# Traffic Information and Learning in Day-to-Day Route Choice

E.A.I. Bogers

To Mark

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# Traffic Information and Learning in Day-to-Day Route Choice

#### Proefschrift

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## Preface

This thesis is the result of five years research on day-to-day route choice under traffic information. Five years in which I enjoyed doing research very much and in which I discovered that everything they say about writing a thesis is true! I am very pleased having completed this task and I want to thank a number of people without whom this would not have been possible.

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I was able to estimate this model on a very nice data set thanks to the ANWB and the programmers of the experiment. As for the ANWB I would like to mention especially Jaap de Haas and Ton Hendriks. I very much appreciated the way you organized the publicity of my experiment (resulting in 2,500 respondents!) and the practical comments on its user friendliness. The programmers Tom de Groot and Marselis Hellendoorn were a pleasure to work with, professionally and personally, which resulted in an ongoing friendship. I would like to thank Conchita van der Stelt and her colleagues from TRAIL research school and the people from the secretarial offices for their practical support in making this thesis. Finally, colleagues who I have not mentioned yet: thank you for interesting conversations, practical help, lunches, playing table tennis, etc.

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Enide Bogers Haarlem, 28 April 2009

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# Notation

This section provides an overview of formulas and symbols frequently used in this thesis.

#### Overall route choice model

$$U_{\text{int}} = RoadType_n + \beta_{Info}TTInfo_{it} + \beta_{ETT}ETT_{\text{int}} + \beta_{choice_i}ChoiceFraction_i + \varepsilon$$
(1)

Symbol	Definition	Explanation
U	Utility	Overall value of the route
i	Route index	Route 'name' (1, 2 or 3)
n	Traveller index	Unique number to define each traveller
t	Time index	Day number (1 to 40)
RoadType	Alternative (road type) specific	Gives the distribution of travellers' intrinsic
	constant ~ $N(\mu,\sigma)$ ; $\mu$ and $\sigma$ to be	preferences for a certain road type
	estimated	(accommodates panel data).
βInfo	Travel time information	Gives weight of travel time information in the
	parameter	total utility.
TTInfo	Travel time as displayed on VMS	Variable containing the travel time
		information in minutes on VMS.
βΕΤΤ	Expected travel time parameter	Gives weight of expected travel time in the
		total utility.
ETT	Expected travel time	Variable containing the travel time
		information in minutes on VMS.
βchoice	Inertia / habit parameter	Gives weight of inertia / habit in the total
		utility.
ChoiceFraction	Fraction of choices for a specific	Variable containing the fraction of choices for
	route over the past 9 days	a specific route over the past 9 days.
3	Error term ~ Gumbel i.i.d.	Random component

### Expected travel time (recency and salience)

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTT_{in(t-1)}$$
 if  $\delta_{in(t-1)} = 1$  (2)

$$ETT_{\text{int}} = (1 - w)ETT_{in(t-1)} + wTTInfo_{in(t-1)} \qquad \text{if } \delta_{\text{in}(t-1)} = 0 \qquad (3)$$

$$w(TT_{\text{int}}) = s(TT_{\text{int}})r(TT_{\text{int}}) \qquad \text{in case i is non-habitual route} \qquad (4)^{1}$$

$$w(TT_{\text{int}}) = \frac{1}{s(TT_{\text{int}})}r(TT_{\text{int}}) \qquad \text{in case i is habitual route} \qquad (5)^{1}$$

 $s(TT_{int}) = \frac{TT_{int}}{ETT_{int}}$ 

(6)<sup>1</sup>

Symbol	Definition	Explanation
W	Weight	Overall weight in updating expected travel time
$\delta_{int}$	Choice dummy	Equals 1 if route i was chosen by individual n at day t
r	Recency effect	Gives the weight of the most recent experience
λ	Recency parameter experience	Parameter to express weight of most recent experience
α	Recency parameter information	Parameter to express most recent received en-route information
S	Salience effect	Expresses the extra impact of a salient experience

Habit and inertia

$$ChoiceFraction_{i} = \left(\frac{\sum_{x=1}^{\min(9,t-1)} \delta_{in(t-x)}}{\min(9,t-1)}\right)$$

\_\_\_\_\_

<sup>&</sup>lt;sup>1</sup> Replace experienced travel times by provided en-route information in case route was not chosen, like in (3)

# **1** Introduction

Traffic congestion is a major problem in many countries. The days that traffic jams were something extraordinary and people actually went out to look at them are long behind us. Traffic congestion is now a source of time loss, economic costs, air pollution, etc. Traffic jams occur when traffic demand is larger than traffic capacity. Various measures exist to decrease the problems of traffic congestion, most of which are currently applied in the Netherlands mobility policy (Rijksoverheid, 2004). Traffic information is one of these measures. By providing traffic information, travellers are assisted in making travel choices. If they are warned for a traffic jam on a certain road, they may for example change their route, their departure time or travel mode to avoid this traffic jam. It is important for a traffic manager to know how a traveller reacts to traffic information, so that he can provide traffic information that is not only beneficial for the individual traveller but also for the traffic system as a whole. Although previous studies (e.g. (Srinivasan and Mahmassani, 2003; Chorus et al., 2006)) have delivered interesting insights into travellers' reactions to traffic information, there are still many questions left to be answered. Therefore, travellers' reactions to traffic information form one of the main topics of this thesis. The other main topics are learning from travel experiences and traffic information and travellers' reactions to travel time reliability.

