Motivational Techniques that Aid Drivers to Choose Unselfish Routes

A Dissertation

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To my family, who have given me the freedom to pursue this academic path.
And to my motherland, the Philippines.

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Abstract

Modern navigation applications are now ubiquitous in the daily commutes of drivers to avoid congested roads in urban areas. This enthuses governments to use it as a potential tool that could promote sustainable routes and promote altruistic driving behaviors among its driving citizens. With a traffic management system that helps avoid traffic congestion, drivers who commute daily can be distributed and be recommended to follow alternative paths. But this ”smart city” approach can face challenges in convincing daily commuters because they already have regular and familiarized routes.

In this dissertation, I posit that route information and navigation guidance provided by modern navigation applications can be redesigned to motivate drivers to choose unselfish routes. I focus on the HCI aspect of the traffic management problem and ask the question of how to encourage drivers to follow system optimal routes for their daily commutes. Motivated by the previous literature around navigation applications, HCI of recommender systems, traffic psychology and behavior, and factors that affect route choice, and my positionality as a non-driver, I begin with an observational study of drivers using modern navigation systems and applications in their daily commutes. It was found that while drivers choose a recommended route in urgent situations, many still preferred recommendations that are familiar to them. Additionally, they make deviations while following their original choice because of unfamiliar roads, lack of local context, perceived driving unsuitability, and inconsistencies with realized navigation experiences.

Then, I rethink navigation applications as a form of civic technology by evaluating two separate techniques, each focused on a different step in the driving navigation task. With the goal of encouraging unselfish route choices while still respecting the agency and self-efficacy of a user or driver, the Self-Determination Theory was used to inform the designs. When a driver plans the trip before driving, the first is a GUI-based technique that provides motivative and familiarity information to route recommendations. By providing motivative information such as critical mass, travel time gains and overall positive benefits of choosing the unselfish route, along with the number and names of familiar roads, drivers were convinced to choose the unselfish route at least once. But it was most likely when driving from home to work and they are provided with information about the overall positive benefit of choosing the unselfish route along with a list of familiar roads. For drivers with moderate impersonal and controlled orientation based on SDT, information that emphasizes social comparison would be more effective. During a trip, traffic conditions along a chosen route might change. The second is a voice-based technique that uses two-party conversations between voice agents in giving alternative turns or routes. It was able to convince drivers to follow alternative routes as they are made available, especially when the alternative route is appropriate for the trip scenario. Hearing conversations between two voice agents gave drivers a point of comparison to reflect better on their realized and forgone choices, possibly affecting future choices. However, drivers can still experience increased workload especially during time-constrained navigational maneuvers and turns.

Refining and combining both techniques, I culminate this dissertation with Navigo, a holistic approach that uses personality-targeted design in providing motivative and familiarity information before a trip. While driving, it plays motivative messages when the driver chooses an unselfish route, and a two-party conversation when the driver chooses otherwise. Its evaluation showed supporting evidence that showing the list of familiar roads and positively framing the benefits of an unselfish route choice can encourage drivers to choose unselfish routes. And this unselfish choice can be sustained by providing them frequently in different trip scenarios. When a driver follows an optimal route, the two-party conversation was successful in encouraging them to switch into following an unselfish route especially when they have diverse experiences of following different routes. When the drivers choose the unselfish route at the beginning, the provision of motivative messages along the trip was successful in encouraging drivers to stick to following unselfish routes. Here, I challenge the rigidity of existing navigation application designs and start a conversation of what navigation applications can and should be. In order to realize further its potential in shaping sustainable driving behavior, designers should include diverse stakeholders (e.g. government, communities) in the co-design of their applications and underlying algorithms.

Publications

Chapter 3: Interaction with Navigation Apps

[1] Samson, B.P.V. & Sumi, Y. (2019). Exploring Factors that Influence Connected Drivers to (Not) Use or Follow Recommended Optimal Routes. In *CHI Conference on Human Factors in Computing Systems Proceedings (CHI 2019)*, May 4 - 9, 2019, Glasgow, Scotland UK. ACM, New York, NY, USA, 14 pages.
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Chapter 6: Conversations for On-Trip Voice Guidance

[2] Samson, B.P.V. & Sumi, Y. (2020). Are Two Heads Better than One? Exploring Two-Party Conversations for Car Navigation Voice Guidance. In *CHI Conference Extended Abstracts on Human Factors in Computing Systems Proceedings (CHI 2020)*, April 25 - 30, 2020, Honolulu, Hawai'i, USA. ACM, New York, NY, USA, 10 pages.
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1
Introduction

Route information and navigation guidance provided by modern navigation applications can be redesigned to motivate drivers to choose unselfish routes. Doing so will realize their potential in managing traffic flow, adding positive social value for daily commuters. In 2050, we will see almost 70% of the global population move to cities, increasing car ownership and potentially affecting our goals of achieving sustainability. These additional vehicles will slowly congest denser urban environments and complex road networks, worsening traffic conditions and bring forth a number of negative consequences[103]. While our current road networks and transportation systems are still keeping up with the rising demand, modern navigation applications such as Waze and Google Maps, and in-car navigation systems found in modern car models today are offering a slight reprieve in dealing with daily traffic conditions. At their core, these tools provide digital maps that show route options, traffic conditions, and other road or traffic advisories. To reduce driving distraction, they also give turn-by-turn directions towards a destination. As commercial products, we are provided with a diverse array options which we can compare in terms of mobility, frequency of map updates and available information (Figure 1.1).

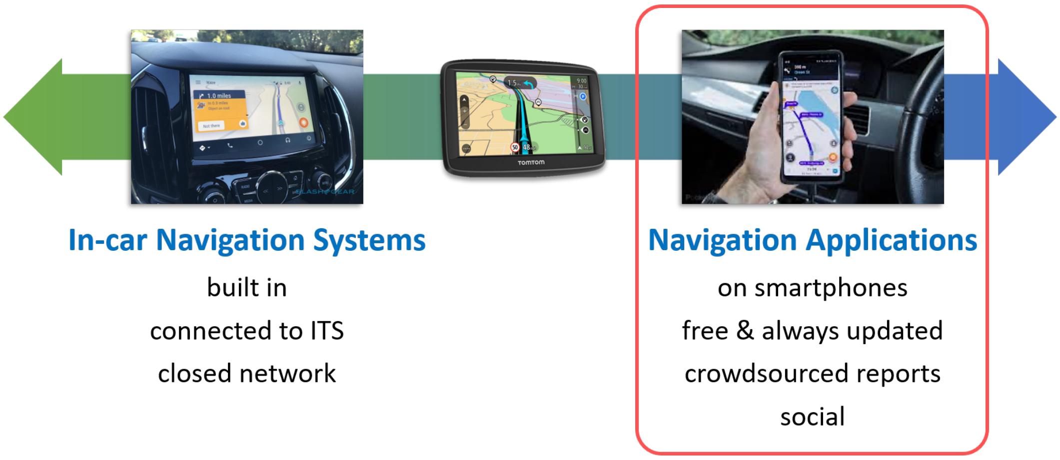

Figure 1.1: The spectrum of navigation tools that are available commercially for drivers. Leftmost are in-car navigation systems which typically come with a vehicle. Such navigation tools are different per car make and model. One of their main advantages is that they can communicate with other cars of the same car make and access to maps do not need connection to the Internet. In the middle are satellite navigation tools or GPS devices. These can be bought separately from navigation companies (e.g. Tomtom and Garmin) and can be mounted on any car. Rightmost are modern navigation applications like Google Maps and Waze. They are run on smartphones and access to the most recent maps and route information is mostly free.

In this dissertation, I focus my investigation and designs for navigation applications, as they democratize the access to navigation services. As their core routing service becomes more advanced with machine learning and sensing capabilities, navigation applications are becoming integral in many commutes to monitor regular routes, to discover new ones and sometimes to avoid traffic congestion. These modern tools are free to download on most smartphones, have the latest maps, and with some utilizing the Intelligent Transportation Systems of advanced cities. Maximizing built-in sensors and modern GPS, they collect floating car data to learn traffic conditions and further augments these with crowd-sourced reports from ordinary users[93,165]. All these information are fed into machine learning algorithms to produce models that can power their sophisticated routing algorithms, allowing drivers to cut through traffic by sometimes suggesting unfamiliar routes and small, residential roads.

1.1 Negative Externalities

Since the first GPS devices were made commercially available to consumers, engineers and designers have always centered their features around the individual driver. Understandably, this has resulted to their modern commercial success as most modern car models include in-car navigation systems by default. For those who do not have that luxury, they can still download free navigation applications like Google Maps and Waze, which also offer turn-by-turn voice guidance.

A large user base has been a benchmark for an application's success. However, the widespread use of such applications can sometimes have negative externalities as shown by a recent work of Bayen et. al. In an agent-based model simulation, they have shown that as more drivers follow the shortcuts provided by navigation applications, smaller residential roads that run parallel or connected to highways experience unlikely congestion. Unlike traffic congestion on highways which can dissipate fast, these small roads will experience congestion for longer because of their low carrying capacity [159]. Insights from this model are also supported by anecdotal evidence of cities like Los Angeles experiencing local unprecedented disruptions because of drivers using Waze [17,161,175]. These unexpected negative effects have prompted some local communities to start gaming the system [172] and some government officials to take legal action [52]. I argue that the major reason for this is how designers of navigation applications continue to only follow the principle that drivers want the fastest or shortest path to their destinations (selfish Wadrop equilibrium [169]). Instead of directly addressing the problem of traffic congestion, these applications provide shortcut routes, promoting individualistic choices at the expense of other stakeholders in the system (e.g. other drivers, households in residential roads). Inadvertently, they cause transportation networks to fall into inefficiency, showing the price of anarchy [169].

As beneficial as these navigation applications can be for individual drivers to avoid traffic congestion or get to their destinations faster, it is worth looking into how we can include other stakeholders into the design of such applications and their algorithms to safeguard the interest of the communities where they operate. At the same time, we should investigate how navigation applications can reduce individualistic choices in other trip contexts.

1.2 Imagining a Distributed Future

Because of their fast technological advancements and ubiquity, many government stakeholders are optimistic of the potential of navigation applications in shaping sustainable driving behaviors [12]. Here, I envision a future in which governments can manage traffic flow on their roads by recommending unselfish routes to drivers. Following Wardrop's

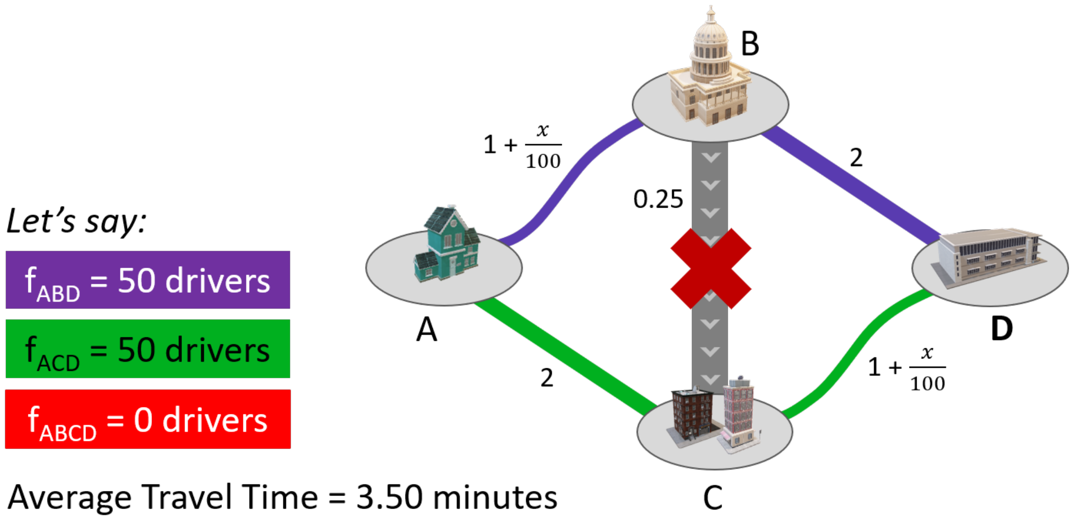

Figure 1.2: A toy problem illustrating a central distribution of drivers. This road network has 3 possible routes, with road BC as a one-way road. In a system optimal scenario, 100 drivers are equally distributed between routes *ABD* and *ACD*. Road *BC* is unused because it significantly increases the traffic flow in roads *AB* and *CD*. Not using all possible routes consequently reduced the average travel time of everyone to just 3.5 minutes, from 3.75 minutes in a user equilibrium scenario. This was recreated from Figure 1 of Colak et. al.[31].

second principle[169], consider the toy problem shown in Figure 1.2. In a *user equilibrium* scenario in which each driver chooses their own fastest route and ends up using all possible paths, many of them will include road *BC* in their routes because it has a small link cost or fast travel time. Eventually, everyone's average travel time becomes 3.75 minutes. Now let' s say cars are centrally distributed in the road network. So instead of letting them use all possible roads, it now distributes 50 cars each to use routes *ABD* and *ACD*. Since nobody is taking the shortcut path anymore (road *BC*), everyone' s average travel time becomes faster, from 3.75 minutes to 3.5 minutes. If we could rethink current features and designs of navigation applications to start encouraging unselfish routes that can lead to more sustainable futures, I believe that navigation applications has the potential for more. Implementing this in free applications can have a great impact because there is higher chance of mass adoption. But realizing this vision will take a concerted effort to address different aspects of the solution. In terms of the underlying infrastructure and sensing capabilities, there are still many open challenges on data sparsity and in ensuring the integrity of crowd-sourced reports[151,124,167]. However in this dissertation, I focus on the human-computer interaction aspect of this problem, specifically on drivers' route choice and navigation behaviors.

1.3 Interaction with Navigation Applications Today

In recent years, in-car navigation systems and their mobile application counterparts have gained popularity among drivers[170], especially those driving in cities and other urban areas with increasingly complex road networks. Looking at the user's experience, several studies have found older drivers experiencing difficulties following the voice navigation[46,99] while younger drivers overly rely on the turn-by-turn navigation[99]. More recently, Brown & Laurier enumerated five *normal, natural troubles* of driving with GPS devices with regards to defining destinations, quality of routes, accuracy of maps and sensors, timing and relevance of instructions, and legality of recommendations[23]. All these have profound effects on achieving a positive experience.

By default, drivers are recommended the fastest route to their destinations, with alternative routes either shown up front (i.e. Google Maps) or hidden for you to discover (i.e. Waze). While many people agree and say that they do want fast or short routes when asked at any given day, asking them again in actual driving contexts shows otherwise[121]. This is further supported by empirical evidence from GPS tracks and recorded actual trips that show drivers' repeated non-preference of recommended fastest routes[127,181,158] and sudden deviations[61,23,144]. While there is great support for drivers to make decisions before starting a trip, there are gaps in current systems and applications that fail to consider their changing needs, contexts and preferences, which ultimately affect their compliance on the recommendation.

In Brown & Laurier's work[23], after they describe the common dilemmas faced by drivers and passengers with traditional GPS devices, they argued that in order for drivers to have more positive experiences and better *instructed actions*, developers should focus more on supporting their interpretation and analysis of new route guidance and information. Instead of assuming that drivers have zero knowledge, navigation applications should allow them figure out what to do next.

Looking at these challenges and how we want future navigation applications to become tools in encouraging sustainable driving behaviors, I focus my line of research on answering this central research question: ***How can we encourage drivers to follow unselfish routes in their daily commutes?*** Specifically, I see two main challenges that needed to be addressed:

- How do we encourage drivers to choose unselfish routes before a trip?

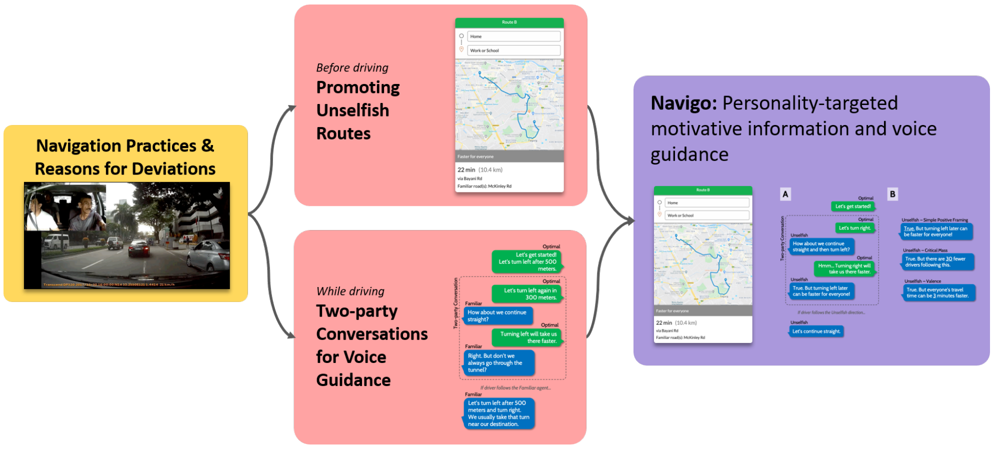

Figure 1.3: Overview of the different studies I conducted over the course of three years as I gained a deeper understanding of driver experiences with modern navigation applications and explored different motivational techniques for displaying route information and delivering navigation guidance.

- How do we make sure that drivers continue to follow an unselfish route (if they choose to do so) or convince them to switch to an unselfish route in the middle of a trip?

Additionally, how do we achieve these while supporting their sense of agency in their navigation decisions?

1.4 Encouraging Unselfish Routes

In order to redesign route information and navigation guidance provided by modern navigation applications to motivate drivers to choose unselfish routes, I started with a formative study that deepened my understanding of a driver' s use of navigation applications. Using key insights and design implications, I refined my research questions and began the process of rethinking navigation applications as a form of civic technology by evaluating two separate approaches – each focused on a different phase of the driving navigation task. I cap-off my PhD research by combining the two approaches and refining their designs to form a holistic approach towards a personality-targeted navigation application. After reading this dissertation, I hope I can convince you that navigation applications can be more than a routing tool and can be transformed into a civic technology for social good. Figure 1.3 shows the different studies I conducted to answer my central research question.

1.5 Structure

I begin this dissertation by reviewing the previous literature around navigation applications, HCI of recommender systems, traffic psychology and behavior, and factors that affect route choice (Chapter 2). In Chapter 3, I describe a formative study that investigates how drivers interact with modern navigation applications and what affects their route choices. In order to support the self-efficacy and agency of drivers, Chapter 4 discusses Self-Determination Theory which focuses on the different types of motivation and what techniques can be used to internalize motivation. It is then used to inform the designs in this dissertation. In Chapter 5, we explore the use of the Self-Determination Theory in designing autonomy-supportive navigation applications and investigate the effects of adding motivative and familiarity information to encourage the choice unselfish routes before a trip. In Chapter 6, I focus on the on-trip voice guidance and explore the use of two-way conversations to influence route choice when an alternative route is made available. Then in Chapter 7, I integrate the display of pre-trip motivative and familiarity information with the delivery of two-party conversations as voice guidance. I conclude this dissertation with a summary of my key contributions as well as an envisioning of future directions towards the design and evaluation of altruistic navigation applications (Chapter 8).

2
Related Works

Advanced driver-assistance systems (ADAS) have become ubiquitous in modern vehicles because of the recent developments in communication and sensor technologies. They are primarily developed to improve driving performance, and car and road safety by providing automation and adaptive capabilities to vehicle systems. One of the most widely used tool for driver assistance are automotive navigation systems, which were initially designed to provide digital maps, route guidance for the shortest path to a destination, and traffic incident information [106]. As more private vehicles occupied our roads and more cities are being designed to accommodate and regulate their widespread use, modern automotive navigation systems now also provide information on the cheapest and fastest routes, and traffic condition.

Today, more than half of the world's population call cities their home due to urbanization and a rising middle class [164]. As we see a consequential increase in car ownership, our efforts in promoting and ensuring sustainable cities are at stake. With dense urban districts and complex road infrastructures, persistent traffic congestion poses a negative effect on our productivity, health, environment, and social equity [103]. The worsening traffic conditions have compelled drivers to circumnavigate congested roads and several solutions have been introduced to address this growing problem. Intuitively, cities invest heavily on improving and increasing road network capacity; but adding more links between origin-destination pairs was proven to be counterintuitive and may cause longer travel times [22,6].

Another approach was to efficiently manage traffic flow on existing road infrastructures by connecting current fleets to Intelligent Transportation Systems (ITS). Cities have already invested heavily on ITS infrastructure such as toll gantries, adaptive traffic signals, variable-message signs, and traffic detection systems, among others – all aimed to regulate road use, to capture and provide situational information to drivers, and to redirect them from congested routes. At the same time, in-car navigation and other advanced driver-assistance systems are continually becoming more context-aware – communicating with other vehicles, the ITS infrastructure, and other smart devices, as well as detecting its immediate environment [8,16,149]. However in some cases, in-car navigation systems are barely used and noticed [79], are becoming too complex to operate [80], are not always updated with the latest maps, and sometimes without access to real-time traffic information, which directly impacts their adoption and forcing drivers to find other options.

In the absence and or shortcomings of in-car navigation systems on some vehicle models, smartphone navigation applications such as Waze and Google Maps, have become a preferred alternative for drivers who experience traffic congestion on a daily basis. In the App Annie Rankings*, Google Maps has consistently been the top choice since its introduction of GPS turn-by-turn navigation in 2008. Meanwhile, Waze reported in 2016 that they are already being used in 185 countries by more than 65 million monthly active users [170]. Other popular navigation applications include HERE WeGo, MapQuest and Bing Maps, and in other countries like Japan, Navitime has been a long time favorite. These navigation applications are free to use and has the latest maps. With the improved sensors in smartphones, these navigation applications started using floating car data from online users to estimate traffic conditions and uses that to suggest optimal driving routes. Maximizing connected drivers, Waze crowd-sources traffic and accident reports, and advisories of police presence, speed traps, and road closures to supplement its turn-by-turn navigation [93,165], setting it apart from traditional navigation systems while supporting the notion of navigation as a social activity among drivers and navigators [58]. At its core, modern in-car navigation systems and navigation applications are routing services, but they are also considered recommender

*Google Maps — App Annie (`https://www.appannie.com/en/apps/ios/app/google-maps/`)

systems because of their sophisticated recommendation engines that use actual and or average road speeds for calculating fastest routes, and learn new routes to suggest to other drivers[†]. These information on existing road infrastructure and driving behavior have inspired governments to consider their use in influencing future mobility patterns[18,12].

2.1 Interacting with Recommender Systems

With the incredible amount of data from digital and social media, and those from connected devices and sensors in the Internet of Things, recommender systems have been a boon to digital natives in making sense of and discovering new information. This popularity has gained significant attention to its evaluation in HCI, especially for a more user-centric approach. Knijnenberg et. al.[86] evaluated collaborative filtering recommender systems and found that increased usage is strongly correlated to a positive personalized experience, but their perceptions, experiences and behaviors change over time. These are also influenced by personal and situational characteristics such as age, gender and domain knowledge. Additionally, they found that when users perceive a recommendation set as more diverse, they see it as more accurate and less difficult to choose from. This is echoed by Ekstrand et. al.[50] when they found users choose a system with more diverse recommendations. They also emphasized the importance of building trust in the early use of recommender systems as their results show negative effects of novelty.

Comparing between collaborative, content-based and hybrid recommender systems, Wu[177] found that users mostly preferred recommendation sets that use hybrid filtering. In particular, users see more benefit in recommendations that match their own behavior history (content-based) than those that match the history of similar users (collaborative). Moving to a different type of system, Rong and Pu[78] developed a personality-based recommender system and found that novice users had an easier time building their profiles using personality quizzes because it doesn't need much domain knowledge. When users were asked to build profiles for themselves and their friends, they perceived the recommendation for their friends as more accurate. Much of these works have focused on user perceptions and behaviors towards the main approaches to recommender systems with a single criterion for matching, and they have demonstrated user-centric evaluations besides algorithmic accuracy. However, further analysis is needed for the growing number of mobile and

[†]Routing server — Wazeopedia (https://wazeopedia.waze.com/wiki/Global/Routing_server)

ubiquitous recommender systems that incorporate multi-criteria preferences, probabilistic models, and temporal, spatial and crowd-sourced information.

2.2 Ongoing Struggles with Navigation Systems

With a focus on GPS devices, Dingus et. al.[46] did camera and instrumented car studies for drivers who use TravTek. They found that older drivers have a difficult time driving and navigating, and despite being more careful, they still made more safety-related errors. Generally, drivers benefited most when using turn-by-turn guidance with voice, resulting to less glances to the device and faster travel times. In their naturalistic field study, most drivers used the GPS device in their rental cars. Al Mahmud et. al.[99] also found old drivers having difficulties with in-car GPS. As a result, they tend to not follow it completely due to reliability concerns and high amount of instructions. On the other hand, the younger drivers were found to be too dependent at times.

Focusing on more portable GPS devices, Brown & Laurier's study[23] documented five problems that drivers usually encounter during trips and came to the conclusion that navigation with GPS devices is a skilled activity. In order for a driver to have a positive experience and make suitable *instructed actions*, other than giving focus on providing very detailed instructions which can overwhelm and cause more confusion, it is equally important to support the driver's interpretation and analysis of an instruction or new information as they move and figure out what to do next. Clearly, these works have shown how driving and navigating performance is affected by the use of early smartphone, dashboard-mounted and in-car GPS devices. But with a new generation of navigation applications that dynamically adjusts to real-time and historical contextual information, and provides sets of crowd-sourced information, further analysis is needed to see whether there are changes in navigating practice and decision making, and whether they are associated with the type of trip, trip context, and road conditions.

More recently, Antrobus et. al. investigated how effective the use of SatNav devices are compared to collaborative passengers in helping drivers learn routes and become more aware of their environments while navigating[9]. They found that drivers learned the routes better after they drove with a collaborative passenger because they were using more landmark, road sign and dynamic landmark descriptors in telling the next navigation instruction. In contrast, the SatNav was only giving distance descriptors. Additionally, the collaborative passengers were more helpful because they confirm what the driver is interpreting as the next navigation maneuver, give confidence boosting words to the driver, and provide proper orientation.

Despite the continuous improvement of such navigation tools, although mostly on the digital maps they use, these recent works suggest that drivers continue to experience problems with the provided information and turn-by-turn navigation guidance. Additionally, they have focused on early smartphone, dashboard-mounted and in-car GPS devices. But with a new generation of navigation applications, I'm curious whether there are changes in navigating practice and decision making, and whether they are associated with the type of trip, trip context, and road conditions.

2.3 Route Choice Behavior

Because of the ubiquity, cost-effectiveness, and positive utility of smartphone navigation applications, there is growing optimism of the potential of navigation applications in improving urban participatory sensing [152,179,151] and in shaping sustainable mobility patterns among driving citizens [18,12]. Key to the realization of this potential is the navigation application's ability to influence the route choice behavior of drivers.

Route choice is a decision making task that actively occurs in driving navigation [47]. It is a driving behavior that is based on their active consciousness of their surroundings, knowledge of relevant travel information about possible routes, and recollection of past navigation experiences. According to Ben-Elia and Avineri, there are three categories of travel information that can affect travel behavior, namely experiential, descriptive, and prescriptive [18]. Experiential information are provided as feedback or repeated information from previous experiences. In actual implementations, they are passively captured in the background but are mainly used to train machine learning models required to improve digital maps and to provide route recommendations for all users. Thus, experiential information has never been utilized for personalized navigation experiences and drivers still rely on their cognitive functions to retrieve experiential information from memory. On the other hand, descriptive information depicts current conditions based on historic or real-time data such as estimated times of arrival and traffic conditions. Utilizing experiential and descriptive information, prescriptive information can come as suggestions (e.g. shortest, fastest, and cheapest routes) and or guidance (e.g. turn-by-turn directions) to help drivers optimize their travel time and positive driving navigation experience. Nowadays, most modern navigation applications provide descriptive and prescriptive information as their main features to inform and redirect drivers [148]. In the absence of in-car navigation systems and navigation applications, drivers can also access these information through variable message signs, which is another type of advanced traveller information system (ATIS) that are physically installed on many major roads in cities. Unselfish routes are typically considered and provided as prescriptive information in many route choice studies and in some modern navigation applications. And even so, there is still relatively few studies about the implications of prescriptive information on route choice.

In Chorus et. al.'s [30] and Ben-Elia & Avineri's [18] surveys of literature, they have highlighted the extensive focus on the positive effects of experiential and descriptive information to influence the travel behavior of car drivers. Experiential information has been proven helpful in adapting to uncertain conditions, while descriptive information is particularly valuable in coping with non-correlated and Black Swan events like road accidents and sudden bad weather. As a universal behavior, Abdel-Aty and Abdalla found initial evidence from a small percentage of their participants who showed more instances of deviation from a regular route when they had access to travel information [1]. In addition, drivers were also shown to be more likely to change and follow a recommended route when they see it provided by variable message signs along the road [120,51].

But the mere provision of such information are sometimes not enough. Route choice and compliance were also shown to be dependent on the quality of route information [30]. In an early study, Chen et. al. conducted an analysis on the effects of information quality and credibility on drivers' compliance to travel information provided by advanced traveler information systems [28]. In an interactive multi-user simulation environment, three aspects of information strategies were tested on participants. First is the nature of information (descriptive or prescriptive). Second is information quality, which are based on six levels of precision, from very precise travel time estimates to random values. Third and last is post-trip feedback. They found that drivers show high compliance when drivers are provided with prescriptive information with very precise travel time estimates. In practice, pre-trip travel times do not sometimes match the realized travel times because of dynamic traffic situations which were not accounted for at the beginning. But since travel time reliability is a major consideration for route choice [98,27], several strategies have been explored like showing ranges [157] and presenting standard deviations from the mean travel time [19].

In a conceptual framework for route choice behavior, Bogers et. al. showed the importance of habit, riskiness and presentation of past information [21]. Habit is when drivers learn and regularly use routes that leads to their unconscious selection of the habitual choice and bias against other alternatives. This study also showed that drivers improve their navigation performance when they are shown the realized travel times of all their past trips, as well as the forgone outcomes. This elaborate and historical information acts as a memory aid for drivers, however it cannot be ascertained how this can be effectively shown in practice. Lastly, drivers were shown to be naturally averse to risk. Thus, they would most likely choose a route with high certainty.

When alternative routes, like side roads, have faster travel time, drivers are more likely to choose them. Ringhand & Vollrath found in 2019 that even just 20-second gains can get around 20% more drivers to shift to side roads [134]. And relative increases in travel time of recommended routes can negatively affect their chances of being selected [1,11,134]. But with better familiarity, chances can be levelled and can lead to some positive impact on driver's route choice and compliance [5,21,150,11].

Other than travel time and familiarity, other types of travel information also showed effects on route choice. In the work of Ramaekers et. al., they showed that a trip's purpose (e.g. work-related) has an effect, along with trip length [128]. In cities with vast networks of roads and intersections, drivers were shown to heavily consider the effects of traffic lights on their travel time. Regardless of whether the recommended route has a longer distance or travel time, drivers would still choose them if it avoids traffic lights [1,118,116,166,132,133]. As much as possible, drivers avoid roads or routes with many traffic lights [116] and those with long waiting times even if there are only a few encounters [132]. Although it should also be noted that drivers often underestimate their judgement of waiting times [178]. Instead of showing just the actual travel time of two route choices, a recent study also showed that routes that positively frame travel time gains were chosen more than the way drivers avoided routes with negatively framed travel time loses [135]. When it comes to variable message signs, Peeta & Ramos found drivers were more willing to follow recommended reroutes when they are shown information about road accidents and travel time delays [120].

Route choice and navigation in general do not only rely in the type and quality of travel information provided. More often than not, drivers make navigational decisions based on a combination of travel information and external events and factors. In the early work of Gärling et. al., they found that time pressure has a combined effect with information on the recommended route[63]. But when Ringhand & Vollrath investigated this further, they found effects of time pressure on decision making time but not so much on route choice[132]. But even though some alternative routes are shown to be faster, their chances of being selected are also affected by the complexity of a route's traffic situation. Considering a variety of factors like speed limit, road and lane widths, intersections, traffic from various directions and sources, disruptions, pedestrian foot traffic, and points of interest, the same authors found that less drivers choose an alternative route when it has high complexity (e.g. has oncoming and pedestrian traffic) even if the route can be faster or shorter[134]. In addition, Thomas & Tutert found that the physical properties and layout of roads within a route also play an important factor in route choice[160]. For example, routes that include circumferential or orbital roads tend to be chosen more by drivers compared to those that are shorter and passes through the city center.

All things considered, it can be a cause for concern whether drivers would ever choose unselfish routes for their daily commutes, especially since these are already familiar and regular routes. In a distributed future wherein traffic management systems provide recommendations, unselfish routes would be sub-optimal alternatives with longer travel times and or distances[133], and is aimed to minimize the marginal cost of one's route choice on other drivers[31]. However, it can also be the case that the recommended unselfish route would be something familiar to the user but seldom used by other drivers. Whichever it may be, designers have to look into applying behavior change techniques in order to increase chances of selection and compliance for unselfish routes. For example, drivers can be nudged to choose unselfish routes by showing them as the default route recommendation, which is similar to how Waze automatically starts its navigation guidance for the fastest route[13]. Aside from the strategy of highlighting or making default the system optimal route to drivers, designers can also show the context and rationale behind the recommendations. This is under the assumption that if drivers would know why they are being recommended a system optimal route, they could somehow align their decisions with it. One way of doing it is by informing the drivers about the source of the recommendation. In two stated route choice studies where drivers were asked to choose between the fastest route and the system optimal route, they were informed that the system optimal route was given by a traffic management system[84,133]. In Kerman et. al.'s study, they found that route advice was considered more by participants when it showed different attributes of the alternative routes and when it shows that it can support traffic management outcomes. There is more effect when it is labelled personal for the driver. However in their stimuli, there is no indication which among the choices are system optimal. Ringhand & Vollrath did a two related studies by investigating the combined effects of presenting the source of recommendation and highlighting the system optimal recommendation[133]. When they only highlighted the system optimal recommendation to the participants, their individual compliance of drivers increased by a small fraction. But when they added information about the source of the recommendation and described a hypothetical traffic management system in a followup study, it did not show any effect on route choice unlike in Kerman et. al.

Recent attempts to nudge drivers into choosing unselfish routes have so far focused on providing information about a hypothetical source of recommendation and on explicitly labeling them as recommended by a traffic management system. Both information strategies seem to appeal to the extent of a driver's altruistic nature. Although results showed that the driver's decision making was partially correlated with their altruism, both strategies were not really designed for behavior change at the onset. In this dissertation, my goal is to explore other types of travel information that are grounded on behavior change theories to achieve desired route choice outcomes.

2.4 Driver's Compliance

Developers have so far focused on the assumption that drivers would always follow the fastest route to a destination. For most navigation applications, drivers are provided with a number of recommended routes based on a criteria and they can select which one to follow. By default, the fastest route criteria is set unless customization are made. In the case of Waze, it immediately starts the turn-by-turn navigation and leaves it to the user to check alternative options[93]. However, this doesn't seem to be the case based on studies examining GPS track data. Zhu and Levinson[181] noticed from GPS tracks that drivers do not always choose the shortest path in their daily commutes. In the follow up work of Tang et. al.[158], some drivers even take a different route each day for their commutes. Recognizing that desired driving experiences have an influence on route choice and vice versa, Pfleging et. al.'s[121] web survey show that the most considered factor for drivers is whether it is the fastest route, but when asked to choose a route from work to home using a prototype navigation screen, 49.1% chose the fuel-efficient route. Only 18.4% and 3.5% chose the fastest and shortest routes, respectively. While these provide rich empirical evidence, it is not clear whether the same prioritization and decision making holds true in real driving scenarios under different circumstances.

Relatedly, Fujino et. al.[61] conducted a more recent study to investigate the phenomena of drivers deviating from the recommended optimal routes of in-car navigation systems and where they usually happen. They analyzed GPS tracks that were collected over 4 years within a 20km^2 area in Kyoto, Japan. They found that drivers have made significant deviations on intersections with poor on-road signages and those near tourist areas. They also speculated on possible reasons for the deviations based on the physical characteristics of the intersections. While these studies already provide empirical evidence on the surprising route choice and non-compliant behaviors of drivers, none of them had prior knowledge whether the observed drivers used prescriptive information from in-car navigation systems or navigation applications. In the case of[181,158,61], they had no information on the intended route of the drivers nor do they know if the drivers were initially following the guidance of the in-car navigation system used to collect the GPS tracks. Thus, further investigation is warranted to understand why drivers deviated from the recommended optimal routes and whether they chose a recommended route in the first place.

In HCI, Brown & Laurier's study[23] also noted instances of drivers not following GPS recommendations from their corpus of naturalistic video data. They argue that GPS use is rather a skilled activity as drivers need competency to overcome the *normal, natural troubles* that GPS devices make. Several of these problems such as complex routes, superfluous instructions, map and sensor inaccuracies, and timing of instructions, offer a glimpse as to why GPS recommendations are not followed. Addressing the complex route problem, Patel et. al.[119] found that drivers prefer simplified route instructions using familiar landmarks.

As more drivers use descriptive and prescriptive information from navigation applications and more government stakeholders seek to use them in managing road networks, it is crucial that navigation applications become successful in shaping the travel behavior of connected drivers. Sharma et. al.[149] argues that behavioral adaptation is directly affected by the degree of compliance a driver has with the information provided by navigation applications. Although they are referring to connected vehicle technologies, the same assertion can also be made for navigation applications because they provide the same kind of information. It is worth exploring how we can better utilize descriptive information and present prescriptive information to create navigation experiences that encourages behavioral adaptation.

2.5 Behavior Theories in HCI

Human behavior is an action that someone does as a response to antecedents[40]. When one responds repeatedly to a situation or stimuli in a similar manner, changing them can be challenging. In order to understand why we stick to regular responses, behavior theories allow us to predict future responses using their underlying concepts, propositions and constructs[65]. Several theories have emerged from psychology in order to help explain and predict desired behavioral outcomes in education, health and sports, to name a few.

In this section, I will discuss some behavior theories that have been used extensively in HCI research[74]. First is Social Cognitive Theory which posits that humans can learn new behaviors by observing other people or models performing that desired behavior[15]. Typically, learning about the behavior and its consequences happens through social interactions, physical environment, and media exposure. As an ecological theory, it can be used to ground interventions that maximize the behavior change potential of these external influences. Focusing on one's beliefs, the Theory of Planned Behavior posits that one's intention to perform an action or behavior is shaped by their normative belief or attitude, subjective norm, and perceived behavioral control or self-efficacy[7]. It links a person's beliefs to their performance of a behavior by incorporating perceived behavioral control with the theory of reasoned action. In a similar manner but specific for the health domain, the Health Belief Model suggests that a person's performance or avoidance of health-promoting behavior can be explained by their perceived susceptibility to and severity of a health problem, perceived benefits of doing the action, perceived barriers to performing the behavior, and self-efficacy[122,136]. Besides balancing these beliefs, the health-promoting behavior must also be triggered with a cue to action. Unlike previous theories that focus on external influences and personal beliefs, people following the Goal Setting Theory write an action plan, which is a physical artifact or document that is meant as a memory guide. By referring to the action plan, they can be motivated to perform the intended behavior[97].

Although the aforementioned theories have already been used to implement interventions for behavioral outcomes in different aspects of life (e.g. education, health and well-being, sports, life goals), all of them are focused on personal gains. In this study, my goal is to promote altruistic behavior for drivers by having them choose unselfish routes. Thus, it would remain a challenge if there is only focus on extrinsic aspects of behavior change (e.g. rewards, challenges, influences). If a person does not have an altruistic behavior, we must design strategies that will allow them to have a conscious valuing of the desired behavior until it becomes part of one's self. This process of internalization can improve the quality of motivation, from amotivation to intrinsic motivation.

Motivation is an important construct of most behavior theories and is what moves us into action. However, what most theories do not consider is that motivation varies from person to person[140]. Self-Determination Theory focuses on the motivation aspect of behavior change and introduces different types, sources and orientations that affect the quality of motivation[139]. Specifically, it suggests that people can have intrinsic motivation, amotivation, and a spectrum of extrinsic motivation towards an event or action. The quality and type of motivation can change over time depending on how the environment supports certain basic psychological needs. Because of SDT's focus on internal processes, it has since been used to understand the development of one's motivation and self-determined behavior[171]. Lastly, they have been applied for interventions and applications designed for life's various aspects and have shown to deliver long term benefits[59]. Here, I inform my designs using Self-Determination Theory as it allows for better sustainment of the desired behavior (i.e. choosing unselfish routes).

2.6 Technologies for Behavior Change

As technology becomes ubiquitous in our everyday lives, HCI researchers and experts from behavioral sciences have been working in parallel and in collaborations to develop interventions that support and sustain behavior change[74]. Other applications use theories from behavioral economics, like Nudge theory[90,70,26], in implementing persuasive technologies[56,55,57,85,91,145] that use persuasion and social influence in order to change a person's behavior. However, Fogg clarifies that these techniques are different from those that coerce users into committing an action[55].

Behavior theories and persuasive techniques have been used extensively in technologies that support health and fitness outcomes[37,95] and other life domains[105]. For example, they have been used to inform the design of whole applications that support healthy eating[77,36,113,92,14,131], regular exercise[32,34,33,60,75,41] and good health maintenance[123,155,115]. They are also used in applications that help users reduce stress[88,64], stop smoking[3,73] and improve privacy decisions[71]. Aside from whole applications, behavior theories have also been used to design specific features of an application[155,73].

Although these theories may seem easy to implement using a number of techniques, an application's design and implementation can only achieve a certain level of persuasion and extent of behavior change [130]. In some occasions, designers would opt for techniques that would maximize persuasion and social influence for quick attainment of behavior change outcomes. Despite well-meaning, this often translates to deceitful strategies like the *dark patterns* in UX [4,69]. This led to ethical considerations that designers must consider in their design of behavior change applications and persuasive technologies, especially for socio-technical systems. In the process of developing behavior change applications, designers make decisions that are guided by values which are either already operational or still latent to them. To help designers discover values they embed in their decisions, Chivukula et. al. introduced the method of Ethicography [29]. Through this method of value discovery, they found their participants inconsistently and indirectly referencing user-centered values. This resulted to designs that enhanced persuasion as opposed to user agency. This might explain the frequent use of deceit in HCI which can result to patterns of breakdown [24].

