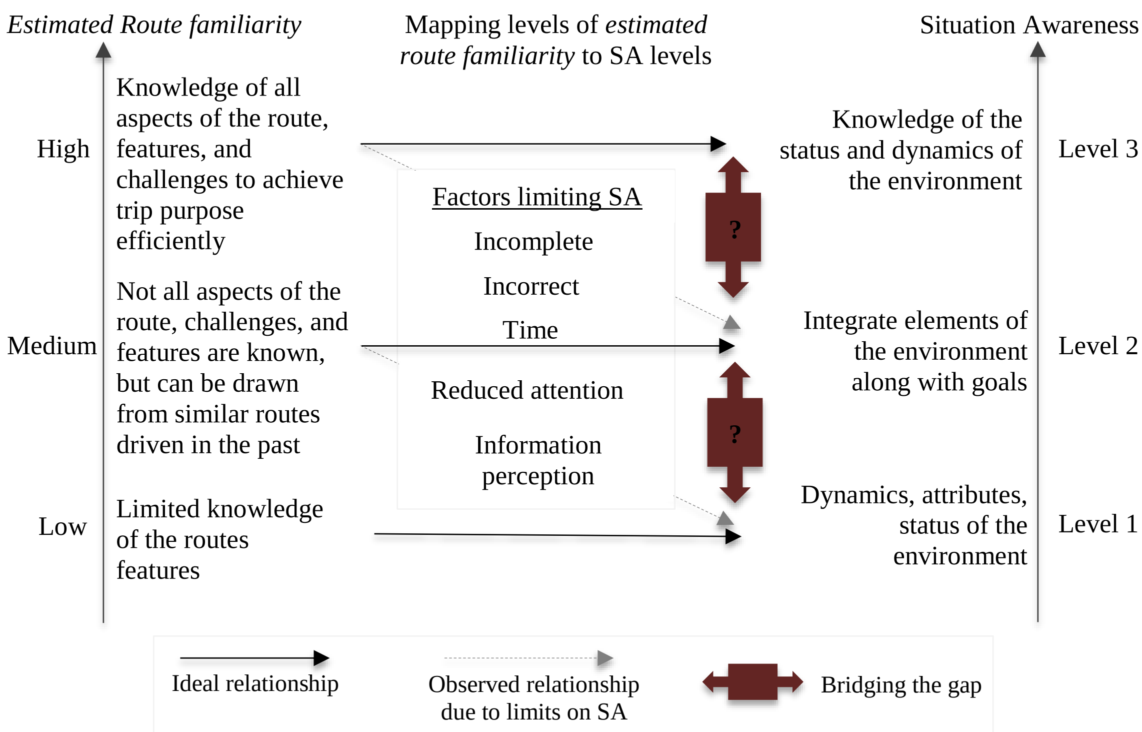


Figure 20: Framework for using *estimated route familiarity* as a marker of SA in the driving domain

5.5 Approach for improving route choice prediction using the perceptual cycle model

Extensive review conducted in this dissertation on the factors that influence route choice among older drivers has shown that older adults tend to avoid risky driving situations such as high volume traffic areas, routes with detours and traffic incidents, unfamiliar routes, poor weather conditions, etc. But results in Chapter 3 showed that route choice depended on a driver's familiarity with the alternate low-risk suggested routes. Additionally, factors such as habit, multiple errands, etc. influenced choice of route. Although the proposed AH framework for describing route familiarity provides insights into factors that influence route choice, it does not take into account the driver's decision making, knowledge base, or process of reaching the decision such as choosing a route. One approach is to incorporate the AH framework used for describing route familiarity into Neisser's (1976) process-oriented *perceptual cycle model* (PCM), which emphasizes the role that both schemata (internal mental templates), and world information play a role in governing actions, and decisions (Figure 21).