This chapter is organized as follows. First, a brief introduction to traffic and traffic management in general is given. Then, we focus on an aspect of traffic that we are interested in: traffic information. In section 1.3 we further zoom into our topic of interest and formulate the research problem and the research scope. The organizational framework of the research and its objectives are discussed next. In section 1.5 the research questions that will be answered in this thesis are formulated. The contributions of this dissertation research are discussed next. The chapter ends with an outline of the remainder of this thesis.

#### **1.1** Traffic and traffic management

A simple and clear overview of how the traffic and transport system works is given by the system diagram for the policy domain transport and traffic (Van de Riet and Egeter, 1998). It describes the traffic and transport system as a market with three interrelated segments:

- Trip market. The demand side consists of activities to be performed; the supply side of the locations (place and time) where they could be performed. The output of this market consists of a number of trips, an allocation of the activities to location and time.
- Transport market. The output of the trip market makes up the demand of this market. The supply side consists of vehicles and services to accommodate the demand. The output of this market consists of an allocation of trips to the transport vehicles and services.
- Traffic market. The output of the transport market makes up the demand of this market. The supply side consists of the available infrastructure with all its attributes, like traffic lights, traffic signs etc. The output of this market consists of an allocation of transport vehicles and services to the infrastructure.

Traffic management measures are aimed at all three markets. They can be divided into three groups:

• Demand management

The aim is to manage (decrease) traffic demand. This works especially at the demand side of the trip market. Examples include fuel taxes, stimulation of working at home and living close to the work location.

• Supply management

This type of measure is aimed at increasing supply of traffic facilities. This works especially at the supply side of the transport and traffic market, e.g. by constructing new infrastructure or increasing the frequency of public transport services.

• Synchronization of demand and supply

These measures do not really increase or decrease traffic demand and supply, but match them better in time and space. Examples include peak-time road charges ATIS (Advanced Traveller Information Systems) and intelligent control of traffic lights. Strictly speaking, they do affect traffic supply, as the supply side of the traffic market includes attributes like traffic lights.

The next section concerns ATIS, a measure aimed at synchronizing demand and supply.

#### 1.2 Advanced Traveller Information Systems

In this thesis, we focus on car drivers' responses to Advanced Traveller Information Systems (ATIS). This section provides some background on ATIS. It describes how ATIS works, what actors are involved in enabling and using the system and what their respective goals are and what types of ATIS exist.

#### 1.2.1 ATIS: how does it work?

Figure 1 gives a rough impression of how information about the current status of the transport system is used to provide travellers with ATIS. Roads and vehicles can be equipped with sensors (e.g. loop detectors, camera's, or GPS) which measure characteristics of the traffic condition. This results in acquired traffic data, which are processed to become information. For example, if the data show very low average car speeds on a road section, this can be processed into queue length information. The information can finally be distributed through various channels (VMS, radio, navigation system, etc.) to users like car drivers and train travellers. As this brief overview shows, many different actors are involved in the functioning of ATIS. This is the topic of the next section.



#### 1.2.2 Actor analysis

The diagram below gives an overview of the main actors involved in traffic information provision, and how these relate to each other. Road users are at the beginning and the end of the ATIS process: they are the ones who produce traffic on the network and they are the ones who receive information about traffic conditions. The network authority (at present typically a governmental department) and service providers (typically a commercial organization) are involved in providing the road user with information.

The first one, the *network authority*, not only monitors the traffic network (for example through loop detectors and camera's), but also controls it through various dynamic traffic management measures. The information offered by the network authority is partly directly offered to all road users, an example is the information on a VMS. The network authority also offers traffic data to *service providers*, who can distribute it to road users. An example is the information on news bulletins. This type of information can often be classified as collective information, i.e. information that is available to everybody. The network authority also uses the information themselves to manage traffic.

Service providers also sell information to individual users. This type of information can be classified as personal information, i.e. information that is available (and tailored) to one person. Information on navigation systems and paid telephone services are some examples of personal information. Service providers obtain their traffic data from the network authority and through their own monitoring activities, using among other things mobile phone data.

The actors from Figure 2 have their own objectives regarding using / providing ATIS. Some possibilities are listed below.

- 1) Goals of road users
- Improve the outcomes of travel choices
- Reduce uncertainty in expected travel conditions
- Increase or correct personal knowledge

2) Goals of network authority (depending on policies)

- Improve utilisation existing infrastructure and reduce duration / severity congestion
- Reduce environmental impacts (also locally!) and use of scarce resources (fuel consumption), e.g. by advising faster routes

- Increase network reliability / robustness, e.g. by advising alternative routes in case of congestion on part of the network
- 3) Goals of service providers
- Develop a solid business and make a profit





#### **1.2.3** Types of traffic information

Many different types of traffic information exist. This section provides a brief overview of the variables involved (content, moment, location, media and target user).