To avoid the risk of deceiving users into performing tasks, Self-Determination Theory provides a framework that allows us to inform our designs towards one's self-determined action and better quality motivation. Studies have looked at existing behavior change applications, classified the techniques they used and some mapped them to behavior change constructs [95,155,37]. However, none of the classifications were mapped to SDT, which seems to suggest that although Self-Determination Theory is a prominent theory for human motivation, commercial applications have yet to inform their designs based on it. In HCI, SDT is most commonly used in games and play research, especially for serious games. Recently, Tyack and Mekler conducted a systematic review of HCI games research which aims to understand how SDT advanced the sub-field and how researchers engage with the theory [163]. They found that SDT-based game designs were mostly focused on needs satisfaction and intrinsic motivation. The other mini-theories, like the Causal Orientation Theory, were rarely engaged with.

In this dissertation, I focus on using behavior change techniques that values user agency and that supports internalization towards higher quality of motivation. In the following chapter, I describe the formative study that deepened my understanding of the driving navigation task. This helped identify potential challenges to developing motivation for the selection of unselfish routes.

3 Interaction with Navigation Apps

Our understanding of driver experiences with navigation tools have so far focused on their use of early smartphone, dashboard-mounted and in-car GPS devices to aid in their navigation [23,46,99]. There is none yet that investigates the presumably new navigation practices and mental models with modern navigation applications. So while I have multiple experiences in using navigation applications, it has always been in the perspective of a navigator and a collaborative passenger. In fact, I don't drive at all. Thus, with my positionality and the research gaps in the literature, I began with understanding the experiences and practices of drivers in using modern navigation applications. Here, I make a broader inquiry into the navigation practices of drivers who augment their driving with in-car navigation systems and or mobile applications. I also sought to understand the human factors behind their use of and compliance with the recommended optimal routes. In this qualitative descriptive study with 17 drivers, I recorded their commute and non-commute trips, and provide insights on how drivers engage with modern navigation systems, especially those that are infused with artificial intelligence from learned driving histories and crowd-sourced information. In this chapter, I:

Table 3.1: Participant demographic, socioeconomic and driving profiles. Legend: Fil - Filipino, Jap - Japanese, PHI - Philippines, JPN - Japan, CAN - Canada.

Participant	Driving Years	Occupation	Nationality	Domicile	Driving Locations
P1 (F, 20)	1-5	Student	Fil	PHI	PHI
P2 (M, 20)	1-5	Student	Fil	PHI	PHI
P3 (M, 28)	1-5	IT Consultant	Fil	PHI	PHI
P4 (M, 28)	1-5	Software Engineer	Fil	PHI	PHI
P5 (F, 28)	1-5	Supervisor	Fil	CAN	CAN; USA
P6 (M, 58)	>10	Self-Employed	Fil	PHI	PHI
P7 (M, 50)	>10	Professor	Jap	JPN	JPN
P8 (F, 28)	1-5	Nurse	Fil	PHI	PHI
P9 (F, 28)	1-5	Consultant	Fil	PHI	PHI
P10 (F, 28)	1-5	Medical Doctor	Fil	PHI	PHI
P11 (M, 30)	5-10	Sales Director	Fil	PHI	PHI
P12 (M, 20)	1-5	Student	Jap	JPN	JPN
P13 (M, 20)	1-5	Student	Jap	JPN	JPN
P14 (F, 42)	>10	Pharmacy Assistant	Fil	JPN	JPN
P15 (M, 29)	1-5	Entrepreneur	Fil	PHI	PHI
P16 (M, 22)	1-5	IT Specialist	Fil	PHI	PHI
P17 (M, 29)	5-10	Data Scientist	Fil	PHI	PHI

1. illustrate how drivers integrate navigation systems and applications into their daily commute and non-commute trips;
2. describe if, when and where deviations from the recommended routes happen, as well as the reasons why certain navigating decisions are made;
3. discuss design implications for supporting the navigation needs of a driver; and
4. reflect on how we can design better navigation experiences to support behavioral adaptation.

3.1 Participants

I recruited 17 driver participants with at least one year of driving experience and is using at least one navigation application or in-car navigation system through word-of-mouth and social network sharing (See Table 3.1). I only recruited drivers with at least a year of driving

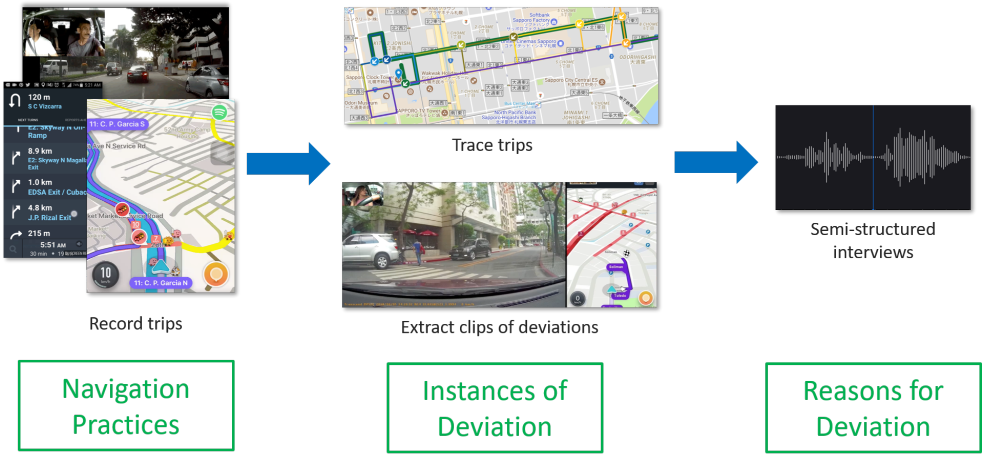

Figure 3.1: Overview of the protocol for the formative study.

experience as they are likely to be adept in navigation and have acquired preferences (e.g. on safety, road condition, familiarity), but I did not recruit participants that involve driving as their main line of work (i.e. Uber drivers). I also made sure they are not novice users and currently using a navigation application or in-car navigation system as they are likely to have a considerable amount of experience with the features (e.g. turn-by-turn navigation, traffic condition, reporting). I recruited participants from Japan and the Philippines mainly because of their wide exposure to in-car navigation systems (in Japan) and navigation applications (in the Philippines). They also comprise an underrepresented driving population (Filipinos) in literature who may largely benefit from technology improvements. I aim to see common behaviors and factors considered despite the difference in driving culture and technologies used.

Participants submitted their personal details (i.e. age, sex, occupation, and monthly income range) and driving background using a Google Form survey at the beginning. This allows for an examination of possible motivations for their commute and non-commute trips. I also asked whether they use in-car navigation systems and or navigation applications, and the number of years they have been using them.

3.2 Study Protocol

After answering the pre-collection survey, I conducted a semi-structured qualitative study[153] by recording trips in a naturalistic setup. Extending the scope of naturalistic driving data of

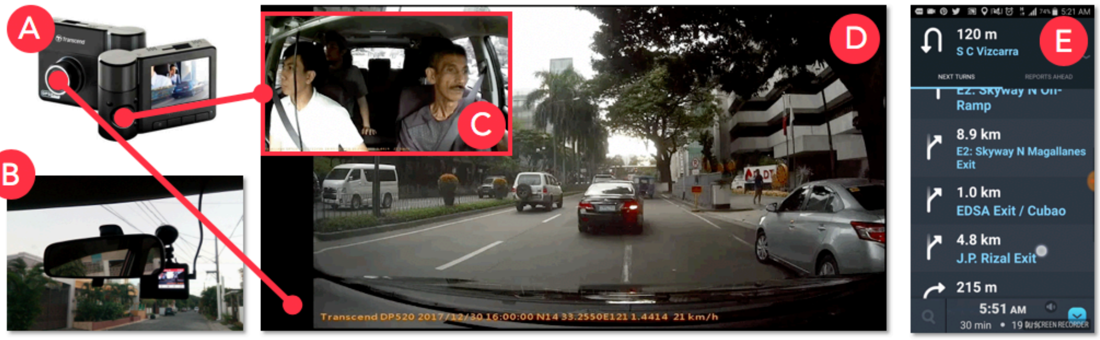

Figure 3.2: The data collection setup. A) The commercial dash camera used; B) Position of the camera for optimal viewing angles; C) View of the driver and passengers; D) View of the road; E) Recording of the navigation application.

Brown and Laurier[23] and Dingus et. al.[46], I focused on collecting data on the practices of using navigation applications for 3 trip types along with their trip context. I also collected data on whether they chose the recommendation or not, and the factors considered. Recordings were processed and trips were traced to extract instances of deviations. I then did a post-collection interview and used the grounded theory method[110,109] for the survey answers, video recordings, trip data, in-car conversations and interviews to better understand their navigation practices and reason for route choices, and to uncover their motivations behind deviations made. Figure 3.1 shows the overview of the study protocol steps.

Trip Recordings

Each participant were asked to record at least one instance of the following types of trips: Home-to-Work, Work-to-Home, and Home/Work-to-Unknown. The Home-to-Work and Work-to-Home trips represent their daily commutes. For the Home/Work-to-Unknown trips, the participants recorded their occasional trips to a location they do not usually go to or haven't been to before.

Inside the participant's vehicles, I attached a commercial dual lens dash camera behind the rear-view mirror (Figure 3.2B) to record the changing conditions on the road (Figure 3.2D), and the driver and passenger/s attention (Figure 3.2C). I wanted to capture how a driver and/or a navigator (because it can be someone besides the driver) behaves and what is seen on the road when a deviation happens. The dash camera also recorded the GPS tracks, speed, and in-car conversations. For P1, P2 and P6, a data collector was riding with them to perform shadowing and asked questions as needed. The rest of the participants collected

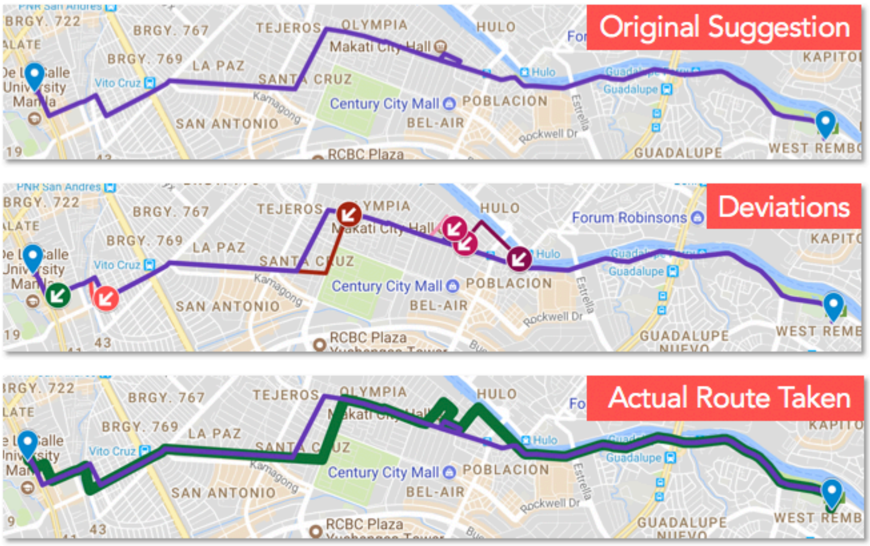

Figure 3.3: Traces of the [Top] navigation application's recommendation in violet, [Middle] deviations made by the driver during the trip (arrows symbols), and [Bottom] the actual route taken by the driver in green.

by themselves and were asked to think aloud. Before each trip, participants noted down their origin, destination, reason for the trip or the first activity to be done upon arrival (e.g. attend a meeting, attend family gathering, etc.), and whether it was urgent. I was able to collect 65 trip recordings in total – 18 work-to-home, 13 home-to-work, and 34 occasional non-commute trips. Among these, 12 trips did not have any deviations, leaving only 53 trips for analysis.

Application Recordings

To keep track of the application behavior and recommended routes, participants recorded the screen of their smartphones with the navigation application open (Figure 3.2E). This allowed us to observe how the driver and/or navigator used the application while navigating. It also allows us to track how the application behaves after every deviation and how the driver adjusts to the changes.

Trip Tracing and Processing

After data collection, I viewed the trip and app recordings and manually traced each trip's actual route taken and the first recommended route using Google MyMaps. I then marked

Figure 3.4: Synchronized video clippings of the [Left] dashboard camera video and [Right] the application screen recording.

the deviations (if any) made, and the app's recommended rerouting after each deviation (Figure 3.3). Trip durations and total distances of both actual and recommended routes were computed using the traces on Google MyMaps. I initially wanted to quantify gaze from the in-car videos but almost all drivers were using voice guidance. I did not pursue it but still observed where they paid attention to.

In preparation for the post-collection interviews, I synchronized the dashboard camera and application screen recordings, and made clippings that focused on parts of the trips when deviations happened (Figure 3.4). I included 10 seconds of video before and after each deviation to provide more context during the interviews.

Post-Collection Interview

In a separate interview after the data collection and processing, I first asked the participants about their daily routines and their motivations and experiences in using navigation applications. I then presented their trip traces and synchronized clippings when deviations happened. The interviews lasted between 60 to 90 minutes on average, and were focused on recollecting navigation experiences and examining the motivations behind choosing a route, the deviations made(if any), perceptions about the road conditions and recommended routes, as well as other observations and insights from the videos.

Data Analysis

Finally, I did an iterative coding and thematic analysis of the interview answers, in-car conversations and videos. I did a pilot analysis with 7 participants while the 10 other participants are still collecting. I achieved saturation after only a few new codes and themes were generated for the next 10 participants. In the following sections, I discuss the key findings of this qualitative descriptive study.

3.3 Navigation Practices

First, I want to investigate the applications used by the drivers, the information they sought, and the order by which the information were used. For this, I looked into the answers from the pre-collection questionnaire and compared it with the recordings and answers to the post-collection interview. I also used trip and app recordings to see associations with the type and purpose of trip.

3.3.1 Applications and systems used

In daily commute trips, Waze is primarily used when drivers have previous experiences of traffic congestion along their regular and familiar routes (H2W=66.7%, W2H=69.2%). They see Waze as an authoritative application especially when they have a clear intention to avoid being late or heavy traffic conditions. Even though Google Maps also provide turn-by-turn navigation and live/historical traffic information, drivers still put a lot of weight on the social aspect of Waze wherein other drivers can manually report traffic conditions, accidents, and road closures. Drivers gain a sense of confirmation as Waze shows manually reported traffic conditions to the ones they derive from the GPS tracks of connected drivers (P3, P4, P8). Since the road incident reports can be quite vague, drivers also acknowledge the usefulness of the public comment feature that allows other drivers who have passed by that area to share details about the incident. P6 shares that once when he was stuck near the tail of a standstill traffic, his passenger checked the public comments feature helped to get real-time updates from the drivers near an accident. It helped him decide whether he should wait longer or start finding other options.

For short commute trips that doesn't have many alternative routes and doesn't normally experience significant traffic congestion, P5 opt to use Google Maps instead. She expects to see her regular route as the recommended route by the application and just checks the estimated time of arrival. Additionally, she shares that because Google Auto is installed in her vehicle, she prefers to use Google Maps because she can view the route guidance in a wider screen compared to her smartphone.

Participants from Japan (P7, P12, P13, P14) were primarily using in-car navigation systems because of its ubiquity in most Japanese vehicles. Aside from the provided basic navigation features and digital maps, they are also connected to the local intelligent transportation systems. P13 shared that in one of his previous trips, his in-car navigation system provided a traffic advisory because of an accident in the national highway. It guided him to leave the national highway using the nearest exit.

In places where the drivers in Japan (P7, P12, P13, P14) drove in, they did not experience any heavy traffic thus, they were not so compelled to download and use another navigation application. However in one of P14's recorded trips, she used and followed Waze when her in-car navigation system started giving incorrect directions. She was noticeably surprised when the in-car navigation system guided her to a direction that's opposite from the destination. She still made the turn as guided by the system but she had already asked one of the passengers to look for the next turn. The passenger then used Waze. P12 particularly used Waze in one of his occasional trips because it shows the location of speed cameras. He found it very useful especially when driving in an unfamiliar location. He shares that this is not provided by his in-car navigation system.

Other than those mentioned above, drivers also sought information from social networking sites (e.g. Twitter and Facebook) to check traffic and incident updates from their friend networks and the pages of local transportation agencies (P3, P4, P6). They access these sources to augment the information that is not yet provided by in-car navigation systems and navigation applications.

3.3.2 Information Sought

From the interviews and in-car conversations, I looked into the number of times that the participants mentioned each type of information as part of their trip planning and navigation (Figure 3.5). Three participants (age=28-29 y.o.) who have at least 5 years of continued application usage seek at most 7 of these, while the two youngest participants (age=20 y.o.) only check the ETA.

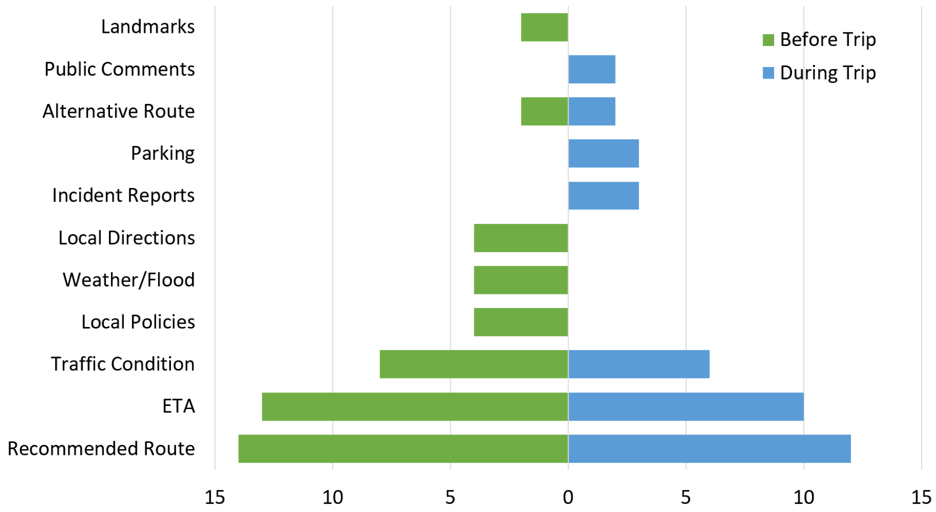

Figure 3.5: The number of participants who accessed certain types of information before and during their trips.

Drivers were mostly checking the estimated time of arrival of the recommended routes, the roads they needed to take, and the traffic condition as their main criteria for choosing a recommended route to follow. Some of the drivers also checked incident reports and updates (P4, P6) to know how much longer they needed to wait in congested roads.

Drivers were also seeking localized and contextual information such as transport policies (e.g. travel demand management policies, truck ban hours) and flooding (P3, P4, P8). Common to Philippine metropolitan areas, travel demand management policies disallow certain vehicles to use public roads on specific time periods, and it can differ per city. P4 sought this information because he wants to know if he needs to leave earlier than usual to avoid getting apprehended or not use his car at all. Although some participants explicitly shared that they do not actually seek for this information anymore (i.e. P15, P16, P17) because they only memorized it once and doesn't change. However, I see this information useful for transport network vehicle (i.e. Uber, Lyft, Grab) drivers who take passengers to unknown destinations, across cities. In one instance shared by P6 as he was riding an Uber, the driver was apprehensive in crossing another city as recommended by his Waze application because the driver was not sure whether he's allowed or not. That city had a completely different travel demand management scheme as the rest of Metro Manila. Lastly, P7 shared that during winter, he is seeking local information about roads that are not too slippery and safe to drive on, especially because the main roads are where most cars will go.

For longer and or occasional trips, drivers were also seeking information about familiar landmarks (P3, P4), good parking spaces and local directions. While in-car navigation systems and navigation applications can provide these information, drivers still seek the knowledge of a local person that knows the ins and outs of an unfamiliar place.

3.3.3 Usage behavior

Drivers have been observed to have different behaviors in accessing information and using these to decide which route to take.

Before starting their daily commute trips, drivers first check the estimated time of arrival (ETA) of the recommended route. They want to have a quick overview of how long it will take them to get to their destinations. Then, they check their familiarity with the roads that were recommended. They usually check how close it is to their regular routes. If it is completely new to the drivers, they check the alternative recommendations and see if their regular route is included. They check the differences between the estimated times of arrival and decide based on a criteria. If they are leaving very late and or in a rush, they only check the ETA (P4, P10).

During the trip, drivers start the turn-by-turn navigation but only some of them chose to follow it. For example, P10 still follows her regular route to work but still keeps Waze on to get traffic updates. However in the case of P8, she shares that she always follows the suggested route.

When they suddenly experience slowing down due to unexpected traffic build up, they first check what caused it using the navigation application. If there are no reports on the application, they sometimes check Twitter and or Facebook (P3, P4). For alone drivers, they only get to check this information once they are slowing down or in a complete stop (P4, P17). But as passengers and navigators, they tend to check why there's a sudden slow down in traffic and try to look for possible alternative routes (i.e. P3, P4, P6, P16, P17).

For shorter trips to unknown locations, they only used one tool for route guidance. For longer trips, some participants use a mix of applications to plan and navigate. For instance, P3 and P4 shared that they use Google Maps for planning the trip and Waze during the actual trip. Using Google Maps, they looked for landmarks that they can use during the trip and familiarized themselves with the area. And then during the actual trip, they have Waze or Google Maps turned on from the beginning, but leave it idle. They would start to

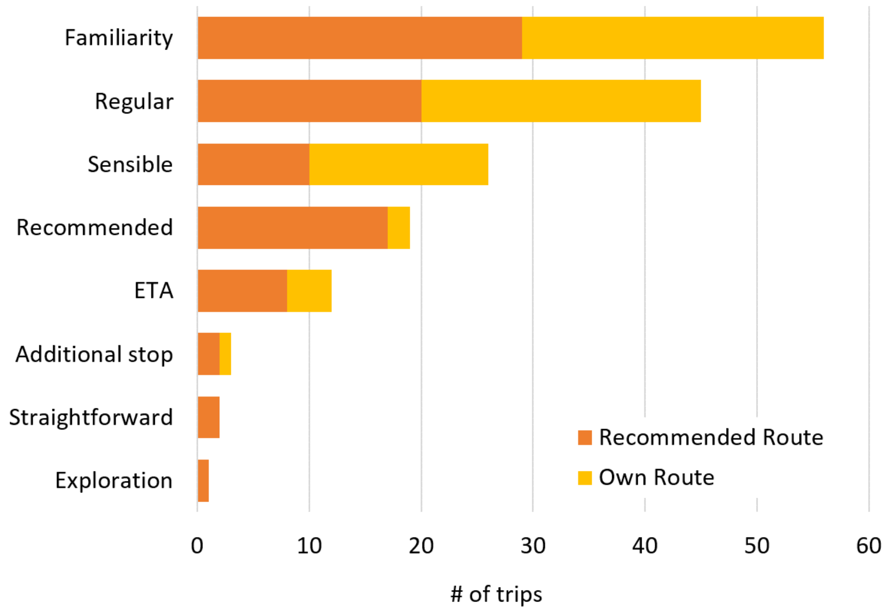

Figure 3.6: The factors considered for route choice and the number of trips that used them when they chose their own or a recommended route.

carefully listen to the directions when they already reach a point that they are unfamiliar with (i.e. P4, P15, P17). This supports Patel et. al.'s findings that drivers preferred routes that use familiar landmarks over very detailed turn-by-turn instructions [119].

In some trips, they switched to another application because of unreliable or missing information. For example in P12's trip, they stopped following the in-car navigation because its map is not updated with the new roads. They then switched to Waze.

3.4 Route Choice

I also wanted to investigate whether our participants chose to follow the recommended routes given by the applications and in-car navigation systems that they use. I used the app recordings to see how they engaged with an application before a trip. I checked if the destination and agenda upon arrival plays a role. I also analyzed what and how the descriptive and prescriptive information provided were used.

After analyzing the trip recordings, I found our results consistent with the findings of Zhu and Levinson [181], and Tang et. al. [158]. Our 17 participants chose a route that is not the shortest nor fastest, as computed, in at least one of their recorded trips. At the beginning of each trip, participants decided to use their regular routes in 28 trips (43.1%), where the occasional non-commute and home-to-work trips each comprised 42.9%, and 14.3% were work-to-home. On the other hand, 37 trips (56.9%) decided to follow recommended routes at the beginning. Majority or 59.5% of those trips were occasional non-commute, while the work-to-home and home-to-work trips comprised 24.3% and 16.2%, respectively. While this contrasts the low preference of drivers for fastest and shortest routes in Pfleging et. al.'s [121] study, this was mainly because Waze and Google Maps do not have options available for eco-routes while the in-car navigation systems used does not make that option apparent to the participants.

Figure 3.6 shows how many trips used a which factors to make a route choice decision. In majority or 65% of the recorded trips, participants considered 3 factors, with familiarity as the most used factor. And while 56.9% of trips used the recommendation at the beginning, only 21.6% chose them because of fast ETA. This contrasts the high importance rating of the fastest route factor in the work of Pfleging et. al. [121].

Before starting their daily commute trips, most participants checked the estimated time of arrival (ETA) and their familiarity with the roads in choosing a route to follow. When they had an important agenda (e.g. meetings, parties) and they were already running late, they chose the fastest recommendation of the application without consideration of familiarity (i.e. P4, P8). For P17, he always turns on the application and follows what recommendation is given. Sometimes, he would inspect the first few roads to decide otherwise.

When some participants were leaving early and not in a hurry, they always compared the ETA of their regular route with the fastest recommendation. They would chose their regular routes over the fastest recommendation if the time difference is negligible. For instance, P15 shared that he would choose a new recommendation from Google Maps when it is at least 10 minutes faster. But when it is only 2-5 minutes faster, he would still choose a familiar or his regular route. Other participants shared that they would choose a recommended route as long as it has less traffic congestion (i.e. P3, P15), shorter distance (i.e. P3, P5) and straightforward paths (i.e. P8, P14). If some parts of the recommendations do not fit their criteria, they would make a decision to not follow it completely and rely on their own knowledge.

For occasional non-commute trips, participants chose routes with familiar landmarks (P3, P4), roads familiar to them (P5, P6, P7), and routes suggested by friends living near their destination (P8, P9). For completely new destinations, most participants would follow the application or in-car navigation system completely.

Interestingly, some participants have other reasons for picking a route. For example, P6 shared the he once chose a route with a gas station along the way because they are taking a long trip while P14 chose a route with a specific restaurant along the way because they haven't eaten lunch yet. Other reasons include the need to visit convenience stores (P6, P7) and toilets (P13), and to drop off passengers on the way to work (P6).

Surprisingly, I also found that some participants will open their applications but choose not to follow whatever the application recommends, especially for commute trips. P9 shares that *"In fact, I have self-awareness that in those moments that I know I can, I try to not [follow]."* She doesn't want to be too dependent on the application as she feels that *"whenever there are cases that I cannot use it, I feel incapacitated."* Other participants like P6 shares that most of the time, he just takes his regular route and leave Waze on because he believes that it can learn his regular route. However, even after some months of doing so, the application still doesn't give his regular route as the first recommendation. This non-compliant and non-use behavior supports the findings of Al Mahmud et. al. that some drivers choose not to be too reliant on GPS devices because they know that it can make mistakes and they still have to make their own judgments[99].

3.5 Deviations

In understanding the motivations behind the deviations, I analyzed the videos, trip data and trip traces to see if any were deliberate or missed turns, and whether they were based on prior knowledge, on information from applications or situational awareness. During the 65 trips, participants deviated 153 times in total. They did it 39 times for home-to-work (M=2.17, SD=5.07), 30 times for work-to-home (M=2.31, SD=6.19), and 84 times for occasional non-commute trips (M=2.47, SD=1.65). 38.5% of them were single deviations made near the beginning or end of trips, while the extreme cases (3.1%) made 14-15 deviations (Figure 3.7). However, there is no clear connection between the types of trips and the number of deviations made.

Comparing the estimated travel time of the recommended routes and the actual travel times, deviating at least once made the trips longer by an average of 3.11 minutes (N=53, SD=12.35). When only 1 deviation was made, travel times increased by an average of 0.13 minutes (N=25, SD=8.72), and 1.07 minutes (N=45, SD=10.24) for up to 4 deviations.

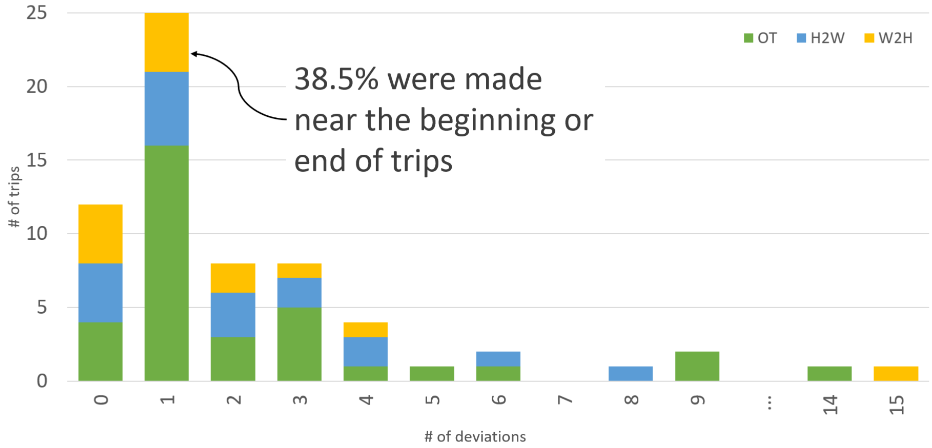

Figure 3.7: The factors for deviation and the number of deviations they caused.

In extreme cases of more than 5 deviations, an average increase of 14.63 minutes (N=8, SD=17.21) was experienced. Although none of the drivers perceived their trips to be longer nor farther after making deviations, this shows that travel time can get worse as more deviations are made.

Looking at trip purpose and urgency, participants made an average of 8 deviations (N=4, SD=5.07) for non-work but urgent trips like catching a flight or appointment, and attending a gathering. When they had to arrive urgently at work, their deviations also increased to an average of 3 deviations (N=12, SD=2.26). But even in non-urgent situations, participants also made more deviations especially when they will only rest (N=13, M=3, SD=3.78) and do leisurely tasks or tours (N=11, M=3, SD=2.5) at the destination. By going through the post-collection interviews, participants revealed various reasons why they deviate from the recommended routes that they choose (Figure 3.8). In 50.98% of deviations, more than 1 factor was cited.

Previous Experiences (1.31%)

Participants were mostly deviating from the recommended routes because of their unfamiliarity with some of the roads. This was commonly observed on home-to-work and work-to-home trips where the drivers were recommended fastest routes but were not particularly in a hurry to get to their destinations. For instance, P12 was observed to follow the same path from their hotel to a museum because that was the same path they took when they got to their hotel the previous day. On the other hand, P7 chose to continue on an unfamiliar

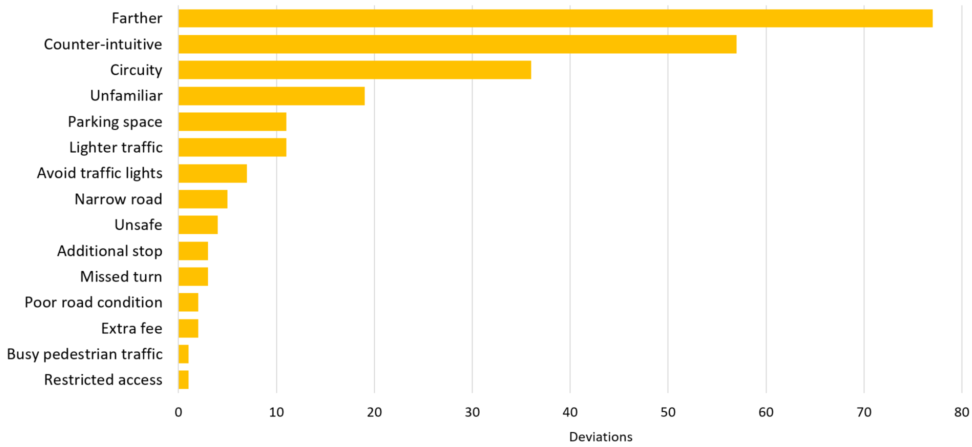

Figure 3.8: The factors for deviation and the number of deviations they caused.

part of the recommended route because *"This is new to me ... but it seems reasonable because I do not have to make a U-turn."* – P7

Some participants also deviated because of their past experiences with long waits on traffic lights. In one of his non-commute trips, P4 decided to make an early left turn from the main road, instead of going straight, because *"the next big intersection has a traffic light and I know that's going to take long."* P6 also shares a similar practice when he is recommended to take a main road with traffic lights on its every intersection. *"I just use the smaller road parallel to the main road because it it doesn't have any [traffic light] at all."* – P6

Participants also consider their negative experiences with past recommendations. P17 shares that he deliberately deviates from a specific road whenever it is recommended. *"Usually, I do not take [street name] ... I opt to go with [another street name] route. I really inspect the route given because I'm avoiding a certain road ... I do not like [taking] [street name] because it's a small road, and when traffic starts, it really regresses along the way. I do not want [to take] it anymore ... It already happened before that Waze asked me to go there and I ended up being stuck there. It happened a lot of times."* – P17

Situational Awareness (33.99%)

In most situations, drivers were in situations wherein they have to make quick decisions when their expectations (based on the information that the applications and systems have provided) do not match what they see on the roads. For instance, P6 chose not to follow the next turn recommended by the Waze application because the traffic condition on that

Figure 3.9: Images of roads recommended to Waze users that are not suitable for driving. [Left] A dirt road and [Right] a residential street that can only be accessed on foot. These were all gathered from Twitter posts which are related to Waze trips.

road was equally bad as the road he's currently in. Based on perceived road conditions, participants deviated 48.48% of the time from recommended roads with *medium* traffic conditions to *light* ones and always from recommended roads with *heavy* traffic to *medium* and *light* ones.

P17 made a similar deviation when he was asked to take a circuitous route through small residential roads, just to return to the road he's currently in. He made a decision to not follow because the traffic is already free flowing on the main road, and not as bad as what is shown on the application. Representing majority of trips with single deviations, participants also deviated near the end of their trips when their initial parking spaces were already full and they had to look for other locations, which was consistent with the findings of Fujino et. al.[61] and the *destination* problem in Brown and Laurier's[23]. This was also the case at the beginning of their trips when they leave their parking spaces.

Other participants also cited instances when they were directed to gated communities with restricted access, and roads that were unexpectedly blocked. Because their applications were not updated with such information, they just made a conscious decision to take another route and waited for the application to re-route.

Perceived Driving Suitability (26.80%)

Some participants shared that they did not feel comfortable driving through some of the recommended roads (Figure 3.9). For instance, P7 was observed to not take a shortcut suggested by the application because *"This is a kind of shortcut but this is a narrow road and it* *is [a] good route for familiar drivers ... Local familiar drivers and many local drivers tend to use this route but this is narrow and ... it is not so good in dark situation[s]. It is very narrow and [a] very local road ... and usually there's no other walkers [t]here. But if there is, it is very dangerous."* P13 shares the same sentiment when he was asked to take a narrow back street from the hotel in one of their recorded trips. He shared that *"It's a very small road. I do not like to drive on a small road. We're using a rental car, so it's very dangerous."*

Other participants shared instances when they were directed to busy streets and deviated from it. P4 shared one instance when he was recommended to a residential road and he deviated because *"... there's so much pedestrian foot traffic there ... there were also tricycles ... on the same road, it's two-way, so there were also [cars] driving on the opposite direction [but it's narrow] ... so you really have to give way and wait sometimes."* Despite being a more experienced driver, P7 was also observed to deviate from busy main roads especially when going home. *"this route is main road, so then I do not have to ride on that main road just for going to my home."* – P7

Lastly, mostly female participants (P1, P5, P8, P9, P10, P14) and P7 shared instances of deviating from recommended roads because of poor street lighting conditions, especially in the evening.

Practicality and Sensibility (94.12%)

Participants were also observed to follow more practical and sensible routes, which goes against most of the recommendations of Waze. Because it was before rush hour and there was still no traffic congestion, P6 was observed to deviate from the recommendation of Waze to take the tolled expressway. Instead, he took a smaller local road, running parallel to the expressway. He argued that since he was not in a hurry, and even if he was, he did not take the tolled expressway because there was no traffic congestion yet. Despite having an option to avoid tolls in the application, he did not enable it at the beginning of the trip because he didn't know the traffic situation until he was near that turn. There was also no way for him to turn it on during the trip as he was already driving. P12, P13 and P14 also showed this behavior when they were recommended to take tolled roads, primarily because of unnecessary extra cost when there is no traffic congestion to beat and they were not in a rush. Aside from P14, the three are students (P12, P13) and self-employed who earn between $500 to $1,000.

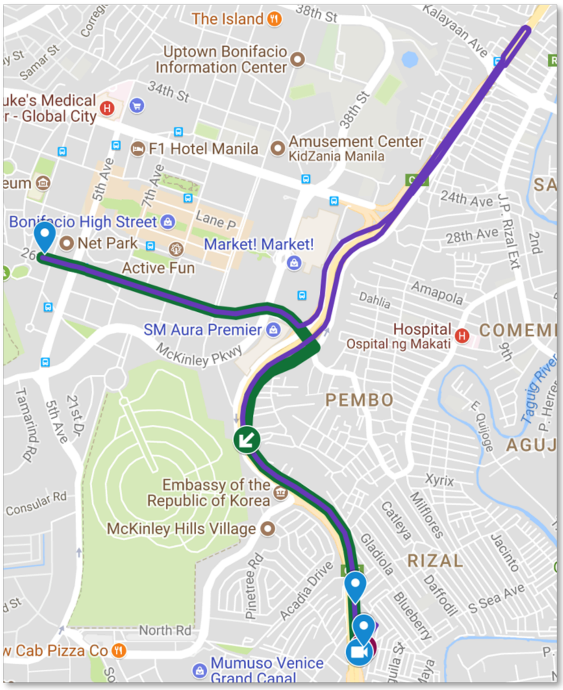

Figure 3.10: A route recommended to P4 in one of their Home-to-Work trips. The purple line shows the fastest recommendation by the navigation application. The green line shows the actual route followed by the participant.

Other participants deviated because they found some recommendations farther, circuity, winding, and counterintuitive. It's also in these rare cases wherein participants made a trade off to transfer from recommended roads with *light* traffic to *medium* and *heavy* traffic roads (2.65% of the time), and from recommended *medium* traffic roads to *heavy* traffic ones (6.06% of the time). For instance, P3 was recommended to take a route that was *"in terms of distance ... when I turn right up to [name of flyover], it is really far."* Instead, he took a route that was comparatively shorter but took longer because of the traffic congestion. Similarly, P4 deviated from a recommendation because it was almost twice as far as his regular route (Figure 3.10). The application's estimated time of arrival was around 19 minutes and the regular route he took was around 15 minutes only. It seems that the application suggested the longer route because one segment of his regular was showing red in the application, meaning there is reported heavy traffic. However, when he was already at that road segment, he shared that *"surprisingly, well not surprisingly, it was okay ... it's like when I took that road, what I usually take, it was okay. It was free flowing."* Upon analyzing the trip recording, I found that one reason that it was reported as heavy traffic and avoided by the application might be the long wait at the traffic light. But unlike the earlier scenario where P4 avoided the traffic light, this time he didn't because the recommendation was twice as long but only shortens the travel time by around 2 minutes, as indicated by the application.

Some participants, like P16 and P9, were observed to deviate from roundabout, circuitous recommendations because they saw that they can easily make U-turns.

Missed Turns

While most of the deviations were deliberate, a number of them were actually missed turns due to late, missing, complex and vague instructions. For instance, P15 shared that when he was instructed to turn right in 100 meters, he was not really sure which corner it was because there 4 consecutive corners that were very close to each other. He ended up missing the correct corner to turn to. Another instance was when P9 was asked to go straight thru an intersection, she couldn't because there were already concrete barriers. She shares *"I was stuck on the left lane and required to turn left because I didn't receive instructions to stay in the middle or right lane ... It was also difficult to cut past the trucks on the middle lane. I stayed on the left lane."*

3.6 Discussion

While it is clear that these applications were mainly designed and developed with the good intention of getting people out of traffic congestion, it is evident from the results that *connected drivers* do not always seek that prescriptive information from navigation applications and in-car navigation systems. For completely unknown destinations, their recommendations made much sense and participants showed high compliance because they do not have prior knowledge to compare with. So they tend to rely on it rather than question its validity. However in most cases during commute trips, they sought traffic and route information relevant to the ones they regularly take. A few of the participants followed whatever is recommended (i.e. P8, P17), many followed recommendations when it matches familiar or regular routes, while some put some constraint on their choices (i.e. P15, P7, P4). These findings cannot be observed in Brown and Laurier's[23] work because they all had their participants follow their GPS device as a condition.

Our list of route choice and deviation factors can be mapped to Pfleging et. al.'s list except for *additional stop*, *parking space*, *restricted access* and *avoiding traffic lights*. Compared to their more generic factors like *least stress*, I expand this work by giving more detailed factors like *circuity* and *counter-intuitive*, which are more useful in coming up with solutions. Surprisingly, their highly rated factor *least fuel consumption* was not considered, along with *no speeding traffic*, *only few trucks*, *low curvature* and *well rated route*, probably because of local considerations. However, this can also be said for factors *avoid traffic lights* and *restricted access* that only appeared in our findings. However in terms of importance and usage, *familiarity* and *known routes* were mostly considered in 86.15% (1st) and 69.23% (2nd) of the trips, whereas in Pfleging et. al., *known route* and *highest driving experience* were ranked low [121]. This shows that even though drivers know there are important factors to consider, their actual use still depends on a trip's purpose, when the choice is being made, and current conditions.

Drivers also seem to be exhibiting cases of the Einstellung effect [20] wherein people are biased towards what they already know, which supports the findings of Patel et. al. [119] that drivers prefer personalized routes that include familiar landmarks. I observed this when some drivers made route choices at the beginning of some trips to follow their familiar path even though it was longer and had a later ETA compared to the first recommendation. This was also evident in many deviations wherein they default back to familiar roads when they are about to follow the recommended, yet unfamiliar routes of the application. In the end, they were willing to trade off shorter travel times and distances just so they can be at ease with their navigation choices.