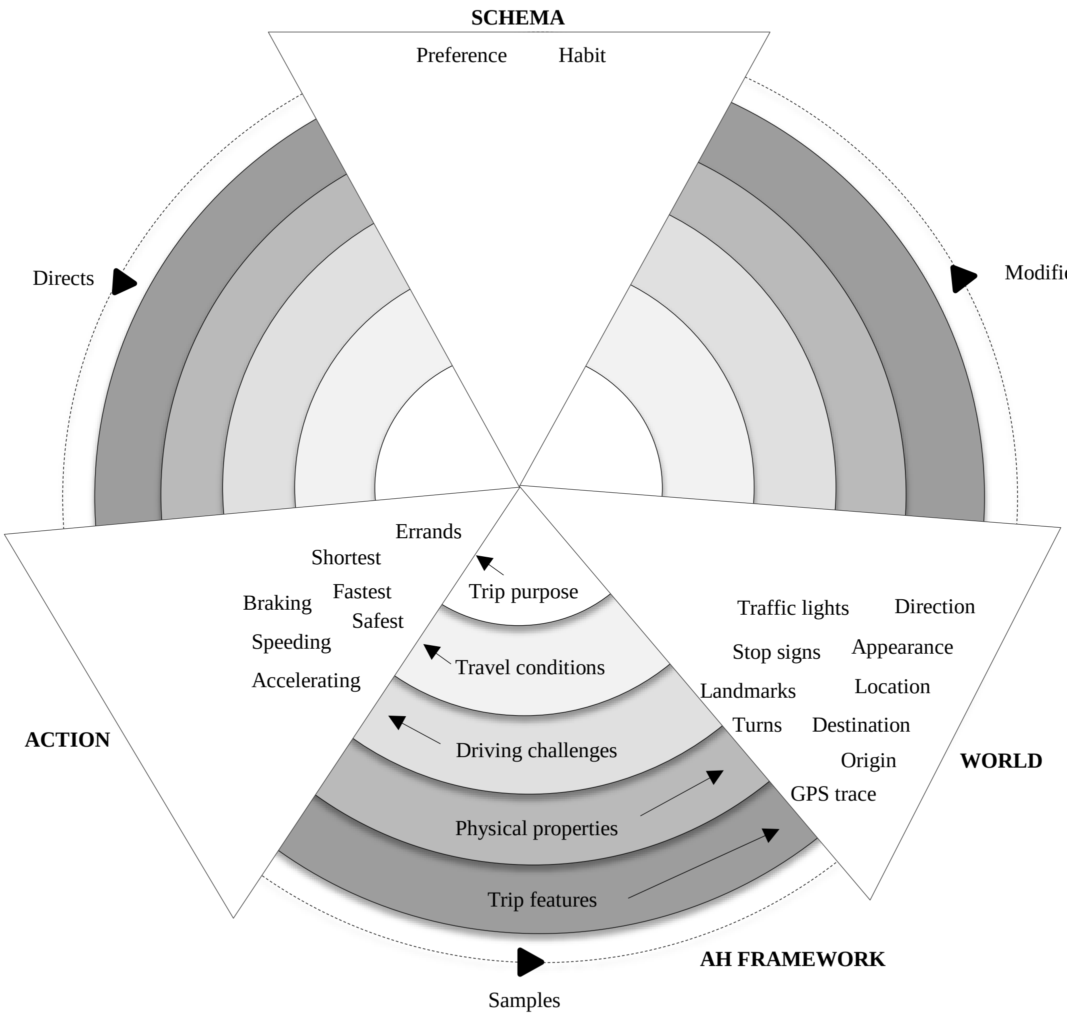


Figure 21: A modified *abstraction hierarchy perceptual model* using Rasmussen's (1986) and Neisser's (1976) model.

In the PCM model, the *schema* highlights the prior knowledge, experience, and expectations; the *action* refers to the actions conducted or potential actions that could be taken; and the *world* involves the physical state and conditions of the environment (Neisser, 1976). When the categories of the AH levels are fit into the PCM model, the *action* and *world* categories are the most representational for the AH framework; with no concepts identified in the *schema* category (Figure 21). Results from the content analysis conducted in Chapter 3, analyzing the feedback responses from older drivers revealed some of the underlying *schema* influencing route choice, such as preference and habit. Such factors that influence the decision to choose a route need to be incorporated in the *estimated route familiarity* measure. Implementing the *modified abstraction hierarchy perceptual model* could be a first step towards understanding the interaction between the *schema* categories and the *action* and *world* categories. By decomposing the *schema* category into more detailed features can provide additional explanatory power for understanding decision-making, especially critical decision-making during situations that might turn into incidents or accidents (Dekker, 2014).