#### What: content of information

Two types of traffic information are usually distinguished: prescriptive and descriptive information. The first tells a traveller what to do, i.e. it provides guidance, whereas the second type only informs the traveller about traffic conditions leaving him free what to decide. An example of the first type is 'Take the southern route'; an example of the second type is 'accident on the northern route' or 'travel time on northern route 34 minutes'. In the first case, a traveller can either comply with the information or not. In the second case, a traveller is completely free to interpret the information and make a choice, either using the information. Travel information can be made based on the target end user of the information. Travel information of the Traffic Information Centre (VID in the Netherlands) is generic: all queues on all motorways are displayed. Travellers with a navigation system like Tomtom only see the information about queues on their route.

Another important characteristic of the information is the quality of its content. Quality can concern the accuracy, timeliness, clearness, etc. The issue is related to the way information is determined from available data (historical data, instantaneous information from loop detectors, predictions, etc.).

#### When: moment of information reception

Typically, a traveller can receive dynamic information before beginning a trip, during his trip, or after his trip. The received information is referred to as pre-trip, en-route and ex-post information respectively.

#### Where: location of information reception

Related to the previous is the location of the traveller receiving information. Obviously, onsite traffic information (like messages on VMS) can only be received when a traveller is enroute, at the specific location. Pre-trip and ex-post information can be acquired nearly everywhere, depending on the communication channel.

#### How: broadcasting and interactive information

With communication channel we refer to the carrier of the information. Examples include incar navigation systems like TomTom, Garmin and VDO Dayton, Variable Message Signs, radio, internet and television.

#### Whom: collective or individual, public or commercial information

Some information is free and available to everybody. This was called collective information in the previous section. It concerns information on the radio and on VMS. Other information can be acquired only by individuals who pay for it. An example is a 'traffic jam subscription' on a navigation system. The system then takes dynamic traffic information into account when advising what route to follow.

#### **1.3** Problem formulation and research scope

This thesis focuses on travellers' reactions to traffic information. Traffic information can influence the choices travellers make. Especially route choice can be influenced. Therefore route choice plays a central role in this thesis. To give an impression of what kind of choices have to be made in traffic in general, a hierarchy of travel choices is discussed in the next section. As 'travellers' reactions to traffic information' and 'route choice' are very broad topics, we need to formulate the exact problem that this research focuses on and the scope that is used. This will be done in section 1.3.2.

#### **1.3.1** A hierarchy of travel choices

In traffic science, the classic four-stage transport model (Ortúzar and Willumsen, 1994) is often used to model and predict traffic flows. We discuss it here, as we will use it to provide an overview of choices a traveller has to make. The four-stage transport model contains the following steps:

#### Step 1: Trip production and attraction

This step results in the numbers of trips that are produced in or attracted to a geographical zone as a function of zonal variables.

#### Step 2: Trip distribution

This step links origins and destinations and results in a table giving the number of trips during a certain period between each pair of zones.

#### Step 3: Modal split

In this step the transport mode (car, bicycle, bus, train, etc) that a traveller uses for each trip is determined.

#### Step 4: Traffic assignment

This last step concerns the route choice of travellers. The trips that were determined in the previous steps are now assigned to specific routes. By aggregating over travellers this results in traffic loads of routes, sections, and intersections. Note that departure time choice is not included here, due to the static nature of the four-stage transport model.

Based on the four steps, we drew a simple hierarchy of travel choices, as seen from the viewpoint of an individual traveller, refer to Figure 3. Departure time choice is added to this figure. Operational choices concerning lane changing, speed, etc. that are made during the trip are omitted from the figure, as they do not have a clear relation with the type of traffic information this thesis focuses on.



Figure 3: A simple hierarchy of travel choices

The steps from both the four-stage transport model and the hierarchy of travel choices do not always occur in the listed order and interactions exist between the levels in the hierarchy. The dashed arrows in Figure 3 express these interactions. Still, when looking at an individual traveller, one can say that his decisions taken in the highest box in Figure 3 are usually longer-term and less frequent than decisions taken in the last box. An example of a decision in the first box is where to live and where to work (taken once every few years).

An example of a decision in the last box is whether to use the highway or an urban road to go to work (taken nearly every day). Traffic information is usually consulted to facilitate decisions from the last two boxes (departure time and route choice). As traffic information is an important topic in this thesis, departure time choice and route choice are potentially important topics as well. In the next section, in which the research scope is discussed, we will explain why we decided to focus on route choice.

#### 1.3.2 Traffic information and learning in day-to-day route choice

Travellers who make the same trip several times, like commuters, business travellers, or truck drivers, form a large part of daily travel demand. Because many of them use their car for these trips during peak hours, they are both an important cause and a 'victim' of congestion. Although these car divers may not be very flexible in their departure time choice (having to be at work at fixed times), traffic information may stimulate them to choose routes more efficiently. In the end, this can help to decrease congestion on the traffic network. However, we do not exactly know what the effects of different types of traffic information on route choice behaviour are and consequently, what type of information should be provided.

# Therefore, this research focuses on the day-to-day route choice of commuting car drivers with limited departure time flexibility in the presence of traffic information.