However, if we observe how navigation applications and in-car navigation systems behave, despite considering traffic conditions in their recommendations, they still lack the personalization and sensibility that drivers desire. And quite surprisingly, this caused some participants to completely disregard the recommendation, leave the application on, and go on their own way, hoping that it will learn what it doesn't know yet. But such applications do not learn routes for a single user only. It learns and identifies the best new routes that will be recommended for everyone. This driver behavior and expectation supports Wu's [177] finding that users have high positive perception when recommendations are matched with their own behavioral history rather than the history similar users. It then raises the question of how much personalization and history is needed.

Finally, it was also observed from the trip recordings that such applications, especially

Waze, aggressively recommend and reroute to faster directions for the smallest of gains. And for some participants (i.e. P8, P14), it can be annoying. However, we also found some participants like P17 and P9 who completely understood how such applications work and tend to regard such behavior in a positive way.

3.7 Design Implications

In this section, I present a series of design implications based on our analysis of trip recordings and interviews. These recommendations should be taken as a starting set of considerations in ensuring that the next iteration of navigation applications can incorporate the nuances of a connected driver to increase the chances of behavioral adaptation.

Make Uncertainty Visible

Given the probabilistic and crowd-sourced nature of information shown and used for recommendations on modern navigation applications, there is a tendency for traffic conditions and reports to be unreliable and outdated. This is due to the open problems on data sparsity and in ensuring the integrity of collected reports[12,124,167]. Because of this concern, I found that drivers were starting to ignore these descriptive information and rely on previous experiences, causing a number of deviations. Although the drivers are unlikely to totally disregard their utility, it is still important to be transparent with the nature of the data we present to users. This can be implemented by considering the uncertain and decaying quality of the crowd-sourced information and try different visualization strategies for improved decision quality. For example, Waze consistently displays a heavily congested road in red and after a few minutes (decay), it either disappears or changes color based on new information. Applying our recommendation, traffic-indicator colors can slowly fade as time passes until an updated information is ready which allows drivers to act properly on information posted minutes ago. For this, we can explore the implementation of value-suppressing uncertainty palettes[35], and or Fernandes et. al.'s[54] dotplot or CDF plots which was already tested in a bus transit application. However, as navigation choices are made very quickly, this has to be evaluated for time-critical tasks and prolonged use. Drivers were also found to rely more on voice guidance during trips, so developers may also consider translating these uncertainty information to voice prompts.

Provide Real Personalization

Drivers are idiosyncratic and yet, existing applications still show the fastest route by default. This was evident when only 18.4% of all trips and 21.6% of those who followed recommended routes considered a fast ETA for route choice. It is also worth noting that in some of the trips, deviations were clustered on certain areas because their applications assume that the drivers just missed turns and needs to be rerouted back to the recommended route. However, drivers were already deliberately ignoring those, either due to a new route they chose on their own or annoyance[99]. While it is difficult to define a concrete set of conditions that will satisfy their needs, applications can start by learning a driver's mostly used routes and frequently visited landmarks which has been proven to improve user perception[119,168,177]. Future navigation applications can show the estimated time of arrival, traffic condition and reports on their mostly used routes so they can properly decide whether they should take a better and new alternative or stick with their regular. Applications may also offer a way to detect when a driver already dislikes the recommended route after a number of deviations, either automatically, by subtle voice commands[143], quick touch interactions, or a combination of these.

Currently, navigation applications know a lot of about the spatial context of the driver. However, drivers were found to make different route choices, and even make deviations, depending on the type of trip, purpose, and urgency. Some of them also shared their desire to explore scenic routes or routes that will allow them to discover new places or stores along the way[127]. Waze and Google Maps already allow integration with personal calendars so that they can make quick searches if the location of the calendar event is already provided. They also allow certain locations to be tagged as *home* and *work*. Future navigation applications may maximize these information and offer drivers to define the intent behind the trip on top of knowing the name of the event. For example, if the driver search directions for tourist destinations, it can infer from the locations that the driver is sightseeing and recommend routes that are scenic and less congested, to maximize the experience. Applications may also use the *home* and *work* tagged locations to offer better recommendations. For example, drivers going home may be recommended straightforward and less stressful routes, which support a common behavior from our findings.

Provide Local Wisdom of Close Network

In uncertain conditions, aside from defaulting to what they are familiar with, drivers are also found to seek information from close friends during trip planning. Some applications already have built-in friend networks while others allow integration with third-party social networks. Hence, applications may offer ways to better maximize these networks to make better recommendations like in the work of Sha et. al.[148] where they use *tweets* from nearby vehicles to improve their route recommendations. They may learn the mostly used routes of a driver's close network of friends and prioritize them in the recommendations. One benefit of this is that it provides a sense of community and familiarity. When combined with recommendations based on personal history like in hybrid filtering, user perceptions can also improve[177]. Additionally, leveraging this information allows the application to improve its recommendations to other drivers who are also going to the same destination.

Be More Persuasive or an Empathetic Other

Our study found that drivers are biased towards what they already know[119,23]. This was evident when 86.2% and 69.2% of route choices at the beginning of trips mainly considered familiarity and closeness to regular routes, respectively – a trade off for longer distances and later ETAs. 12.4% and 37.3% of deviations where also because of unfamiliarity and counter-intuitiveness. Following the notion of *instructed action*[23], navigation applications may offer a way to engage drivers in giving route guidance and informing with traffic conditions and crowd-sourced reports, instead of assuming they are docile actors. Antrobus et. al.[9] found that collaborative navigation with passengers yield better route knowledge compared to just using SatNav. Thus, applications may offer dialogic route guidance that models collaborative navigation with passengers. Several studies have used a virtual agent[94], an affective robot[174] and even 3 robots in multi-party conversations[82] to reduce cognitive load and distraction. These may be explored so drivers can properly consider options once the rationale behind the recommendations are known.

3.8 Limitations

In this study, participants were mostly from the Philippines and Japan, with more Filipinos than Japanese users. Because I only recorded trips that participants naturally took within a fixed period, many of the participants did not give a complete set of trip recordings for us to analyze. Lastly, I acknowledge that the recorded trips have varying origin-destination pairs thus, controlling some variables like the unknown destination could give us clearer results.

3.9 Conclusion

As governments see potential in navigation applications to shape travel behavior, it is crucial to understand how drivers integrate these in their trips and assess how well the route guidance is complied to and perceived. In this chapter, I make a first investigation of how users engage with recommender systems enriched with probabilistic and crowd-sourced information. I echo the findings of[127,181,158,61,23] that drivers do not always choose the fastest route. Further, I uncovered the difference in practice, sets of information sought and used for route choice, and how these are associated with the type of trip, trip context, and driving situations. With all participants making a deviation, I investigated how, when and why they were made. I found that deviations can happen when the recommended route has unfamiliar roads, is impractical and nonsensical, perceived as unsuitable for driving, and the shown descriptive information does not match what they see on the road. These provide further evidence that algorithmic sophistication, or less of it, plays an important role in driver compliance and behavioral adaptation. Lastly, to improve the quality of route recommendations and make sure drivers stick to what is recommended, I argue that designers should support a driver's self-efficacy and agency, so that they can make instructed actions[23]. First, trust is not only achieved with perfect accuracy. Embracing the uncertainty and sparseness of crowdsourced data, designers should make these transparent to the driver so that they know whether they have complete control of the situation. Second, provide real personalization by learning the regular routes and familiar roads, and incorporating them into future recommendations. Additionally, designers should maximize embedded social networks and learn what is familiar to their friends. This way, recommendations can be adjusted based on information from people they could trust.

He who loves practice without theory is like the sailor who boards ship without a rudder and compass and never knows where he may cast.

Leonardo da Vinci

4 Self-Determination Theory

Using key insights from my formative study (Chapter 3), I designed and evaluated two equally important approaches, each focusing on a particular step in the driving navigation task. Towards my goal of rethinking route information and navigation guidance so that they can motivate drivers to choose unselfish routes, I sought to address two specific research questions. First, how can we encourage drivers to choose the unselfish route from a list of options before they even start a trip? Second, when they choose an unselfish option and start the trip, how do we make sure that they continue following that route? And if they choose otherwise, how can we convince them to switch to an available unselfish route along the way? From here on, I focus my attention to daily commutes because these trips are the main contributors to daily traffic, unlike trips to new locations which do not happen frequently.

In this chapter, I discuss the characteristics of unselfish routes and how we can use Self-Determination Theory as as theoretical framework in designing future navigation applications as civic technology.

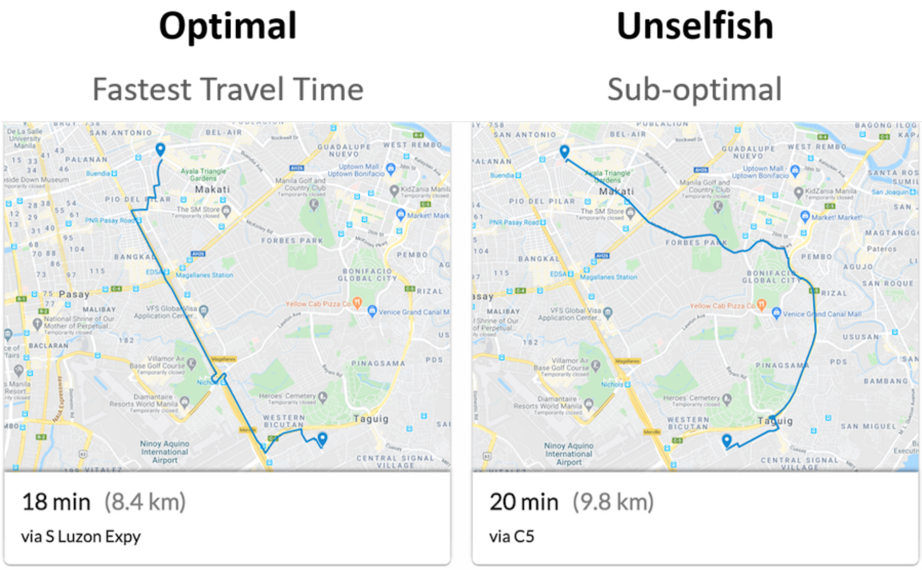

Figure 4.1: Examples of an optimal and an unselfish route between home and work locations.

4.1 Unselfish Routes

Central to my dissertation is the recommendation of unselfish routes. In Wardrop's second principle (system optimal)[169], any route followed by a driver can be considered unselfish as long as it was chosen in cooperation with other drivers in the transportation network, and that these results to keeping the average journey time at a minimum. In Colak et. al.'s approach in modeling this problem, unselfish routes were characterized by the marginal cost they impose on other drivers in the same road segment[31]. Whereas in Ringhand & Vollrath's investigation of factors that affect route choice, they characterized unselfish alternative routes as those with longer travel times or the route with more waits in traffic lights[133].

For simplicity and consistency, here I define unselfish routes as alternative routes which have few overlaps with an optimal route in terms of roads included (Figure 4.1). They have longer distances and travel times, which make them sub-optimal for a driver. In practice, not all alternative routes should be recommended as unselfish. We still need to make sure that it is acceptable to the driver by ensuring its familiarity to the driver. Additionally, their time and distance differences are kept at a minimum, so that the unselfish route will not seem too novel. For these reasons, it can be a challenge to recommend them to drivers who already have regular routes to their everyday destinations. Further, choosing an unselfish route means drivers will have to give up or volunteer some of their time, which is not always ideal when going to or from work.

4.2 Navigation Apps as Civic Technology

If future navigation applications will become tools to aid government stakeholders and urban planners in accomplishing their traffic management and sustainability goals, we have to start designing technical solutions from the point of view of civic technologies. By definition, civic technologies are tools that facilitate the collaboration between governments and their citizens for the public good [100]. In future traffic management systems, it would require a great amount of effort from governments to establish communication and technology platforms that will allow long term behavioral transformation among its citizens. On the part of the citizens, they have to be motivated enough in order to sustain or even be convinced that they should adopt or participate in such prosocial behavior.

In our envisioned future, drivers on the road must collectively work together towards the common goal of avoiding traffic congestion. A more sustainable future is when citizens will voluntarily change their driving behaviors and daily routes because they are increasingly aware of its benefits for them and others.

Civic technologies have been used to organize citizens or small communities towards common goals. And in order for them to achieve tangible outcomes, citizens are usually asked to volunteer their time and effort for a number of reasons, most of the time without monetary incentives. Thus, despite effectively communicating lofty goals of achieving social good, designers of civic technologies still face the challenge of encouraging citizens to contribute and continue participation. In a similar context, it can be challenging to convince drivers that they should give up some of their time and choose an unselfish route for their daily commutes.

Behavioral theories have been a cornerstone in HCI research especially in designing computing solutions that implement interventions for behavior change. The cross-pollination between the two fields have resulted to better interventions, systems and theories, and we have to continue this practice in order to achieve better behavioral outcomes [74]. To inform my designs, I used Self-Determination Theory as a conceptual framework for the succeeding chapters.

4.3 Self-Determination Theory

Motivation is the primary driving force in starting and performing any work, learning or task. These are often categorized as intrinsic and extrinsic motivation, wherein the former was proven to have positive effects on work performance[62]. One established theory on motivation, growth and well-being, the Self-Determination Theory (SDT)[139], expands this categorization by introducing a spectrum of extrinsic motivation[142,43,45]. Past theories mainly consider the task as the origin of motivation. On the contrary, SDT posits that humans are active organisms that can regulate the internalization of external stimuli in developing one's self. We are given a framework to understand how humans who perform the task and their internalization of its reasons and goals affect their motivation[138].

SDT is comprised of six mini-theories that characterizes different facets of motivation and personality functioning. Hereon, I will describe three mini-theories that primarily informed my designs.

4.3.1 Motivation

SDT posits three types of motivation as shown in Figure 4.2: intrinsic motivation, a spectrum of extrinsic motivation and amotivation. *Intrinsic motivation* is the tendency of a person to pursue an activity or task because they find it inherently exciting, enjoyable or interesting, while *extrinsic motivation* is the pursuit of an activity for an independent outcome (e.g. rewards, money). Devoid of any intention, a person who is *amotivated* experience detachment from the task or activity that they are doing. But regardless of type, motivation always require energy to perform a task and this energy gets moved in a certain direction in the continuum[43](Figure 4.2). Thus, when *"an individual acquires an attitude, belief, or behavioral regulation and progressively transforms it into a personal value, goal, or organization,"*[139] these get internalized into autonomous and controlled motivation, or lack of motivation. As one person's motivation towards an activity moves to the right of the continuum, the motivational quality improves and the perceived locus of causality becomes internal, leading to stronger *autonomous motivation*. But if the motivation's energy moves to the left of the continuum, the motivational quality of the activity becomes lower, requiring more *controlled motivation* to perform a task.

There are two mini-theories that particularly address the facets of motivation. The first is *Cognitive Evaluation Theory* (CET) which focuses on the factors that affect a person's *in-*

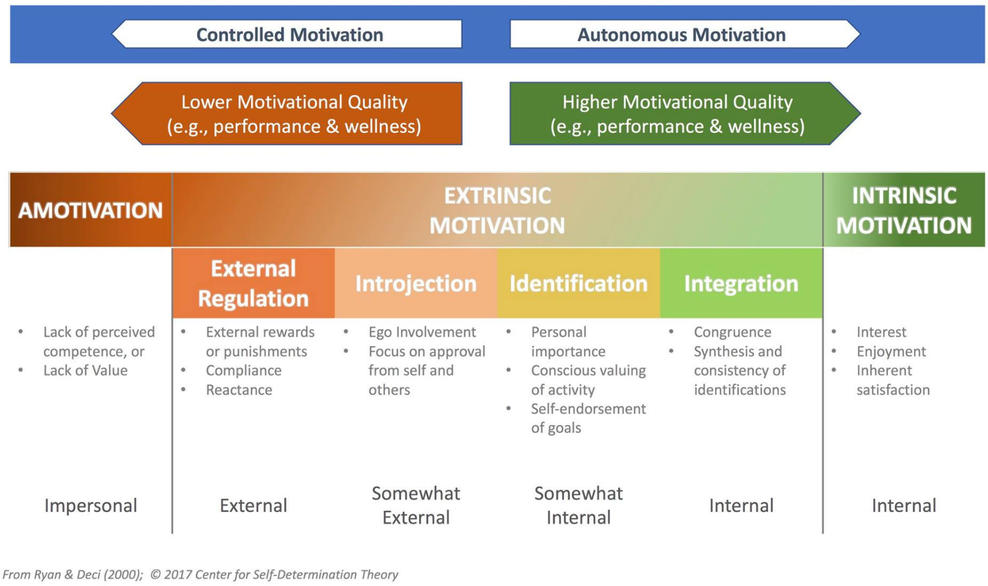

Figure 4.2: The different types of motivation and behavioral regulation. In this continuum, different forms of extrinsic motivation and behavioral regulation result to different motivational qualities. As you move to the right and develop a more self-determined extrinsic motivation, the motivational quality improves until intrinsic motivation is fostered. Going towards the left end of the spectrum means a person starts to lose whatever inherent interest they have and has to be controlled to perform a task with external rewards. This was adapted from [139,141] and stylized by the Center for Self-Determination Theory.

trinsic motivation towards a task or activity. It states that social context and the functional significance of a stimulus or activity have an effect on need satisfaction and internalized intrinsic motivation [43]. It emphasizes the importance of supporting the needs for competence and autonomy in developing *intrinsic motivation* towards a task. However, it also posits that *intrinsic motivation* can be diminished by the use of extrinsic rewards.

The second mini-theory focuses on the various types of *extrinsic motivation* and how they can be internalized by humans [139,44,141]. *Organismic Integration Theory* (OIT) posits that *extrinsic motivation* corresponds to behavior that aims for instrumental outcomes external from the activity itself. In a continuum (Figure 4.2), the quality of extrinsic motivation changes based on how they are internally valued through internalization. In its least self-determined and internalized form, *external regulation* is when a person acts purely for compliance or rewards. Moving towards the right of the continuum but still partially internalized, *introjected regulation* is when someone acts out of guilt or for the approval of other people. It suggests that that person realizes the social value of the activity or task but has not fully aligned it yet with their personal values or goals. Moving towards an autonomous motivation, a person with *identified regulation* performs a task or activity because they now see it as personally important. Lastly, the most self-determined form is when a person exhibits *integrated regulation* or the performance of an activity because they perceive it as congruent to their personal values and goals, and are already internalized as part of their self. Thus, higher motivational quality can be achieved by working towards fully internalizing the extrinsic motivation. However, like in CET, the process of internalization is also affected by social contexts. And ensuring that the needs for autonomy and relatedness are supported can impact internalization.

4.3.2 General Causality Orientation

In designing civic technologies, it is ideal that we engage citizens with causality orientations and behavioral regulation styles that foster autonomous motivation. SDT's framework describes a set of general causality orientations that describe ways people orient themselves across different environments and regulate their behavior. These temporally stable traits affect their perception of how self-determined their actions are. Persons who are autonomy oriented typically initiate tasks or activities on their own especially those that are interesting and challenging. They seek environments that are optimally challenging and allows choice. They take responsibility of their actions and when they encounter external events, they see it as informational rather than being controlled. Control oriented people usually act as a response to external demands like rewards, directives and ego involvements. They feel less autonomy because external events put pressure on them. Lastly, people with impersonal orientation tend to feel that they are not in control of situations and focus on obstacles towards intended outcomes. This makes them feel amotivated and leave things as they are.

4.3.3 Autonomous and Controlled Motivation

If a person has a *identification* or *integration* regulatory style, and is autonomy oriented, they are predicted to internalize *autonomous motivation*. On the other hand, if a person needs to be *externally regulated* or has *introjection* regulatory style, and is control oriented, they are predicted to internalize *controlled motivation*.

4.3.4 Basic Psychological Needs

In order to foster autonomous motivation and enhance the internalization of extrinsic motivation, SDT also claims that the environment within which a person performs a task must support three basic psychological needs that are universal: autonomy, competence and relatedness[140]. Supporting the need for autonomy gives a sense that they are willingly performing self-endorsed actions. The need for competence requires us to make people feel they have an effect and to give them a sense of proficiency in their chosen work. Lastly, supporting the need for relatedness means providing a feeling of belonging and community with others.

Thus, if we are to design future navigation applications as autonomy-supportive tools, the basic psychological needs have to be met, regardless of causality orientation and behavioral regulation style. To see how SDT can be implemented for navigation applications, the next chapter describes a GUI-based approach that adds motivative and familiarity information when displaying the list of choices to a driver.

5
Promoting Unselfish Routes

Traffic congestion has been a perennial problem in many highly urbanized cities across the globe. As government stakeholders tackle this issue by implementing policies and building infrastructure, they are also becoming aware that there is a greater need to promote sustainable driving behaviors among its citizen drivers to fully achieve their goals[12,39]. It would take long term transformations on the route choice behavior of everyday drivers.

Navigation applications have a great potential in helping cities manage traffic flow at the onset of a traffic congestion. Drivers who commute daily to and from their work, school or business can be distributed and guided to a number of alternative routes with the goal of preventing traffic jams. If the road network is already experiencing traffic congestion on some of its roads, drivers can be directed to less used roads. And crucial to this is the timely delivery of navigational information that will aid the driver in their decision making.

There are a number of factors that affect individual route choice[18,30]. Arguably, the most important factor is travel time[18] and we see this information constantly highlighted whenever we search for driving directions in most modern applications. While this is especially true in urgent circumstances, we found in Chapter 3 that in most cases, road and route familiarity and their closeness to what drivers use regularly play a bigger role in the decision making process. For these reasons, it can be a challenge if we suggest unselfish routes to daily commuters. Unlike optimal routes that are recommended because they have the fastest travel time or shortest distance, unselfish routes are alternatives that are typically sub-optimal (slower or longer). So now the question is if it would be possible to convince drivers to choose a sub-optimal unselfish route over an optimal one at the beginning of a trip. In this chapter, I:

- describe a GUI-based approach that uses different combinations of motivative and familiarity information to route recommendations;
- show how these types of information and their combinations give promise for autonomy support for an unselfish route choice;
- elaborate how their causality orientations and behavioral regulatory styles explain their individual route choice;
- discuss how participants were more likely to choose an unselfish route when presented with simple and explicit descriptions of its possible outcomes; and
- discuss how more support for relatedness is needed for drivers with moderate impersonal and controlled orientation.

To end this chapter, I argue the need for a more personalized motivation. In coming up with personalized and theory-based information displays, designers must be cautious as to how they will be interpreted. This is besides making sure that the information are properly supporting a psychological need. I also suggest exploring other types of information to support the basic psychological needs and other ways of presenting them (e.g. how to display on map?).

5.1 Review of Behavior Change Techniques

In the Antecedent-Behavior-Consequence (ABC) model of behavior, antecedents are stimuli or events that trigger a current or target behavior. Behavior theories characterize them as psychological factors like motivation, self-efficacy, attitudes and benefits and risk perceptions, which can be influenced by a number of techniques. In traditional behavioral psychology, interventions can be delivered through personal interactions or other types of media (social influence). On the other hand, technology-based interventions are delivered through HCI or computer-mediated communication. As I described in Chapter 2, HCI researchers continue to develop technology-based interventions, most of them targeted towards health, well-being, sustainability and privacy behavior outcomes. In Chapter 4, I also discussed how it is being used to increase motivation for active and continuous use of and participation in civic technologies.

An early review of behavior change technologies by Hekler et. al. revealed that even though HCI researchers draw on behavior theories to derive design decisions, translating them into single features or full-blown applications and technologies still remain trivial[74]. They argue that there has to be better bridging efforts whenever we design new technologies. Cowan et. al. found health and fitness applications to lack engagement with theory when they performed content analysis of app descriptions[37]. This is further echoed by Tyack and Mekler in their systematic review of HCI games research[163]. They found that SDT-based game designs were mostly focused on needs satisfaction and intrinsic motivation, and other important mini-theories, like the Causal Orientation Theory, were rarely engaged with.

However, HCI researchers also innovate on behavior change interventions without strict reference to theory, as this can open opportunities to extend existing theories or introduce new ones. And in order to scope how far innovations on behavior change have gone and what directions the field can go next, there were several attempts to classify them in categories. In the work of Lister et. al., they identified 13 behavior change constructs after looking into different gamification strategies used to promote physical activities and healthy diets[95]. Stawarz et. al. found 10 classes of behavior change techniques used by commercial applications for habit formation[155]. With a focus on health, Edwards et. al. examined applications that use gamification methods to promote health outcomes, and found 16 types of behavior change techniques used[49]. Aside from developing techniques that trigger target behaviors, another critical aspect that leads to successful behavior change is consistency in user engagement. In the most recent work of Caraban et. al., they found 23 nudging techniques and grouped them to the following 6 categories: facilitate, confront, deceive, social influence, reinforce, and fear[26].

Although previous findings suggest that such technology-based interventions have resulted to some changes in behavior, most can only claim modest effectiveness. One pos-

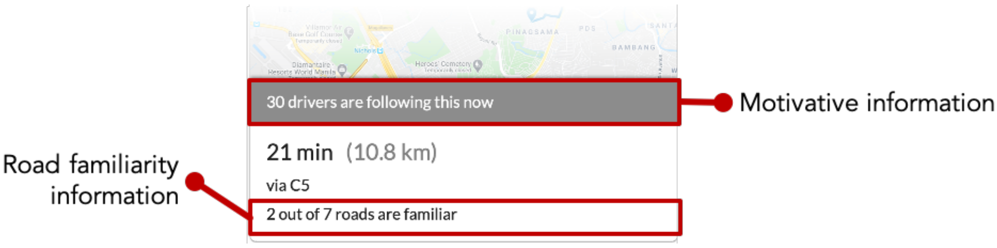

Figure 5.1: The motivative and familiarity information added to the typical travel information for each route recommendation.

sible reason is that the techniques we introduce might not be the most effective in changing the antecedents or psychological factors that promote a target behavior. Aside from the domain-specific classifications discussed above, this issue can be resolved with the development and use of taxonomies. As a first attempt, Abraham and Michie developed a taxonomy of 26 behavior change techniques that allowed other researchers to identify the different components of proposed interventions [2]. Since then, it has been widely adopted by many researchers, but conceptual problems and overlaps in definitions were later discovered. This was addressed by the CALO-RE taxonomy which now includes 40 clearly defined behavior change techniques [104]. Working with a larger team, Michie et. al. expanded the taxonomy further with 93 behavior change techniques that are hierarchically structured, which they named "BCT Taxonomy v1" [105]. Unlike previous versions of the taxonomy, this step change has international consensus, but they indicate that there will be more development and evaluation. Besides taxonomies, Oinas-Kukkonen et. al. also introduced 28 principles that are part of the Persuasive Systems Design Framework [112]. In this dissertation, I used the CALO-RE [104] and BCT Taxonomy V1 [105] as main reference for the proposed techniques. For the pre-trip approach discussed in this chapter, the behavior change technique of information provision is used by adding two new sets of information to describe both routes and their possible outcomes when chosen and followed (Figure 5.1). The first is motivative while the other shows familiarity.

5.2 Motivative Information

In order to promote the use of unselfish routes without any explicit messaging diversification and incentive structures, the addition of relevant navigational information must sup-

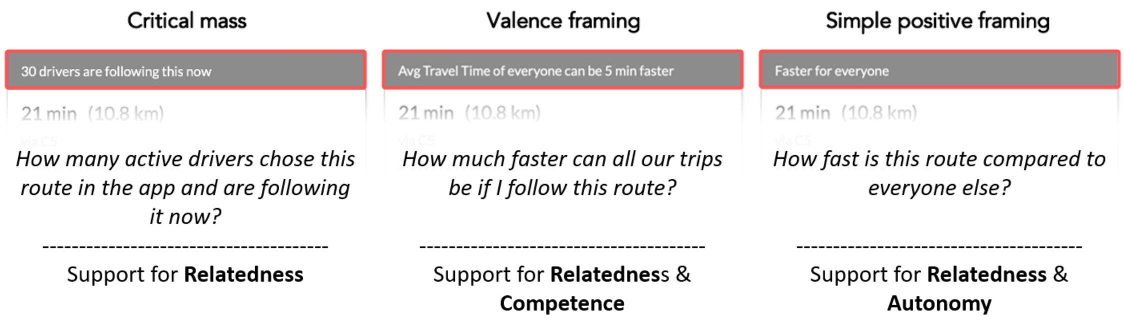

Figure 5.2: The three types of motivative information used. At the bottom of each design are the basic psychological needs supported by the information provided.

port the three basic psychological needs for autonomy, competence, and relatedness. Figure 5.2 shows the three types of motivative information used in this approach: critical mass, valence framing, and simple positive framing. Each type of information is aligned with techniques 1, 2 & 4 of the CALO-RE taxonomy [104] and the different information provision techniques under codes 5 (*Natural Consequences*) and 6 (Comparison of Behaviour) of BCT Taxonomy V1 [105]. The following subsections will discuss the rationale behind each type of motivative information and the limitations and nuances in their design.

5.2.1 Critical Mass

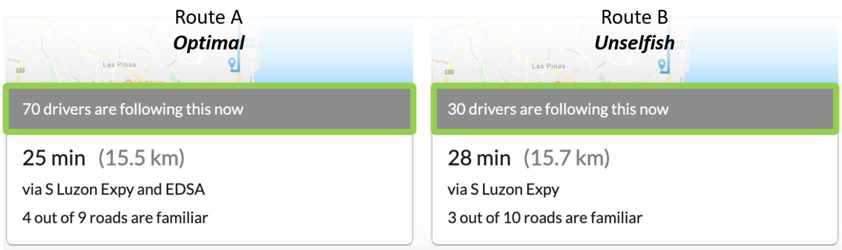

Figure 5.3: The critical mass information shown for the optimal and unselfish routes. Because of induced demand brought about by a faster travel time, the number of drivers shown in the optimal route (left) is relatively more than the number of drivers taking the unselfish route.

To address the need for relatedness, critical mass information was used to show a hypothetical number of drivers that are currently taking the recommended route (Figure 5.3). This follows technique 4 (Information provision of other's behavior) from the CALO-RE taxonomy [104] and code 6.2 (Social Comparison) of BCT Taxonomy V1 [105]. The technique aims to show information about what others typically do with regards to the target behavior.

In psychology, critical mass is used to regulate the belief that a large number of people are thinking or doing the same, and it is a common strategy to produce collective action [114]. In this study, instead of highlighting that there are many drivers currently taking a route (something that should be avoided because of traffic congestion), critical mass information was used to emphasize that there are less people taking the unselfish route. I hypothesize that by seeing this information, drivers would be encouraged by the low number and discouraged by the high number for the optimal route. To maintain the sense of autonomy and control for the user, and reduce social desirability bias, both route choices showed a critical mass number.

5.2.2 Valence

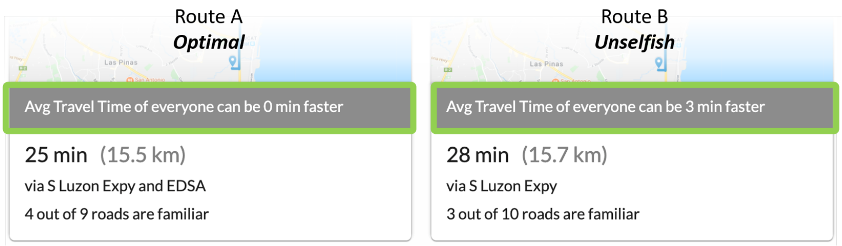

Figure 5.4: The valence information shown for the optimal and unselfish routes. For both route choices, it shows the estimated average travel time of all active drivers after the user makes a choice.

Another popular strategy into convincing people to choose between options is by highlighting differences between them. In the context of driving, these could be differences in travel time or total distance. This follows techniques 1 (Information provision - general) and 2 (Information provision to the individual) from the CALO-RE taxonomy [104] and code 5.2 (Salience of consequences) of BCT Taxonomy V1 [105]. The technique aims to "emphasize the consequences of performing the behaviour with the aim of making them more memorable," [105] both for the individual and in a general sense.

Recently, Ringhand & Vollrath [135] found that routes that positively frame travel time gains were chosen more than the way drivers avoided routes with negatively framed travel time loses. Here, gain or valence framing was used to highlight the amount of travel time that drivers can hypothetically and potentially win back if they choose a certain route. The optimal route always show a 0 minute gain because it only benefits an individual driver. But theoretically, there might be a loss in travel time especially when it actually leads to traffic congestion. On the other hand, varying gains for the unselfish route was shown depending on the type of trip and recommended routes. For example in Figuree 5.4, if the optimal route will take 25 minutes and choosing the unselfish route will take 28 minutes, it will be shown that the driver can experience a 3 minute gain if they choose the unselfish route. This number is the difference between the two travel times. This means that if a driver cooperates with everyone and follows a sub-optimal unselfish route, they can actually reduce their travel time and still arrive at their destination with the same travel time as the optimal route. The phrase *"Avg Travel Time of everyone can be..."* was used to denote uncertainty because we cannot expect that everyone will follow their unselfish routes. In here, we deliberately emphasized the uncertainty of this information to give the ultimate decision on the driver and not give authoritative numbers that they might regret not following later.

5.2.3 Simple Positive Framing

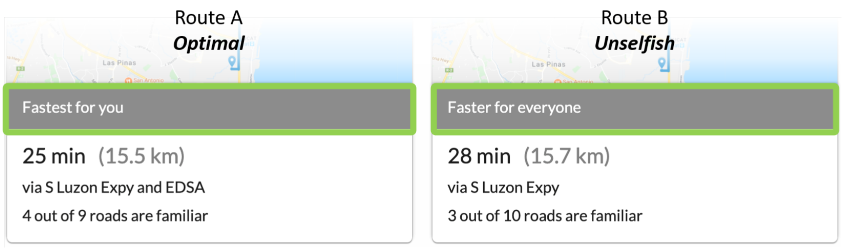

Figure 5.5: The navigational information that uses simple positive framing of the consequences of choosing a certain route.

The last motivative information is the simple positive framing of the kinds of benefit drivers might experience by following either routes. Similar to the valence information, this also follows techniques 1 (Information provision - general) and 2 (Information provision to the individual) from the CALO-RE taxonomy [104] and code 5.2 (Salience of consequences) of BCT Taxonomy V1 [105]. Again, the goal is to "emphasize the consequences of performing the behaviour with the aim of making them more memorable," [105] both for the individual and in a general sense. But unlike the previous technique of showing quantitative values, this technique focuses on using qualitative information to convince drivers.

Currently, Waze puts an *"Optimal"* label with its top recommendation while Google Maps uses the phrases that read like *"Fastest route, lighter traffic than usual."* Instead of those leading labels and using "Unselfish" for the sub-optimal route, I opted for phrases that does not overemphasize one recommendation over the other (Figure 5.5). While it is a typical technique to nudge drivers into choosing a desired route, which in this case is the unselfish one, I also want to give the impression that there is no wrong choice between Route A and B. Whichever they choose, someone or everyone will eventually benefit, and we are leaving that for them to decide. The pronouns *"you"* and *"everyone"* were used to indicate the main beneficiaries of the choice.

5.3 Familiarity Information

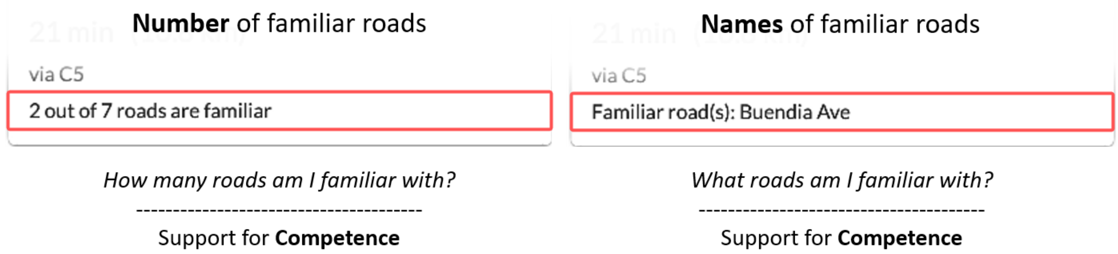

Figure 5.6: The two types of road familiarity information shown to drivers for both route choices. The left version shows the number of distinct roads that are familiar, while the right version shows the exact names of some familiar roads.

Aside from benefits in travel time, drivers exhibit strong bias towards routes that are familiar to them[144,119]. In current navigation applications, the name of a major road is typically shown along with the travel time and total distance. Given that unselfish routes are relatively sub-optimal, I hypothesize that adding information about the roads that are familiar to them will increase their motivation to make the unselfish choice. Figure 5.6 shows the two types of familiarity information. The first one shows the number of familiar roads out of the total number of distinct roads in the route. The second lists up two names of familiar roads. Both information supports the need for autonomy and competence.

In the prototypes used in this study, the number of familiar roads was based on the number of unique roads in the route that the participant has recalled to be familiar with. The total number of unique roads in the recommended route is also shown along with it.

For the *Name of familiar roads* information, at most two road names was shown at a time. If the participant is familiar with more than 1 road along the route, we will show the familiar road that is not shown as a major road according to Google Map results. If there is only 1 familiar road and it is the same as the major road(s) returned by Google Maps, then we will just repeat that information.

The familiarity information was gathered from the preliminary survey where participants are asked to list down all roads that they can possibly recall. In practice, there might be more roads that a driver knows.

5.4 Method

This study focuses on investigating the effects of adding motivative and familiarity information to the route choice of drivers. In particular, I want to investigate if adding motivative and familiarity information will make drivers choose the unselfish route more, regardless of trip purpose. Additionally, I want to see if the stated choice for the unselfish route will be higher in non-commute trips. Thus, we conducted an online experiment with a 4x3x2 within-subject design. There were three types of independent variables, namely:

- **Purpose of trip:** Work-to-home (**W2H**), home-to-work (**H2W**), work-to-frequent place (**W2F**) and home-to-frequent place (**H2F**)
- **Motivative Info:** Critical mass (**C**), valence framing (**V**) and simple positive framing (**F**)
- **Road Familiarity Info:** Number of familiar roads (**P**) and names of familiar roads (**R**)

We added four (4) baseline conditions that show route choices for each purpose of trip but without any motivative or road familiarity information. In total, there are 28 experimental conditions that each participant will perform a task for. To avoid ordering effects, conditions were balanced using a Latin square.

5.4.1 Participants

We recruited 28 participants in multiple rounds. They were included in a lottery where one winner will receive a cash reward of 2,500 Japanese yen. They were recruited through snowball sampling. An initial call for participation was posted on two private groups on social media composed of people from academic institutions and alumni. As an inclusion criteria, we only recruited participants who are adults (18 to 60 y.o.), has an active or valid driver's license and drives to work, business or school on most days of the week (more than 3 times). They are comprised of people who identify as men (N=17), women (N=10) and non-binary (N=1). Their ages range between 21 to 52 years old (M=28). In terms of driving years, 2 are driving for less than a year, 12 for 1 to 5 years, 5 for 5 to 10 years, and 9 of them are driving for more than 10 years. Looking at driving experience, 6 participants have been driving for less than 15,000km, 11 have driven between 15,000km to 25,000km, and 11 have driven more than 25,000km.

When asked about how often they switch between their regular and alternative routes, half of them (N=14) switch once a week when going to work or school. Six (6) of them do it twice or more in a week while 8 participants never switch to an alternate route. When going back home from school or work, half of them switch once a week while 8 are doing it twice or more. Six of them never switch.

5.4.2 Protocol

Participants were tasked with answering a preliminary survey, an online experiment, and two post-hoc questionnaires (Figure 5.7).

Preliminary Survey

The preliminary survey consists of four sections. The first section asks for their consent to participate, age, gender and driving experience. Because the online experiment will be administered through email, they were required to provide an email address. For those who do not check their emails regularly, they were given the option to provide their Facebook Messenger or Line details.

The second section asks about the places that they frequently drive to (home, work or school, and two frequently visited places) and roads they are familiar with (free text). They were also asked to find those locations on Google Maps and submit the URLs. Then in

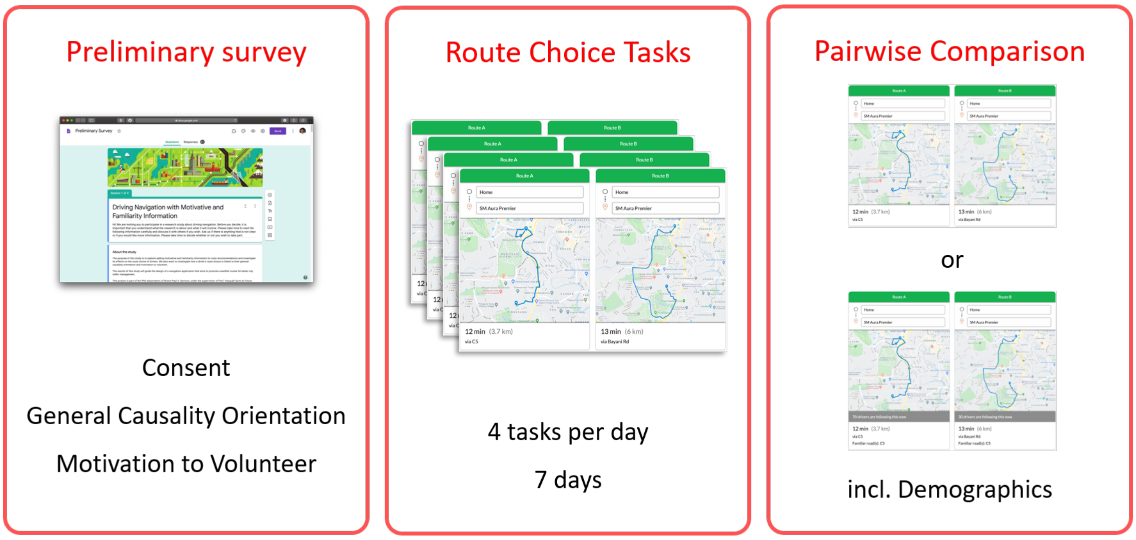

Figure 5.7: An overview of the study protocol.

the third section, they are asked to complete the 12-item General Causality Orientations Scale (GCOS) which represent their orientation towards autonomy, relatedness, and competence. In the fourth and last section, they are asked to complete the 24-item Motivation to Volunteer Scale to learn about their behavioral regulatory styles according to SDT, and their recent experiences of volunteering.