5.6 Using ***estimated route familiarity*** as a marker for assessing driver's situation awareness

As vehicles become more automated, both the driver and the automation play a role in vehicle control and engagement. For the driver and the automation to work jointly, there is a need to understand the issues when working with automation within a joint cognitive system. One useful approach to study driver-automation interaction is to treat the driver and automation as agents collaborating in a workspace. Workspace awareness (WA) involves *knowledge about where someone is working, what they are doing, and what they are going to do next* (Gutwin, Greenberg, & Roseman, 1996). The information gathered by the agents in the workspace can then be used for collaboration, action coordination, managing coupling, anticipating actions, and opportunities to assist the other agent.

Previous work studying human-automation interaction within a computational workspace (human and automated agents) has shown that awareness is not easy to maintain as there is a) lesser information than actions generated in a computational workspace, and b) manipulation of information is less direct when working in a computational workspace (Gutwin & Greenberg, 1998). The computational WA framework derived from Endsley's (1995) three levels of situational awareness (SA) is organized around: a) *what* kinds of information agents need to keep track of in the shared workspace, b) *how* agents should gather WA information; and c) *how* agents can use the WA information for collaboration. But while SA can be limited at all 3 levels, computational WA focuses on only the first and second SA levels as the primary levels where awareness problems occur.