In the situation as illustrated above, there is an opportunity to **learn** about the characteristics of the available routes. The driver can learn about their normal travel times and about the **reliability** of these travel times. This will probably play a role in his route choice. **Traffic information** can also influence the route choice, both directly and indirectly by influencing the learning process. Finally, as the route choice is made repetitively, there is also a possibility of habit formation. How these processes exactly work is not known. Therefore, this research will try to acquire more insights into the relations between these three concepts: learning, reliability and traffic information in the situation as described above. These insights can then be used to improve traffic information in such a way that it is beneficial to the individual driver and effective to the traffic system as a whole.

A topic which is influenced by learning and by traffic information is the topic of choice set generation. Route choice set generation is about how travellers form a subjective route choice set from an objective route choice set. There are often several routes that lead from origin to destination (the objective choice set). A traveller usually knows only a fraction of these routes (the subjective choice set). Traffic information can help travellers to learn about these possible routes and thereby to increase their subjective choice set. Nevertheless, we do not study the topic of choice set generation in this thesis, as it is too complex to receive the appropriate attention next to the other topics in this thesis. For an overview of the state-of-the-art in choice set generation we refer to the thesis of Hoogendoorn-Lanser (2005).

#### **1.4 Research framework and objectives**

The research presented in this thesis is project 1 of the NWO-Connekt program AMICI (Advanced Multi-agent Information and Control for Integrated multi-class traffic networks). The objectives of the complete AMICI programme are discussed first and are followed by a discussion of the AMICI 1 objectives.

#### 1.4.1 AMICI Research objectives

The AMICI R&D program focuses on traffic congestion management in and around large cities. As an example studies have been made of the cities Beijing, Rotterdam, Amsterdam and Shanghai<sup>2</sup>. In particular, it aims at coming up with solutions to efficiently manage traffic congestion by means of Dynamic Traffic Management.

 $<sup>^{2}</sup>$  These cities form the 'BRAS-cities'. Studies in these cities found that especially the connection between the motorway network and the arterial road network is a cause of traffic congestion. The BRAS concept says that these networks have to be managed in an integrated way (Chen et al., 2004).

It is argued that to improve congestion management, approaches should consider the motorway network and the underlying urban and rural networks in an integrated way. Judging from the first explorations, it is believed that approximately 30% of all traffic congestion can be solved using an integrated approach. Furthermore, traffic management measures should be coordinated: a lot can be gained by jointly considering ramp metering and providing queue length information. Finally, efficient approaches will need to anticipate on future traffic conditions, rather than merely react to them (Chen et al., 2004).

To attain the AMICI research objectives, five research themes have been set-up. These themes relate to the following multidisciplinary PhD research projects:

- 1 Impact of traffic information and traffic control on travel behaviour
- 2 Multiclass Traffic Flow Theory for Modelling of Motorway and Urban Traffic Networks
- 3 Development of advanced multi-agent control strategies for multi-class traffic networks
- 4 Optimal presentation of traffic information based on personal preferences and needs
- 5 Market for traveller information

Figure 4 shows how the AMICI projects relate to each other.



# Figure 4: Relations between the five AMICI research projects (source: http://www.amici.tudelft.nl)

#### 1.4.2 Dissertation research objectives

The objectives of AMICI 1 are to get a deeper understanding of the influence of traffic information and experiences on route choice and the behavioural mechanisms behind it, especially by

- Developing a conceptual paradigm which incorporates the topics of learning and travel time reliability of route choice under traffic information,
- Modelling the route choice under traffic information,
- Estimating the model on experimental data in order to accept / reject the conceptual paradigm.

#### **1.5** Research questions

In section 1.3.2 we hypothesized learning, traffic information and travel time reliability to be three important aspects that play a role in the described day-to-day route choice behaviour. In this section these three aspects are briefly discussed and the resulting research questions are formulated.

#### 1.5.1 Learning

Learning can lead to an expectation of the travel time on a route. Travellers can learn both from their experienced travel times and from traffic information provided to them. To learn from them, they have to be stored in memory.

From psychology literature we know that the strength with which an experience is stored in memory is among others dependent on the recency of the experience (Ebbinghaus, 1885). The term recency relates to how long ago the experience took place. The recency effect means that recent events have a stronger presence in memory than older events.

We hypothesize memory strength to be also dependent on the salience of the experience. By this we mean the extremeness of the experience compared to earlier experiences. Literature is not clear on how this salience effect could work. Familiarity is an important aspect in recognition memory (Mandler, 1980). Still, unfamiliar things are sometimes remembered better (Gregg, 1976; Marmurek, 1984). As salience is related to familiarity, we think it may have an effect on memory strength. Alternatively, salient experiences may be easier to remember, because they draw attention. They may also provoke certain feelings that can bias the development of an expectation as well as a decision directly, as can be concluded from (Shiv et al., 2005).

Finally, the primacy of an experience could affect memory strength. This primacy effect means that the first item in a series is often remembered relatively well (Murdock Jr, 1962).