After submitting the preliminary survey, they were sent an introduction about the online experiment and on what to prepare and expect. The preliminary survey took approximately 25-30 minutes to complete. For full details, please refer to Appendix F.

Online Experiment

The online experiment was divided into 7 questionnaires with 4 items each. They were sent daily to their emails at 10:00AM local time for 7 working days (Monday to Friday only). Their first questionnaires were sent at most two (2) days after they completed the preliminary survey form. This protocol was designed in order to avoid learning effect.

The daily questionnaire has 4 route choice scenarios which represent work-to-home (W2H), home-to-work (H2W), work-to-frequent (W2F) and home-to-frequent(H2F) trips, given in that order. To illustrate, Table 5.1 shows the order of conditions for Participant 22 during the 7-day online experiment. Everything can be accomplished in less than

Table 5.1: The order of conditions for Participant 22 during the 7-day online experiment. The acronyms stand for the pair of motivative and familiarity information for that condition. For example, BL means baseline condition while FR represents the condition that uses simple positive framing (F) and shows the name of familiar roads (R).

	W2H	**H2W**	**W2F**	**H2F**
Day 1	BL	CP	VR	VP
Day 2	FR	VP	CR	FP
Day 3	CR	BL	FR	CR
Day 4	FP	FP	FP	CP
Day 5	CP	FR	BL	BL
Day 6	VR	CR	VP	FR
Day 7	VP	VR	CP	VR

10 minutes. Each item in the questionnaire presents a navigation scenario and two images of the prototypical navigation app interfaces that show the recommended routes A and B (Figure 5.8). The map shown is not interactive and is only meant to give a visual representation of the route suggestions. Below the map is the set of navigational information which varies depending on the experimental condition.

Before answering the first route choice scenario, participants were asked prepare a timer or clock nearby. For each scenario, they were asked to record the amount of time it took them to make a choice. They were allowed to answer the questionnaire any time within the day but they have to be submitted before the day ends. Sample screenshots of the daily questionnaire can be seen in Appendix A.

Post-Hoc Questionnaires

On their last day of the online experiment, they were given two post-hoc questionnaires along with the Day 7 questionnaire. The first questionnaire asks about their demographic and socioeconomic information, and driving experience. The second questionnaire ask them to make pairwise comparisons between the different experimental conditions used in the online experiment.

Interviews

After all 28 participants are completed, we will send invitations for a short interview. I will ask about their qualitative feedback on the sets of motivative and familiarity information shown to them. They will also be presented with their most preferred condition after the

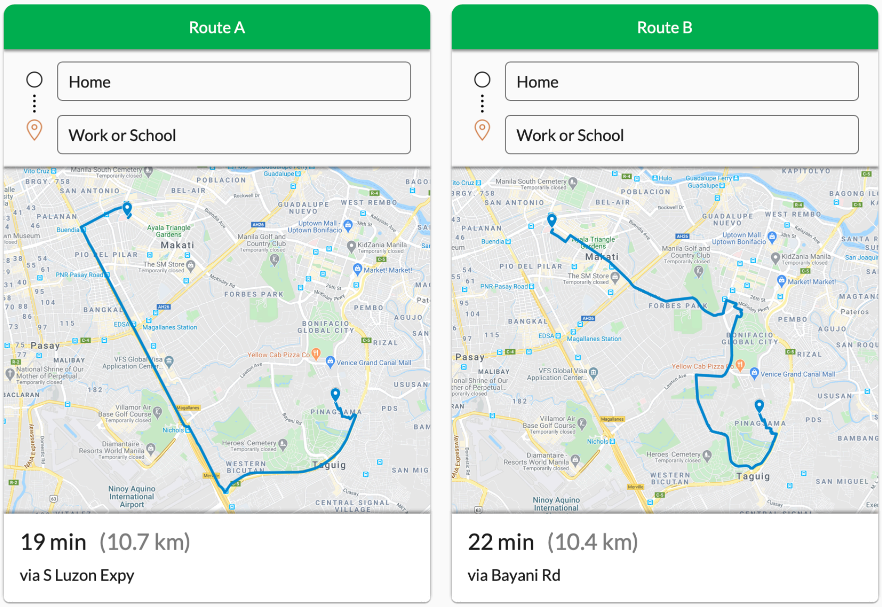

Figure 5.8: The baseline (BL) version of the prototypical navigation app interface. Routes A and B are shown side-by-side. The top part shows the origin and destination with the map below it. The bottom part shows the navigational information that you would typically find in most navigation applications. This part has 27 other versions for each experimental condition.

pairwise comparison task and asked why they think that is the most convincing combination for them.

5.5 Design

The interface prototype mimics the typical design of most modern navigation applications in the market (e.g. Google Maps, Waze). The screen shows the origin and destination of the trip at the top and a map in the middle. The bottom of the screen shows the navigational information section, for which we created 7 versions. But for all versions of the navigational information section, it always contains the basic set of estimated travel time, total distance and name(s) of major roads. Figure 5.8 shows the baseline (BL) version that features the basic set of information. For the six other versions, new information are added on top and bottom parts of the navigational information section. In Figure 5.9, the motivative information is added on the gray box at the top and the familiarity information is added below the name of a major road. Both use the same font size to reduce bias in visual hierarchy.

Figure 5.10 shows all six versions for each combination.

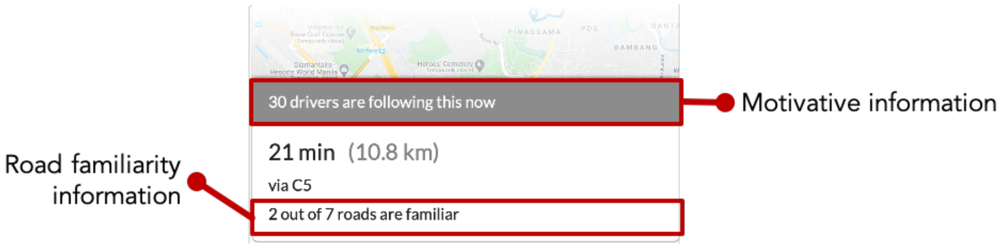

Figure 5.9: The additional parts of the navigational information section for the 6 treatment conditions.

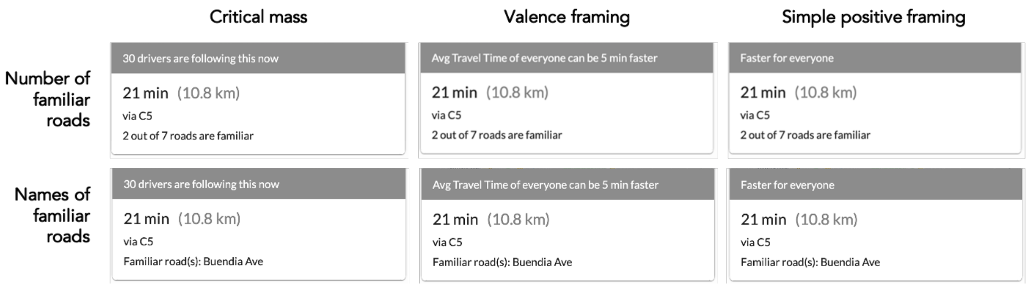

Figure 5.10: The design versions of the navigational information section that adds different combinations of motivative and familiarity information. The versions aligned in the same column use the same motivative information. For example, the two versions in the leftmost column both show critical mass (C) information. The versions in the same row use the same familiarity information.

5.6 Materials and Measures

Because of the remote nature of this study, the participants were asked to answer a number of questionnaires using Google Forms.

5.6.1 Measuring Motivation

We are also interested in understanding whether our autonomy-supportive motivative information are effective in promoting the unselfish route for different regulatory styles and causality orientations. We used two standard questionnaires to measure motivation based on SDT constructs.

The General Causality Orientation Scale (GCOS)[42] measures people's causality orientations on three sub-scales, namely autonomy, control and impersonal. We used the standard 12-item vignette and followed the recommended scales and ordering. Each question presents a scenario with three possible responses. Participants are asked to rate on a scale of 1 to 7 the likelihood that they will respond to the given situation in a certain way.

On the other hand, the Motivation to Volunteer Scale (MVS)[67] measures a person's volunteering motivation based on 24 items. Each of the 6 behavior regulatory styles is represented by 4 items. Participants were asked to what extent do each item correspond to their personal motives for engaging in volunteering. They gave ratings on a scale of 1 (does not correspond at all) to 5 (corresponds exactly). Items were randomized to avoid ordering effect. Because the MVS questionnaire is relatively long, we also added an attention check item. At the end of the preliminary survey, we also asked them about their volunteering experience: "How often have you participated in volunteering activities in the past three months on average?" Because the COVID-19 pandemic has unexpectedly motivated people to volunteer, we asked a second question "How often have you participated in volunteering activities on average from October to December 2019 (before COVID-19 pandemic)?" for them recall their volunteering frequency before the pandemic and to check for consistency with the first question. Both questions were answered using three options: Never, Once a week and Twice a week or more.

For both GCOS and MVS, we will compute the mean score per sub-scale and use it in the analysis.

5.6.2 Route Recommendations

The route recommendations used in the questionnaires were personalized for each participant using the information they provided from the preliminary survey. For each type of trip, we searched for the fastest route and a sub-optimal route using Google Maps. Searches were done during mid-day to maintain consistency across participants. The fastest route is the route recommendation with the shortest travel time while the sub-optimal route is the recommendation with the longest distance and or longer travel time. The sub-optimal route was used as the unselfish route and assigned as Route B. Route A is always the fastest. To prepare the maps used in the prototypes, we traced the recommended routes using Google My Maps.

For each participant, a total of 8 route recommendations were prepared.

5.6.3 Stated Route Choice

The daily route choice questionnaires contain 4 binary route choice tasks. They were instructed that they will be making 4 independent trips:

- Work/School to Home
- Home to Work/School
- Work/School to a frequently visited place
- Home to a frequently visited place

Before seeing the prototypes, they were asked to imagine the following scenario:

> In each trip, imagine that you are just about to leave and go to a destination. Before leaving your point of origin, you bring out your smartphone and open a navigation application. You are not driving yet. You type your destination in the navigation application and search for routes. Two route suggestions are shown and you have to choose which one to follow. For all route suggestions, you are shown a static map of the route, the estimated travel time, distance and a major road included in the route. Assume that these navigational information are reliable and that you will arrive at your destination on time regardless of choice.

Participants were also asked to imagine that a hypothetical Traffic Management System is active during the trips using the following prompt:

> Imagine that your city has implemented a Traffic Management System (TMS) to help optimize the traffic flow on its roads. It is run by the city government and receives constant traffic updates in order to make proper traffic assessments. Assume that the information they collect and use are reliable. Its goal is to equally distribute active cars in the road network so that everyone benefits. In order to achieve this, it gives recommendations to connected drivers. However, it does not always distribute drivers to optimize traffic flow. It only happens when they anticipate that many drivers will start using the roads.

> Your navigation application is connected to this system and it adjusts the route suggestions based on what the TMS recommends. When it predicts that traffic congestion will occur or has already happened, it will now recommend a route that will help ease traffic flow in other areas, along with the usual recommendation of the fastest route. The route suggestions may include 2 types of additional information to help you with your route choice. The first type of information describes how the route can contribute to everyone's travel time. The second information describes how familiar it is to you. You are free to accept or ignore the recommendations and additional information. You will not receive any penalty.
>
> In all of the trips, assume that the TMS is detecting traffic congestion on some roads. The traffic flow is now being distributed and you are part of it.

After reading the scenarios, participants were asked to prepared a timer. The following sections of the questionnaire gave the 4 route choice tasks. Participants were asked to choose between Route A and B. They were also asked to time their decision making from the moment they saw the prototypes up to the time they selected their final choice.

5.6.4 Pairwise Comparison

On top of recording their stated preferences after seeing different types of navigational information, I also wanted to measure their relative preferences using pairwise comparison. For this, I only used the prototypes for the home-to-work trips. Participants were asked to compare 21 pairs of the 7 design versions that were randomly ordered. One (1) item was repeated to act as attention check and to check for consistency of answers. In total, there were 22 pairwise comparisons made. Sample screenshots of the questionnaire can be seen in Appendix B.

5.7 Results

I begin the discussion of results with the analysis of their stated route choice in the online experiment. Lastly, I present the results of the pairwise comparison task.

5.7.1 Causality Orientation and Motivation to Volunteer

A Shapiro-Wilk normality test suggests that all sub-scale scores for both causality orientation and motivation to volunteer are normally distributed except for the Control sub-scale of causality orientation. In terms of data symmetry, only the GCOS Impersonal sub-scale scores were nearly symmetrical with a skewness of 0.06. The GCOS Control and the MVS Introjected, External and Amotivation sub-scales are right-skewed, in which their means are larger than their medians and have larger right-handed tails. The rest of the sub-scales are left-skewed.

For the purpose of my analysis, the scores were binned into low, moderate and high categories. GCOS sub-scale scores less than 3 are considered low while those greater than 5 are considered high. Scores that fall between 3 and 5 are moderate scores. As for MVS sub-scale scores, those below 3 are also considered low, while those above 3 are coded as high. MVS sub-scale scores that are exactly 3 are considered moderate.

In terms of causality orientation, most of the participants scored highest on the Autonomy sub-scale ($\mu = 6.02$, M = 6.08, $\sigma = 0.55$) with 2 moderate scores and 26 high scores. All participants scored moderately (N = 27) in the Control sub-scale ($\mu = 4.18$, M = 4.25, $\sigma = 0.69$) except for one outlier that had a high score. Expectedly, the Impersonal sub-scale scores are relatively lowest but more diverse ($\mu = 3.587$, M = 3.585, $\sigma = 0.98$) with more than half of the participants having moderate scores (N = 18) while 8 of them are low. All of these suggests that our participant pool are mainly oriented towards environments or tools that provide informational feedback and allow choice, where they can have greater agency and intrinsic motivation. Their low Impersonal orientation suggests they believe that their desired outcomes can be attained, not just by luck or fate. Even so, they still show moderate tendency to be controlled by rewards, structure and the directives of others in order to perform tasks.

In terms of behavioral regulation, the Motivation to Volunteer Survey gave scores to the different styles according to SDT. Most of the participants scored high in the Intrinsic motivation ($\mu = 3.85$, M = 4, $\sigma = 0.89$), Integrated ($\mu = 3.25$, M = 3.13, $\sigma = 0.94$) and Identified ($\mu = 4.05$, M = 4.13, $\sigma = 0.59$) sub-scales. On the other hand, they scored low in the Introjected ($\mu = 2.44$, M = 2.5, $\sigma = 0.82$), External ($\mu = 2.08$, M = 2.13, $\sigma = 0.77$) and Amotivation ($\mu = 1.96$, M = 2, $\sigma = 0.82$) sub-scales. A Pearson correlation test suggests that the Intrinsic, Integrated and Identified sub-scale scores are more positively correlated as they are adjacent in the self-determined continuum. The same positive correlation was observed for the adjacent Introjected and External sub-scale scores. These are consistent with the Self-Determination Theory which posits that adjacent regulatory styles in the continuum are more associated with each other than those farther away [137]. Similar to Standage et. al. (2008) [154], the Intrinsic, Integrated and Identified sub-scale scores were averaged to have a score for autonomous motivation (μ = 3.72, M = 3.71, σ = 0.6), while the Introjected and External scores were averaged to form the controlled motivation score (μ = 2.26, M = 2.19, σ = 0.73). These results suggest that the participant pool has a stronger quality of intrinsic motivation towards volunteering and that they have a more internal perceived locus of causality.

When asked about the average frequency of their volunteering activities for the past 3 months, twelve participants reported to have done some form of volunteer work at least once or more. Considering that the ongoing global pandemic have inspired people to volunteer more than they used to, we asked them about their average frequency of volunteer work between October to December 2019. They reported the same frequency.

Combining the insights from the causality orientation and behavioral regulation scores, it suggests that the recruited participants would be more receptive to the proposed designs as they are intended to be autonomy-supportive.

5.7.2 Stated Route Choice

From the results of the 7-day route choice task, I first investigate how often the unselfish route was chosen compared to the optimal one. Then, a Generalized Estimating Equations (GEE) model was created to estimate the population average effects and investigate the likelihood that the population will change their route choice given a pair of motivative and familiarity information.

Choice of Unselfish Route

In absolute numbers, the unselfish route (Route B) was chosen in 177 (22.6%) out of 784 trip conditions answered by all participants (Figure 5.11A). Many participants (N=21) chose it at least once with a median selection rate of 25% (μ = 0.301). The lowest rate is at 3.6% (once) while the highest is at 89.3% or around 24 times (Figure 5.11B). Seven (7) participants never chose the unselfish route at all.

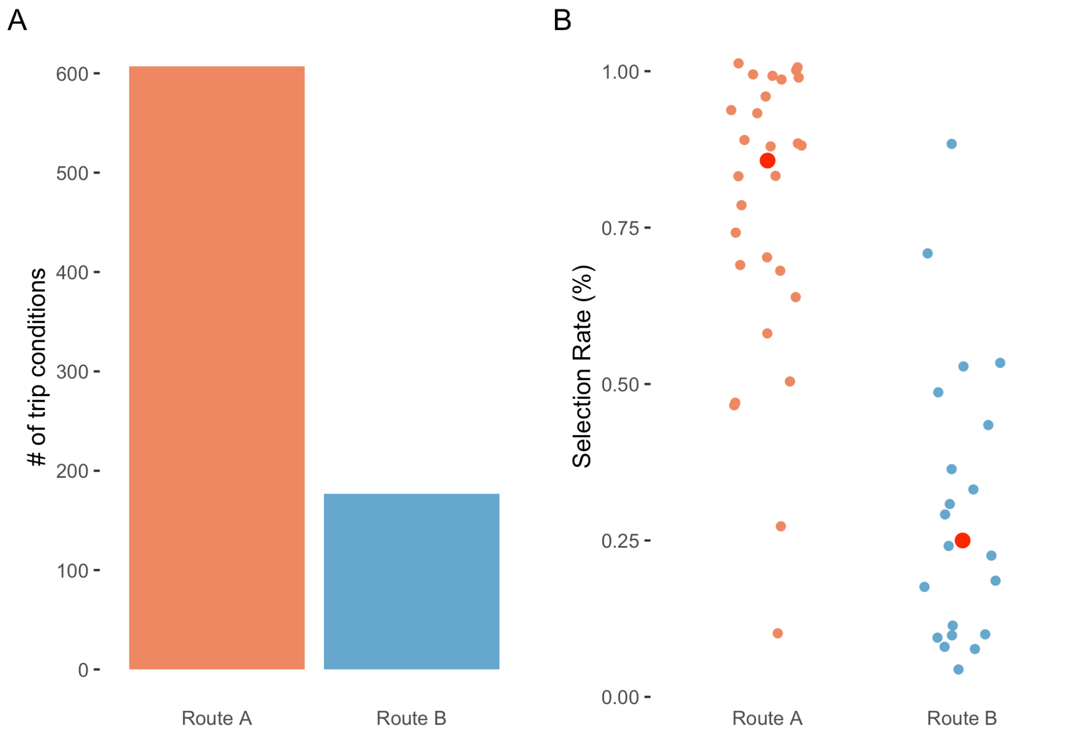

Figure 5.11: A) The absolute number of trip conditions in which the participant chose each route. B) The rate by which each participant selected Routes A and B. The red dot shows the median selection rate.

For the baseline (BL) condition in which no motivative and familiarity information is shown, the unselfish route was selected by six (6) participants at least once. Two of them selected Route B in all four (4) trip scenarios. Notably, they have also reported high autonomous orientation and high autonomous motivation. When they are shown the different combination of motivative and familiarity information, the number of times that Route B is selected relatively increases (Figure 5.12A). The most number of Route B selections happened when the **VR** (N=32) and **FP** (N=32) design versions were shown. Among the three (3) motivative information, participants chose the unselfish route the most when either the simple positive framing (N=60) or the valence information (N=60) was shown. This suggests that motivative information which explicitly highlights potential benefits of a future decision can positively impact the chance of selecting the unselfish route. On the other hand, the versions that showed the critical mass information (**CP** and **CR**) might

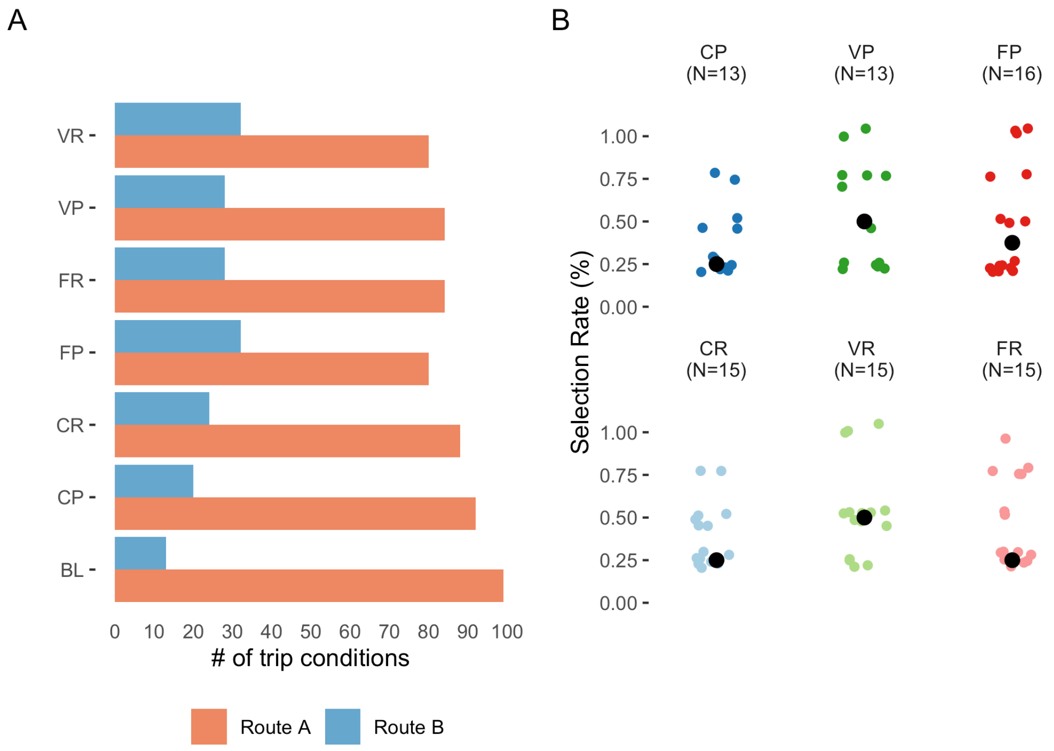

Figure 5.12: A) The number of trip conditions in which the participant chose each route and distributed by the combination of motivative and familiarity information. B) The rate by which participants selected Route B per combination. The black dot shows the median selection rate.

have given a different impression which resulted to less instances of Route B being selected.

Looking at the selection rate of each participant, the **FP** design version had the most number of participants (N=16) that selected Route B at least once in the four (4) trip scenarios. This is followed by all design versions that show the list of familiar roads (**CR**, **VR** and **FR**) with 15 participants selecting Route B at least once. Overall, participants had the highest selection rates when they were shown the **VP** (μ = 0.538, M = 0.5) and **VR** (μ = 0.533, M = 0.5) design versions. These results are indicative that if we want more drivers to adopt an unselfish route but with some inconsistency, we can focus on presenting them with information about the positive effects of choosing an unselfish route and or showing them the list of familiar roads. On the other hand, if we want drivers to be more consistent in choosing the unselfish route regardless of the trip scenario or type, the positive gain (i.e. decrease in travel time) should be explicitly shown.

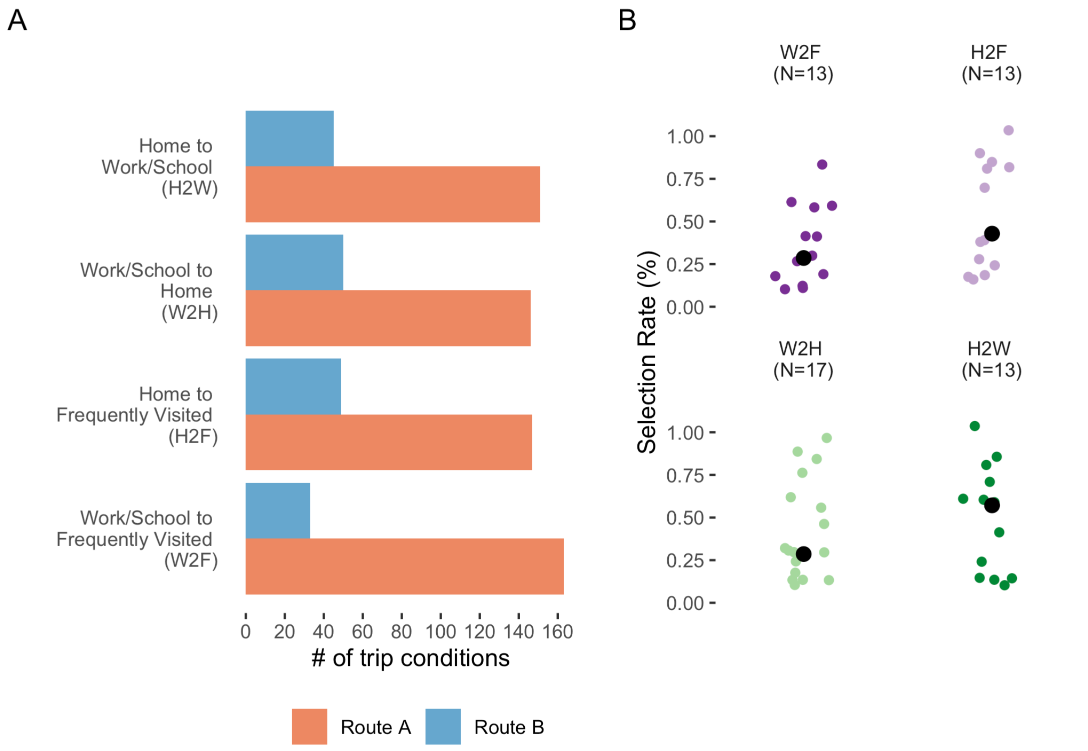

Figure 5.13: A) The number of trip conditions in which the participant chose each route and distributed by the trip scenario/type. B) The rate by which participants selected Route B under a trip scenario/type. The black dot shows the median selection rate.

When they are under different trip scenarios or types (Figure 5.13A), participants selected the unselfish route more when they plan to go from work or school back to their homes (N=50) and when they leave home to go to a frequently visited location (N=49) like shopping malls or groceries. Route B was selected the least when they are going from work or school to a frequently visited place (N=33). For each of the four (4) trip scenario or type, a participant selected a route for seven (7) times, with a different design version each time. Looking at their selection rates, there were more participants that chose the unselfish route at least once when they drive from work or school to their homes (N=17). But overall, trips from home going to work or school had the highest median selection rate of 57.1% (μ = 0.495) among participants. This suggests that regardless of the design version, they were more consistent in choosing the unselfish route in this trip scenario.

But how do each design version perform under different trip scenarios? In Figure 5.14,

Figure 5.14: The number of times the unselfish route (Route B) was chosen under each trip scenario and design version.

we can see the number of times the unselfish route was chosen when shown a specific design version. This was further distributed among the different trip scenarios. In terms of success rate, 11 or 39% of the participants selected the unselfish route when the **FP** design version was shown in the work to home (W2H) trip scenario. Across the different trip scenarios, there was consistently more than 25% of participants that select the unselfish route when they were shown the **VR** design version. It also has the highest success rate among the design versions in the W2F (25%), H2F (32%) and H2W (29%) trip scenarios. This suggests and echoes the general utility of the valence or positive gain information in encouraging drivers to select the unselfish route.

Modeling Route Choice

As mentioned, a Generalized Estimating Equation (GEE) model was fitted to help us compute for the likelihood of drivers in choosing the unselfish route under different trip sce-

Table 5.2: Results of the GEE model with significant main and interaction effects. The full table with all terms are in Table C.1 in Appendix C.

Variable Name	Estimate	SE	Wald	Pr(>|W|)	
(Intercept)	**-1.7918**	**0.5401**	**11.01**	**0.00091**	***
Valence	**1.2040**	**0.5519**	**4.76**	**0.02916**	*
Framing	**1.3564**	**0.4788**	**8.02**	**0.00461**	**
H2W * Framing	**-1.1558**	**0.4741**	**5.94**	**0.01477**	*
H2F * Framing	**-1.1741**	**0.5807**	**4.09**	**0.04317**	*
Framing * Road Names	**-1.1741**	**0.5501**	**4.56**	**0.03280**	*
H2W * Framing * Road Names	**1.5832**	**0.6418**	**6.08**	**0.01363**	*

narios and design versions. Because our route choice task produced binary discrete choice data, the binary logit link was used. Here, the outcome variable is the decision to follow the unselfish route or not. I want to model the main effects and two-way interactions of three predictor variables, namely trip scenario, motivative information, and familiarity information. After fitting with different correlation structures, the exchangeable correlation structure was used because it had the best model fit with a QIC[117] value of 779. The coefficients with siginificant effects are shown in Table 5.2.

Among the three factors, only the motivative information had a significant main effect, specifically when the valence is shown (β=1.2040, p<0.01) and simple positive framing (β=1.3564, p<0.001) is used. Among the interaction terms between trip type and motivative information, there are significant interaction effects when drivers are travelling from their homes (H2W and H2F) and they are shown a simple positive framing of the unselfish route. There is also a significant interaction effect when simple positive framing is used with the list of familiar road names (β=-1.741, p<0.01). Lastly, there is a significant 3-way interaction effect when drivers travel from their home to work or school and the unselfish route is presented with both simple positive framing and list of familiar road names (β=1.5832, p<0.01).

In terms of likelihood (Table C.2), the odds ratio shows that drivers are around 3.3 times more likely to choose the unselfish route if valence information is shown. When simple positive framing (i.e. "*Faster for everyone*") is shown, the chances are 3.9 times more likely for the unselfish route. However, when simple positive framing is used when drivers are driving from their homes to their work, school or frequently visited location, the likelihood of following an unselfish route drops by around 0.31 to 0.31 times. It is also becomes less likely when simple positive framing is shown with the list of familiar road names (about 0.31 times less likely) in most trip types. But if that combination is used in a trip from their homes to their work or school, drivers are 4.9 times more likely to choose the unselfish route again.

5.7.3 Design Version Preference

From the results of the pairwise comparison task, a Loglinear Bradley-Terry model was created to analyze the design version preferences using the R package `prefmod`[72]. The model is fitted using a generalized non-linear model (GNM) and estimates the likelihood or worth estimate of each design version. The sum of the worth estimates are always equal to 1.

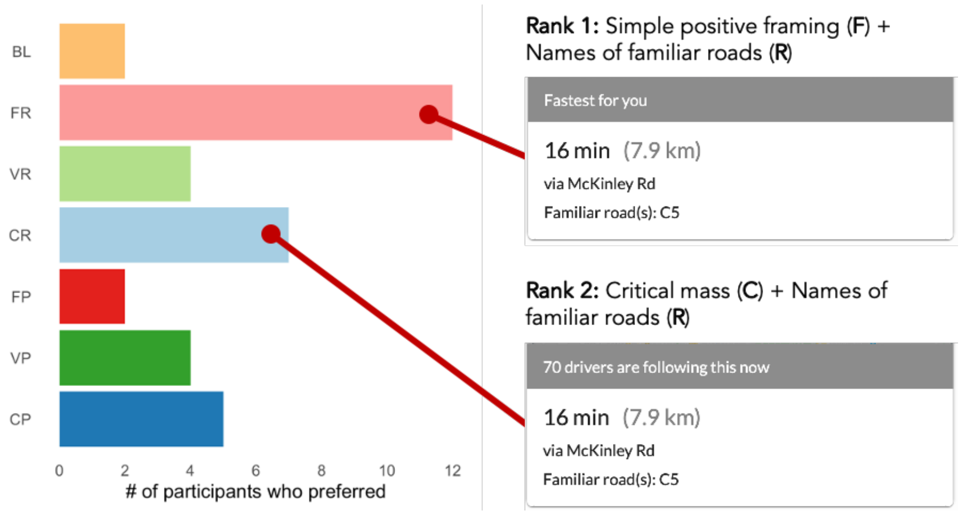

Figure 5.15: The absolute number of participants who preferred each design version. Note that there were ties with at most 2 versions.

Looking at the most preferred design version of each participant, there was no consensus on the best design version (Figure 5.15). In a plurality, the **FR** design version that uses simple positive framing and lists the names of familiar roads was the most preferred (N = 11). This was followed by the **CR** design version which shows the number of drivers following the route and also lists the names of familiar roads (N = 7). Among the three motivative information, design versions that use simple positive framing (**F**) was most preferred (N = 13). Between the two types of familiarity information, the versions that lists the names of familiar roads (**R**) was most preferred (N = 22). From these absolute numbers, it is indicative that drivers would be more encouraged to follow a recommended unselfish route if the presented additional information is simpler to process and explicit like the names of familiar roads.

Remarkably, all versions were chosen by at least one participant and there were participants who still preferred the baseline version (N = 2). There were also ties between 2 design versions. These were usually between versions that use either the same motivative (e.g. FP and FR) or familiarity (e.g. CR and VR) information.

Overall Worth Estimates

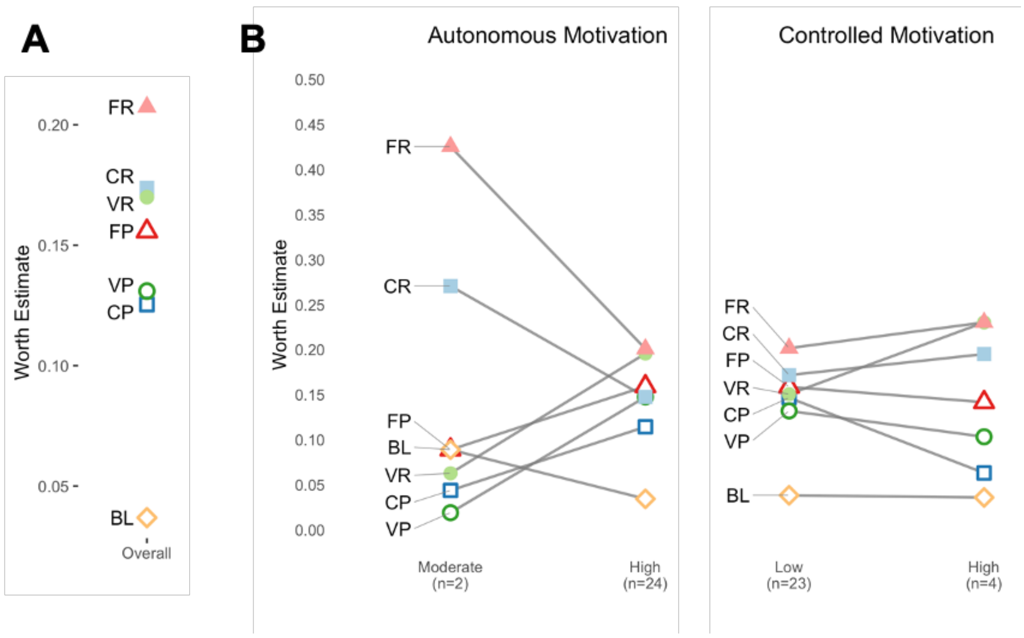

Figure 5.16: The worth estimates of each design version. A) On the left is the plot of preferences without considering other factors. B) On the right is the plot of preferences of participants based on their autonomous and controlled motivation scores. Only score categories with more than 1 participant were included in the plot.

Looking at the fitted model, all design versions were more preferred than the baseline version with significant differences in worth estimates (Figure 5.16A). Because the model uses the ranking of all versions from each participant, the estimated preferences have some differences from the absolute numbers discussed before. Here, the **FR** ($p>0$) and **CR** ($p>0$) design versions have the highest worth estimates which is consistent with its ranking in Figure 5.15. The marked differences are with the worth estimates of the **VR** ($p>0$), **FP** ($p>0$) and **CP** ($p>0$) versions. This suggests that even though **CP** was most preferred by more people, those who did not prefer it ranked **CP** lower compared to **VR** and **FP**.

In Figure 5.16A, it is also shown that versions that lists the names of familiar roads (**FR**, **CR**, **VR**) were significantly more preferred than the baseline compared to those that just show the number of familiar roads. It might be because there is greater recall when they see the road names, which helps in their decision making. And among the motivative information types, simple positive framing (**F**) is always preferred, followed by the critical mass (C) and valence (V) information.

Worth Estimates by Behavioral Regulation Type

I was also interested to see if there are differences in worth estimates based on their behavioral regulation type. I fitted another model which had the autonomous and controlled motivation scores as subject covariates. Because the model only accepts categorical data for subject covariates, these two scores were binned into low, moderate and high categories. Those below 3 are considered low scores, while those above 3 are coded as high scores. Scores that are exactly 3 are considered moderate.

Figure 5.16B shows the worth estimates for participants with moderate to high autonomous motivation, and low and high controlled motivation scores. The **FR** design version was consistently preferred the most but in this case, the differences are not significant. Only the preferences of people with high autonomous motivation for **CP** ($p<0.05$), **VP** ($p<0.001$) and **VR** ($p<0.05$) design versions were shown to be significant.

Worth Estimates by General Causality Orientation

Considering people's general causality orientation, Figure 5.17 shows that the **FR** design version would most likely encourage participants with high autonomy orientation, moderate control orientation and low impersonal orientation to take the recommended unselfish route. However, only those with moderate control orientation have shown significant preference.

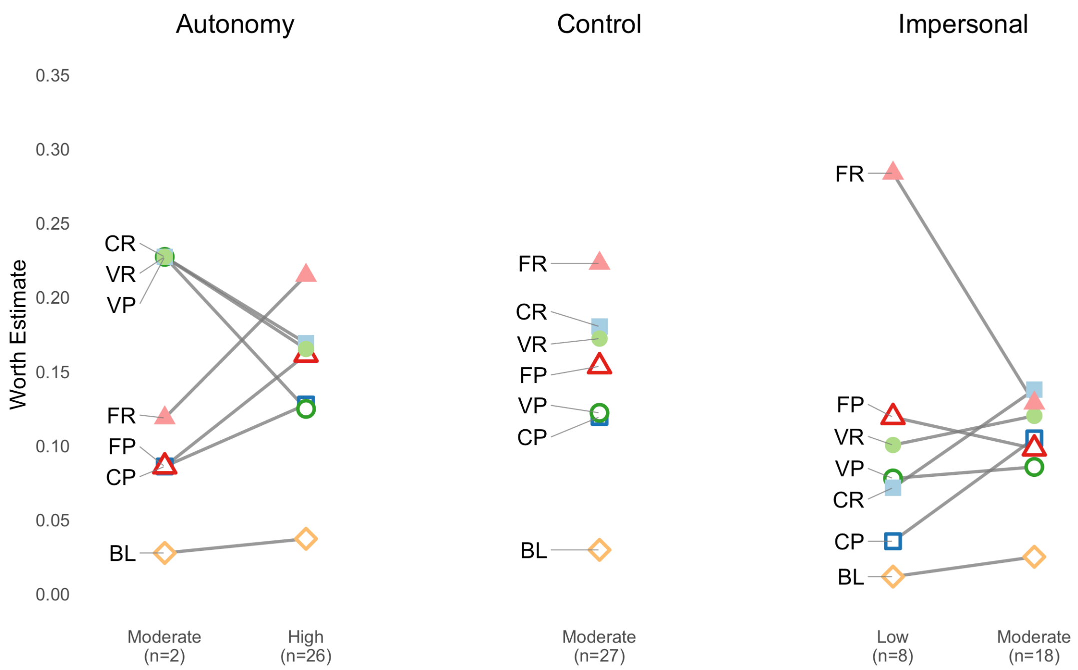

Figure 5.17: The worth estimates of each design version when the general causality orientation is considered. Only score categories with more than 1 participant were included in the plot.

Looking at the autonomy orientation, there were significant preferences for the **CR** ($p<0.05$), **VR** ($p<0.05$) and **VP** ($p<0.05$) design versions for those with moderate scores. The rest are non-significant.

The worth estimates for participants with moderate control orientation all have significant differences ($p<0$) compared to the baseline. Remarkably, the order of preference closely resembles that of the overall model.

In terms of impersonal orientation, participants with low scores showed significant preference for the **FR** design version ($p<0.05$). For those with moderate scores, the **CR** design version ($p<0$) was the most preferred, followed by the **FR** version. This and all other worth estimates showed significant differences compared to the baseline ($p<0$).

5.7.4 Comparison of Stated Route Choice and Preference

Knowing their most preferred design versions from the pairwise comparison task, did the participants really choose the unselfish route when those were presented to them in the route choice experiment? Out of the 21 participants who selected the unselfish route at least once, only eighteen (18) of them were consistent with their most preferred design version. They had an average selection rate of 26% when presented with their most preferred design version. Two participants selected the unselfish route in all four (4) times that their most preferred was used. On the other hand, three (3) participants never selected it.

5.8 Towards Better Adoption of Unselfish Routes

This study provides insights into how Self-Determination Theory can be used to identify and design motivative information that can help increase the likelihood that drivers will select an unselfish route. Here I present the key findings from the results from the results.

5.8.1 Case for Autonomy Support

In this study, the main design goal was to ensure that the different design versions are autonomy-supportive. In Self-Determination Theory, that means the environment or tool has to address the three basis psychological needs, namely autonomy, competence and relatedness. That is how I decided to incorporate the three motivative information used in the prototypes: a simple positive framing of choosing unselfishly, the critical mass of active drivers currently following the recommended routes, and the positive gain in everyone's travel time if at least one driver chooses an unselfish route. With a participant pool that mostly have high autonomy orientation and high autonomous motivation scores, it should be expected that almost all of them would choose the unselfish route at least once. However, the stated route choice results only show partial support. Although 75% of participants selected the unselfish route at least once, it should be noted that all seven (7) participants who chose the optimal route completely have high autonomy orientation and high autonomous motivation scores. So it would be interesting to unpack this counter-intuitive behavior in future studies.