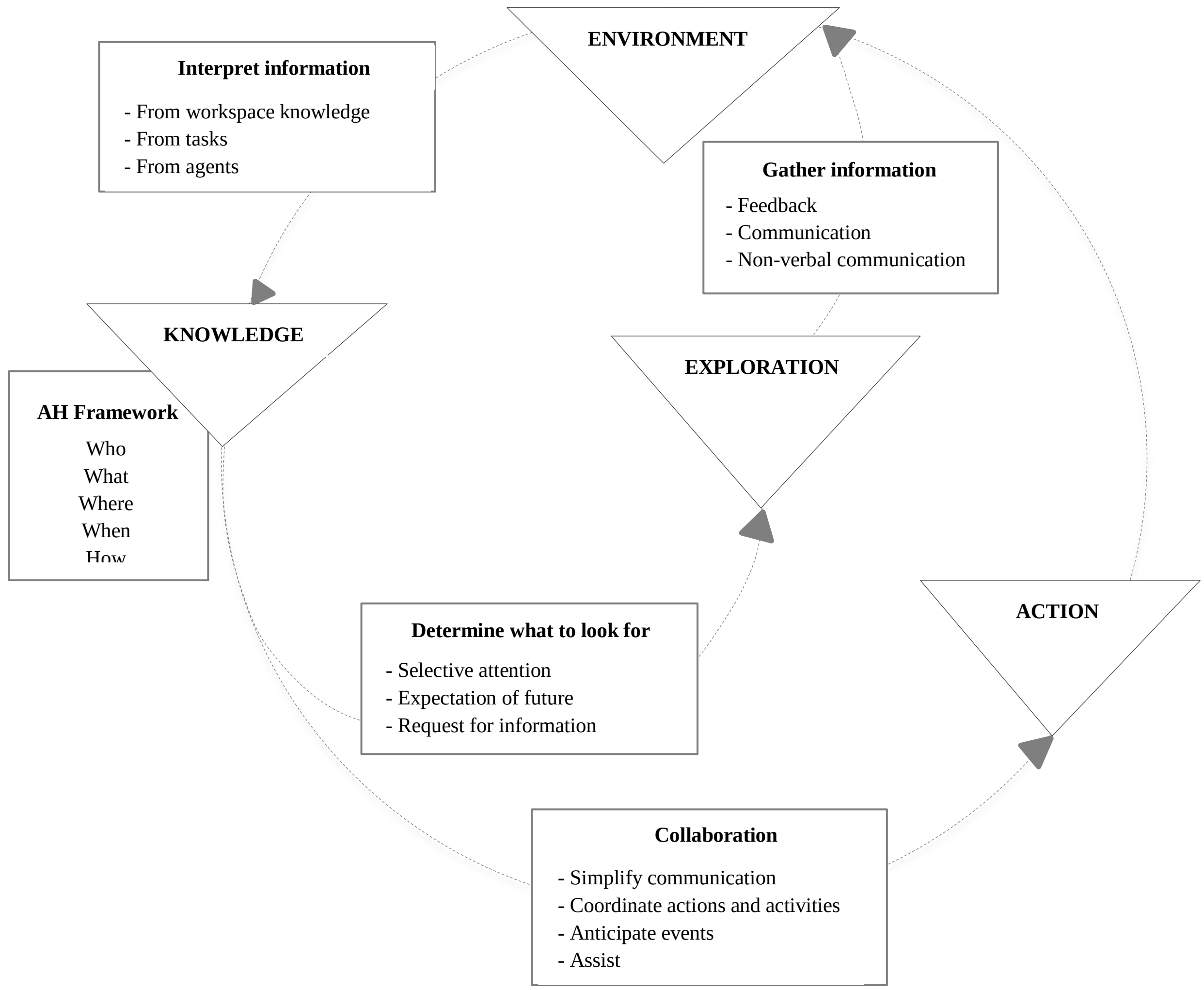


Figure 22: Using the AH framework and the perceptual cycle model to build a workspace awareness framework representing driver-automation information interaction loop with driver and automation as agents in the workspace (Gutwin et al., 1996).

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APPENDIX: Model assumptions and mathematical formalization of the AH levels describing route familiarity

The mathematical formulation of the AH levels presented in the dissertation are detailed in this appendix. The underlying assumptions and technical aspects are discussed. To mathematically represent each of the AH levels to describe familiarity, we recap the definitions of trips for all origin O and destination D pairs. For each *O-D* pair, there are N possible route choices to get from O to D. Then the route associated with that *O-D* pair is the route driven. Thus each individual has a set of all routes driven to create their own route reference set R^I, where R^I is the set of routes ordered by when they were driven, and I is a distinct individual in the population. R^I is ordered, if for any 2 subsets i, j of R^I, $R_i = R_j$, iff two conditions hold,

- $|R_i| = |R_j|$, and
- The first element of R_i equals the first element of R_j, and so on till the nth element of R_i equals the nth element of R_j.

We assume that R^I is not a set of distinct routes, i.e., any route can occur multiple times in R^I. And the ordering of $R^I$is based on the absolute point in time that each route was driven. In the reference set, for each of the levels of the AH framework, the ordering of the routes captures *recency*, and the aggregation of routes driven captures the *frequency* of the routes driven.

We then represent familiarity by *the degree of similarity between routes*, where similarity is characterized by *the degree of relatedness between shared features of two or more routes*, and relatedness by the measure of overlap or distance between the two features. For the proposed mathematical framework, the similarity measures across the five levels of abstraction – functional, abstract, generalized, physical function, and physical form are represented below.

A. AH Level 1: Trip purpose

Trip purpose represents the overall goals and purpose of the system, objectives, and the external limits on the system due to the environment. The system's purpose remains relatively constant, while the objectives and external limits of a system are dynamic – changing with respect to the situation (Burns & Vicente, 2001). The system can have multiple objectives. The external limits refer to the properties of the environment that impose on the system's purpose (Naikar, 2013). For example, the purpose of a trip is to reach the destination. Whereas there might be multiple objectives for the trip – primary objective to arrive for dinner on time; and the secondary objective is to stop and pick up dessert before dinner. External limits by the driving environment on the trip could include traffic regulations. Thus at the trip purpose level, purpose, objectives, and external limits govern the interaction between the system and the environment.

At the trip purpose level, familiarity can be determined by the *similarity of the trip purposes, objectives, and external limits between two or more trips,* S_F. To measure similarity at the functional level, we make the following assumptions:

- The purpose, objectives, and external limits of a trip will be a countable set of distinct purposes P, objectives O, and external limits E.
- For any one or more purposes $p_i \in P$, a measure M on them will have the following properties,

The similarity of any single purpose is 0; $M(p_i) = 0,\ for\ all\ i$

The similarity of no purpose is 0; $M(\emptyset) = 0,\ for\ all\ i$

The similarity between any two distinct purposes lies between [0,1); $0 \leq M(p_i, p_j) < 1$, $if\ p_i \neq p_j\ for\ all\ i\ and\ j$

The similarity between identical purposes is 1; $M(p_i, p_j) = 1,\ if\ p_i = p_j\ for\ all\ i \neq j$

The similarity between multiple purposes is the same as the pairwise similarity between all combinations of two purposes; $M(\cup p_k) = \sum_{i,j}^{\binom{k}{2}} \frac{M(p_i, p_j)}{\binom{k}{2}}$, where k are the purposes in the union being measured, and the sum across i and j form all pairwise combinations of $\cup p_k$.