From psychology literature we also know that cognitive learning (also referred to as *explicit learning*) can be viewed as constructing new knowledge by integrating new information in what is already known (Cobb, 1994), (Piaget, 1977) and (Piaget, 1978). Therefore, we can regard learning from an experience as updating the current expected travel time with the new experienced travel time. The same applies to learning from traffic information. We do not know exactly how this updating is affected by recency, salience and primacy effects.

Besides an expectation of a route's travel time, learning can also lead to habit formation (also referred to as the ultimate stage of *implicit learning*). Habit has been found to play a role in travel choices by Aarts et al. (1997). The more an activity is carried out, the more likely it is to be to some extent automated and to become habitual. The relative influence of habit formation compared to cognitive learning on route choice, the travel choice that we focus on in this thesis (refer to section 1.3.2), is not known in detail.

The previous leads to the following research questions:

L1 How do travellers learn from travel time experiences?

*L1.1* Explicit learning: What is the role of the recency, salience and primacy of an experienced travel time in updating a traveller's expected travel time?

*L1.2* Implicit learning: What is the relative influence of habit formation compared to cognitive learning on route choice?

*L2* How do travellers learn from traffic information?

*L2.1* Explicit learning: What is the role of the recency, salience and primacy of an informed travel time in updating a traveller's expected travel time?

#### **1.5.2** Traffic information

As the previous section outlined, traffic information is likely to influence learning in the sense of updating expected travel times, which can influence future route choices. We will call this the long-term effect of traffic information throughout this thesis.

Furthermore, traffic information can influence route choice directly, by giving the traveller an estimate of the current travel time. How large this short-term influence of traffic information is compared to the influence of the expected travel time and habit is not known exactly. This leads us to the following research question:

*II* What is the influence of traffic information on route choice?

*II.1* Short-term effect: How does the provision of traffic information influence the current route choice?

*II.2* Long-term effect: What is the role of the recency, salience and primacy of an informed travel time in updating a traveller's expected travel time?

Note that I1.2 is in fact the same as L2.1 from the previous section. For the sake of completeness, we included the question in this section as well.

#### **1.5.3** Travel time reliability

In section 1.5.1 it was argued that the salience of informed or experienced travel times can influence the updating of the expected travel time. Salience of travel experiences is related to reliability: a route that always takes more or less the same time does not have very salient travel times and is very reliable. We can therefore say that travel time reliability influences learning, the updating of the expected travel time, and therefore also route choice.

But even if a traveller holds a higher expected travel time for route A than for route B, he may still prefer route A when it is more reliable. This depends for example on a traveller's risk attitude and on the travel goal. A person that doesn't like to take any risks and has to catch a train to an important appointment will probably have a strong preference for reliable routes (and / or depart very early). This risk avoidance, or positive valuation of reliability has been found in various studies, e.g. (Bates et al., 2001; Bogers and Zuylen, 2004; Liu et al., 2004; Brownstone and Small, 2005).

Finally, there is a relation between the provision of traffic information and the perceived attractiveness of unreliable routes. Even very unreliable routes can become very predictable if the en-route information gives an accurate estimate of the current travel time on the route. Another type of information can also influence the perceived attractiveness of unreliable routes: ex-post information. This type of information gives realized travel times on all alternative routes. This can help a traveller to have a more realistic perception of the travel

times and their reliability on all routes. If, for example, a traveller experienced a very long travel time on a route he may feel that this route is very unreliable and decide to never choose it again. The ex-post information, however, may show that this very long travel time was exceptional for this route as the route is usually very fast and reliable.

The following research questions result:

*R1* How does travel time reliability influence the updating of the expected travel time (learning)?

*R2* How does travel time reliability influence the perceived attractiveness of a route?

*R3* How can en-route and / or ex-post traffic information influence the perceived attractiveness of (unreliable) routes?

#### 1.5.4 Relative influence of learning, reliability and traffic information

The previous questions concentrated on one of the three important aspects that play a role in the described day-to-day route choice situation. We are also interested in how these aspects relate to each other. A mathematical model that comprises all aspects would be very useful to this end. Therefore, we formulated the following research question:

*T1* What is the relative influence of learning, reliability and information on day-to-day route choice?

*T2* How can we formalize this mathematically?

#### **1.6 Main research contributions**

The contributions of the research described in this thesis can be divided into scientific contributions and practical contributions. They are presented in the next two subsections.

#### **1.6.1** Scientific contributions

This thesis contributes to both the theory and modelling of day-to-day route choice under traffic information. In detail the contributions include:

- A conceptual framework of day-to-day route choice under traffic information integrating notions from traffic science, psychology (especially about various types of learning), neuroscience (about the role of emotions in decision making) and experimental economics (about risk behaviour) which is (partly) calibrated using experimental data. Some of these insights from other sciences, such as risk avoiding behaviour and recency effects in learning, have been used already in traffic science. The contribution is that they have been described here together in an interrelated way for a day-to-day route choice situation and that they were calibrated on experimental data.
- A day-to-day route choice model under traffic information based on the conceptual framework. State-of-the art discrete choice modelling is used to this end. The elements from the conceptual framework, like explicit learning, habit formation, traffic information, recency and salience effects, are represented.
- An innovative method for modelling travel time reliability. It is modelled in a way that relates the salience of an experienced travel time to the current expectation of travel time for a route. Furthermore, it is modelled differently for habitual routes than for non-habitual routes. Cognitive dissonance theory was used to explain the results.
- A method to estimate highly complex utility models involving many higher-order terms within a reasonable amount of time.