Despite that, the majority who choose unselfishly at least once included participants who have moderate autonomy orientation and low to moderate autonomous motivation. Results suggest that the design versions were able to facilitate the internalization of extrinsic motivation and positively influence the choice of unselfish routes, which supports the case for autonomy support in driving navigation applications.

5.8.2 Simplicity and Explicitness

Considering both stated route choices and preferences, the design version that combines simple positive framing and the list of familiar roads showed universal positive utility in increasing the likelihood of choosing an unselfish route. In terms of preference, the **FR** design version was the most preferred except for participants that reported moderate autonomy orientation. Design versions with either simple positive framing or the list of familiar roads also resulted to higher selection rates for the unselfish route regardless of trip scenario/type. This design version can convince more drivers compared to other versions but it might not be as successful in motivating them to continue with their unselfish choices. These can all be attributed to the simplicity of the messaging that immediately conveys the positive benefit of making the unselfish choice. The explicitness of listing the names of some familiar roads also helped in the positive response to this design version. Showing the familiar road names can help drivers reduce the need to recall and make them easily recognize what is familiar to them.

The valence information also helped motivate participants to choose unselfish routes. Although not many participants chose unselfishly when they were shown design versions that use this motivative information, they showed the most consistency regardless of the trip type. Also from the GEE model, it is shown that participants were 3 times more likely to choose the unselfish route when shown information about the positive gain of everyone. However, the current message that reads "Avg Travel Time of everyone can be `N` min faster" might have different interpretations from drivers. In the interviews, some participants recall that they were not sure whether the displayed estimated travel time for them would also be reduced by some minutes. Although it is now suggested to convey uncertainty when showing predicted values, especially for transparency, this messaging had some effect as to whether they would consider this information for decision making or not.

5.8.3 Need for Relatedness

Looking at the version preferences, the **CR** design version consistently ranks second to the **FR** version. This suggests that even though the participant pool are mostly with high autonomy orientation and high autonomous motivation, they still highly prefer a design version that addresses their need for relatedness. In SDT, this is the psychological need of a person to feel connected and interdependent with others. The critical mass information was chosen specifically for that purpose. Commonly used in e-commerce websites, this motivative information make people feel they are about to belong to a group of other individuals when they perform a task. The participants with moderate impersonal and control orientation mostly prefer the use of the **CR** design version. This might be because they have a weak tendency to leave things as it is. It might encourage them more to choose unselfishly if they explicitly see how much impact they can have in the system, which is by joining a smaller number of drivers taking the unselfish route. The same need can also be said for participants with moderate autonomy orientation. However, the current messaging for the unselfish route that reads "30 drivers are following this now" might have different interpretations for drivers. For one participant, they avoided the unselfish route because they thought more drivers would choose this since there are less people.

5.8.4 Personalized Motivation

Although the **FR** design version was the most preferred, the results from the stated route choice experiment reveals that a personalized motivation and messaging might be required to ensure that drivers will consistently or at least be more inclined to choose the unselfish route. This was also supported by the fact that there was no clear winner in ensuring consistent and high selection rate across trip types, causality orientation and behavioral regulatory styles.

In particular, a personality-targeted design [111,108] might be worth exploring but with a focus on using SDT constructs since we are dealing with motivation. One inspiration could be the work of Grau et. al.[68] in which they used personalized motivation-supportive messages to help increase the number of reported community issues. One challenge for this approach is the collection of proper data to inform the personalization. It could be achieved either through proxy variables within the context of driving or navigation, or the simplification of the GCOS and MVS surveys so that users do not have to answer long forms at the beginning of their driving navigation experience.

5.9 Limitations and Future Work

This study focused on collecting stated route choices using online surveys. Although ecological validity was maintained by using the real home, work and frequently visited locations of recruited participants, the trip scenarios were still hypothetical contexts. Aside from that, the recommended routes gathered from Google Maps that were used in the prototypes were taken at days and times that might not match when the participant would actually answer the survey forms. The 28 conditions were given to participants in 7 working days. Because it follows a within-subject study design, this approach was intended to avoid respondent fatigue and learning effect. However, there were still participants who forgot to answer on a daily basis and had to answer more than one (1) survey form in a day. While it is totally out of our control, this might have affected some of their answers. Lastly, the pairwise comparison was done by the same participants in the stated route choice experiment. Ideally, more respondents should answer it to have a more statistically significant result.

I also envision several directions for future work, specifically on the messaging and presentation of the proposed motivative and familiarity information, and the use of other types of information that drivers might consider in trip planning and navigation. In my design versions, the motivative and familiarity information were purely text displayed below the map. While that works to control confounding effects from other factors (i.e. color, form) and let the participants focus on the value of the information, it leaves little creativity for more different ways of presenting the proposed motivative and familiarity information on the navigation application. The current prototype design also makes the area below the map too cluttered with text. As the primary goal of this study is to increase the likelihood of choosing an unselfish route, additional work needs to be done in exploring whether some of these information can be presented on the map, along with the display of the route. We also have to acknowledge the fact that most drivers do visual inspection using the interactive map more than checking the texts of navigational information presented below it.

Another critical avenue for exploration is improving the messaging if the proposed motivative and familiarity information are found to be better presented as text to users. In the current prototype, the wording are based on certain assumptions about language use and culture of the recruited participants. However, results from the interviews have shown that the current messaging had different interpretations among participants which had an effect on their stated route choices. Future exploration might want to consider co-design with drivers and serious consultation with communications experts in order to achieve proper messaging.

Finally, future explorations might also consider using more practical navigational and contextual information. My proposed motivative information are prosocial in nature, intended to highlight the potential choice's benefit to other people and society as a whole. It might be worth considering the addition of contextual information such as the number of traffic lights and or the estimated waiting times. This could provide a balance of information that could highlight a potential unselfish choice's benefit to drivers and others while still being familiar to them.

5.10 Conclusion

In this chapter, I focus on the trip planning step of the navigation task and explored adding motivative information to encourage drivers to choose an unselfish route. Guided by the Self-Determination Theory, I used three types of motivative information: the simple positive framing of a potential choice's benefit to the driver and others, the critical mass or the number of drivers who chose the recommended routes, and the positive valence or the decrease in everyone's travel time. Using insights from Chapter 3 on what drivers mostly value in choosing a route to follow, I also explored adding two types of familiarity information: the absolute number of familiar roads, and the names of a few familiar roads. In a stated route choice experiment, I investigated the effects of trip types, motivative information and familiarity information on the likelihood that the unselfish route will be chosen before a trip begins. After this, a pairwise comparison task was also conducted. This is to estimate which combination of motivative and familiarity information is the most preferred in encouraging drivers to choose an unselfish route. My results show that drivers are more likely to choose an unselfish route when the motivative and familiarity information are simple and explicit, like the combined use of simple positive framing and names of familiar roads. Although there is universal positive utility for this combination, my results also suggests that a personality-targeted motivation and messaging would be ideal especially if we want to cater to different trip scenarios and to people with different causality orientations and behavioral regulatory types.

6

Conversations for On-Trip Voice Guidance

While nudging drivers to choose an unselfish route can be achieved through theory-based design as shown in Chapter 5, we are only halfway into achieving our goals. Chapter 3 extends empirical evidence from GPS tracks and recorded actual trips that show that drivers do not always prefer the fastest routes[127,181,158,61,23,144] and shows that after choosing a route to follow, drivers are still likely to deviate because of *normal, natural troubles* that they experience with GPS devices[23], road unfamiliarity, and perceived impracticality and driving unsuitability[144]. Thus, it is equally important to rethink how voice guidance can be improved to effectively support driver during a trip. Because despite being offered in GPS devices since the 1990s, there are still gaps in current systems and applications that fail to consider the changing contexts and preferences which shapes the realization of a navigation task.

Echoing Brown & Laurier[23] in their call to not think of drivers as docile actors and to focus more on helping them make *instructed actions* when designing voice guidance, our design goal is to support a driver's ability to interpret and analyze new route guidance and information in order to help them make better navigation decisions. Specifically, we focus on exploring how to provide ample route information and alternative suggestions for some turns during a trip, providing them agency.

Essentially, navigation is a social activity among drivers and navigators[58,101]. And despite our growing reliance on modern navigation systems, we still perform better in terms of navigation and route learning when we are with an active collaborative partner in the task[9,10,23]. However, actively engaging the driver while driving might pose a distraction and increase cognitive workload[83]. As a step towards supporting *instructed actions* by drivers, we explore a concept that use two-party conversation between voice agents. But instead of being an active participant in the conversation, the driver remains as an observer and not engaged in the conversations. In this chapter, I discuss the results of a Wizard-of-Oz study in a within-subject design with 30 participants. Participants were asked to drive 9 times under different conditions – three (3) without and six (6) with conversation. During each simulated drive, their navigation choices, workload, and confidence with their choices were recorded. In this chapter, I:

- describe a nascent concept of giving turn-by-turn voice guidance using two-party conversations;
- describe how different combinations of voice agents affect the navigation decisions and confidence of drivers in their choices; and
- discuss design implications for better voice guidance and supporting the *instructed actions* of drivers.

6.1 Related Works

Recent works on HCI and human-robot interaction have explored using conversational user interfaces and multi-party conversations in various contexts. The early works of Sumi & Mase[156] and Todo et. al.[162] show how advantageous multi-party conversations can be in engaging users and giving new information about a topic. In the work of Yoshiike et. al.[180], they even saw reduced workload and conversational burden from users when they listened to a conversation between three social robots.

In the automotive context, Antrobus et. al. investigated how effective the use of SatNav devices are compared to collaborative passengers in helping drivers learn routes and become more aware of their environments while navigating. They found that drivers learned the routes better after they drove with a collaborative passenger because they were using more landmark, road sign and dynamic landmark descriptors in telling the next navigation instruction. In contrast, the SatNav was only giving distance descriptors. Additionally, the collaborative passengers were more helpful because they confirm what the driver is interpreting as the next navigation maneuver, give confidence boosting words to the driver, and provide proper orientation[9]. In a follow up study[10], they expanded the experiment conditions by including an informed passenger and a Natural Language Interface (Wizard-of-Oz) tha simulates the conversations of the collaborative passenger. Similar to the first study, they echoed the finding that active forms of navigational support (e.g. collaborative passenger and Natural Language Interface) were more beneficial for the route learning of the driver. Additionally, they also found that although the collaborative passenger and Natural Language Interface were engaging the driver more often than the SatNav and informed passenger, they did not see significant increase in the amount of workload. In the end, they argue that two-way conversations can be effective in providing navigation instructions. Similarly, Large et. al.[89] found that engaging drivers in one-to-one conversations with a digital assistant can reduce driver fatigue. while Karatas et. al.[83] found that keeping the driver as a bystander in a multi-party conversation between social robots can help them find good places to go while keeping their focus on the road. We build on this body of work by focusing our attention to the time critical task of turn-by-turn guidance and see whether it can maintain a reduced workload for drivers while helping them compare the value of two route suggestions.

6.2 Two-Party Conversations

In this early concept, I identified different routes that will be suggested, designed the voice agents and the two-party conversations, and planned when they will be delivered during the trip.

6.2.1 Route Suggestions

All routes in Figure 6.1 resemble a home-to-work trip and starts in the residential area of the map. They all had the same destination, which is opposite diagonally from the start point. This pair of points allowed us to identify the following routes based on Zhu & Levinson and Tang & Cheng's categories of trips that drivers usually take[158,181].

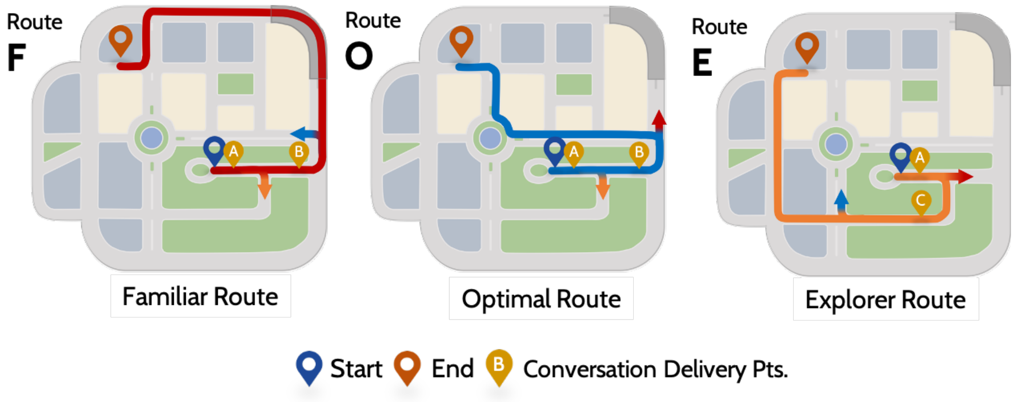

Figure 6.1: The selected routes from the map. The start and end points are the same for all routes. The orange markers are where the conversations are delivered, only once per trip. The 2 diverging arrows from each route show the alternative turns given in the conversations, colored to represent the type of route they lead to.

- **Route F** (Figure 6.1b) - This route is straightforward and has a prominent landmark (i.e. a tunnel) that participants can easily remember and recognize [10].
- **Route O** (Figure 6.1c) - This route uses the roundabout to avoid long waits at traffic signals [132,144]. It makes early turns compared to the Familiar route and is relatively the shortest among the three routes.
- **Route E** (Figure 6.1d) - This route is the longest and uses roads that are farther from the end pt on the other side of the map. This was based on the way modern apps suggest novel routes that are not short distance but algorithmically determined to be faster to avoid busy routes [144].

6.2.2 Voice Agents

We created four voice agents that deliver turn-by-turn instructions to the participants, two for Route F and one each for Route O and E.

Table 6.1 shows the four voice agents used in this study, along with their assigned routes. All voice agents give out route descriptors for next turns and sometimes an absolute distance towards the next turn. The Generic voice agent give instructions patterned after the instructions commonly delivered by current navigation applications like Waze and Google Maps. Its phrasing is direct and authoritative (i.e. *Turn Right* and *Go Straight*). On the

Table 6.1: The four voice agents, their assigned routes and their sample give turn-by-turn instructions.

Voice Agent	Route	Sample Instruction
Generic	F	In 500 meters, turn left.
Familiar	F	Let's turn left after 500 meters. We take that direction on most days.
Optimal	O	We can turn left again in 300 meters. It will take us faster.
Explorer	E	Let's turn right. I think we haven't gone in this direction before.

other hand, the Familiar, Optimal and Explorer voice agents are designed to sound more suggestive and promotes a partnership between the voice agent and the driver, mimicking the way a human collaborative navigator would give out instructions[9]. We also phrased them as such because we are aiming for a more suggestive tone so that drivers can have agency in making instructed actions, and for them to not panic as much when they miss turns[23,144]. To achieve this effect, we designed them to always start their instructions with "Let's," which is the shortest phrase we can add to the route descriptors without making them too long.

Aside from the typical route descriptors, the instructions given by the Familiar, Optimal and Explorer voice agents also include the rationale for their suggestion. The Familiar voice agent says a phrase or sentence that reminds how regular the driver takes a road (i.e. We take that direction on most days). The Optimal voice agent adds a phrase or sentence to emphasize fastness or having less waits on traffic signals (i.e. It will take us faster). Lastly, the Explorer voice agent adds a phrase or sentence that highlights the novelty of the suggestion (i.e. *I think we haven't gone in this direction before*).

We first created the instructions in English. But because of the diversity of our participants who were recruited before the actual sessions, we eventually created versions in Filipino and Japanese languages, for a total of 12 voice agents. We translated the turn-by-turn instructions to Filipino and Japanese with the help of one Filipino and two Japanese native speakers.

We generated an audio file for each line of instruction using the Google Cloud Text-to-Speech API * because it supports our three languages with high-fidelity speech synthesis. Specifically, we used their WaveNet voice types. Since the voice agents will also be used in two-party conversations, we chose different voices and genders to differentiate them

*https://cloud.google.com/text-to-speech/

from each other. While previous works have shown that people have certain bias based on the gender of the voice agent[81], we were limited to the voices available in the API. The English versions used two male (Familiar and Explorer) and one female (Optimal) voices. The Japanese agents also used two male (Familiar and Optimal) and one female (Explorer) voices. As a limitation of a low-resource language, the Filipino agents all used female voices which only varied by pitch – high (Familiar, pitch=3.6), regular (Explorer, pitch=0) and low (Optimal, pitch=-3.2). The assignment of gender to voice agents was arbitrary.

6.2.3 Conversation Design

Table 6.2: The conversation flow between the Familiar and Explorer voice agents when activated in the FE condition.

Turn	Voice	Instruction
T1	Familiar	"Let's go straight and then turn left."
T1	Explorer	"How about turning right before that?"
T2	Familiar	"That's possible. But we take a left on most days."
T2	Explorer	"That's true. But we haven't gone in this direction before."

The main goal of this study is to explore how turn-by-turn instructions delivered in two-party conversations affect the navigation choices of drivers. Following the Participation Framework[66], we assume the scenario of a driver driving with two collaborative passengers acting as navigators. Similar to Karatas et al.[83], the driver participates as a bystander or a passive addressee to remove the conversational burden and to not distract the driver from driving. The active interlocutors are two voice agents which give different types of suggestions.

We designed the conversations to have each voice agent speak in two turns, for a total of four turns. Each voice agent speaks in polite and friendly tones[180] and acknowledges the suggestion of the other agent. The intention was to not make the conversation sound confrontational even though the voice agents may be presenting totally different suggestions. The voice agents split the typical route information they provide in two turns. They say their suggested direction in their first turn followed by their rationale in the second turn, and they do this alternately.

Table 6.2 shows a sample conversation between the Familiar and Explorer voice agents in the FE condition. The first voice agent (Familiar) suggests a direction followed by a counter-suggestion from the second voice agent (Explorer). In most cases, the counter-suggestion is also phrased as a question (i.e. Explorer: "How about turning right before that?"). In their second turn (T2), each voice agent shares the rationale behind their suggestion. They usually start with an affirmation or another question (i.e. Optimal: "Are you sure? Turning left will take us faster"), followed by the rationale. All route information shared in conversations are the same as when they are giving suggestions by themselves (i.e. pure conditions). For a full list of all voice guidance utterances and conversations, please refer to Appendix D.

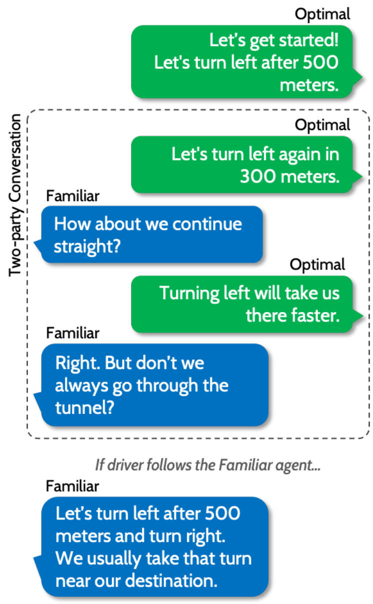

Figure 6.2: A sample sequence of turn suggestions given in the OF (*Optimal-Familiar*) condition. It has a two-party conversation between the Optimal and Familiar voice agents. In this sequence, turn suggestions are first given by the 1st voice agent in the pair. They also start the conversation with the 2nd voice agent. After choosing a suggestion between the two, the trip continues with turn suggestions from the chosen voice agent, in this the Familiar.

6.2.4 Delivery as Voice Guidance

In the conversation conditions, participants heard a conversation only once, which was either at the beginning or in the middle of the trip. Before a conversation, they heard only one voice agent giving route information. This is the first voice agent in the upcoming conversation. After the conversation is played, they continued hearing route information from the voice agent that they chose. Figure 6.2 shows the sequence of voice guidance for the whole trip in the OF condition. The voice guidance is started by the Optimal voice agent followed by the conversation. Assuming that the participant chose the Familiar suggestion, the voice guidance continued with the Familiar voice agent. Once they reach the destination, they heard the message "We've arrived at our destination." If they deviate from the designed routes, there are also generic route information prepared for each voice agent (i.e. "Let's turn left," "Let's go straight.").

6.3 Method

6.3.1 Participants

We recruited participants with at least 1 year of driving experience and has a driver's license mainly through word-of-mouth from a public university and local communities. Because not many students has a driver's license, we also used snowball sampling wherein our early participants recommended other people they know that fits our recruitment criteria.

We successfully recruited 30 participants with an almost equal mix of people who identify as men (N = 16) and women (N = 14). Their ages range from 19 to 64 years old with an average of 29 (SD = 10.6). They comprise of 12 Filipinos and 18 Japanese nationals. The Filipino participants do not drive in their current place of residence but they drive in their country of origin. Thirteen of them are students while eleven are foreign workers. All participants do not drive as part of their occupation. When asked about their driving experiences, three have been driving for more than 10 years while the rest are only driving for 1 to 5 years. In terms of application usage, they have experienced using Google Maps (N = 25), in-car navigation systems (N = 8), Waze (N = 4) and NaviTime (N = 1). However, three of them have not used a navigation application before. Two Japan residents have been using these applications for more than 5 years while the rest are using them for less than 5 years. All of them use navigation applications only when going to an unknown destination and only one participant use it almost anywhere they go. When it comes to using voice guidance, 18 of them do not use it. For those that do, they frequently use it when they go on trips to new or seldom visited places.

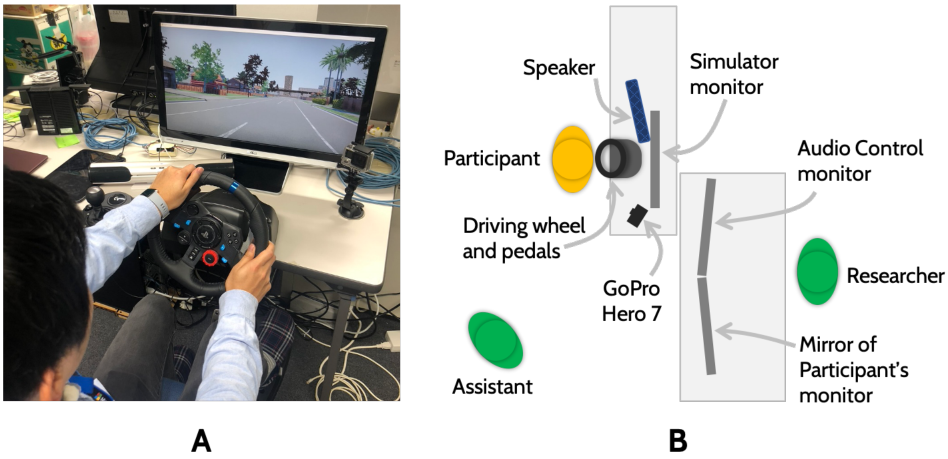

Figure 6.3: The Wizard-of-Oz setup. [A] A participant driving in the virtual environment and [B] the overhead view of the room with the location of participant, researcher and assistant.

6.3.2 Setup

The physical driving setup (Figure 6.3) uses one wide screen monitor and a Logitech G29 Driving Force steering wheel and pedals. On the other side of the table, the researcher sees a mirror of the participant's monitor. Every time the driver comes near a decision point, the researcher plays the recorded instructions and conversations. We used ordinary speakers for playing the voice guidance and this was placed in front of driver, positioned on their left. To record what the participants are saying while driving and thinking aloud, we also set up a GoPro Hero 7 that faces the driver. We only start recording once the actual driving sessions have started.

We used the open-source CARLA simulator[48] as our virtual driving environment. We selected its Town3 map (Figure 6.4) because of its grid-like layout with many options for alternative routes. The map also features distinct land use areas and buildings that participants can easily distinguish (i.e. residential, commercial and industrial areas) for easy orientation in the environment. The virtual driving environment was used as is. For every participant session, we generate 60 random vehicles of different types around the map and they drive autonomously.

Figure 6.4: The Towm3 map of the CARLA simulator.

6.3.3 Conditions

Using the routes discussed in the Route Suggestions subsection, we designed the study to have three pure conditions and 6 conversation conditions. The pure conditions use only one voice agent namely and does not play any conversarions, *PF* for Familiar voice agent only, *PO* for Optimal voice agent only, and *PE* for Explorer voice agent only. The conversation conditions use combinations of voice agents and are named the following: *FO* (Familiar+Optimal), *FE* (Familiar+Explorer), *OF* (Optimal+Familiar), *OE* (Optimal+Explorer), *EF* (Explorer+Familiar) and *EO* (Explorer+Optimal). The suggestion of the 2nd agent in conversations is the expected choice (*appropriate*).

6.3.4 Protocol

We conducted a within-subject Wizard of Oz study which tasks each participant to drive 9 times under different navigation conditions. To reduce any ordering effect, we prepared 30 randomly ordered sequences of the 9 conditions and randomly assigned the participants to them. In the room, there is the participant and the experimenter. For the Japanese participants, a Japanese student assistant who is knowledgeable about the study and can translate English to Japanese is also present. For the duration of the actual driving sessions, the experimenter and assistants cannot talk nor react to the participant.

Orientation

At the beginning of each session, we briefed them about the project and the purpose of the experiment they are about to perform. Then, we obtained their consent to the procedures of the study and their answers to a pre-trial questionnaire that asks about their demographic information, driving background and experience with using navigation applications and voice guidance. Then, we oriented them about the steering wheel and pedals, and the simulation environment. For Japanese participants, it was emphasized that the environment is configured for driving on the right side of the road, which was different from what they are used to. We also mentioned the presence of a roundabout which does not exist in Japanese roads. During the whole orientation, we showed them a map. We gave them 3 minutes to drive around and get comfortable with the controls.

Familiarization with Voice Agents

After they became comfortable with the controls and environment, we asked what language they prefer for the voice guidance. All participants chose to use the local language versions, with nobody using the English voice guidance. We told them that they will hear 3 types of voices during the driving sessions and then played them the synthesized voices. Each voice was assigned a name and a number just for this step. To check how well they can differentiate the voices, we played them again but this time, they had to tell which voice was speaking (i.e. first voice, Tanaka-san, Olive). This step was done in order for them to easily detect when a conversation is being played already.

Remembering a Regular Route

Once they are familiar with the voices, the next step required them to familiarize with a route that served as their regular route to the destination. We showed them a map with the route drawn in red and they made two trips in the simulation following it. We played voice guidance so they can focus on the road and practice hearing the guidance. After this, they were asked to drive again to the destination but without voice guidance. In this step, we wanted to check how familiar they were with the route we asked them to follow. Once they reach the destination, we asked them to rate how good they think the route is, 1 being very bad and 7 for very good. For this question, we wanted to know later if their score affects how often they follow this route.

Trial of NASA-TLX

Since this was the first time that the participants have done this kind of study, we gave them a trial. We asked them to rate their workload using the NASA Task Load Index (TLX) questionnaire after following the voice guidance in the route familiarization step.

Driving Sessions

Each participant drove 9 times. Before anything, we reminded them that they are not obliged to follow the directions given by the voice guidance. After hearing the suggestions and conversations, it is up to them to decide which direction to go based on the given scenario and their personal preference. At the beginning of each drive, they were told to forget their previous drives and assume that they are hearing the voice guidance for the first time. They were also asked to think aloud. While we were starting their environments, we told them to internalize one of the following scenarios:

Table 6.3: The different scenarios given to the participants before each condition.

Scenario	Description
Regular Day	It is a regular day. You woke up on time and you have your regular schedule at the destination.
In a hurry	You have a meeting in the morning and you overslept. You are already running late.
Lots of time	You have no morning meetings but you woke up very early. You now have more time to spare.

Each scenario in Table 6.3 corresponds to a set of conditions. The Regular Day scenario is given in the PF, OF and EF conditions while the In a hurry scenario is given in the PO, FO and EO conditions. Lastly, the Lots of time scenario is given in the PE, FE and OE conditions. After each drive, they answered a post-task questionnaire that includes questions discussed in the Post-Task Questionnaire subsection. They can choose to have a break anytime during each session. After all 9 drives, they accomplished the Source-of-Workload Comparison sheet to complete the workload assessment. Each session lasted around 75 to 90 minutes.

6.3.5 Post-Task Questionnaire

First, participants assessed their amount of workload using the standard NASA TLX questionnaire. We did not use a modified version like in Karatas et al.[83] because this study does not intend to measure driving workload per se. To focus their assessment, we asked participants to assess based on the following aspects of the navigation task: a) listening to the voice guidance, b) choosing a direction after hearing the agents, and c) checking where to make the turn. The questionnaire was translated to Japanese following the work of Miyake[107]. Additionally, participants shared the reason behind their navigation choices (free text field) and how confident they were after choosing them (from 1 to 7).

6.4 Results

6.4.1 Unanticipated Challenges

We begin by discussing some challenges we encountered in running this study. While the driving in the simulation environment, there were multiple instances that we had to restart because the vehicle will not move. Usually at the beginning after they have heard the first voice guidance, they would notify us. This happened at most 5 times for one participant and five participants experienced this at least once.

We chose the simulation tool because we wanted to control the number of other vehicles, putting the participants in a more realistic driving environment. However, because the other vehicles are stochastic, there was one instance wherein we had to restart the environment midway because of a traffic jam. In that moment, our prepared audio files for voice guidance were not enough to direct the participant out of the traffic jam. But instead of immediately running that same condition, we changed the order so that the participant can forget the given instructions.

6.4.2 Impact on Choices

In this study, one of our main goals is to explore the impact and limitations of adding conversations in making navigation choices. We analyzed how associated their choices were for each given scenario and condition, along with a discussion of their reasons, and then discuss how combinations of these voice guidance affected their choices.

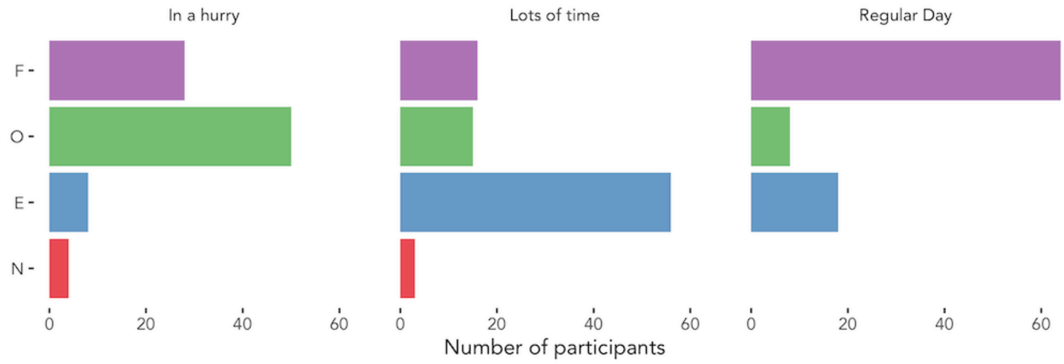

Figure 6.5: Distribution of navigation choices per scenario. D refers to those who chose the Familiar suggestion, O for Optimal suggestion, E for Explorer suggestion, and N for those who chose neither of the given suggestions.

First, we wanted to see how aligned the participants' choices were based on the scenario that was given to them at the beginning of each condition. We tallied the participants' choices and found that all types of suggestion were chosen at least once by the participants in each scenario (Figure 6.5). Looking at the contingency table of choices versus scenario, a chi-square test shows that choices made by participants are dependent on the current context of their driving ($\chi^2 = 123.35$, $p < 0.05$).

Examining this association further, a chi-square test of the breakdown of choices made by participants under each condition (Figure 6.6) shows that the type and combination of voice guidance was associated with their navigation choices ($\chi^2 = 229.87$, $p < 0.05$). Many participants navigating under the PF, FO and OF conditions were likely to choose the Familiar suggestion, while those under the PO and EO conditions were likely to choose the Optimal suggestion. In the PE, EF and FE conditions, participants were attracted to choosing the Explorer suggestion, while both Optimal and Explorer suggestions were positively associated with the OE condition.

Regular Day Conditions

Given the prompt in the Regular Day scenario, the Familiar suggestion comprise almost 3/4 of the choices (N = 64) suggesting a strong association. And although there were those who chose the Optimal scenario, it was only chosen 8 times across the three conditions (PF, OF, EF).

In the PF condition, all 30 participants chose the Familiar suggestion. Four participants

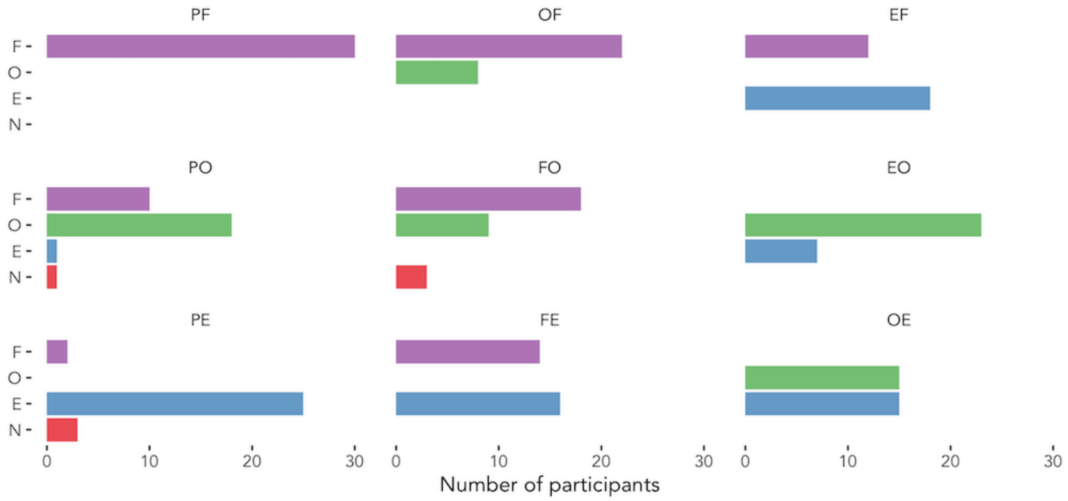

Figure 6.6: Distribution of navigation choices per condition. The first row shows the conditions under the *Regular Day* scenario, followed by the conditions in the *In a hurry* and *Lots of time* scenarios.

chose it primarily because the voice agent always reminded them of how often they take the suggested roads (P17, P20, P21, P30) while three participants add that it is because that is the only given suggestion (P11, P20, P28). Two participants also cited trust because "*it knows the way, [there is] no need to think*" - P19. Participants also felt at ease (P9) that they can arrive at the destination without thinking (P5, P7, P28) because of the easy-to-understand road navigation (P18, P27). Six participants also felt it appropriate because they "*...have nothing to do or [they are] not in a rush*" (P15). Interestingly, one participant chose it because they "*don't want to go the other way because I might get lost*" - P23.

When suggestions were given in two-party conversations (OF and EF), their positive association with the Familiar suggestion was only maintained in the OF condition. Even in a two-party conversation with the Optimal voice agent, participants still chose the Familiar suggestion because they thought it was correct (P12), easier to follow (P7, P22-23) and familiar (P13, P16, P18, P26). They also chose it because they were not in a rush to go to their destination (P14-15). Commenting against conversations, two participants chose the Familiar route because they found the conversations confusing (P6, P9) leading them to default to a suggestion they felt at ease with. On the other hand, two participants shared that they would have followed the Optimal suggestion had its rationale been delivered earlier in the conversation (P19, P29). For those that did choose the Optimal suggestion, P20 thought that it was easier to follow compared to the Familiar suggestion —without much elaboration, while three other participants were mostly in agreement with the rationale spoken by the Optimal voice agent (P4, P11, P27). Two participants found it an opportunity to explore a new route because they were not in a rush (P10, P17) while another two participants chose the Optimal suggestion because it was the first thing they heard from the conversation.

In the EF condition, more participants chose the Explorer suggestion (N = 18) than the Familiar suggestion. They did not see it as a bad choice (P30) while some actually chose it because they wanted to explore a new route (P4, P6-7, P20, P24-25, P27) and they had ample time (P18, P26). Like in the OF condition, there were also participants that chose the Explorer suggestion because it was the first one they heard (P5, P8, P15, P19). Familiarity is still the main reason of the six participants that chose the Familiar suggestion, while three others chose it because they think they have plenty of time. Interestingly, P13 and P22 chose the Familiar suggestion, and P12 and P28 chose the Explorer suggestion because they all thought their choices were faster. This was their criteria despite having no time constraint in the Regular Day scenario.

In a hurry Conditions

In the In a hurry scenario, participants were most attracted to choosing the Optimal suggestion with more than half of the choices made (N = 50). However, almost a third (N = 28) of the choices were still Familiar suggestions, indicating participants' tendency to default to regular routes even though they were in a hurry[144,181,158].

In the PO condition, more than half of the participants chose the Optimal suggestion (N = 18) primarily because they believed that the suggestion will take them faster towards the destination. P12 adds that they followed the suggestion because there is "*no hassle, [and it is] no[t] much effort.*" Highlighting the benefit of hearing why they were given that suggestion, P27 shares that "*The usual way was good, but I did not have time. I got it when it taught the shortest way, so I went to the shortest way as instructed.*" On the other hand, two participants shared that they were unsure where to go especially when the instruction "*Let's turn left again in 300 meters*" was given to them. This suggestion is played immediately after they make the first left turn at decision point B. P10 was not sure when to make the next turn: "*I didn't know where [is] 300 meters away.*" Additionally, P5 was "*suddenly confused when told to go left. I ignored it because it was a little over.*" Hence, while the rationale behind the suggestion was appreciated and encouraged participants to follow, the addition of the distance information made it confusing for others[9]. This resulted to them following the Familiar suggestion instead. Aside from being comfortable with the Familiar route (P23), two other participants chose the Familiar suggestion because they thought it was faster than the Optimal suggestion[?] .

After listening to a two-party conversation in the FO condition, the number of participants who chose the Optimal suggestion drops to less than a third in the pure condition (N = 9). Participants had the same reasons why they continued to follow the Optimal suggestion (i.e. belief that it is faster, with less waits). On the other hand, two participants chose the Familiar suggestion because they got confused while listening to the conversation: "*Two agents were proposing many ways along the way, and I couldn't understand what they were saying, so I went to the usual road while listening to the suggestions*" - P27. Speaking about the timing and length of conversation, four participants eventually followed the Familiar suggestion because it was already too late for them to make the turn suggested by the Optimal voice agent. "*After listening to the conversation between the agents, I couldn't turn to get there quickly*" - P29. Lastly, the rest of the participants did not believe the Optimal voice agent's rationale and thought the the Familiar suggestion is still faster.

Having the opposite effect, participants in the EO condition followed the Optimal suggestion the most number of times in the In a hurry scenario (N = 23). This time, most of the participants agreed with the rationale of the Optimal voice agent and decided that it was more appropriate. However, when we traced their complete trips after following the Optimal suggestion from the conversation, five participants eventually followed the familiarization route, not the optimal route. This suggests that even though they agreed with the suggestion and thought it will take them faster, familiarity was still a contributing factor.

Lots of time Conditions

In the Lots of time scenario, they mostly chose the Explorer suggestion (N = 56) when they were told that they had much time to spare. This preference was consistently observed in the PE condition wherein 25 of them chose the Explorer suggestion. Two participants (P6, P8) followed it because that was the only suggestion given while six others were just open to the suggestion given the scenario they are in (P10, P12, P18, P24, P26, P29). There were also some participants who really wanted to explore new routes that they can use in the future: "*I chose to go that route so that I can expand my knowledge of the different ways I can get to work*" - P16. For those who chose otherwise, one participant ignore the Explorer suggestion and drove the familiar route because "*the agent says turn right twice instead of left to pass the tunnel. Wrong direction*" - P25. Interestingly, three other participants completely went their own ways.

When the Explorer suggestion was given in the FE condition, there were less participants who chose it because they were also reminded with the Familiar suggestion. Focusing on participants who chose the Familiar suggestion, they cited reasons of familiarity (P7, P14, P20-21, P28) and correctness (P12). Interestingly, two participants who chose the Explorer suggestion in the PE condition now followed the Familiar suggestion because "*I'm not confident about the other road*" - P4.

In the OE condition, participants were evenly split between the Optimal and Explorer suggestions. Everyone who chose the Explorer suggestion are driven by the non-urgency of the scenario, making them more open to explore new routes. However for those who chose the Optimal suggestion, while they also considered the non-urgency of the situation, they prioritized comfort (P12, P20, P23) and familiarity (P14, P21, P23, P28) in choosing. In addition, P30 did not choose the Explorer suggestion because "*it is not good to go on a road that [the] Navi does not know*." This impression might have been because the Explorer voice agent says this as one of its suggestions: "*Let's turn right. I think we haven't gone in this direction before.*"

Goodness of Familiarization Route

At the beginning of each study session, we asked the participants to rate how good the familiarization route is. Out of the 27 participants who were able to do so, 23 of them gave good ratings (between 5-7) while only four gave low scores of 3 and 4.

We found that participants who rated it as good were following it more than we expected. In the PO and PE conditions, eight and two participants followed the Familiar suggestion respectively even though there was no mention of Familiar suggestion in the voice guidance. However, looking at the association between choice and their goodness rating, a chi-square test shows that they are actually independent of each other.

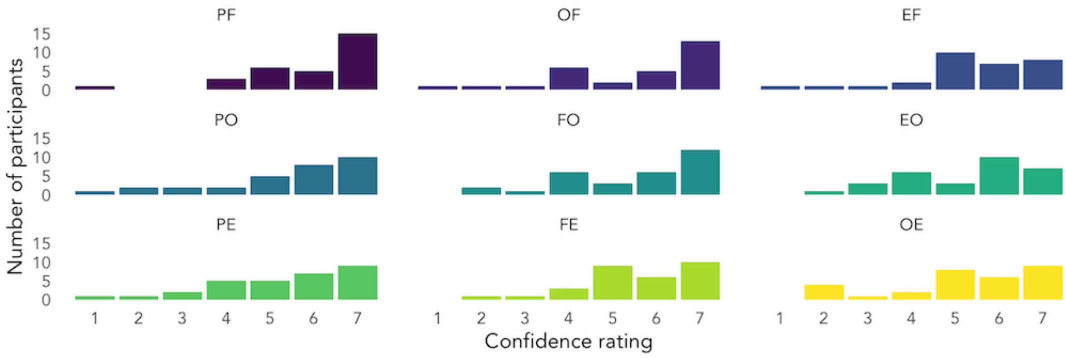

Figure 6.7: Distribution of confidence rating per condition. The first row shows the conditions under the *Regular Day* scenario, followed by the conditions in the *In a hurry* and *Lots of time* scenarios.