- Every route R_j in the reference set R^I will have one and only one $p_i \in P$

Then similarity (Eq. 1) can be represented as a function of the similarity of the trips purpose S_p, objectives S_o, and constraints S_c, where $\mathrm{S_p} = \mathrm{f_p}(p)$, $\mathrm{S_o} = \mathrm{f_o}(o)$, and $\mathrm{S_e} = f_\mathrm{e}(e)$, and f follows the rules for M stated above.

$$\mathrm{S_F}(\mathrm{R_j}) = f(S_p, S_o, S_e) \tag{1}$$

B. AH Level 2: Travel conditions

This level represents the values and priority measures needed to fulfill the purpose of the system (Naikar, 2013). For example, for the trip where the purpose is to arrive at the destination, with the primary objective to arrive on time for dinner, and secondary objective to stop and pick up dessert; several criteria can be employed for evaluating how the purpose is fulfilled. Criteria such as selecting the shortest, selecting the fastest route, etc., can allow the driver to compare, prioritize, and allocate resources so as to achieve the trip purpose. Assessing these criteria can help evaluate whether the purpose is fulfilled.

At the travel conditions level, familiarity can be defined as *the similarity in the overlap and ranking of travel conditions for two or more routes*, S_A. To measure similarity at this level, we make the following assumptions:

- The travel conditions for a trip is an ordered, countable set of distinct criteria C, ordered by the importance of each criteria
- Let O be a measure of similarity on C, where O has the same properties as M (see *Purpose level*), such that for each $c_i \in C$,

If a criteria appears in only one route there is no similarity

$O(c_i) = 0 \; if \; c_i \in C_1$ and $c_i \notin C_2$ or $c_i \in C_2$ and $c_i \notin C_1$, where C_1 and C_2 represent the order of criteria for routes 1 and 2

If a criteria appears in two or more routes, but is in different order, then it will have a similarity between [0,1)

$0 \leq O(c_i) < 1, if \; c_i \in C_1$ and $c_i \in C_2$ and order of c_i is not the same in C_1 and C_2

If a criteria appears in two or more routes, and in the same order, then it has a similarity of 1

$O(c_i) = 1 \; iff \; c_i \in C_1$ and $c_i \in C_2$ and order of c_i is the same in C_1 and C_2

Then similarity S_A (Eq. 2) can be represented as a function of the overlap of the ranked travel conditions criteria between 2 routes j and k, where $k \neq j$ as we are not measuring the similarity of a route to itself, T_{jk} is the travel conditions for routes j and k, and R^I is the reference set.

$$S_A(R_j) = f(O, T_{jk}) \tag{2}$$

C. AH Level 3: Driving challenges

This level represents the functions that must be supported to fulfill the system's purpose, independent of the underlying physical objects or object-related processes needed to implement them (Naikar, 2013). For example, for the trip where the primary objective is to arrive on time for dinner, the secondary objective to stop and pick up dessert, and criteria such as time of departure is used to evaluate fulfillment of the trip purpose; requires a number of purpose-related functions that need to be supported. These include challenges such as maintaining a certain speed and acceleration with other drivers on the road, overtake vehicles if they are driving to slow, etc. (Kesting et al., 2010). While there are no reported variations in how factors at this level are characterized, these functions needs to be represented in general terms using terminology common to the field, such that the functions indicate the type of system but not the specific system (Naikar, 2013; Rasmussen, 1994).