- Experimental knowledge about the significance and relative importance of the listed parts of the route choice model. As all parts prove to be significant, this can also be regarded as a validation of the conceptual paradigm. The values that are found for the recency effect are especially relevant, since little experimental and empirical knowledge exists on this point.
- Experimental knowledge about the type of reliability that is preferred (a usually fast but sometimes very slow route, or an on average slow but very reliable route, or an on average fast but highly fluctuating route).
- Experimental knowledge about the impact of en-route and ex-post traffic information on route choice behaviour.
- Knowledge on how to set up an enriched SP experiment. The various choices that were made in designing the experiment and the considerations regarding the consequences of these choices can be a practical aid for other researchers in setting up such an experiment.

#### **1.6.2** Practical relevance

The practical relevance pertains to the implications of the experimental knowledge on travellers' reactions to traffic information that has been acquired in this thesis. The implications are summarized here.

- It is good to provide en-route information. This thesis shows that it helps travellers in developing a more accurate long-term expectation and current estimate of travel time and results in travel time savings. It also increases the use of routes which are otherwise thought as too unreliable. Travel time savings are not only beneficial to individual travellers. It also means that total car hours are reduced, leading to less traffic and hence less damage to the environment.
- En-route traffic information has to be accurate. Otherwise unforeseeable reactions can occur which make it hard to manage and plan traffic.
- Travellers' perceptions of routes (and therefore route choices) can be influenced by expost traffic information. This insight can be used as one of the tools in dynamic traffic management. Perhaps this mechanism can also be used to increase use of public transport.
- Despite the above, one should acknowledge that it is hard to change habits. Habits can be strong and automatically determine behaviour. Furthermore, travellers are possibly much more forgiving for bad experiences on habitual routes than on non-habitual routes. When combined with the previous remark, one should make it very explicit in the ex-post information which routes are best. The traveller should be made aware of the bad characteristics of the habitual route.
- It is good to invest in increasing reliability of routes. Especially when the routes lead to important goals (like the airport) and / or no traffic information is available, travellers prefer reliable routes over slightly faster but less reliable routes.
- When measuring reliability, skewness should be incorporated. The nature of unreliability is important for travellers and their travel behaviour. Only looking at variance may therefore lead to wrong inferences regarding travel behaviour.

Finally, the route choice model can be used for dynamic traffic management purposes. It can be implemented into traffic simulation models, in order to improve the accuracy of the traffic simulation models and make them a more reliable decision support tool.

#### 1.7 Thesis outline

This thesis has a structure that can easiest be described as introducing – diverging – converging. The structure is shown in Figure 5 .

The first three chapters have an introductory character. In the present chapter the topic of this thesis was introduced, the scope was set and the research questions were formulated. Three important aspects of day-to-day route choice were identified: learning, traffic information and travel time reliability. Chapter 2 gives an integral framework of day-to-day route choice in which these three topics play an important role. Both the experiment that is carried out to answer the research questions and the mathematical model we use to analyze the outcomes of the experiment are based on this framework. Chapter 3 is dedicated to this mathematical model. It presents the complete model and relates it to the conceptual framework. In chapter 4 the collection of the data used to estimate the mathematical model is presented.

Chapters 5, 6 and 7 have a diverging character and focus each on one of the three mentioned topics respectively: travel time reliability, learning and traffic information. The chapters each have more or less the same structure:

- an overview of relevant literature on the subject,
- a synthesis section in which we analyze what is missing in the literature and what we will contribute to it,
- the presentation of the mathematical model part related to the current topic, including a discussion on why we chose to operationalize the subject in our model the way we did and
- an analysis of the results from the experiment.

At the end of chapter 7 the estimation results of the three parts of the mathematical model (so travel time reliability, learning and traffic information) are related to each other.

The literature review from these chapters has been used to improve the conceptual framework. As such chapter 2 can be regarded as a chapter in which only the most important results from the literature study from chapters 5, 6 and 7 are presented in an integral way. This is why the arrows in Figure 5 are two-directional. The same line of reasoning holds for chapter 3: the essential modelling choices from chapters 5, 6 and 7 are presented in an integral way in chapter 3.

Chapter 8, conclusions and recommendations, has a converging character. The research is summarized and the findings from chapters 5, 6 and 7 are listed. Based on these findings, conclusions are drawn. The implications of these conclusions for policy and practice are also discussed in this chapter. Finally, the chapter presents a reflection on the research and recommendations for future research.