6.4.3 Impact on their Confidence with Choices

Overall, confidence in their choices was generally lower when suggestions were given in conversations. When the *Familiar* suggestion was given on its own (PF condition), average confidence was 5.9 (M = 6.5, σ = 1.41) – the highest among conditions – with half of the participants giving a score of 7. Compared with other conditions given in the *Regular Day* scenario, their average confidence then drops to 5.6 for the OF condition (M = 6, σ = 1.7) and 5.4 for the EF condition (M = 5.5, σ = 1.5).

When participants heard suggestions that are different from what they are familiar with, they self-reported relatively lower confidence with their choices. Under the *In a hurry* scenario, their average self-reported confidence was 5.4 (M = 6, σ = 1.73) when they only heard the *Optimal* suggestion (PO condition). This was slightly lowered to 5.3 (M = 6, σ = 1.47) when they heard it with the *Explorer* suggestion. In the *Lots of time* scenario, they had average confidence ratings of 5.3 (M = 6, σ = 1.64) and 5.27 (M = 5.5, σ = 1.68) when they only heard *Explorer* suggestions and when it was mixed in a conversation with the *Optimal* suggestion.

The only increases happened when the familiar route suggestion was also given in conversations in the FO (μ = 5.5, M = 6, σ = 1.6) and FE (μ = 5.6, M = 6, σ = 1.3) conditions compared to when it was only the *Optimal* and *Explorer* suggestions mentioned. These suggests that the addition of novel suggestions, *Optimal* and *Explorer*, in conversations for all scenarios negatively affects how they perceive their choices. However we are not yet certain whether they actually felt less confident after making a wrong choice or even with the right choice for the scenario. Additionally for all scores, there are no significant differences after a Wilcoxon Signed-rank test.

High Confidence on Familiar and Optimal Suggestions

Based on a chi-square test, the self-reported confidence of drivers are choice-dependent (χ^2 = 23.90, $p < 0.05$). In trips where the *Familiar* suggestion was followed (N=108), participants had an average confidence rating of 5.58 and this choice has a positive association with the confidence rating of 7, primarily because it is what they are already familiar with.

For all *Regular Day* scenario trips, participants who chose the *Familiar* suggestion were more confident (N=64, μ = 5.84, M = 6). In the OF condition, while many trips chose the *Familiar* suggestion (N = 22) over the *Optimal* suggestion (N = 8), participants were equally as confident in choosing the *Optimal* suggestion (μ = 5.6, M = 6.5, σ = 1.85) compared to choosing *Familiar* (μ = 5.5, M = 6, σ = 1.68). Due to the low stakes nature of the scenario, even though the participants chose an unnecessarily faster suggestion, they did not mind it as much unlike when they chose the totally novel *Explorer* suggestion (μ = 4.89, M = 5) overall. The low stakes nature of the *Lots of time* scenario also made participants more confident in following *Familiar* even though it was followed less often (N=16, μ = 5.63, M = 6) and intentionally less appropriate compared to the *Explorer* suggestion (N=56, μ = 5.23, M = 5). However in the *In a hurry* scenario, confidence with the *Familiar* suggestion was remarkably lower (μ = 4.96, M = 5) even though it was chosen by participants in 47% of the trips in the PO and FO conditions.

Despite being chosen the least among the three suggestions, the *Optimal* suggestion (N=73) was still positively associated with high confidence ratings of 6 to 7. This is can be attributed to the fact that the *Optimal* and *Familiar* suggestions are identical (*"Turn left after 500 meters"*) except for the rationale said. Overall, participants reported an average confidence of 5.75 after choosing the *Optimal* suggestion.

In the *In a hurry* scenario, participants who chose the appropriate *Optimal* suggestion reported a 5.8 average confidence (N=50, M = 6) which was consistently the highest in the PO (μ = 5.94, M = 6, σ = 1.3), FO (μ = 6.33, M = 1, σ = 1) and EO (μ = 5.48, M = 6, σ = 1.27) conditions. Half of the participants were also confident with choosing the *Optimal* suggestion in the OE condition (μ = 6.33, M = 1, σ = 1) despite it being the less appropriate choice. However, despite choosing the *Optimal* suggestion, eight (8) of them never really followed the complete *Optimal* route and went on to follow the familiar route instead. So this suggests that they were confident in their choice not because they thought choosing a faster route was correct but more because of their familiarity with the turn.

Low Confidence for Explorer Suggestion

Choosing the *Explorer* suggestion is strongly positively associated with the confidence rating of 5 and strongly negatively associated with confidence rating 7. The novel nature of the suggestion made drivers less confident in their choices. This is consistent with previous works. Participants also felt unsure whether they will receive continuous guidance if they deviate from the familiar route.

After choosing the *Explorer* suggestion in the *Lots of time* scenario, participants reported average confidence scores of 5.12 in the PE condition (M = 5, σ = 1.67) and 4.87 in the OE condition (M = 5, σ = 1.41). Their confidence was low despite choosing the *Explorer* suggestion 67% of the time for both conditions. Only in the FE condition did the participants felt more confident with following the *Explorer* suggestion (μ = 5.75, M = 5.5, σ = 1), but still not as much compared to the *Familiar* and *Optimal* suggestions.

Choosing Alternatives

We also looked at how confident the participants were when they chose the alternative suggestion over the appropriate ones. In the EF condition, participants started self-reporting low confidence scores of 1 to 4 (N = 4) after choosing the *Explorer* suggestion (μ = 4.89, M = 5, σ = 1.57) compared to those that chose the *Familiar* suggestion, who mostly reported scores between 5 to 7. In the *Regular Day* scenario, we expect them to prefer the *Familiar* suggestion over the *Explorer* one. It shows that even though they made a wrong choice, they must have realized after performing the task that they should have chosen the *Familiar* suggestion instead. The same lower level of confidence was also reported after participants chose the *Familiar* suggestion in the FE (μ = 5.43, M = 6, σ = 1.65) and FO (μ = 5.11, M = 5, σ = 1.75) conditions. They were not expected to prefer the *Familiar* suggestion, but 14 and 18 participants did in the FE and FO conditions respectively. And although some of them self-reported scores of 6 to 7 — because they are familiar with it — we also observed more participants reporting lower scores from 2 to 4 (N_{FE}= 4, N_{FO}= 7).

Good and Bad Pairs

Pairing novel suggestions in conversations made participants less confident with their choices even when they made appropriate ones. Participants in the EO condition who chose the *Optimal* suggestion reported confidence scores (μ = 5.48, M = 6, σ = 1.27) with seven of them giving scores between 3 and 4. This is lower compared to when they chose the same suggestion in the PO condition (μ = 5.94, M = 6, σ = 1.30) with only two participants reporting scores between 2 and 4. This was also the case in the OE condition where the average confidence score of 4.87 (M = 5, σ = 1.41) after choosing the *Explorer* suggestion was lower compared to the 5.12 average confidence score in the PE condition (M = 5, σ = 1.67). Four more participants gave scores between 1 and 4 in the OE condition. This is consistent with previous works that highlighted people's tendency to not prefer suggestions when they are too novel, putting them under a lot of uncertainty[50].

On the other hand, the delivery of the *Familiar* suggestion as an alternative in the FO and FE conditions made participants feel more confident in choosing the *Optimal* and *Explorer* suggestions. Even though less participants chose the *Optimal* suggestion in FO (N=9) compared to PO (N=18), and the *Explorer* suggestion in FE (N=16) compared to PE (N=25), they felt relatively more confident with average scores of 6.33 (M = 7, σ = 1) and 5.75 (M = 5.5, σ = 1) respectively. Including the *Familiar* suggestion gave participants a recognizable point of comparison. This was in contrast to their experience in the all-novel conditions (EO, OE) wherein they had to process two new suggestions and also recall their regular choices.

6.4.4 Impact on Workload

Because our concept gives more information than the typical voice guidance, we wanted to see how much the two-party conversations impact the workload of the participants. Figure 6.8 shows the NASA TLX scores of the 30 participants in each of the conditions. A box plot is superimposed on each dotplot. The total NASA TLX scores show that the PF condition (M = 26.84, σ = 17.31) resulted to less workload compared to the PO (M = 47.5, σ = 20.8) and PE (M = 37.5, σ = 19.86) conditions. In Student's Paired lower-tailed t-tests between PF and PO, and PF and PE, $p<0.001$ and $p<0.05$ respectively, indicating significant decrease in the PF condition. Comparing between PO and PE, a Student's Paired upper-tailed t-test resulted in $p<0.01$ indicating a significant increase in workload for the

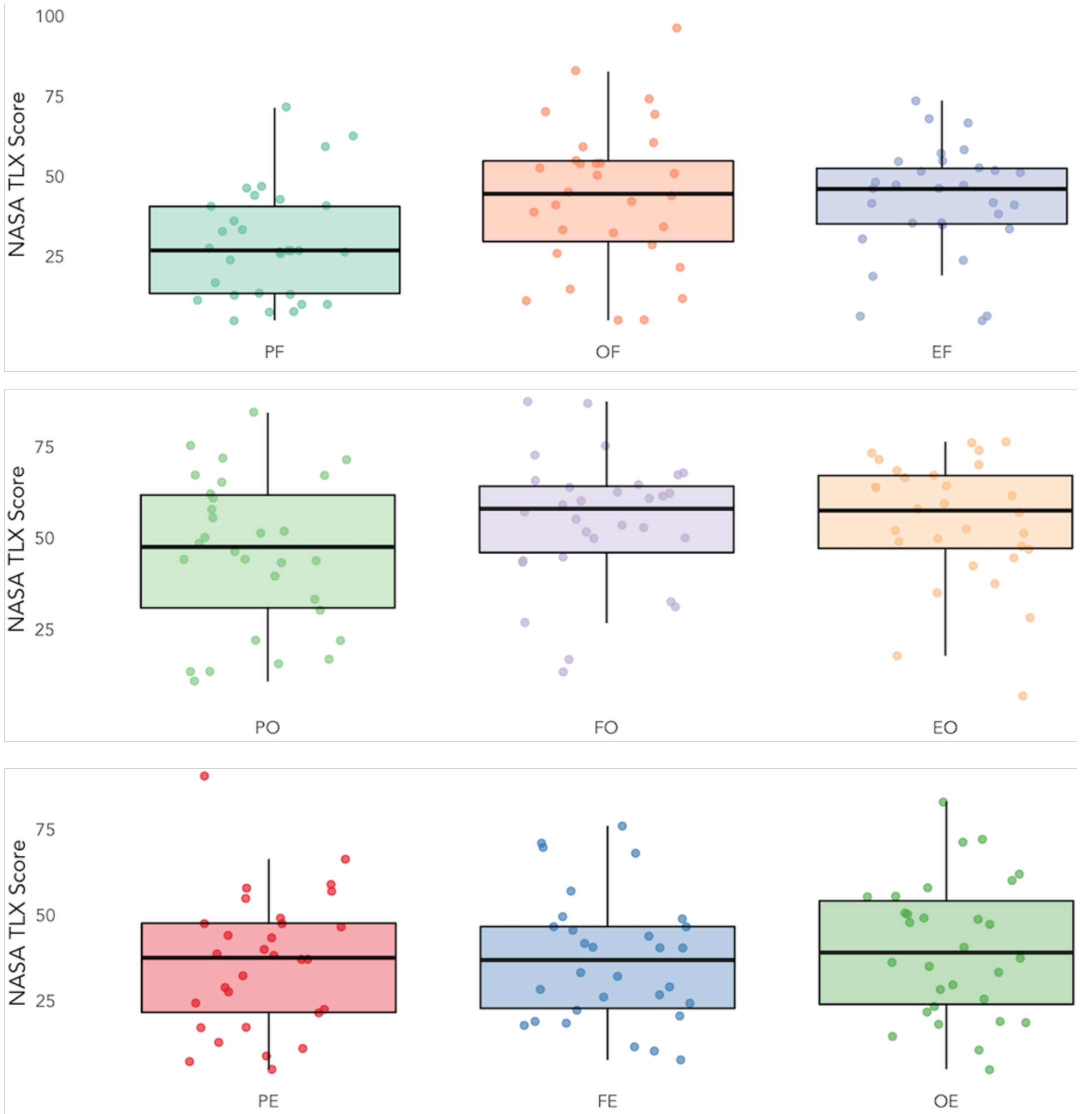

Figure 6.8: NASA TLX scores of each participant after each condition. The first row shows the conditions under the *Regular Day* scenario, followed by the conditions in the *In a hurry* and *Lots of time* scenarios.

PO condition.

Internalizing the Regular day scenario, participants reported higher workloads when the Familiar suggestion was mixed in conversations. Both EF ($M = 46$, $\sigma = 17.34$) and OF ($M = 44.5$, $\sigma = 22.76$) show significant increases in a Student's Paired upper-tailed t-test with $p < 0.001$. This increase must have been because they had to recall the first suggestion which was relatively new to them. Suggesting the regular route must have distracted them into considering the new suggestions. Although that does not seem to be the case in the EF condition wherein more participants chose the Explorer suggestion.

Compare to the PO condition in the In a hurry scenario, workload increased for both FO ($M = 58$, $\sigma = 17.73$) and EO ($M = 57.5$, $\sigma = 17.1$) conditions. However, after a Student's Paired t-test with the FO scores and a Wilcoxon Signed-rank test with the EO scores, only the FO condition showed a significant increase with $p < 0.05$. This was mainly due to the short amount of time between the moment the conversation was played and the point where they had to make a turn, which was a limitation of our concept design and chosen simulation environment.

When navigating under the Lots of time scenario, participants reported almost similar workloads for the Pure Explorer, FE ($M = 36.83$, $\sigma = 18.61$) and OE ($M = 39$, $\sigma = 19.75$) conditions, and a Student's Paired t-test did not show significant differences between them. Although the conversations did not significantly increase the workload, this somehow suggests that participants were consistently challenged considering the Explorer suggestion because of its novelty.

6.5 Towards Better Voice Guidance

This study provides initial insights into how voice guidance delivered as two-party conversations can impact the way drivers make navigation decisions. Here we present a summary of key findings from the results and provide design considerations for future iterations of navigation applications and recommender systems, in general.

6.5.1 Supporting Instructed Actions

Just by looking at the distribution of navigation choices made by participants, we can see clear patterns of choices being made in the pure conditions than in the conversations. When alternative suggestions get mentioned, their choices changed as well. While this can be considered as a negative result, we see it supporting our initial goal of encouraging drivers to have instructed actions[23]. Although we designed our scenarios to give more reasons for the participants to choose and follow certain suggestions (i.e. We expect the Optimal suggestion to be chosen more in the In a hurry scenario), we certainly do not consider choosing the alternative suggestions as a wrong decision. Our intent is to design and explore a new technique that will empower them with a handful of choices, rather than constrain them into following something that was already decided for them.

From the video recordings of their sessions, we observed them listening completely to the conversations, with some participants even slowing down a bit to focus on what was being said. When they shared their reasons why they made those choices, we observed more comparative and convinced answers, with some of them even citing the voice agents. The way the voice agents took turns and built up the conversation also made them feel convinced about the correctness of both suggestions. For example, P19 shared that they "heard the second agent. I just felt more confident with the first agent because in the end, the second agent agreed with the first agent's suggestion." Participants were encouraged to believe that both suggestions are true and they have the ability chose whichever they prefer or feel is appropriate for the situation. However, this approach also brings the challenge of drivers having too much affinity with the voice agents. Based on the shared reasons and utterances from the video recordings, some participants felt less confident with the Explorer voice agent because it says the phrase "I think we haven't gone in this direction before." It made them think that it will not know where to go if they follow its suggestion. While the design intent was for the voice agent to remind the driver of what roads it has and has not taken before, the driver's affinity made it think they know the same things.

6.5.2 Order, Timing and Amount of Information

One of the main challenges in this concept is time criticality. Recommender systems giving multiple options is not uncommon. Even for navigation applications and in-car navigation systems, they allow drivers to browse through alternative routes. However, they do so in situations and tasks that allow time for their users to choose. In our Wizard of Oz study, the slow reveal and the amount of information in the conversations made it less effective in certain decision points like in the FO and OF conditions. Future work might want to consider combining the direction information and the rationale in one turn. This will allow drivers to ascertain immediately whether they should follow the suggestion or not. Then, it can be delivered in two turns instead of four like in the current concept. For turns that will be made in close distances, we suggest removing distance information (i.e. "in 300 meters") and fixing the order of suggestions in the conversation. In the FO condition, the Optimal suggestion is said after the Familiar suggestion, and its rationale on the last turn. This made some drivers feel it is too late and they ignore the Optimal suggestion despite being the more appropriate choice. Overall, the time-critical nature of this task requires proper balance of timing and amount of information for the drivers so that they are not mentally burdened and end up confused.

6.5.3 Effective Combinations

Despite being delivered in different scenarios and in different orders, participants show similar patterns of choices for each combination of suggestions. For conversations that share the Familiar and Optimal suggestions, participants still prefer the Familiar suggestion which supports the findings of Samson & Sumi [144]. In future navigation applications, designers might want to prioritize the recommendation of the driver's familiar or regular routes first, assuming that they learn it on the device. The optimal suggestion can follow in the list of choices which may result to more recognizable routes and less deviations. When we give the Explorer and Familiar suggestions together in conversations, participants shift their preference to the Explorer suggestion due to the non-urgent nature of both the Regular Day and Lots of time scenarios. Additionally, participants seem to take that opportunity to learn new routes going to their regular destination. Navigation applications may have more success in recommending novel routes if they can present it relative to regularly taken routes, emphasizing unexpected benefits of taking the route (i.e. tree-laden streets, quiet) [127]. And to address possible uncertainties from drivers, applications may orient or familiarize them using landmarks that they can recognize [9,147]. Lastly, we found that optimal routes are more likely to be chosen by drivers when they are presented in a conversation with a really novel suggestion like the Explorer suggestion, regardless if they have much or little time. Using this insight, navigation applications may find more success in getting drivers to try fast and or system optimal routes [173] if they present it with route recommendations that are relatively novel but not outlandish and nonsensical.

6.5.4 Better Reflection

The two-party conversations were designed to deliver an alternative suggestion followed by the suggestion appropriate for the scenario. Despite participants making less appropriate choices in some scenarios, the low self-reported confidence on their choices shows the potential of such conversations to support and encourage proper reflection for drivers. The delivery of two suggestions gave drivers a concrete and recent point of comparison which might be difficult if they try to recall choices in previous trips. Their late realization might positively impact their future choices when they encounter similar suggestions under the same circumstances.

6.6 Limitations

In this study, our within-subject design required participants to make 9 trips in one 90-minute session. Although we gave them some breaks in between drives and asked them to forget their previous drives before starting a new one, there might still be learning effects. Second, Our physical setup only used one monitor which may have made it difficult for the participants to verify the suggested turns, especially when they take the outer lanes. Considering the best options for Route O (*optimal*), we were limited by the existing roads in the simulation environment. A minor lengthening of that road segment where most participants ignored the Optimal suggestion may change the preference for it. Lastly, we acknowledge that the scenarios were few and could have been worded vaguely, leaving it to interpretation.

6.7 Conclusion and Future Work

Motivated by supporting drivers to make *instructed actions*, in this chapter I introduced a nascent concept of a navigation application that integrates a two-party conversation in its voice guidance. Our within-subject Wizard of Oz study suggests the potential of this technique in encouraging drivers to follow certain suggestions with the right combination of voice agents. Although the conversations contributed to a higher workload unlike in previous studies that used the same technique, the participants' reported confidence suggests the potential to encourage them into making better navigation choices in succeeding drives. For future work, we would like to implement a prototype of this concept and explore in a longitudinal study whether the repeated use of such technique can actually change their navigation choices.

7
Navigo

In the previous chapters, I proposed two approaches for encouraging drivers to follow certain routes, each focusing on a different phase of the navigation task. With a focus on the trip planning phase before a driver embarks on a trip, Chapter 5 describes an approach that is grounded on Self-Determination Theory. Aside from displaying the usual estimated travel time, total distance and name of major roads that will be taken, there I explored the addition of motivative information to help drivers see the societal benefit of selecting an unselfish route. Familiarity information was also added to reduce the chances of non-selection because of high novelty. All design versions showed potential in encouraging the selection of unselfish routes. And although the combined use of simple positive framing and list of road names showed universal positive utility, preference, and can increase the likelihood of unselfish selection, it has less effect in making sure that drivers will keep on choosing unselfishly for other trip scenarios. Further, the participants in the earlier study performed the route choice task without realizing their stated choices in a real driving task. In this last chapter, my goal is to find support for the effectiveness of the most preferred motivative and familiarity information, and investigate whether drivers would continue following their unselfish choice after the first instance. I ask the question of "*Can motivative and familiarity information help sustain the selection of an unselfish choice?*"

When a driver is already on a trip, Chapter 6 describes the approach that uses two-party conversations between distinct voice agents. When a driver approaches a decision point on the road (i.e. intersections) that allows for the discovery of an alternative route, a two-party conversation will be played that presents two different driving directions. In a driving simulation study, the technique was successful in convincing drivers to consider an alternative route while still preserving their agency. It was also found that having a point of comparison allowed drivers to reflect better on their choices, possibly affecting their future choices. However, the conversational approach increased driver workload, which will require further work on the timing of conversation delivery and control on the amount of information it gives. In improving the en route approach, I ask two further questions. First, "*can two-party conversations convince drivers to switch to an unselfish route?*" And if they do choose an unselfish route at the beginning, "*can two-party conversations encourage drivers to continue following an unselfish route?*"

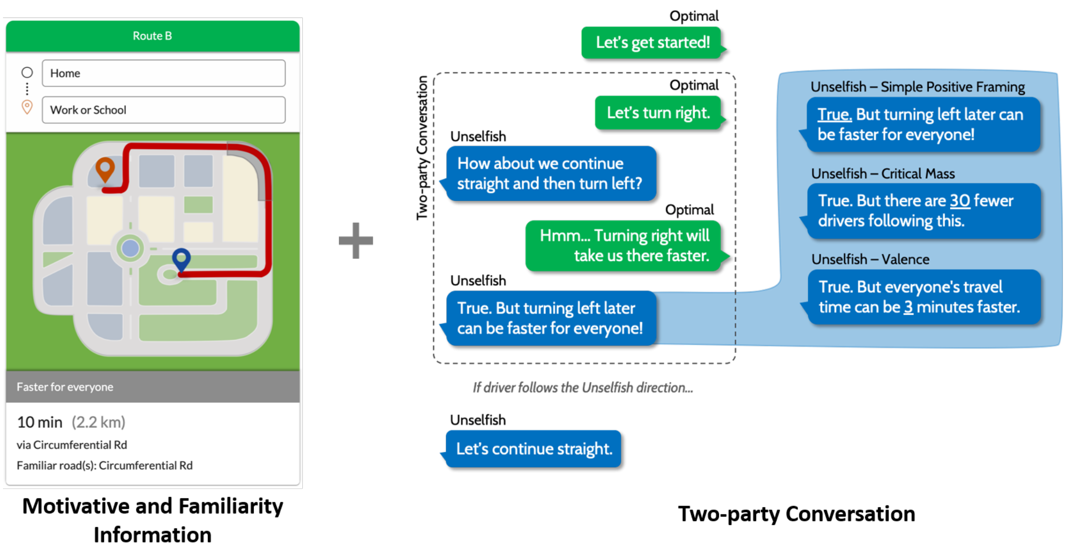

Figure 7.1: A holistic approach, Navigo refines the pre-trip (Chapter 5) and en-route techniques (Chapter 6), and combines them following a personality-targeted design.

In this chapter, I culminate my thesis by refining the two previous approaches and combining them to provide a holistic approach in encouraging drivers to choose and stick to following unselfish routes (Figure 7.1). This combined approach, which I call Navigo, uses personality-targeted motivative information in displaying recommended routes and in its voice guidance. When an unselfish alternative route is possible to follow, a conversation will play between two voice agents to present the next turn directions.

7.1 Holistic Approach

Navigo's concept is close to the design approaches described in Chapters 5 and 6. In this section, I will highlight the significant changes from the original ones.

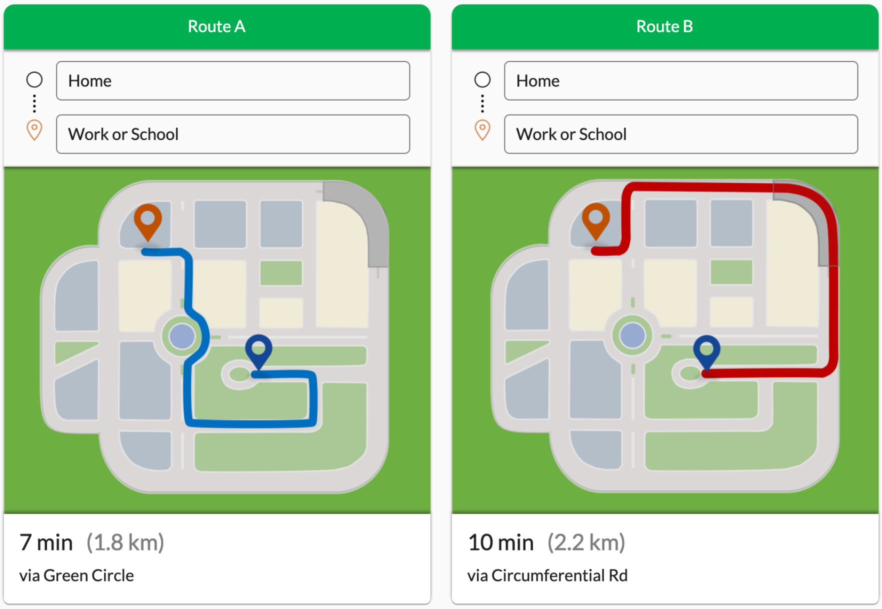

Figure 7.2: The baseline version of the Navigo interface. It shows the origin and destination at the top, a map in the middle, and the trip information at the bottom.

7.1.1 Pre-Trip: Route Selection Interface

Like in the interface described in Chapter 5, the Navigo prototype also consists of three parts (Figure 7.2). The top shows the name of the origin and destination. The middle shows the map with an overlay of the recommended routes. The bottom area shows the trip information, which typically consists of the estimated travel time, total distance, and name of one major road included in the route. This was loosely based on the Google Maps interface.

This interface will also have seven (7) versions that uses different combinations of the same motivative and familiarity information. The seventh design version is the baseline which shows the default set of trip information as in Figure 7.2.

Personality-Targeted Design

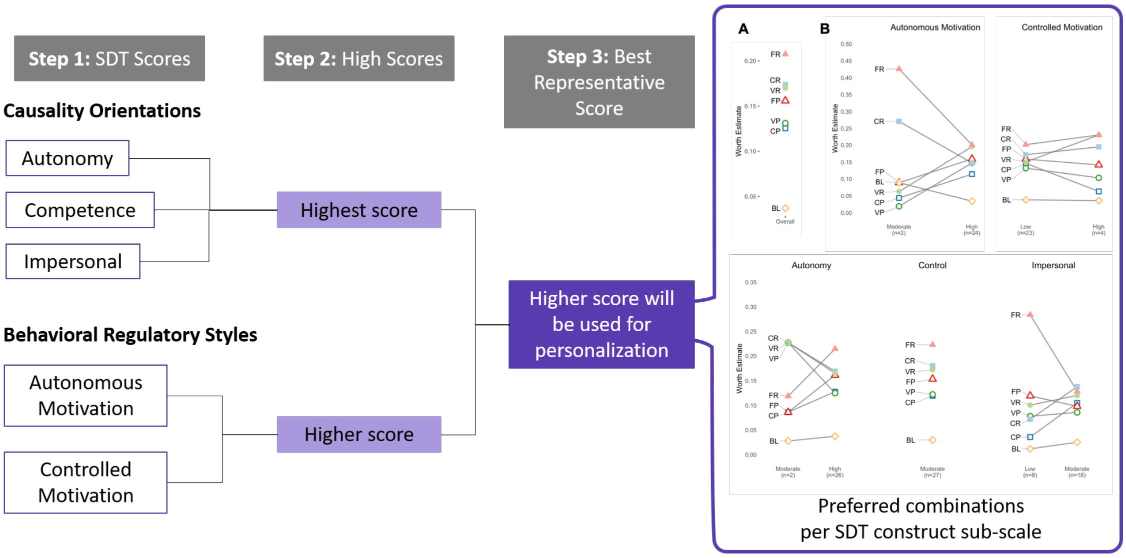

Figure 7.3: The personality-targeted design is based on the best representative score of a driver. This is an overview of the step-by-step process of selecting the the best representative scores from the causality orientation and behavioral regulatory style scores.

Following the personality-targeted design framework, the version of the interface shown to drivers will depend on their causality orientation and behavioral regulatory style (Figure 7.3). Within each SDT construct, the highest score among the 3 causality orientations and the higher score between autonomous motivation and controlled motivation will be used for further comparison. Between the 2 representative scores, the score belonging to a higher category (e.g. low, moderate, high) will already be used as basis for personalization. If both belong to the same score category (i.e. high autonomy and high controlled motivation), the raw scores will be converted into percentages and the higher percentage will finally be used as basis for the selection of the design version. The selection will be based on the most preferred design versions per SDT sub-scale in Chapter 5. As an example, if a driver has moderate impersonal orientation as basis of personalization, the **CR** design version will be used for them (as in Figure 5.17).

7.1.2 En Route: Two-Party Conversation

To address the issues on timing and high amount of information of the original approach, the utterances of the voice agents were shortened, especially when giving instructions in short and quick turns. For example, the long rationales associated with some turn directions like "We usually take that turn near our destination" are now removed. Figure 7.4A shows the flow of conversation between the optimal and unselfish voice agents. The second utterance of the unselfish voice agent changes depending on the motivative information used. In Figure 7.4A, the personalized design version uses simple positive framing.

Conversations are only played as voice guidance when a driver chose the optimal route to follow. In this approach, the two-party conversation is a strategy to convince drivers to consider following an unselfish route for the rest of the trip. No conversations are played when the unselfish route is chosen at the beginning. To see all the voice guidance utterances for each route, please refer to Appendix E.

Voice Agents

The Navigo approach will only use two voice agents. One will be a male voice and the other, a female voice. The default voice agent for delivering voice guidance will be the male voice. When a conversation is played, the female voice will say the recommended turn direction of an unselfish route. I opted to use distinctly different voices here because the evaluation of the original approach showed that some participants could not recognize that a conversation is already being played, especially when the two voice agents have the same gender.

After the utterance of a two-party conversation, the voice guidance will be continued by the voice agent that uttered the selected turn direction. As an example, if the unselfish turn direction was followed, the voice guidance will be continued by the female voice agent. This gives the driver a sense of continuity and consistency, avoiding possible confusion.

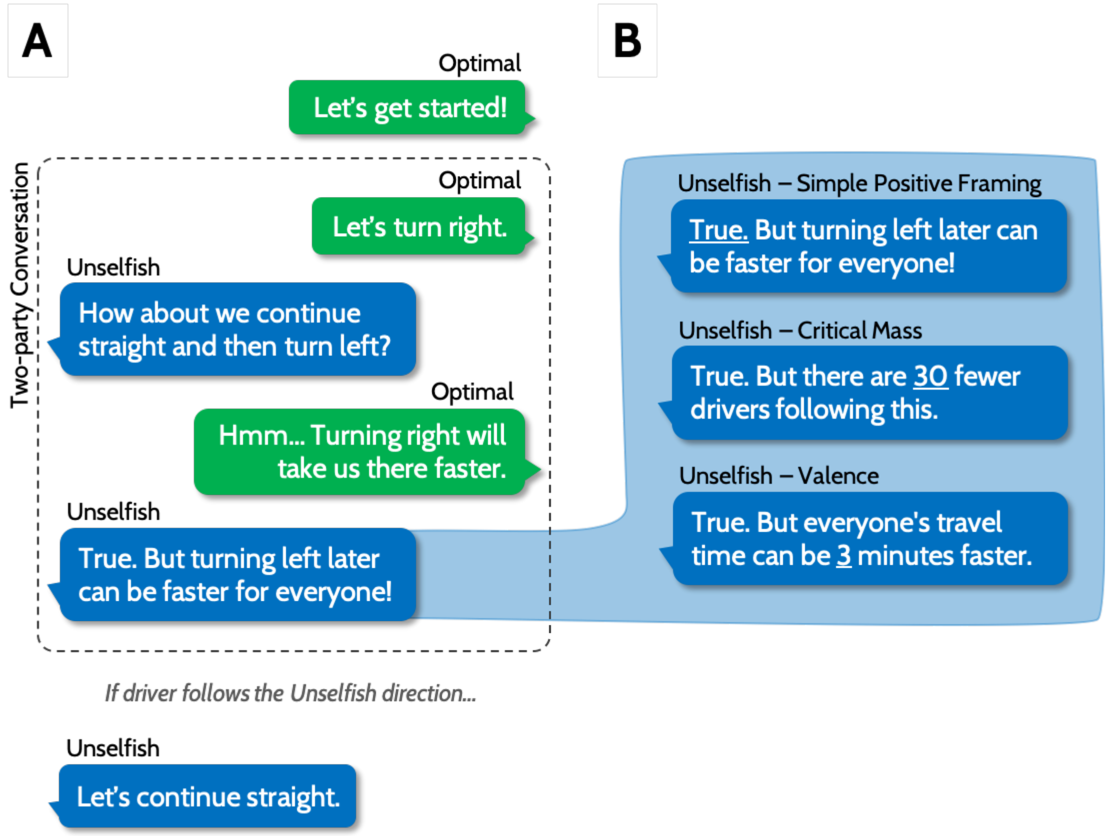

Figure 7.4: A) The sequence of voice guidance when a two-party conversation is played in the middle of following a route. B) The rationale spoken by the unselfish voice agent which differs depending on the motivative information of the personalized design version selected for a driver. The underlined items are different depending on the trip type. The values shown here are used during a home to work trip.

Motivative Messages

Instead of saying generic rationale during conversations, the female voice agent diversifies the rationale or second utterance based on the personalized motivative information. As an example, if the navigation application of a driver was personalized to use valence as motivative information, all the rationales spoken by the female voice agent in conversations will include the valence information. Table 7.1 shows the rationale that is spoken depending on the motivative information used.

When the unselfish route is chosen at the start, the motivative information shown in Table 7.2 are spoken by the voice agent after a successful turn is made or when driving in a long road segment.

Table 7.1: The different rationales spoken by the female voice agent that is based on the personalized motivative information.

Unselfish Route from Home to Work	
Framing	True. But turning left later can be faster for everyone!
Critical Mass	True. But there are 30 fewer drivers following this.
Valence	True. But everyone's travel time can be 3 minutes faster.
Unselfish Route from Work to Home	
Framing	Hmm turning left on the next one can be faster for everyone!
Critical Mass	Hmm there are 30 fewer drivers turning left on the next one.
Valence	Hmm turning left on the next one can be 5 minutes faster for everyone and you.

Table 7.2: The spoken motivative information by the voice agent that is based on the personalization.

Unselfish Route from Home to Work	
Framing	Staying on this route makes it faster for everyone!
Critical Mass	Only 30 drivers are taking this.
Valence	Staying on this route can make everyone's travel time 3 minutes faster.
Unselfish Route from Work to Home	
Framing	Staying on this route makes it faster for everyone!
Critical Mass	Only 30 drivers are taking this.
Valence	Staying on this route can make everyone's travel time 5 minutes faster.

7.2 Related Works

Navigo's concept builds upon previous works on diversification strategies, as well as personality-targeted design.

7.2.1 Diversification Strategies

Message and strategy diversification have been a cornerstone in many intelligent systems and web applications, especially in recommender systems and e-commerce websites. Typically, they would account for individual differences of users in deciding which message framing or recommendation to give. Other than using diversification strategies for commercial gain, several works have started investigating its use to promote behavior change in various contexts.

With a focus on behavior change, Kocielnik and Hsieh [87] used a positive motivational strategy to diversify the messages shown by an application to remind the performance of certain actions. They hypothesized that diversifying the messages based either on the action or the message recipient will avoid users from getting annoyed after seeing multiple messages. They found that messages that use concepts that are more familiar to the person were perceived as less annoying, thus supporting behavior change. In the context of incentives, Kocielnik and Hsieh [76] based their diversification strategy on a person's values and motivations and evaluated whether this can encourage diverse participation from different types people. They found correlations between the self-reported human values and the rewards that they chose. Similar to the concept of Navigo, motivative information in displaying recommended routes and voice guidance will be diversified based on Self-Determination Theory's causality orientation and behavioral regulation type.

In terms of messaging, several works on promoting social activism and increased participation in online communities have used message diversification strategies with some success. To encourage increased participation of new users and one-time posts in online communities, McInnis et. al. [102] investigated the effect of diversifying call-to-action messages on the responsiveness of users to posts. For social activism, Savage et. al. [145] developed Botivist which uses Twitter bots to identify and target users who has potential to enact activist causes. They used various message framings like evoking relatedness when reaching out to these identified users. However, the diversification was not so useful as the most direct call-to-action was found to be more effective in recruiting social activists. In the recent work of Grau et. al. [68], they explored personalizing motivation-supportive call-to-action messages to encourage students in a university to report community-related concerns on a crowd-civic platform. In a pairwise comparison of different call-to-action messages that is based on Self-Determination Theory, they found that there is no one message framing that will appeal to people with different types of motivation. Building on this insight, they built a design probe and investigated whether a personalization strategy will increase the number and length of reports submitted by volunteers. However, this was unsuccessful because they had issues in correctly identifying the type of motivation of their users.

In this chapter, I also focus on diversifying messages delivered in voice guidance to encourage drivers to reconsider or stick to an unselfish route. Instead of using persuasion strategies, my goal is to use simple message framings based on Self-Determination Theory that will help drivers internalize their extrinsic motivation towards consistently choosing an unselfish route.

7.2.2 Personality-Targeted Design

Personality-targeted design was first investigated by Nov and Arazy[111] when they showed how someone's level of conscientiousness can affect their level of engagement in a certain version of an interface. In gaming, a study showed that people prefer different gamification affordances based on their personalities. In a related study, Moon[108] found that people are more likely to be receptive of the recommendation when the recommendation style matches their personality. Similarly in this work, I investigate how the different causality orientations and behavioral regulation types affect the selection of unselfish routes.

7.3 Method

In this section, I describe the methodology used for evaluating the feasibility of the Navigo approach. Because of the current mobility restrictions and the distancing requirements, all user studies were done online.

7.3.1 Participants

I recruited 10 participants from a convenience sample. As an inclusion criteria, they must be adults (18-60 y.o.) and have an active driver's license. They are composed of 7 males and 3 females, with ages that range from 25 to 47 years old. It was made sure that they are all new to the study and have not been part nor heard of the previous studies described in this thesis. They were not rewarded for participating in this study.

In terms of driving years, 2 have only been driving for less than a year while 5 are driving for 1 to 5 years already. Only 3 participants have been driving for more than 5 years. In terms of driving experience based on total distance travelled, 3 participants have driven for less than 15,000km while 6 have driven for more than 25,000km already. All participants have used a navigation application while driving, with Google Maps and Waze as the popular tools. Two participants have been using them for less than year while 5 of them have been using theirs for 1 to 5 years already. Three (3) participants have been using their applications for 5 to 10 years. Most of them report that they often use navigation applica-

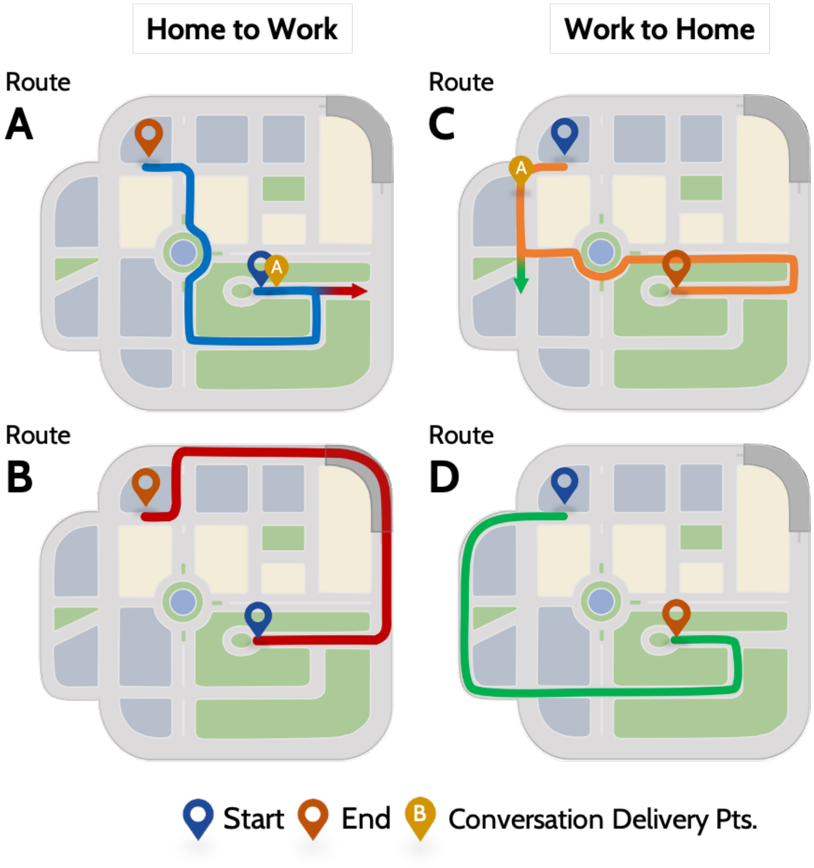

Figure 7.5: The four routes used in the conduct of this user study. Route A and C are optimal routes while Routes B and D are unselfish routes. The route illustration for Routes A and C includes points on the map where the conversations were played. It also includes the turn direction that was suggested by the unselfish voice agent.

tions when they go on trips to a seldom visited or unknown location. Only 1 participant reported that they use it almost every time. When asked if they use voice guidance, only 4 participants answered Yes.

7.3.2 Setup & Routes

I used again the open-source CARLA simulator[48] as our virtual driving environment. The Town3 map (Figure 7.5) was selected because of its grid-like layout with many options for alternative routes. The map also features distinct land use areas and buildings that participants can easily distinguish (i.e. residential, commercial and industrial areas) for easy orientation in the environment. The virtual driving environment was used as is. For every participant session, we generate 60 random vehicles of different types around the map and they drive autonomously.