At the driving challenges level, familiarity can be represented by the similar driving challenges to overcome to fulfill the trip purpose, *defined as the similarity in the overlap of driving challenges between two or more routes,* S_G. To measure similarity at this level, we make the following assumptions:

- Let G be a countable set of driving challenges, where each $G_i \in G$ has a countable set of M dimensions D, with values in D^{m_i} for each $m_i \in M$.
- Let $D_{jk}^{m} = D_m\left(G_i \in R_j\right) - D_m(G_i \in R_k)$, difference between any driving challenge for one route and the same driving challenge in another route.
- To relate the difference in driving challenges between routes, we create a measure O that takes values in [0,1] to be a function on D_{jk}^{m}, such that,

If the difference in driving challenges between routes is zero, then the overlap of driving challenges is the same

$$\mathrm{O}\left(D_{jk}^{m}(\mathrm{G_i})\right) = 1 \quad iff \quad D_{jk}^{m}(\mathrm{G_i}) = 0$$

If the difference in driving challenges between routes is not zero, then the overlap of driving challenges will take a value between [0,1)

$$0 \le \mathrm{O}\left(D_{jk}^{m}(\mathrm{G_i})\right) < 1 \quad if \quad D_m\left(G_i \in R_j\right) \neq D_m\left(G_i \in R_k\right)$$

Then similarity S_G (Eq. 3) can be represented as a function of the overlap of driving challenges between 2 routes j and k, where $|R^I|$ is the size of the reference set R^I, and $D_{jk}^{m}(\mathrm{G_i})$ is the measure on driving challenges i between routes j and k, where $k \neq j$.

$$\mathrm{S_G}\left(\mathrm{R_j}\right) = \mathrm{f}\left(\mathrm{O}, D_{jk}^{n}, \mathrm{G_i}, M, R^I\right) \tag{3}$$

D. AH Level 4: Physical properties of the environment

This level represents the object-related processes or parts of the system that are used to characterize the functional states (Rasmussen, 1986). The object-related processes or parts are tightly related to the physical objects, and represented by their reason for use, or by their limiting properties. The resolution of the details represented in this level depends on the specific task or interaction with the system. For a trip, the number of stop signs, street parking, etc. (*at the physical properties level*), influences the purpose-related functions such as speed maintenance, start-stop events, etc. (*at the driving challenges level*), affecting the evaluation criteria such as duration of travel (*at the travel conditions level*), and the goals and objectives of the trip such as reaching on time at the destination (*at the trip purpose level*). The physical representation is tightly coupled with the functional states, where changes at the physical functional level propagate up the hierarchy, and influence the higher levels (Rasmussen, 1986).

It is important to note that the purpose-related functions (*at the driving challenges level*) represent the intentionality in how the physical objects of a system are used, whereas object-related functions (*at the physical properties level*) represent what these physical objects can afford. Thus familiarity at the physical properties level can be represented by the affordance of the physical objects. But a route consists of a sequence of object-related processes or parts (Vrotsou, Ynnerman, & Cooper, 2014). Hence we define familiarity at the physical properties level as the *similarity in the sequence of the physical processes or parts between two or more routes*, $S_{Pfunction}$. To measure similarity at the physical properties level, we make the following assumptions:

- Each route has a countable ordered set of object-related processes or parts, N
- For each object-related process or part $e_i \in N$, there is a measure M as defined in the *functional purpose* level
- For any two routes j and k, let one be the target route j and the other be the reference route k, such that, there is a measure of similarity M between e in the i^{th}position of the route j and the i^{th} position of route k

$$M(e_{ij}) = 0, \qquad for\ M(\emptyset) \neq 0$$

$$0 \leq M(e_{ij}, e_{ik}) < 1, \qquad if\ e_{ij} \neq e_{ik}, and\ j \neq k$$

$$M(e_{ij}, e_{ik}) = 1, \qquad if\ e_{ij} = e_{ik}, and\ j \neq k$$

- For each $e_i \in N$, there is an associated probability measure P on [0,1], such that,

$0 \leq P_{e_i}(S) \leq 1$, for any S subset of [0,1)

- For each route j there are n_j events and let $Prop_j$ be the function that measures the proportion into route j, such that

$$Prop_j(first\ event) = \frac{i}{n_j}$$

- To measure how similar M_1 an object-related process or part e_i is, let

$$M_1 = \max\{ M_1(e_{ij}, e_{ik})\}$$

If $M_1 \geq 0$, then $M_2 = 0$, else $M_1 > 0$

- To measure how far apart in a route M_2 an object-related process or part e_i is, let

$$M_2 = \min\{ P\left(Prop_{e_{ij}}\right) - P\left(Prop_{e_{jk}}\right)\}$$

- The final measure of how similar and how far apart an object-related process or part e_i can be represented as

$$M_o = \prod M_1(e_i).M_2(e_i)$$

Then similarity (Eq. 4) can be represented as a function of the measure M_o on the set of object-related processes or parts in the i^{th} and j^{th} routes and the reference set R^I.