Figure 5: Thesis structure

# 2 Conceptual framework of day-to-day route choice

In this chapter the conceptual framework is presented. Knowledge from traffic science, psychology, experimental economics and cognitive neuroscience is used to form an integrated view on the described day-to-day route choice situation. The framework will serve as a basis for the development of the route choice model presented in chapter 3. The estimation results of this model will be used to calibrate it and finally answer the research questions. More details on the specific purposes of the framework are provided in the first section of this chapter. After this section, the complete framework is discussed in general terms. This will help the reader understand the relations between all different elements, which are discussed separately in sections 2.3 through 2.6. Note that, as explained in section 1.7, these main elements are not discussed in detail in order to keep this chapter readable. More details and literature references are given in chapters 5, 6 and 7. We continue this chapter with a short note on some alternative conceptual frameworks and the reasons why we developed our own framework instead of using one of them. The chapter ends with conclusions.

#### 2.1 Purpose of the framework

The general purpose of the route choice framework is to give an overview of the route choice process that can serve as a guideline in route choice research in general and in this thesis. More specifically:

- the framework provides insight into the route choice process by relating results from previous studies as far as they affect route choice behaviour,
- the hypothesized elements and their relations served as a starting point for literature research and an improved version formed an important end result of our literature research as well,
- the framework supported the design of the experiment. As the framework increased our understanding of route choice, we were for example better able to decide what variables had to be present in the experiment,
- it formed a starting point for a mathematical route choice model, as it helped in deciding
  - what elements to include in the model,
  - how to include them in the model,

- what the effects could be if something from the framework is not put into the model,
- the framework helps the reader of this thesis to put everything correctly into place when reading the individual chapters,
- with some minor adjustments, the purpose and applications of the route choice framework can also be reached for *other* travel choices like departure time choice and mode choice. Refer to section 1.3.1 for an overview of travel choices.

#### 2.2 The framework at a glance

The conceptual framework of route choice is given in Figure 6. In this section we give a very brief introduction to the framework. Its elements are discussed further in the remainder of this chapter. Some of the elements form the focus of this thesis. To these elements we devote the chapters 5, 6 and 7.



#### Figure 6: Conceptual framework of route choice<sup>3</sup>

In the centre of the framework we find the box 'decision mechanism / habit'. This central place is not a coincidence, as this is where all inputs come together and are transformed into our dependent variable of interest: route choice. More specifically, depending on

<sup>&</sup>lt;sup>3</sup> With some adjustments, the route choice framework can also be used for *other travel choices* like departure time choice and mode choice and similarly for *other attributes* than travel time only.

- the preferences of the traveller (what type of road does he like, how reliable should a route be, etc.),
- his personal characteristics that do or do not allow him to make a 'good' choice (like motivation, ability and opportunity),
- the estimates of the travel times on the routes that he can choose from and
- emotions he holds regarding the (travel time reliability) of the alternative routes,

he decides what route to choose. Note that in case the traveller has a strong habit, this entire decision making process may be replaced by an automatic choice. The route choice affects the traffic situation and leads to outcomes like realized travel time, traffic jams, etc.

The estimates of the current travel times on all alternative routes are one of the inputs of the decision making process. The estimate is a combination of the en-route traffic information, which gives information on current traffic conditions on the routes, and the expected travel time, by which we mean a more or less long-term expectation that a traveller holds of the travel time on a route.

This expected travel time is the result of a learning process. The traveller can combine past experiences and past information to form an expectation of travel time. The recency of the experience (referring to how long ago it took place) and the salience of the experience (referring to how much it stands out from earlier experiences and expectations) influence how well it is remembered and hence how well it is used in this learning process. The same can be said about the recency and salience of past information.

Note that past information can have various meanings. It can be the en-route information of previous days, but it can also be ex-post information which gives the realized travel times on all routes of the previous days. So ex-post information can give information on foregone outcomes, meaning outcomes of non-chosen alternatives.

#### 2.3 Decision making and travel time reliability

Decision making, resulting in a route choice, lies in the centre of the conceptual framework. As many different types of decisions exist, which can involve different decision making processes, we start this section by giving the main characteristics of the decision type that we are interested in. The next sections (2.3.2 and 2.3.3) provide insights into decision mechanisms and the effect of uncertainty in decision making. Uncertainty plays a role in route choice due to (a lack of) travel time reliability. Section 2.3.4 presents the decision mechanism that we used in this thesis for modelling route choice. It further discusses the advantages and limitations of the followed approach in this thesis by relating the insights from sections 2.3.2 and 2.3.3 to the characteristics of route choices listed in 2.3.1. In the final section the role of decision making in the conceptual framework is discussed.

#### 2.3.1 Day-to-day route choice characteristics

Day-to-day route choice can be described as a decision which

- is discrete, this means that a traveller can only choose entire routes, as opposed to fractions of routes.,
- entails some degree of uncertainty as travel times can not be known for certain,
- is operational, Fastenmeier and Gstalter (2007) for example state in their driving task analysis (modified after (Rasmussen, 1986)) that navigation is one of the many operational tasks a driver has to perform,

- often has to be made under time pressure, especially in response to en-route traffic information, route choices have to be adapted while driving within a few seconds. In case of repetitive route choices, however, one can reflect afterwards without time pressure in order to improve future choices and
- offers opportunities for learning and habit development because of their repetitive nature.