I met the recruited participants and conduct the user study on Zoom. They were asked to use a headphone so that they can hear the voice guidance clearly. On my desktop that shares the screen, Figure 7.6 shows how the window of the virtual simulation and the prototype interface was laid out. The whole call was recorded with the participant's verbal consent.

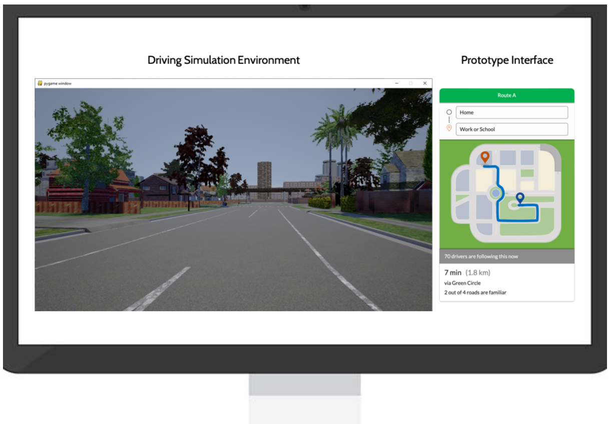

Figure 7.6: The layout of the driving simulation window and the prototype interface during the driving task. THis is what the participants see while the experimenter is sharing the screen.

For the purpose of this user study, I identified four (4) routes within the Town3 map, two (2) each for the Home-to-Work and Work-to-Home trips (Figure 7.5). The optimal routes (Route A & C) were chosen because they used quick and short turns, similar to shortcut paths. Both of them also use the roundabout because I wanted to lessen the number of traffic lights that the participants will encounter. The unselfish routes (Route B & D) were more straightforward but required the participants to drive farther distances and with more traffic lights. I made sure that the optimal and unselfish routes are distinct, with little to no shared roads in their recommendations.

7.3.3 Conditions

The goal of this user study is to find support to the key findings of the study described in Chapter 5. Specifically, I am curious how likely the participants will choose the unselfish route if they are shown a design version that is personalized to their causality orientation

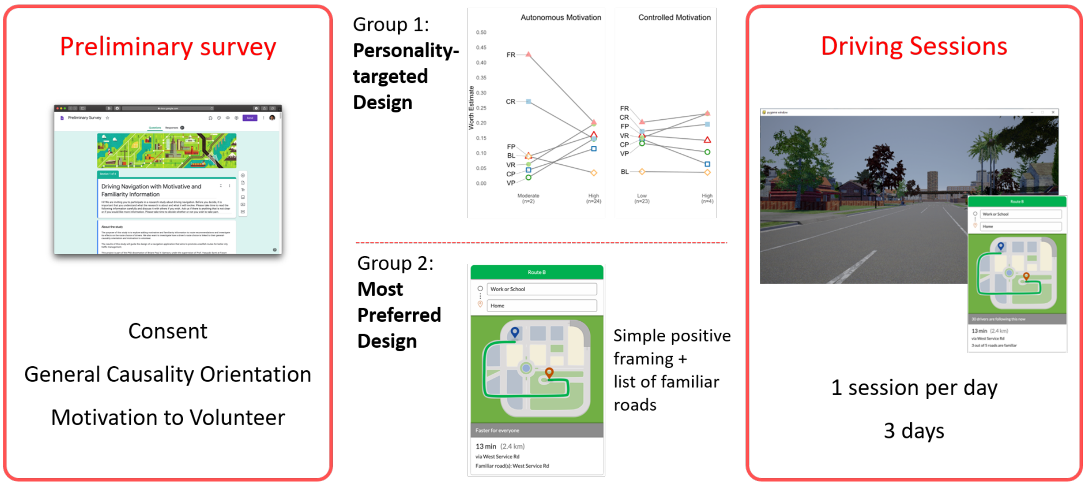

Figure 7.7: An overview of the study protocol. After the preliminary survey, participants were assigned randomly to two groups. After which, they were scheduled for driving sessions that spanned for 3 days. They were not always consecutive days.

and or behavioral regulation styles. Thus, I designed this study to have 2 conditions. The first condition used the design version that was most preferred and significantly increased the likelihood of choosing an unselfish route. Participants in this condition are always shown thew combined use of simple positive framing and list of familiar roads. In the second condition, participants was shown personalized motivative and familiarity information.

7.3.4 Protocol

Before anything, participants were asked to answer a preliminary survey, which includes the consent form, questions that confirm they fit the inclusion criteria, the General Causality Orientation Survey, and the Motivation to Volunteer Survey. As shown in Figure 7.7, this is almost similar to the preliminary survey described in Chapter 5. Then, their causality orientation and behavioral regulation style scores were computed. These were used later to identify their personalized motivative and familiarity information.

I conducted a between-subject Wizard of Oz study in which participants were asked to drive 2 times (Home-to-Work and Work-to-Home) in 3 separate sessions or Zoom calls. Participants were randomly assigned to 2 groups and were scheduled for the 3 sessions. In the first session, participants were given the baseline versions of the navigation application prototype (no motivative and familiarity information) and the voice guidance (no conversations and motivative information). The next 2 sessions were similar in which they were shown either a personalized motivative and familiarity information or the most preferred version. They also experienced the voice guidance with conversations and motivative information.

At the beginning of the first session, I gave them an orientation about the goals of the research without giving away too much that would bias their performance. Then I asked if they would verbally consent to having the call recorded. All participants agreed and the tasks began.

Before they drive in the driving simulation environment, participants were asked to choose between 2 routes (Route A & B). Based on their route choice, the voice guidance began uttering turn directions and the driving task began. Because the driving simulator experiment is done remotely, I was actually the one controlling the vehicle using keyboard commands. The participant was oriented to say what they want the vehicle to do. I did not move the vehicle in the simulation environment if I did not hear any command. I also stopped the vehicle at intersections and turning points to wait for the participant's next command. To keep things simple, participants were asked to just say "turn left" or just "left", "go straight" or "follow this road", and "turn left" or just "left". I and the participant did trial drives in the simulation environment to practice our coordination in controlling the vehicle. I was also constantly monitoring the video lag so that I can slow down the vehicle if the video rendering is late on their end.

Each session begins with the task to drive from home to work. After they arrive at the destination, participants were given a short break then we continued with the return trip. For each trip, I took note of their pre-trip route choice and the turns they make after hearing a conversation or motivative information. These continued for 3 sessions and in the end, I asked them a few questions about their feedback on the information they saw when choosing a route, and their experience of hearing the voice guidance.

7.4 Results

In this section, I discuss the results of the route choice and driving navigation tasks. Further, I investigate how their route choices changed after each session and when they were shown additional motivative and familiarity information. I also discuss how often partic-

Table 7.3: The general causality orientation and behavioral regulation style scores of the participants assigned to the personalization group. Unexpectedly, their personality-targeted design will use simple positive framing and show the list of roads (FR).

	Causality Orientation			Behavioral Regulation			Personality-Targeted
	Raw	%	Category	Raw	%	Category	Version
P1	6.75	0.96	High	4.25	0.85	High	FR
P3	4.25	0.61	Moderate	4.25	0.85	High	FR
P4	5.83	0.83	High	4.25	0.85	High	FR
P5	3.50	0.50	Moderate	5.00	1.00	High	FR
P8	5.92	0.85	High	4.00	0.80	High	FR

ipants reconsidered their initial route choice after hearing two-party conversations in the voice guidance.

7.4.1 Personalization

Because of the between-subject design, 5 participants were randomly assigned to the group which will experience personalized motivative and familiarity information. Despite being in the personalization group, all 5 participants were assigned the **FR** design version which is similar to the design version assigned by default to the other group (Table 7.3).

7.4.2 Making the Unselfish Choice

In the first session, when there was no motivative and familiarity information shown to the participants, those with higher autonomy orientation already chose the unselfish route, Route B. There were already four (4) participants that chose the unselfish route in the H2W trip and two (2) in their W2H trips. P1 and P2 were consistent in choosing the unselfish route for both trips even with a baseline version. It should be noted that they have some of the higher autonomy orientation scores among participants.

When presented with the motivative and familiarity information in the next sessions, Figure 7.8 shows that more participants made the unselfish choice. Consistent with the results in the previous study, drivers were more likely to choose Route B when the possible outcomes are presented. After using simple positive framing and showing the list of familiar roads in the 2nd session, 2 participants maintained their unselfish route choice while 3 participants shifted from following an optimal route to the unselfish route in their H2W

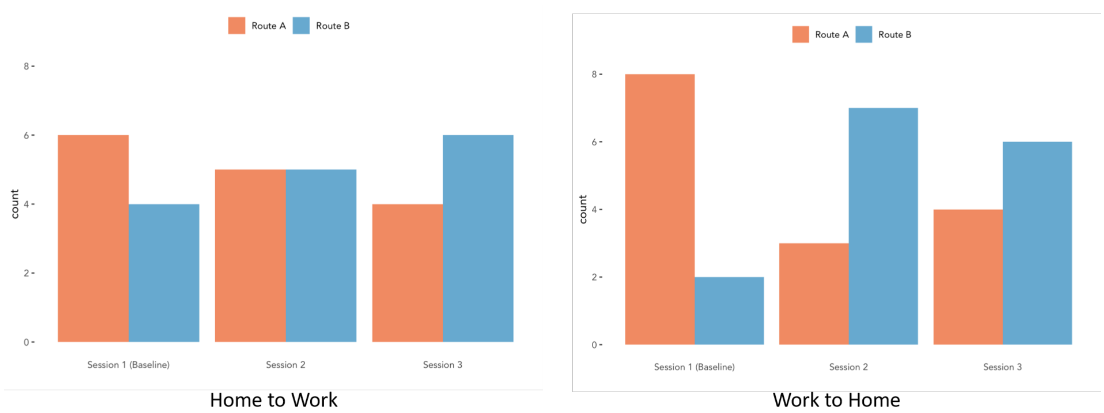

Figure 7.8: How effective is it in encouraging an unselfish choice after the first session? This shows the number of times each route choice was selected by drivers in every session. The bar graph on the left shows the numbers for home to work trips, while the graph on the right shows the numbers for work to home trips.

trip. In the W2H trips, 7 participants chose the unselfish route. Two (2) participants were consistent with their first unselfish choice while 5 of them changed their mind to follow the unselfish route.

In terms of trends, more and more participants choose Route B when driving from Home to Work, which supports the findings of my earlier study. However, in the Work to Home scenario, although there were also 6 participants who chose Route B, they were relatively less in the last session compared to the second session. Lastly, there were more participants who chose Route B in the last session.

7.4.3 Sustaining an Unselfish Choice

Results also show evidence of how effective it is in encouraging the driver to continuously choose Route B. In Figure 7.9, half of the participants (N=5) maintained their unselfish choice in both trip scenarios. The design of this study allowed us to see some evidence of sustained unselfishness unlike in the earlier one which only allowed one-shot decisions. Here, we were able to see how their decision-making change through repeated exposure to motivative and familiarity information. In the earlier study, a key finding was that most preferred combination was good in encouraging more drivers to follow the unselfish route but was not consistent in convincing individual drivers to continue choosing the unselfish route in different trip scenarios. Here, we found indicative evidence that this design version

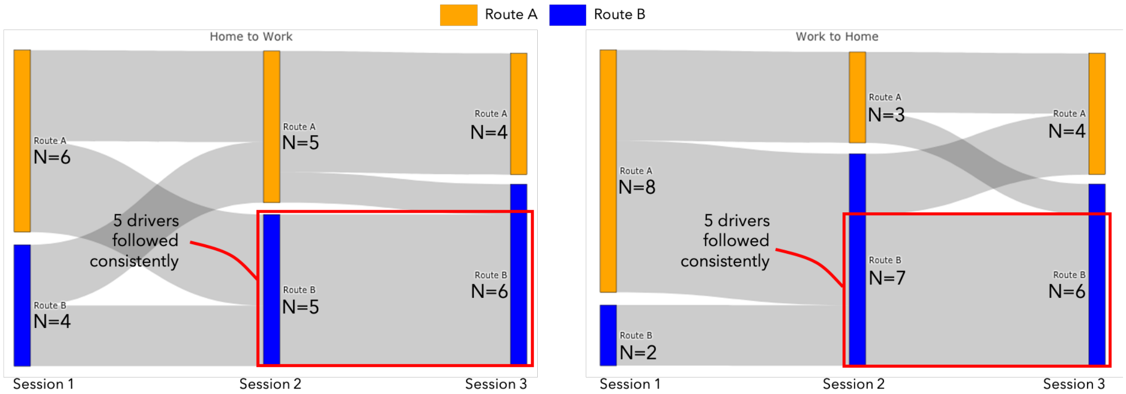

Figure 7.9: Can motivative and familiarity information help sustain the selection of an unselfish choice? This shows the route choices of the 10 participants after each session. The flow from one session to the next indicates the switch in route choice. After following Route B in their second session, 5 participants continued to choose unselfishly in the third session.

can make drivers continue following the unselfish route regardless of trip scenario. Based on the post-session interviews, another factor behind the sustained choice is that Route B was more straightforward compared to Route A. This is despite Route B being longer in terms of distance.

7.4.4 Switching to the Unselfish Route

When the motivative and familiarity information were presented in sessions 2 & 3, six participants still chose Route A over B for a total of 16 times – 8 times in session 2 and 8 more times in session 3 (Figure 7.10A). In my approach, a two-party conversation is played as voice guidance to give alternative turn directions following the unselfish route. And a switch did happen in the last session of a participant when they were going home from work.

Now, I will focus this analysis on the subset of participants who chose Route A when they were going home from work on the third and last session. Figure 7.10B shows the series of decisions made by 6 drivers. In their first and third sessions, all of them chose to follow the optimal route (Route A). The last column in Figure 7.10B shows the route that they continued to follow after hearing the conversation, and one of them switched to follow the unselfish route (Route B). When interviewed, they cited familiarity as reason for deviation. P10 answered that because they already tried both Route A and B, it was easier

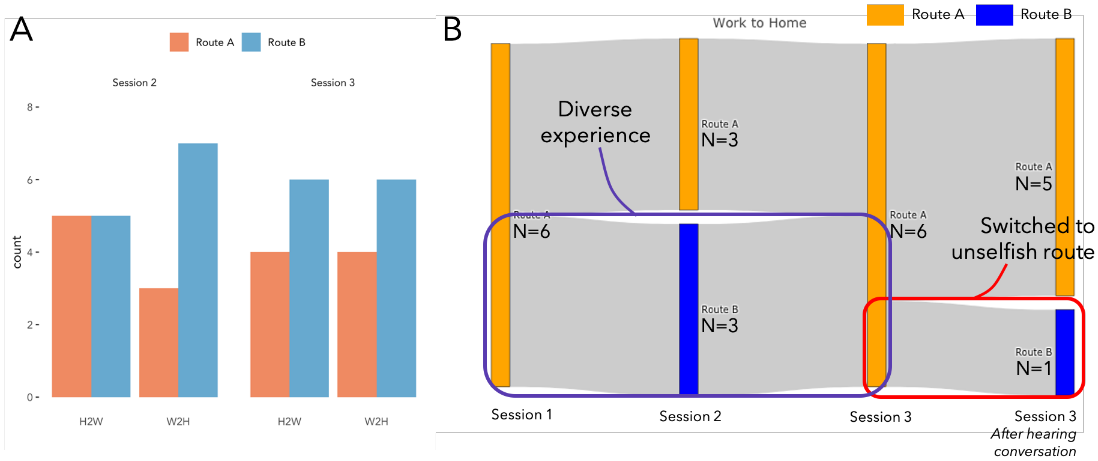

Figure 7.10: Can two-party conversations convince drivers to switch to an unselfish route? This shows the A) number of times the two routes were chosen in sessions 2 and 3, separated by the trip purpose. On the right are B) the different route choices made by 6 drivers who chose Route A in the third session.

for them to assess the alternative unselfish route that was given in a conversation. In most cases, participants shared that they were rattled when they first heard the conversation between voice agents but as they got to hear it more in succeeding sessions, they were able to consider it more in their decision making. Indeed, this participant had a more diverse route choice before driving in session 3. Although this might seem like an outlier compared to those who did not make a switch at all, it should be noted that out of 6 participants who chose route A in the last session, only 3 of them had experience following both routes. This is indicative that diversity of previous choices and experiencing their outcomes can influence the effectiveness of the conversational technique. Another reason for the switch could be because participants feel less time pressure in the Work to home trip as shared in the interviews, which increases their tendency to explore.

7.4.5 Continuing an Unselfish Route

When a participant selects the unselfish route, no conversations will be played. Instead, motivative information were spoken throughout the trip. When the motivative and familiarity information were presented in sessions 2 & 3, eight participants decided to follow Route B for a total of 24 times – 12 times in session 2 and 12 more times in session 3 (Figure 7.10A). In the Navigo approach, the voice agent utters motivative information that were like what

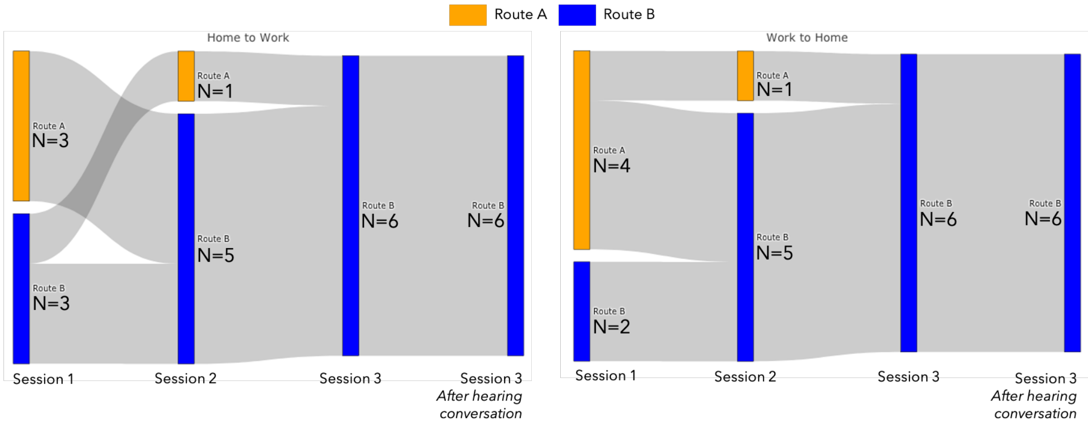

Figure 7.11: Can two-party conversations encourage drivers to continue following an unselfish route? The two figures show the route choices made by all participants in the home to work (left) and work to home (right) trips.

was presented in the list of choices. Figure 7.11 shows the series of decisions made by 4 drivers. Results show that the participants did not switch to the optimal route after choosing to follow the unselfish route. And even though 4 and 3 participants had diverse route choices before the last session, it did not seem to affect their decision to follow route B. Participants found it nice to hear the reassuring words of the voice agent and they agree with what was said.

From the post-session interviews, participants shared that it was nice to hear the reassuring words of the voice agent and they agree with what was said. While it seems participants are positive with this approach, it is still hard to say whether these utterances actually encourage drivers to keep following the unselfish route. There are not much complex scenes in the driving simulator environment that could trigger changes in priority and behavior, except for stochastic traffic conditions.

7.5 Discussion & Design Implications

The results from this user study provided valuable insights on the value of providing a more holistic approach to encouraging better route choice and navigation.

7.5.1 Better Together

In my earlier studies, I have identified specific design implications and a number of improvements that could improve the potential of each individual approach. Combining them in this study made it easier to realize those improvements. One major limitation of the original conversational approach was that the voice agents were trying to say too much information, even in critical turns. This led to higher subjective measures of workload and made it difficult to time when exactly they should be spoken. Since the pre-trip approach (Chapter 5) already provides familiarity information that the conversational approach also tries to provide, it was easier now to remove some information that made the voice agents verbose. Now in this holistic approach to motivating drivers to follow unselfish routes, it becomes more strategic and effective when we can use a number of media and modalities to deliver information and nudge our users.

7.5.2 Motivative Voice Guidance

Participants appreciated the motivative information spoken by the voice agent in the Navigo approach compared to my earlier approach. In the early work described in Chapter 6, the voice agent says the rationale behind the recommendation immediately after the turn suggestion. The timing and verbosity of that approach led some participants to ignore it in order to focus on making the navigational move. Here, the motivative information were spoken by the voice agent only when the driver is in a long stretch of road and not near or immediately turns. Another contributing factor could be the motivative information's positive and encouraging message (i.e. "Staying on this route makes it faster for everyone!").

7.5.3 Diversification in Personalization

In this approach, personalization was achieved by identifying one Self-Determination Theory construct or sub-scale that best represents a person (i.e. autonomy orientation, controlled motivation). However, that approach seems less personalized to some degree. If we inspect closely the causality orientation and behavioral regulation style sub-scales, it should be noted that the autonomy orientation and autonomous motivation scores are more likely to be higher compared to the other constructs. This means that the information strategy associated with consistently high constructs would always get used. One future exploration is the extension of my approach's personalization to consider all sub-scale scores. For example, if a driver has high autonomy and moderate controlled orientation, when should the navigation application personalize based on their high autonomy score and when to base it on their moderate controlled orientation?

Our results in this chapter strongly supports the finding in Chapter 5 that there is greater likelihood for a driver to choose an unselfish route when it is presented using simple positive framing and with a list of familiar roads. Thus it is safe to assume that most drivers would be convinced by its simplicity and explicitness. However, using the same messaging, despite being personalized, might start to seem boring, and reduce its positive utility and effect leading to annoyance and completely ignoring the message. Future exploration can learn from the work of Kocielnik and Hsieh[87] in implementing diversification strategies that connect more to the person than the task of driving itself.

7.6 Limitations

The between-subjects design of the study was intended to see and compare the effect of using personalization in delivering motivative and familiarity information to the likelihood of choosing the unselfish route and its sustained selection. However, the biggest limitation of my convenient sample is that they did not have much diversity in general causality orientation and behavioral regulation styles. At the same time, even though I can achieve greater diversity, there also is not much personalization choices based on the results in Chapter 5. So far, there is only **FR**, **CR**, **VR** and **VP** design versions as options for personalization.

Another big limitation is the driving simulation setup. While driving simulator experiments are believed to have better external validity[53], using it remotely might have confounding effects that we might not be aware of.

7.7 Conclusion

In this chapter, I present Navigo, a holistic approach to encourage drivers to choose, follow, and stick to driving unselfish routes. Built on top of two previous approaches, I described various improvements based on their limitations. For example, I showed how the verbosity of the early conversational approach was reduced by off-loading the familiarity information on the list of choices. Then, I described how personalization can be achieved using causality orientation and behavioral regulation style scores, and how the voice guidance and two-party conversations were personalized. In a user study, I found supporting evidence that the use of simple positive framing combined with showing the list of familiar roads can encourage drivers to choose unselfish routes without explicit nudges. Their decisions were also sustained in succeeding trips after repeated use. Results also indicate the potential of personality-targeted two-party conversations in encouraging a driver to switch into following an unselfish route, although this would be more effective for someone with diverse route choice experiences. Lastly, the motivate messages uttered along the trip was appreciated by drivers and the lack of deviations indicate its potential in encouraging them to stick to flowing unselfish routes.

8
Conclusion

8.1 Contribution

In this dissertation, I focus on the critical HCI question of how to encourage drivers to follow unselfish routes for their daily commutes. I explored motivational techniques that support making informed decisions during navigation towards unselfish, purposeful, and effective driving behaviors.

As someone who is not a driver, I began with an observational study of drivers using modern navigation applications in their daily commutes. I found that while drivers choose a recommended route in urgent situations, many still preferred to follow familiar routes. They also made deviations from their original choice because of unfamiliar roads, lack of local context, perceived driving unsuitability, and inconsistencies with realized navigation experiences. Here, I argue that we should rethink our longstanding assumptions and mental models about drivers and navigation tools which are limiting the progress of navigation tools. Instead of treating drivers as docile actors, designers should instead support their self-efficacy and agency in performing navigation tasks. Navigational applications are only as good as the data it senses and estimates from models. While we are still far from having near accurate navigational information, designers should explore visualizing uncertainty and missing data on maps and other sections of the application. Modern navigation applications, like Google Maps and Waze, passively collect GPS data and other trip information to improve their maps and routing algorithms. Designers should maximize this information and provide true personalization in terms of route recommendations and voice guidance. In relation to personalization, designers should also consider maximizing the embedded social networks in applications. We learned from the results that aside from trusting what is already familiar to them, drivers also trust information coming from their close contacts, especially those living near their destinations.

I continue this line of research by designing and evaluating two separate techniques that aim to help drivers make better informed navigation decisions. Both are informed by the Self-Determination Theory. The first is a GUI-based approach that focuses on the trip planning phase of a driving task. Using Self-Determination Theory, I show how the simple addition of motivative and familiarity information can help navigation applications positively encourage the use of unselfish routes. Through route choice experiments and pairwise comparisons, all combinations of motivative and familiarity information were able to convince drivers to choose the unselfish route at least once. Specifically, drivers were most likely to choose the unselfish route when a simple positive framing is used along with a list of familiar roads. Aside from the effectiveness of simple and explicit motivational and familiarity information, results also showed that drivers with moderate impersonal and controlled orientation need more support for relatedness. Thus, information that emphasizes social comparison would be more effective. The use of motivational and familiarity information shows the potential of navigation applications as a civic technology, transforming it to empower positive societal impact.

En route to a destination, traffic conditions along a chosen route might change or there might be alternative routes the are worthy to discover. The second voice-based technique explores the use of two-party conversations between voice agents in giving alternative turns or routes. I show how designers of navigation applications can slowly move away from designing voice guidance as authoritative figures that drivers would have no choice but to rely on. Indeed, results suggest that two-party conversations were able to convince drivers to follow alternative routes as they are made available. This is especially true when the alternative route is appropriate for the trip scenario. Additionally, having a point of comparison allowed drivers to reflect better on their choices, possibly affecting future choices. However, designers must still be careful in using voice-based techniques as it can increase experienced workload especially during time-constrained navigational maneuvers and turns. This voice-based technique contributes to an understanding of how navigation voice guidance and voice UIs and assistants, more broadly, can be suggestive while still respecting the agency and self-efficacy of a user or driver. It adds to the potential of designing voice guidance that are autonomy-supportive for the driver.

Addressing the shortcomings of the first two techniques while also leveraging on their strengths, my final contribution is the design and evaluation of Navigo, a holistic technique that motivates the selection of an unselfish route and encourages drivers to keep following it towards a destination, covering the whole driving navigation task. Similar to the first two techniques, Self-Determination Theory was used in providing personality-targeted motivative and familiarity information to encourage unselfish choices. In its evaluation, there is supporting evidence that the showing the list of familiar roads and positively framing the benefits of an unselfish route choice can encourage drivers to choose unselfish routes before the start of a trip. Additionally, providing these information frequently to drivers sustained their unselfish choice in succeeding trips. Navigo also provides personality-targeted two-party conversations when a driver decides to follow an optimal route at the beginning. The conversational technique was successful in encouraging drivers to switch into following an unselfish route when they have diverse experiences of following different route choices. When the drivers choose the unselfish route at the beginning, the voice-based technique provides motivative messages along the trip. It was successful in encouraging drivers to stick to following unselfish routes. Participants liked being reminded about the positive societal benefits of their decision.

Finally, my dissertation hopes to challenge the rigidity of existing navigation application designs and hope my contributions can serve as conversation starters towards a reimagining for future designs. To build navigation applications that caters to the idiosyncratic needs of drivers while reducing its negative externalities in the communities where they operate, it is worth looking into how we can include diverse stakeholders into the co-design of such applications and their algorithms to safeguard and balance the interest of everyone.

8.2 Future Directions

Altogether, my dissertation offers a different perspective on how navigation applications can be redesigned to balance the needs of drivers and the greater sociotechnical system they are part of. Moving forward, I plan to move on to the actual implementation and field test of my techniques. So far, they have been evaluated using driving simulators with hypothetical scenarios so I am really looking forward to realize them into tangible products. And while I have always envisioned my approaches to offer positive societal effects, it still remains to be seen whether a widespread adoption of these solutions can actually make a difference in our road networks and encourage behavior change among drivers. The following future directions are focused on exploring other behavior change techniques, providing other navigational information that can emphasize familiarity, improving digital maps for better driving routes, visualizing uncertain and time-decaying navigational information, and evaluating navigation applications as a sociotechnical system.

8.2.1 Variety of Techniques

The techniques evaluated in this dissertation focused on providing information about the benefits of following the unselfish route to the individual and to others. In order to encourage behavior change, simply providing estimated benefits was shown to be effective for drivers with high autonomous motivation and autonomy orientation. However, they may pose limitations on how the choice for unselfish route can be sustained for drivers with controlled motivation and or orientation, and amotivated drivers.

Still informed by Self-Determination Theory, there are other behavior change techniques and navigational information that can be explored to encourage an unselfish choice in different driving contexts and to help internalize their value for drivers. To help drivers internalize the value of an unselfish route choice, techniques that reward or praise the effort of trying to follow an unselfish route can be used. Once they have made the unselfish route as one of their regular routes, drivers can then be encouraged to try following unselfish routes for other destinations and driving contexts. By providing a variety of techniques and using them in progression, we may be able to fully realize the potential of navigation applications to shape sustainable route choices.

8.2.2 Highlighting Route Familiarity

One of the major contributing factors to route choice is the familiarity of a whole route or the roads involved. In this dissertation, drivers were made aware of the number or the names of familiar roads. While they proved to be effective especially for boosting the preference of unselfish routes, there are other navigational information that can be used to further support a driver's need for autonomy, competence and relatedness. One example is by learning a driver's frequently used roads and visited landmarks, and incorporate them in the route recommendations [119,168,177]. Another is providing information about the number of traffic lights and or the estimated waiting time on them. By expanding the types of information that drivers can access, we may be able to improve the perception of unselfish routes, which can be sub-optimal in terms of travel time or distance.

We can also explore displaying these information in other parts of the application. For example, how can we incorporate familiarity information on the map alongside other traffic-related information? Although motivational and familiarity information can easily be provided as text, drivers still prefer exploring route choices visually, using interactive maps [146]. Thus, displaying them on the map may be more useful to make sure that the familiarity information will be properly considered in their route choice.

8.2.3 Improving Maps for Driving

In current digital maps, roads are categorized into types such as whether they are primary or secondary roads, or whether they are toll roads or highways. While these are enough for modern navigation applications to provide routes using weights or link costs, drivers don't just rely on such information for their navigation. In deciding which route to take, drivers also decide whether a road on a map is actually suitable for driving (Chapter 3). For example, unpaved dirt roads are passable but difficult to drive on. Narrow roads in residential areas can be difficult to pass through. Roads with poor lighting and those with a lot of pedestrian foot traffic can be tricky to drive on because of security and road safety concerns. These gaps in map context affects the positive utility and reception of the recommended routes. With the use of StreetView images, remote sensing combined with artificial intelligence can be explored to collect more contextual data about our roads and incorporate them into digital maps. Crowdsourcing can also be explored to annotate roads in terms of their perceived driving suitability and security, similar to the approaches by Quercia et. al.

when they created happy[127] and smelly maps[125,38], as well as mapping the emotions people feel about a place[126]. As more data that drivers care about when navigating gets incorporated into digital maps, we can explore how these can improve the route recommendations and how drivers would perceive and follow them.

8.2.4 Uncertainty Visualization

Navigation applications incorporate model predictions in the traffic information they display. In Chapter 3, drivers were found to ignore uncertain and time-decaying descriptive information (e.g. traffic condition) and rely on previous experiences, causing a number of deviations. It might be worth exploring how to properly display uncertain and time-decaying information in maps so that everything is transparent to the driver, supporting their autonomy and competence for improved decision quality. For example, Waze consistently displays a heavily congested road in red and after a few minutes (time-decay), it either disappears or changes color based on new information. Following this recommendation, traffic-indicator colors can slowly fade as time passes until an updated information is ready which allows drivers to act properly on information posted minutes ago. It can be implemented using value-suppressing uncertainty palettes[35], sketchy rendering[176], and or Fernandes et. al.'s[54] dotplot or CDF plots which was already tested in a bus transit application. In the same vein, it might also be worth exploring how these uncertain and time-decaying navigational information can be sonified and incorporated into voice guidance for eyes-free access to crucial information.

8.2.5 Navigation Applications in a Complex System

The provision of network information has the potential to reduce travel time for individual drivers and consequently improving overall performance of a road network[30]. But the effects of information inaccuracy remain in dispute as a decline in performance was noticed by Rapoport et al.[129], while Litescu et al.[96] saw negligible effects and even suggested that system performance can sometimes benefit with lower precision information. The characteristics of presented information and the information dynamics manifested by state-of-the-art social navigation applications, and the route-choice behavior brought about by the presented information have shown varied effects in the overall performance of road networks. But more recently, the selfish and insensitive nature of such applications is seen to

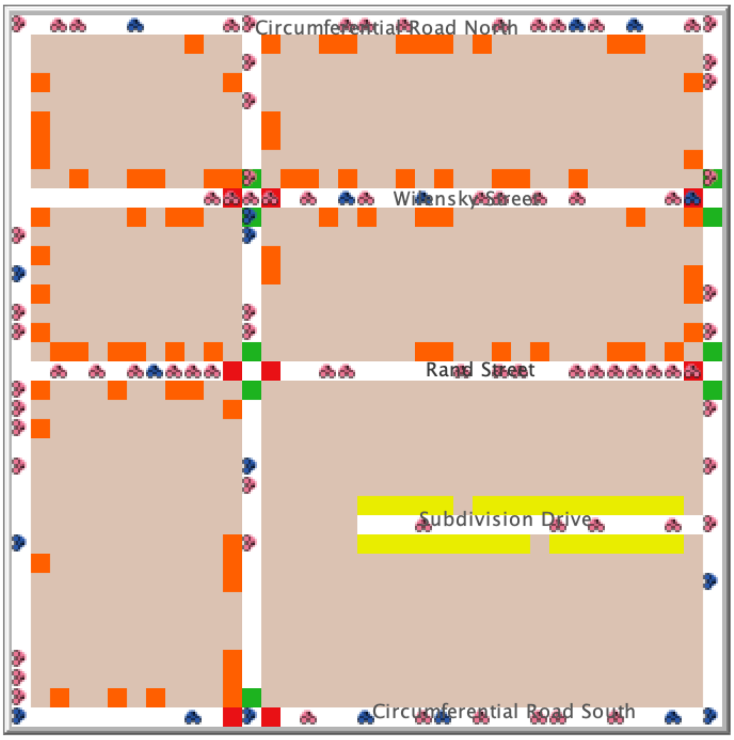

Figure 8.1: An initial prototype of an agent-based model of drivers that follow navigation applications. It shows the effects on the traffic flow when a certain percentage of them follow the navigation applications completely. Cars that follow navigation applications are colored pink while those that do not are colored blue. Each have unique origins and destinations. Origins are indicated by the yellow boxes while destinations are in orange. Traffic lights are also present in the model.

cause an increase in traffic on smaller capacity roads in suburban areas due to occasional disruptions and congestion trends[25]. In this work, an agent-based model was used to simulate the effects of having a certain percentage of drivers use and follow route recommendations from a navigation application. The percentage was progressively increased to observe effects on traffic patterns. This supports the phenomenon called Online Information Paradox[173] in which the presentation of online information to drivers can deteriorate travel conditions for all users of the road network compared to when no information is provided.

Despite how navigation applications are currently being designed and evaluated for commercial use, they are not operating in a vacuum and do not only benefit an individual user. As a sociotechnical system, it is part of a feedback loop. It adapts its recommendations based on the state of the road network, and as drivers try to follow recommendations, it indirectly affects the future state of the road network. Currently, user and lab studies are primary methods in evaluating the usability and effectiveness of HCI solution prototypes. However, in the case of sociotechnical systems like social networking platforms, online communities, and navigation applications, there is a gap in evaluating how it affects the overall system and its stakeholders. Moving forward, I plan to develop an agent-based model that simulates a simple road network in which a certain percentage of the drivers are using navigation applications. I already created an initial prototype of the model as shown in Figure 8.1. By incorporating the route choice and navigation behaviors found in my previous works, my goal is to evaluate how the deployment of such prototypes can have mesoscopic and macroscopic effects on the system. Ultimately, I want to develop an evaluation framework that HCI and CSCW researchers can use to evaluate their proposed technological solutions for large sociotechnical systems, without the need of a large field study which can be costly.

A

Chapter 5 Daily Route Choice Questionnaire

The following are screenshots of the route choice questionnaire given to participants for seven working days during the online experiment described in Chapter 5.

Day 5 - Driving Navigation with Motivative and Familiarity Information

Hi! Welcome to Day 5 of the Online Experiment phase of this study.

Once you are ready, please read through the following instructions.

Instructions

Today, you will be making 4 independent trips:
1. Work/School to Home
2. Home to Work/School
3. Work/School to a frequently visited place
4. Home to a frequently visited place

In each trip, imagine that you are just about to leave and go to a destination. Before leaving your point of origin, you bring out your smartphone and open a navigation application. You are not driving yet. You type your destination in the navigation application and search for routes. Two route suggestions are shown and you have to choose which one to follow. For all route suggestions, you are shown a static map of the route, the estimated travel time, distance and a major road included in the route. Assume that these navigational information are reliable and that you will arrive at your destination on time regardless of choice.

In each trip, a different set of navigational information is shown to you, along with the static image of the route. Your task is to choose a route using only the information provided.

Traffic Management System

Imagine that your city has implemented a Traffic Management System (TMS) to help optimize the traffic flow on its roads. It is run by the city government and receives constant traffic updates in order to make proper traffic assessments. Assume that the information they collect and use are reliable. Its goal is to equally distribute active cars in the road network so that everyone benefits. In order to achieve this, it gives recommendations to connected drivers. However, it does not always distribute drivers to optimize traffic flow. It only happens when they anticipate that many drivers will start using the roads.

Your navigation application is connected to this system and it adjusts the route suggestions based on what the TMS recommends. When it predicts that traffic congestion will occur or has already happened, it will now recommend a route that will help ease traffic flow in other areas, along with the usual recommendation of the fastest route. The route suggestions may include 2 types of additional information to help you with your route choice. The first type of information describes how the route can contribute to everyone's travel time. The second information describes how familiar it is to you. You are free to accept or ignore the recommendations and additional information. You will not receive any penalty.

In all of the trips, assume that the TMS is detecting traffic congestion on some roads. The traffic flow is now being distributed and you are part of it.

Next

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Get Ready

Before proceeding to the next section, please prepare a timer or clock nearby. The first route choice task will begin after you click "Next".

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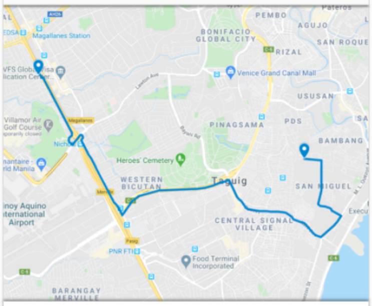
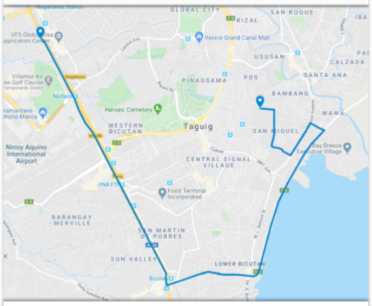
Trip #1

You are going home from work/school. A different set of navigational information is displayed below the map.

Route A	Route B
Work or School	Work or School
Home	Home



22 min (9.6 km)
via Maria Rodriguez Tiñga Ave



24 min (14.2 km)
via S Luzon Expy and C6

Using the navigational information below the map, what route will you choose? *

- Route A
- Route B

How long did it take you to make the choice? *

Please indicate whether in seconds or minutes.

Your answer

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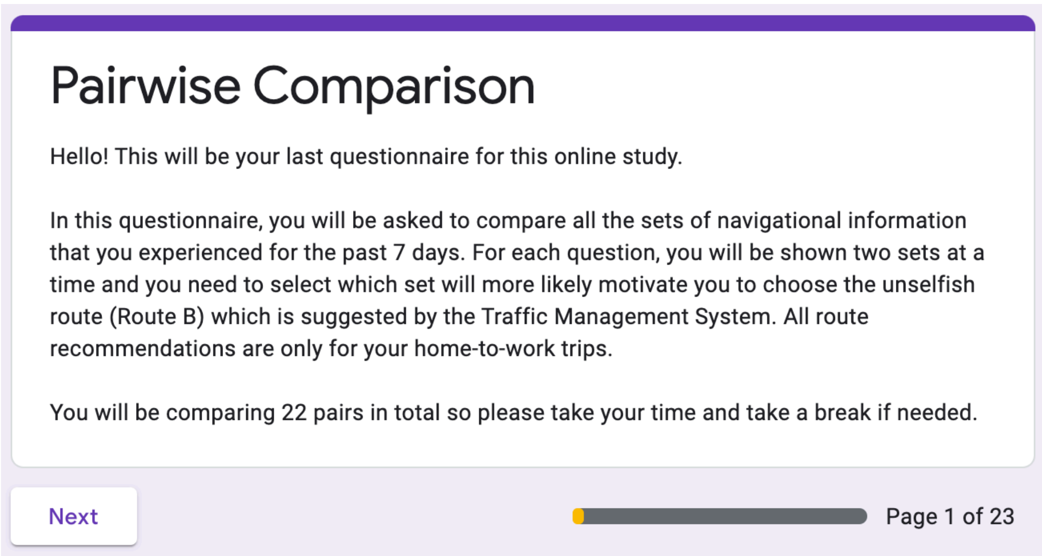
B

Chapter 5 Pairwise Comparison

The following are screenshots of the pairwise comparison given to participants at the end of the online experiment described in Chapter 5.



Pairwise Comparison

Hello! This will be your last questionnaire for this online study.

In this questionnaire, you will be asked to compare all the sets of navigational information that you experienced for the past 7 days. For each question, you will be shown two sets at a time and you need to select which set will more likely motivate you to choose the unselfish route (Route B) which is suggested by the Traffic Management System. All route recommendations are only for your home-to-work trips.

You will be comparing 22 pairs in total so please take your time and take a break if needed.