$$\mathrm{S_{Pfunction}}(\mathrm{R_j}) = \mathrm{F}(M_o, R^I) \tag{4}$$

E. AH Level 5: Trip features

The bottommost level represents the physical appearance and configuration of the system and its parts (Rasmussen, 1986). Representation of the system and its parts at this level reflects what parts are vital for interaction with, and manipulation of the system to achieve the purpose-related functions of the system. For example, for the trip where the primary objective is to arrive on time for dinner, and the secondary objective to stop and pick up dessert, based on the route chosen –

trip features of the route can include information about the name and type of road, appearance of the road (winding, curvy), location or position (cardinal points, origin, destination), and physical distribution and connections (GPS trace, proximity, overlap) (Naikar, 2013). Thus, this level is represented by names or attributes that can help identify and distinguish objects and their properties for navigating the system (Rasmussen, 1986).

Familiarity at the trip features level can be represented by the sameness of the names and physical attributes of the system, and defined as function of the *similarity in the appearance, location, and spatial distribution of the physical attributes between two or more routes*, S_{Pform} (Eq. 5). To measure trip features level similarity, we make the following assumptions:

- Let A be a countable set of physical appearances of a route.
- Let Pr be a continuous space in the x, y, z, t direction.
- Let O_A be a function on A, and O_{Pr} be a function on Pr, such that,

The similarity of 1 physical appearance is 0

$$O_A(a_i) = 0, \qquad for\ all\ i$$

The similarity of no physical appearance is 0

$$O_A(\emptyset) = 0, O_{Pr}(\{x, y, z, t\}_i) = 0,\ for\ all\ \{x, y, z, t\}_i \in Pr$$

Similarity of a point in space has 0 similarity

$$O_{Pr}(\emptyset) = 0$$

Non-identical physical appearances between routes has a similarity between [0,1)

$$0 \leq O_A(a_i, a_j) < \ if\ a_i \neq a_j\ for\ all\ i\ and\ j$$

Identical physical appearances and points of time or space between routes have similarity between [0,1)

$$0 \leq O_{Pr}(\{x, y, z, t\}_i, \{x, y, z, t\}_j) < 1\ if\ \{x, y, z, t\}_i \neq \{x, y, z, t\}_j\ for\ all\ i\ and\ j$$

$$O_A\ (a_i, a_j) = 1,\ if\ a_i = a_j\ \ for\ all\ i\ \neq\ j$$

$$O_{Pr}(\{x, y, z, t\}_i\ , \{x, y, z, t\}_j\ ) = 1, \qquad if\ \{x, y, z, t\}_i = \{x, y, z, t\}_j\ \ for\ all\ i\ \neq\ j$$

Then trip features similarity S_{Pform} (Eq. 5) can be represented as a function of

$$\mathrm{S_{Pform}}\left(\mathrm{R_j}\right) = \mathrm{F}(A,\ Pr, O_A, O_{Pr}, R^I) \qquad (5)$$

F. Estimated route familiarity measure

Thus the mathematical representation of the five levels of familiarity described in the AH framework is a function of the similarity between trip purposes, travel conditions, driving challenges, properties of the driving environment, and trip features, shown in Eq. 6 (Tenenbaum, 1996). Since recency and frequency arise from the set of routes driven by an individual; they are represented in the set of all routes driven to create their own route reference set R^I. R^I is defined as the set of routes ordered by when they were driven, where *recency* is represented in R^I by the ordering of each trip, and *frequency* is represented by how many times a distinct route is in R^I. For Eq. 6 we assume that route familiarity is a continuous, bounded variable defined on a subset of the unit interval.

$$Estimated\ \text{Route Familiarity} = \mathrm{f}(\mathrm{S_F}, \mathrm{S_A}, \mathrm{S_G}, \mathrm{S_{Pfunction}}, \mathrm{S_{Pform}}, R^I) \in [0,1] \qquad (6)$$