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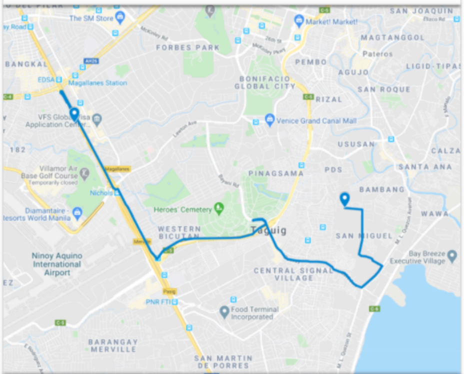
Pairwise Comparison

* Required

Pair #1

Set A

Route A	Route B
Home	Home
Work or School	Work or School

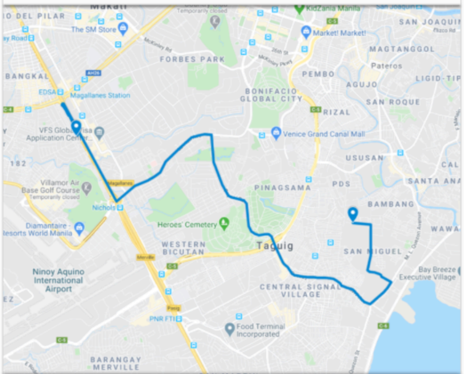


Fastest for you

28 min (11.4 km)

via Maria Rodriguez Tiñga Ave

Familiar road(s): S Luzon Expy



Faster for everyone

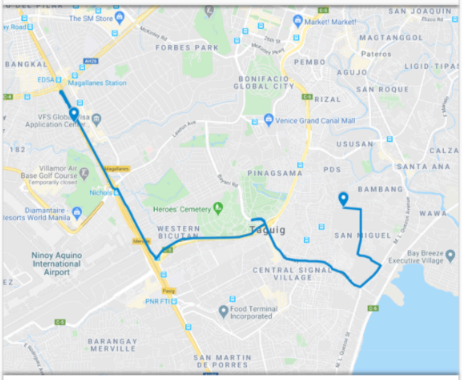
30 min (11.6 km)

via Bayani Rd

Familiar road(s): S Luzon Expy

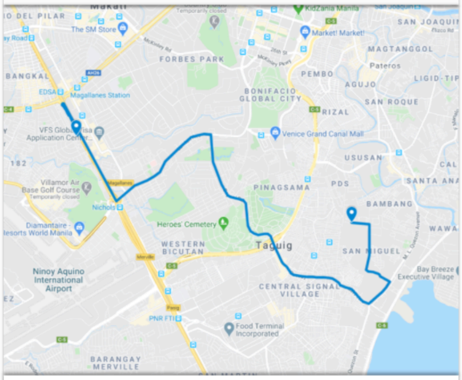
Set B

Route A	Route B
Home	Home
Work or School	Work or School



28 min (11.4 km)

via Maria Rodriguez Tiñga Ave



30 min (11.6 km)

via Bayani Rd

Using which set of navigational information would you personally be more likely to choose Route B (the unselfish route)? *

○ Set A

○ Set B

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C
Route Choice GEE Model

This is the fitted GEE model for the route choice task discussed in Chapter 5. The following tables show the coefficients and odd ratios for the different main and interaction effects.

Table C.1: Results of the GEE model with main and interaction effects. Significant results are highlighted in bold.

Variable Name	Estimate	SE	Wald	Pr(>|W|)	
(Intercept)	**-1.7918**	**0.5401**	**11.01**	**0.00091**	***
H2W	0.4925	0.6020	0.67	0.41330	
W2F	-0.3285	0.8708	0.14	0.70600	
H2F	0.6931	0.6944	1.00	0.31816	
Valence	**1.2040**	**0.5519**	**4.76**	**0.02916**	*
Framing	**1.3564**	**0.4788**	**8.02**	**0.00461**	**
Road Names	0.6931	0.5098	1.85	0.17396	
H2W * Valence	-1.2040	0.6470	3.46	0.06277	.
W2F * Valence	-0.3830	0.8399	0.21	0.64839	
H2F * Valence	-1.4046	0.7396	3.61	0.05753	.
H2W * Framing	**-1.1558**	**0.4741**	**5.94**	**0.01477**	*
W2F * Framing	-0.5355	0.9164	0.34	0.55899	
H2F * Framing	**-1.1741**	**0.5807**	**4.09**	**0.04317**	*
H2W * Road Names	-0.9199	0.5431	2.87	0.09030	.
W2F * Road Names	-0.0989	1.1266	0.01	0.93002	
H2F * Road Names	-0.6931	0.6660	1.08	0.29801	
Valence * Road Names	-1.0217	0.5960	2.94	0.08651	.
Framing * Road Names	**-1.1741**	**0.5501**	**4.56**	**0.03280**	*
H2W * Valence * Road Names	1.6314	0.8755	3.47	0.06239	.
W2F * Valence * Road Names	0.6281	1.1721	0.29	0.59205	
H2F * Valence * Road Names	1.5737	0.8973	3.08	0.07947	.
H2W * Framing * Road Names	**1.5832**	**0.6418**	**6.08**	**0.01363**	*
W2F * Framing * Road Names	0.0874	1.0519	0.01	0.93375	
H2F * Framing * Road Names	1.1741	0.7394	2.52	0.11230	

Table C.2: Odd ratios of the main and interaction effects from the GEE model. Odd ratios for significant main and interaction effects are highlighted in bold.

Variable Name	Odd Ratio	OR Lower CI	OR Upper CI
(Intercept)	**0.167**	**0.0578**	**0.480**
H2W	1.636	0.5029	5.325
W2F	0.720	0.1306	3.968
H2F	2.000	0.5128	7.800
Valence	**3.333**	**1.1300**	**9.833**
Framing	**3.882**	**1.5188**	**9.924**
Road Names 2.000	0.7363	5.432	
H2W * Valence	0.300	0.0844	1.066
W2F * Valence	0.682	0.1314	3.537
H2F * Valence	0.245	0.0576	1.046
H2W * Framing	**0.315**	**0.1243**	**0.797**
W2F * Framing	0.585	0.0972	3.527
H2F * Framing	**0.309**	**0.0990**	**0.965**
H2W * Road Names	0.399	0.1375	1.156
W2F * Road Names	0.906	0.0996	8.241
H2F * Road Names	0.500	0.1355	1.845
Valence * Road Names	0.360	0.1119	1.158
Framing * Road Names	**0.309**	**0.1052**	**0.908**
H2W * Valence * Road Names	5.111	0.9190	28.425
W2F * Valence * Road Names	1.874	0.1884	18.643
H2F * Valence * Road Names	4.825	0.8311	28.008
H2W * Framing * Road Names	**4.871**	**1.3844**	**17.136**
W2F * Framing * Road Names	1.091	0.1389	8.577
H2F * Framing * Road Names	3.235	0.7595	13.782

D

Chapter 6 Voice Guidance and Conversations

These are the voice guidance and conversations played to the participants when evaluating the voice-based technique described in Chapter 6.

Table D.1: Voice guidance for the Familiarity route in Japanese and Filipino languages.

English	
1.	Let's get started!
2.	In 500 meters, turn left.
3.	Go straight.
4.	In 500 meters, turn left and then turn right.
5.	You've arrived at your destination.

Japanese	
1.	案内を開始します
2.	500 メートル先で左折です。
3.	直進です。
4.	500 メートル先で左折、その後右折です。
5.	目的地に到着しました。

Filipino	
1.	Magsimula na tayo
2.	Kumaliwa pagkatapos ng 500 metro.
3.	Deretso lang.
4.	Pagkalagpas ng 500 metro, kumaliwa tapos kumanan.
5.	Nakarating na tayo sa destinasyon.

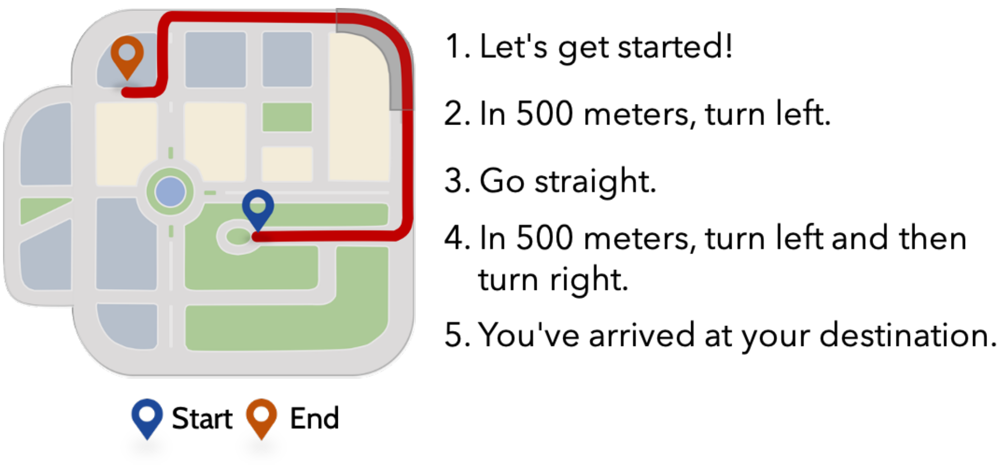


Figure D.1: The Familiarity route and the voice guidance in English.

Table D.2: Voice guidance for the Familiar route (Route F in Figure D.2) in three languages.

English	
1.	Let's get started!
2.	Let's turn left after 500 meters. We take that direction on most days.
3.	Let's continue straight. We always go through the tunnel.
4.	Let's turn left after 500 meters and then turn right. We usually take that turn near our destination.
5.	We've arrived at our destination.

Japanese	
1.	案内を開始します
2.	500 メートル進んだ先を左折です。 いつもこの道を通りますよね。
3.	直進を続けてください。 そのトンネルをよく通っていますよね。
4.	500 メートル先を左折、その後右折です。 いつもどおりの行き方で目的地に行きましょう。
5.	目的地に到着しました。

Filipino	
1.	Magsimula na tayo
2.	Kumaliwa tayo pagkatapos ng 500 metro. Madalas nating dinadaanan yan.
3.	Dumeretso tayo. Lagi tayong dumadaan sa ilalim ng tunnel.
4.	Kumaliwa tayo pagkatapos ng 500 metro tapos kanan. Ganyan ang daan natin pag malapit na tayo.
5.	Nakarating na tayo sa ating destinasyon.

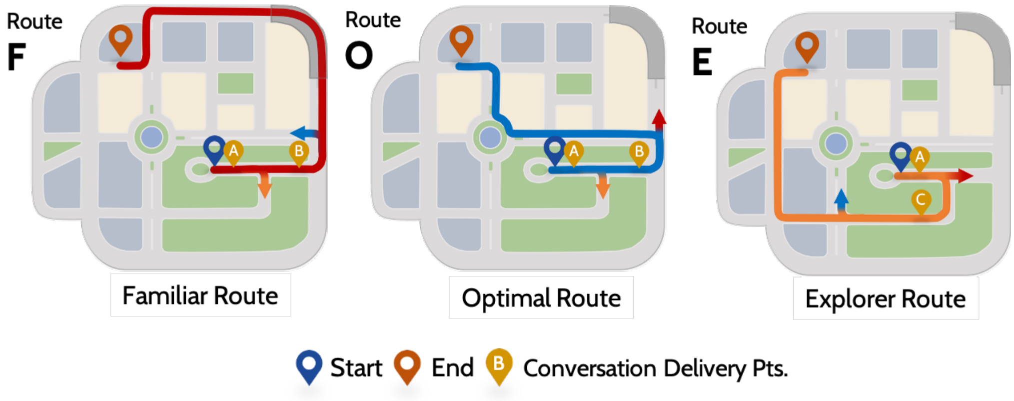


Figure D.2: The different routes used for the voice-based technique described in Chapter 6.

Table D.3: Voice guidance for the Optimal route (Route O in Figure D.2) in three languages.

English	
1.	Let's get started!
2.	Let's turn left after 500 meters.
3.	We can turn left again in 300 meters. It will take us faster.
4.	Let's go straight to the roundabout and take the first exit. There are less traffic signals to wait for.
5.	Let's turn left after 500 meters.
6.	We've arrived at our destination.

Japanese	
1.	案内を開始します
2.	500 メートル先で左折です。
3.	再び、左折してください。こちらだと早く着くでしょう。
4.	直進しラウンドアバウトの最初の出口を出ましょう。 こちらだと信号待ちが少ないです。
5.	500 メートル先左折です。
6.	目的地に到着しました。

Filipino	
1.	Magsimula na tayo
2.	Kumaliwa tayo pagkatapos ng 500 metro.
3.	Kumaliwa tayo ulit bago mag-tunnel. Mas mabilis doon.
4.	Dumeretso tayo sa rotonda at lumabas sa unang exit. Mas kaunti hihintayin nating stop light.
5.	Kumaliwa tayo pagkatapos ng 500 metro.
6.	Nakarating na tayo sa ating destinasyon.

Table D.4: Voice guidance for the Explorer route (Route E in Figure D.2) in three languages.

English	
1.	Let's get started!
2.	Let's turn right. I think we haven't gone in this direction before.
3.	Let's turn right in 500 meters. We should see a new part of town there.
4.	Let's turn right after 500 meters to our destination.
5.	We've arrived at our destination.

Japanese	
1.	案内を開始します
2.	右折しましょう。この方向には行ったことがないと思います。
3.	500 メートル先を右折です。 私たちは町の新しい所を見るのも良いでしょう。
4.	500 メートル先、右折です。
5.	目的地に到着しました。

Filipino	
1.	Magsimula na tayo
2.	Kumanan tayo. Hindi pa yata tayo nakakadaan dito dati.
3.	Kumanan tayo pagkatapos ng 500 metro. Puwede natin makita yung kabilang banda ng barangay dun.
4.	Kumanan tayo pagkatapos ng 500 metro papunta sa ating destinasyon.
5.	Nakarating na tayo sa ating destinasyon.

Table D.5: Voice guidance when the Familiar + Optimal conversation is played.

English	
1.	Let's get started!
2.	Let's turn left after 500 meters. We take that direction on most days.
3.	F: Let's continue straight.
4.	O: We can also turn left before the tunnel.
5.	F: But we always go through the tunnel.
6.	O: Yes, but turning left will take us faster.
continue voice guidance based on what was chosen...	

Japanese	
1.	案内を開始します
2.	500 メートル先を左折です。いつもその道を通りますよね。
3.	F: そのまま直進してください。
4.	O: トンネルの前で左折することもできます。
5.	F: でもいつもよくトンネルを通っていますよね。
6.	O: はい、でも左折すると早くなります。
continue voice guidance based on what was chosen...	

Filipino	
1.	Magsimula na tayo
2.	Kumaliwa tayo pagkatapos ng 500 metro. Madalas nating dinadaanan yan.
3.	F: Dumeretso tayo.
4.	O: Alam mo, puwede rin tayo kumaliwa bago mag-tunnel.
5.	F: Oo, pero hindi ba lagi tayong dumadaan sa ilalim ng tunnel.
6.	O: Tama ka, pero mas mabilis pag kumaliwa tayo.
continue voice guidance based on what was chosen...	

Table D.6: Voice guidance when the Familiar + Explorer conversation is played.

English	
1.	Let's get started!
2.	F: Let's go straight and then turn left.
3.	E: How about turning right before that?
4.	F: That's possible. But we take a left on most days.
5.	E: That's true. But we haven't gone in this direction before.
continue voice guidance based on what was chosen...	

Japanese	
1.	案内を開始します
2.	F: 直進してください、その後左折です。
3.	E: 右折するのはどうですか？
4.	F: それもいいんですけど、いつも左折しますよね。
5.	E: そうですね。しかし、この方向には行ったことがありません。
continue voice guidance based on what was chosen...	

Filipino	
1.	Magsimula na tayo
2.	F: Deretso lang tayo tapos kaliwa.
3.	E: Eh kung kumanan tayo bago yan?
4.	F: Puwede naman. Pero madalas doon pa tayo kumakaliwa.
5.	E: Totoo yan. Pero hindi pa tayo nakakadaan dito dati.
continue voice guidance based on what was chosen...	

Table D.7: Voice guidance when the Optimal + Familiar conversation is played.

English	
1.	Let's get started!
2.	Let's turn left after 500 meters.
3.	O: Let's turn left again in 300 meters.
4.	F: How about we continue straight?
5.	O: Turning left will take us there faster.
6.	F: Right. But don't we always go through the tunnel?
continue voice guidance based on what was chosen...	

Japanese	
1.	案内を開始します
2.	500 メートル先左折です。
3.	O: 300 メールでもう一度左折です。
4.	F: 直進はどうですか？
5.	O: 左折すると目的地に早く着きます。
6.	F: いいですね。でもいつもトンネルを通って行ってませんか？
continue voice guidance based on what was chosen...	

Filipino	
1.	Magsimula na tayo
2.	Kumaliwa tayo pagkatapos ng 500 metro.
3.	O: Kumaliwa tayo ulit bago mag-tunnel.
4.	F: Eh kung dumeretso kaya tayo?
5.	O: Mas mabilis kung kakaliwa agad tayo.
6.	F: Tama. Pero hindi ba lagi tayong dumadaan sa ilalim ng tunnel?
continue voice guidance based on what was chosen...	

Table D.8: Voice guidance when the Optimal + Explorer conversation is played.

English	
1.	Let's get started!
2.	O: Let's go straight and then turn left.
3.	E: How about turning right before that?
4.	O: I don't know about that. Going straight then left is a closer route.
5.	E: That's true. But we haven't gone in this direction before.
continue voice guidance based on what was chosen...	

Japanese	
1.	案内を開始します
2.	O: 直進して、それから左折です。
3.	E: 手前を右折したらどうですか。
4.	O: それは知りません。直進した後、左折すると近いです。
5.	F: そうですね。しかし、この方向には行ったことがありません。
continue voice guidance based on what was chosen...	

Filipino	
1.	Magsimula na tayo
2.	O: Deretso tayo tapos kaliwa.
3.	E: Kung kumanan kaya tayo bago yan?
4.	O: Hindi ko alam. Mas malapit pag dumiretso tayo tapos kaliwa.
5.	E: Tama. Pero hindi pa tayo nakakadaan dito dati.
continue voice guidance based on what was chosen...	

Table D.9: Voice guidance when the Explorer + Familiar conversation is played.

English	
1.	Let's get started!
2.	E: Let's turn right.
3.	F: Why don't we go straight then turn left?
4.	E: We can but I think we haven't gone in this direction before.
5.	F: That's true. Although we take a left on most days.
continue voice guidance based on what was chosen...	

Japanese	
1.	案内を開始します
2.	E: 右折です。
3.	F: 直進した後、左折しませんか。
4.	E: 右折しましょう。この方向には行ったことがないと思います。
5.	F: そうですね。大体は左折しますが。
continue voice guidance based on what was chosen...	

Filipino	
1.	Magsimula na tayo
2.	E: Kumanan tayo.
3.	F: Eh Bakit kaya hindi tayo dumeretso tapos kaliwa?
4.	E: Puwede naman. Pero tingin ko hindi pa tayo nakakadaan dito dati.
5.	F: Tama ka. Kumakaliwa nga lang tayo madalas.
continue voice guidance based on what was chosen...	

Table D.10: Voice guidance when the Explorer + Optimal conversation is played.

English	
1.	Let's get started!
2.	Let's turn right. I think we haven't gone in this direction before.
3.	E: Let's go straight and then turn right.
4.	O: How about we immediately turn right?
5.	E: We should see a new part of town if we go straight.
6.	O: Is that so? Although turning right will take us closer.
continue voice guidance based on what was chosen...	

Japanese	
1.	案内を開始します
2.	右折です。この方向には行ったことがないと思います。
3.	E: 直進した先、右折です。
4.	O: すぐ右折するのはどうですか。
5.	E: 直進すれば、新しい街が見えます。
6.	O: そうですか。右折すると、もっと近くなりますが。
continue voice guidance based on what was chosen...	

Filipino	
1.	Magsimula na tayo
2.	Kumanan tayo. Hindi pa yata tayo nakakadaan dito dati.
3.	E: Dumeretso pa tayo tapos kanan.
4.	O: Eh Kung kumanan kaya tayo agad?
5.	E: Puwede naman. Pero pag dumeretso kasi, makikita natin yung ibang daan.
6.	O: Ganun ba? Pero pag mas malapit na pag kumanan tayo.
continue voice guidance based on what was chosen...	

E
Navigo Voice Guidance and Conversations

These are the voice guidance and conversations played to the participants when evaluating the personality-targeted voice-based technique described in Chapter 7.

Table E.1: Baseline voice guidance when Route A is chosen in the Home-to-Work trip.

1.	Let's get started!
2.	Turn right.
3.	In 300 meters, turn right.
4.	At the roundabout, take the second exit.
5.	In 300 meters, turn left.
6.	You've arrived at your destination.

Table E.2: Baseline voice guidance when Route B is chosen in the Home-to-Work trip.

1.	Let's get started!
2.	In 300 meters, turn left.
3.	Go straight.
4.	In 300 meters, turn left and then turn right.
5.	You've arrived at your destination.

Table E.3: Baseline voice guidance when Route C is chosen in the Work-to-Home trip.

1.	Let's get started!
2.	Turn left.
3.	Make another left towards the roundabout.
4.	At the roundabout, take the second exit.
5.	In 300 meters, turn right and then another right.
6.	You've arrived at your destination.

Table E.4: Baseline voice guidance when Route D is chosen in the Work-to-Home trip.

1.	Let's get started!
2.	Go straight.
3.	Continue going straight.
4.	Continue going straight.
5.	In 300 meters, turn left.
6.	You've arrived at your destination.

Table E.5: Voice guidance when Route A is chosen in the Home-to-Work trip.

1.	Let's get started!
2.	Optimal: Let's turn right.
3.	Unselfish: How about we continue straight and then turn left.
4.	Optimal: Hmmmmm... turning right will take us faster.
5a.	Unselfish: True. But turning left later can be faster for everyone! (*Framing*)
5b.	Unselfish: True. But there are 30 fewer drivers following this. (*Critical mass*)
5c.	Unselfish: True. But everyone's travel time can be 3 minutes faster. (*Valence*)
continue voice guidance based on what was chosen...	

Table E.6: Voice guidance when Route B is chosen in the Home-to-Work trip. These are played when the motivative messages provided along the trip.

1.	Let's get started!
2.	In 300 meters, let's turn left.
3.	Let's continue straight.
4.	In 300 meters, let's turn left and then turn right.
5.	We've arrived at our destination.

Table E.7: Voice guidance when Route C is chosen in the Work-to-Home trip.

1.	Let's get started!
2.	Let's turn left.
3.	Optimal: Let's make another left towards the roundabout.
4.	Unselfish: How about turning left on the next intersection.
5.	Optimal: Are you sure? Turning left now will take us faster.
6a.	Unselfish: Hmmmmm... turning left on the next one can be faster for everyone! (*Framing*)
6b.	Unselfish: Hmmmmm... there are 30 fewer drivers turning left on the next one. (*Critical mass*)
6c.	Unselfish: Hmmmmm... turning left on the next one can be 5 minutes faster for everyone and you. (*Valence*)
continue voice guidance based on what was chosen...	

Table E.8: Voice guidance when Route D is chosen in the Work-to-Home trip. These are played when the motivative messages provided along the trip.

1.	Let's get started!
2.	Let's go straight.
3.	Let's continue going straight.
4.	Let's continue going straight.
5.	In 300 meters, let's turn left.
6.	We've arrived at our destination.

F
Chapter 5 Preliminary Survey

The following sections show screenshots of the preliminary survey given to participants in the within-subject study described in Chapter 5. The preliminary survey in Chapter 7 is derived from this with only a few modifications.

F.1 Project Description and Consent

This section of the survey gives a brief description of the study, as well as the benefits and expectations for the participant. At the end is the consent and screener questions to make sure that the participant fits the inclusion criteria.

Driving Navigation with Motivative and Familiarity Information

Hi! We are inviting you to participate in a research study about driving navigation. Before you decide, it is important that you understand what the research is about and what it will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information. Please take time to decide whether or not you wish to take part.

* Required

About the study

The purpose of this study is to explore adding motivative and familiarity information to route recommendations and investigate its effects on the route choice of drivers. We also want to investigate how a driver's route choice is linked to their general-causality orientation and motivation to volunteer.

The results of this study will guide the design of a navigation application that aims to promote unselfish routes for better city traffic management.

This project is part of the PhD dissertation of Briane Paul V. Samson, under the supervision of Prof. Yasuyuki Sumi at Future University Hakodate, Japan.

Participant criteria

In order to fully participate in this study, you must meet all of the following:
- an adult (18 to 60 y.o.)
- has an active/valid driver's license
- drives to work, business or school on most days of the week (more than 3 times)

Voluntary participation

Your participation in the study is completely voluntary. If you do decide to participate, you will be asked to fill out an online consent form for confirmation. While your participation is ongoing, you are still free to withdraw at any time and without giving a reason.

What will happen?

You will be tasked with answering a preliminary survey, an online experiment, and a post-hoc questionnaire.

==Preliminary Survey==
The preliminary survey consists of 3 sections. The first section will ask about the places you frequently drive to and roads you are familiar with. The second section will ask you to complete the General Causality Orientations Scale (GCOS) which represent your orientation towards autonomy, relatedness, and competence. The third section will ask you to complete the Motivation to Volunteer Scale, a scale to learn about your volunteering motivation.

Once you complete the third section, we will ask you to submit your email and or Facebook Messenger name. We will use one of these information to contact you directly about the online experiment and the post-hoc questionnaire.

The preliminary survey will take approximately 25-30 minutes.

==Online Experiment==
The online experiment will be divided into 7 parts. In each part, you will be given scenarios wherein you have to select a route between two choices. You will also be asked to take note of how long it took you to make a decision. Once you complete the last part, you will be given the post-hoc questionnaire.

Each part will take approximately 10 minutes to complete and will be given on a daily interval. In total, the online experiment will run for 7 days, with 10 minutes time allotment per day.

==Post-Hoc Questionnaire==
The post-hoc questionnaire consists of 2 sections. The first section will ask you to make pairwise comparisons between the types of navigation information used in the online experiment. The second section will ask about your demographic and socioeconomic information, and driving experience.

The post-hoc questionnaire will take approximately 15-20 minutes to complete.

Benefits

After you complete the preliminary survey, online experiment and post-hoc questionnaire, you will be entered into a draw for a 2,500JPY (~1,200PHP) prize. Once the study is completed, one random participant will receive this amount.

We will also share the results of your General Causality Orientations Scale (GCOS) and Motivation to Volunteer scale (MVS). We will send it to the email you will provide.

Confidentiality

The researcher ensures that all research data will be used only in appropriate and ethical ways; location data collected from participants will be protected and will not be distributed. We will be storing them locally but we might also be transmitting them momentarily over the internet. We will not be storing and using confidential and personally identifiable information, and information unrelated to our purposes. You will be contacted and asked for permission should any of your confidential and personally identifiable data will be used for publications and presentations.

Contact for further information

If you wish to ask for additional information about the study before starting or wish to remove yourself from the study, contact:
Briane Paul V. Samson through his email: b-samson@sumilab.org

Thank you for volunteering to participate in this study.

Consent *

Before you proceed, please take time to give your consent by reading and checking all the items below.

- [ ] I have read and understood the information provided above.
- [ ] I have been given the contact email to ask questions about this preliminary survey, the online experiment, and the post-hoc questionnaire.
- [ ] I understand the I may not be contacted to participate in the studies.
- [ ] I can withdraw at any time without giving a reason and there is no penalty for withdrawing.
- [ ] The use of data being cited in part in scientific publications and presentations has been explained to me.
- [ ] The confidentiality of personally identifiable data as been explained, in particular that it will all be anonymized and I should not be identified by the data.

Age *

Your answer

Gender *

- [ ] Female
- [ ] Male
- [ ] Non-binary
- [ ] Prefer not to say
- [ ] Other:

Driving Experience *

- [ ] I have an active driver's license.
- [ ] I drive to work, business or school on most days of the week

Email address *

We will need this in order to give the online experiment and post-hoc questionnaire. We will also use this to contact you should you win the 2,500JPY (~1,200PHP) prize draw. This information will be deleted as soon as a random winner is determined and will not be stored with any privately or publicly available data.

Your answer

Messenger/Line

For the online experiment that will run for 7 days, it might be easier to contact you using Facebook Messenger or Line. If you agree to this arrangement, kindly provide your FB Messenger or Line username below. For FB Messenger, you can go to your browser's URL field and it should look something like this: messenger.com/t/<username>

Your answer

F.2 Travel Information

This section asks for the home and work/school locations of the participants. It also asks for two frequently visited locations and names of familiar roads. Lastly, it asks how often they switch between their regular and alternative routes before the pandemic. All information gathered here will be kept confidential and will be deleted after the study.

Driving Locations

Thank you for choosing to participate in this study!

In this section, we need you to provide information about your home, work and some frequently visited locations. This will help contextualize the online experiment to your daily commutes.

We understand this these are highly confidential and private information. Once this study is completed, we will delete all these information from our local storage.

Home Address *

Please write the complete address of your home

Your answer

Home in Google Maps *

Please search or pin your HOME location using Google Maps and copy the URL in this field

Your answer

Work/School Address *

Please write the complete address of your workplace or school

Your answer

Work/School in Google Maps *

Please search or pin your WORK/SCHOOL location using Google Maps and copy the URL in this field

Your answer

Frequently Visited Locations

Other than your work and home locations, we would also like to know 2 places that you frequently visit, at least once a week. This can your preferred shopping mall/complex, barber/salon, church or place of worship, etc.

Frequent Place #1 Address *

Please write the complete address of your first frequently visited place.

Your answer

Frequent Place #1 in Google Maps *

Please search or pin your Frequent Place #1 location using Google Maps and copy the URL in this field

Your answer

Frequent Place #2 Address *

Please write the complete address of your second frequently visited place.

Your answer

Frequent Place #2 in Google Maps *

Please search or pin your Frequent Place #2 location using Google Maps and copy the URL in this field

Your answer

Familiar Roads *

Please enumerate the roads that you are familiar with when you go to the locations you mentioned above. Familiar roads are roads you have taken at least once. Please list as many as you can remember.

Your answer

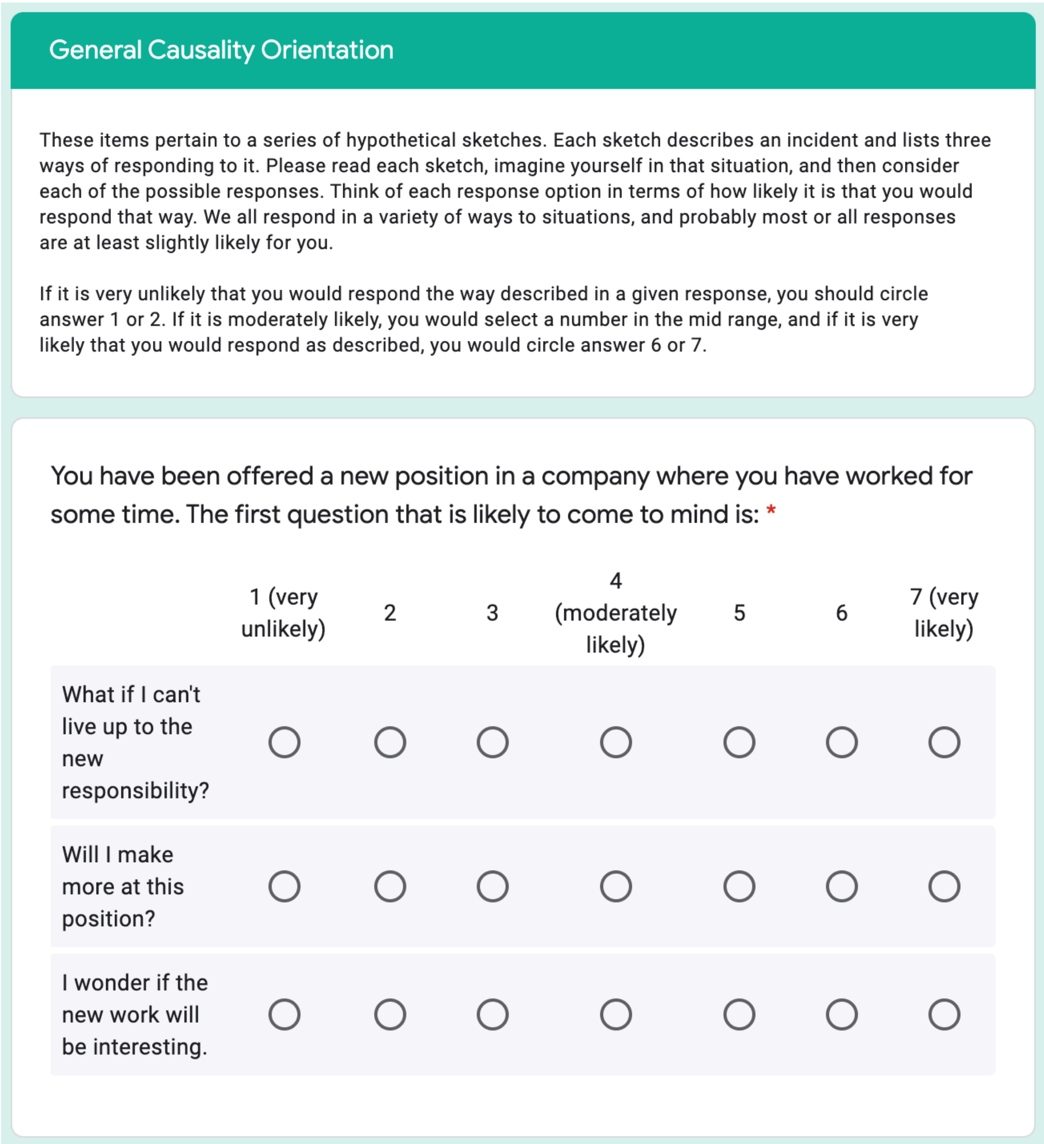
In October to December 2019, how often did you switch between your regular and alternative routes from Home to Work/School within a week? *

- Never
- Once a week
- Twice a week or more

In October to December 2019, how often did you switch between your regular and alternative routes from Work/School to Home within a week? *

- Never
- Once a week
- Twice a week or more

F.3 General Causality Orientation Survey



General Causality Orientation

These items pertain to a series of hypothetical sketches. Each sketch describes an incident and lists three ways of responding to it. Please read each sketch, imagine yourself in that situation, and then consider each of the possible responses. Think of each response option in terms of how likely it is that you would respond that way. We all respond in a variety of ways to situations, and probably most or all responses are at least slightly likely for you.

If it is very unlikely that you would respond the way described in a given response, you should circle answer 1 or 2. If it is moderately likely, you would select a number in the mid range, and if it is very likely that you would respond as described, you would circle answer 6 or 7.

You have been offered a new position in a company where you have worked for some time. The first question that is likely to come to mind is: *

	1 (very unlikely)	2	3	4 (moderately likely)	5	6	7 (very likely)
What if I can't live up to the new responsibility?	○	○	○	○	○	○	○
Will I make more at this position?	○	○	○	○	○	○	○
I wonder if the new work will be interesting.	○	○	○	○	○	○	○

The General Causality Orientation survey is derived from Self-Determination Theory[42] which assesses the strength of an individual's motivational orientations. The survey presents a series of hypothetical sketches that requires participants to imagine themselves in a situation. For each sketch, they must answer how likely it is they think they would respond in a particular way. Each item are answerable with a Likert-type scale from 1 to 7, with 1 being very unlikely and 7 as very likely. The figure above shows how the survey looks in Google Forms. The following are the 12 vignettes shown to the participants.

1. You have been offered a new position in a company where you have worked for some time. The first question that is likely to come to mind is:
    (a) What if I can't live up to the new responsibility?
    (b) Will I make more at this position?
    (c) I wonder if the new work will be interesting.
2. You have a school-age daughter. On parents' night the teacher tells you that your daughter is doing poorly and doesn't seem involved in the work. You are likely to:
    (a) Talk it over with your daughter to understand further what the problem is.
    (b) Scold her and hope she does better.
    (c) Make sure she does the assignments, because she should be working harder.
3. You had a job interview several weeks ago. In the mail you received a form letter which states that the position has been filled. It is likely that you might think:
    (a) It's not what you know, but who you know.
    (b) I'm probably not good enough for the job.
    (c) Somehow they didn't see my qualifications as matching their needs.
4. You are a plant supervisor and have been charged with the task of allotting coffee breaks to three workers who cannot all break at once. You would likely handle this by:
    (a) Telling the three workers the situation and having them work with you on the schedule.
    (b) Simply assigning times that each can break to avoid any problems.
    (c) Find out from someone in authority what to do or do what was done in the past.
5. A close (same-sex) friend of yours has been moody lately, and a couple of times has become very angry with you over "nothing." You might:

   (a) Share your observations with him/her and try to find out what is going on for him/her.
   (b) Ignore it because there's not much you can do about it anyway.
   (c) Tell him/her that you're willing to spend time together if and only if he/she makes more effort to control him/herself.

6. You have just received the results of a test you took, and you discovered that you did very poorly. Your initial reaction is likely to be:

   (a) "I can't do anything right," and feel sad.
   (b) "I wonder how it is I did so poorly," and feel disappointed.
   (c) "That stupid test doesn't show anything," and feel angry.

7. You have been invited to a large party where you know very few people. As you look forward to the evening, you would likely expect that:

   (a) You'll try to fit in with whatever is happening in order to have a good time and not look bad.
   (b) You'll find some people with whom you can relate.
   (c) You'll probably feel somewhat isolated and unnoticed.

8. You are asked to plan a picnic for yourself and your fellow employees. Your style for approaching this project could most likely be characterized as:

   (a) Take charge: that is, you would make most of the major decisions yourself.
   (b) Follow precedent: you're not really up to the task so you'd do it the way it's been done before.
   (c) Seek participation: get inputs from others who want to make them before you make the final plans.

9. Recently a position opened up at your place of work that could have meant a promotion for you. However, a person you work with was offered the job rather than you. In evaluating the situation, you're likely to think:

   (a) You didn't really expect the job; you frequently get passed over.

(b) The other person probably "did the right things" politically to get the job.

(c) You would probably take a look at factors in your own performance that led you to be passed over.

10. You are embarking on a new career. The most important consideration is likely to be:

    (a) Whether you can do the work without getting in over your head.

    (b) How interested you are in that kind of work.

    (c) Whether there are good possibilities for advancement.

11. A woman who works for you has generally done an adequate job. However, for the past two weeks her work has not been up to par and she appears to be less actively interested in her work. Your reaction is likely to be:

    (a) Tell her that her work is below what is expected and that she should start working harder.

    (b) Ask her about the problem and let her know you are available to help work it out.

    (c) It's hard to know what to do to get her straightened out.

12. Your company has promoted you to a position in a city far from your present location. As you think about the move you would probably:

    (a) Feel interested in the new challenge and a little nervous at the same time.

    (b) Feel excited about the higher status and salary that is involved.

    (c) Feel stressed and anxious about the upcoming changes.

F.4 Motivation to Volunteer Survey

The Motivation to Volunteer Survey is intended to measure an individual's motivations for volunteering by measuring their different behavioral regulatory styles based on SDT. Each item is answerable with Likert-type scale from 1 to 5. The figure below shows how the survey looks in Google Forms. The following are the 24 vignettes shown to the participants with one attention check item.

1. I volunteer because I would feel very bad if I did not help others. (*Introjected*)
2. I volunteer because it's a good way to contribute. (*Identified*)
3. I volunteer but I don't know; I can't see how my efforts are helping others when I volunteer. (*Amotivation*)
4. I volunteer because I would feel guilty if I did not volunteer. (*Introjected*)
5. I volunteer because other people will be sorry if I didn't do it. (*External*)
6. I volunteer but I don't know; I can't see how all this helps. (*Amotivation*)
7. I volunteer because I would be ashamed if I did not volunteer. (*Introjected*)
8. I volunteer because it is one of the ways I live my life. (*Integrated*)
9. I volunteer for the pleasure I feel in doing something new. (*Intrinsic*)
10. I volunteer because it's something that contributes to my personal growth. (*Identified*)
11. I volunteer for the pleasure I feel when I master the situations I'm dealing with. (*Intrinsic*)
12. I volunteer because this activity has become an integral part of my life. (*Integrated*)
13. I volunteer for the recognition I get from others. (*External*)
14. I volunteer because volunteering has become a part of who I am. (*Integrated*)
15. I volunteer for the pleasure I feel in finding new ways of help. (*Intrinsic*)
16. I volunteer because it's something that is fulfilling for me as a person. (*Identified*)
17. I volunteer because volunteering is a suitable activity for me. (*Integrated*)
18. I volunteer to avoid being criticized. (*External*)
19. I volunteer but I don't know; I can't see what I' m getting out of it. (*Amotivation*)

20. To show that you are still concentrated, please select 5 for this question. (*Attention Check*)

21. I volunteer because I would regret not doing volunteering. (*Introjected*)

22. I volunteer because I know others are pleased that I volunteer. (*External*)

23. I volunteer for the pleasure and interest I feel in doing this activity. (*Intrinsic*)

24. I volunteer but I don't know; Sometimes I have the impression I'm wasting time when I volunteer. (*Amotivation*)

25. I volunteer because it is a wise thing to do. (*Identified*)

The survey also asked how often they participated in volunteering activities in the past three months on average. It was answerable with "Never," "Once a week," and "Twice a week or more." Because the study was conducted during the COVID-19 pandemic and more people tended to volunteer in a crisis, participants were also asked about their average volunteering frequency before the pandemic (October to December 2019).

Motivation to Volunteer

Why do you volunteer? In this section, we want to understand your motivations for volunteering.

To what extent do each of the following items correspond to your personal motives for engaging in volunteering? Please select a rating on a 5-point Likert scale ranging from 1 (does not correspond at all) to 5 (corresponds exactly).

I volunteer because I would feel very bad if I did not help others. *

	1	2	3	4	5	
does not correspond at all	○	○	○	○	○	corresponds exactly

I volunteer because it's a good way to contribute. *

	1	2	3	4	5	
does not correspond at all	○	○	○	○	○	corresponds exactly

I volunteer but I don't know; I can't see how my efforts are helping others when I volunteer. *

	1	2	3	4	5	
does not correspond at all	○	○	○	○	○	corresponds exactly

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