#### 2.3.2 Decision mechanisms

Various decision mechanisms exist. The goal of this section is not to provide a complete overview, but to give an idea of how decision mechanisms can work and to introduce a mechanism that is used in this thesis. Payne et al. (1993) argue that people use a variety of strategies to make judgments and choices. The importance of making a good decision, time pressure and cognitive abilities all affect the choice for a decision strategy. A trade-off between accuracy and effort is made. We will provide two examples of decision mechanisms that are each others opposites in terms of accuracy and effort. Payne et al. (1993) provide a more complete overview.

The first example of a decision mechanism can be characterized as a high accuracy - high effort decision mechanism. It is called the *weighted additive rule*. The rule works as follows:

- Each choice alternative i has specific attribute values v
- Each attribute (i.e. decision criterion) has a certain weight
- The total value of the choice alternative is  $w_1v_1 + w_2v_2 + ... + w_nv_n$
- Choose the alternative with the highest value

Utility theory, which is used in the modelling part of this thesis, is based on this weighted additive rule. In utility theory the overall value of an alternative is called utility. The implicit requirements of this approach are that all attribute values are expressed in a ratio scale (additive and multiplicative) and that the decisions are controlled by the result that is obtained by the decision. In section 3.2 more information on (the mathematics behind) utility models is given.

The second example of a decision mechanism can be characterized as a low accuracy - low effort decision mechanism. Simon (1955) argues that people are bounded in their rationality. Applying the weighted additive rule, which requires a lot of mental effort and a rather long decision time, may be beyond their bounds. Alternatively, the *satisficing heuristic* (Simon, 1955) is a low accuracy – low effort decision strategy. This heuristic states that the first alternative that is evaluated that meets some minimum aspiration level is chosen. It is in line with the concept of bounded rationality, by the same author.

Rasmussen does not relate the choice of a decision strategy to desired levels of effort and accuracy, but to the degree of automation or experience with a decision that a person has (Rasmussen, 1982). In an article, which deals with human errors, he gives a classification of different types of human behaviours (leading to different types of errors). The classification is now known as the *Skill - Rule - Knowledge framework*. Skill-based behaviour refers to behaviours which are very frequently performed and are automated. They can be compared to habits. Rules are used for less frequently performed behaviours and can be of the form "if A happens then do B and if C happens then do D". General knowledge is used for completely new tasks as a person has no skills or rules for them (yet).

#### 2.3.3 Decision making under uncertainty / Reliability

In uncertain environments the value of choice alternatives is not known in advance. If a traveller has to choose between two routes, for example, he does not know the travel time on the routes with complete certainty. These uncertain attribute values can be replaced by the expected attribute values, as is done in expected utility theory.

Kahneman and Tversky (1979), however, found that people are not risk neutral. Uncertain alternatives should according to them *not* be described in terms of expected value, but in terms of a characteristic that they call the prospect value. Travellers have also been found to exhibit risk averse or risk seeking behaviour. Many studies showed that travellers are prepared to choose a reliable route over an unreliable route, even if the reliable route takes on average less time (Bates et al., 2001).

The underlying explanation for the found deviations from expected utility theory may be the negligence of the role of emotions in decision making. Bechara and Damasio (2004) point to this missing role of emotions in the way economists (and this applies also to most behavioural modellers in transportation) explain choice behaviour. They conclude with respect to decision making in uncertainty that

- knowledge and reasoning are not sufficient for making good decisions and that the role of emotions should be recognized,
- the process of rationally considering different options is slow, the decision behaviour is in practice much faster and apparently not fully conscious,
- emotions form a good mechanism in decision making when they are related to the task (and can be disruptive when they are not related),
- decision making under certain conditions and uncertain conditions involve different neural circuitry.

They base their opinion on well known cases of persons with brain damage who repeatedly make bad decisions in uncertain situations.

Section 5.1 presents an overview of research findings concerning risk behaviour in general and effects of travel time reliability on route choice behaviour.

#### 2.3.4 Approach in this thesis: advantages and limitations

In this thesis we use an adapted version of the expected utility rule for modelling route choice. In this section we relate the characteristics of expected utility to the characteristics of route choice in order to assess the advantages and limitations of our approach.

Expected utility theory is from a mathematical point of view well able to model discrete choices under uncertainty. Route choices are discrete choices under uncertainty (the first two characteristics in section 2.3.1). In fact, many mathematical formulations and software have been developed to estimate expected utility models. By estimating the models, one can gain insight into the statistical significance and the values of the various attributes in the decision, calculate elasticities, calculate ratio's, compare them across groups, try if different model specifications explain the choices better or worse, etc.. This mathematical argument represents an important advantage of using expected utility models.

Characteristics 3 and 4 of route choices (operational level and time pressure) are not completely in favour of using expected utility models. According to Payne et al. (1993) these characteristics would not require a high effort decision strategy as high accuracy is not needed. High effort is probably not even possible due to time pressure and bounded

rationality. For repetitive route choices one can argue that higher accuracy is welcome (as the consequences of the choice have to be suffered repeatedly) and that higher effort is partly possible, since one can reflect on the choice afterwards.

Characteristic 5 (repetitiveness) could in the long run lead to habitual or in Rasmussen's terms skill based behaviour. In that case, there is no decision making at all, since the decision is automatic. Finally, the role of emotions in decision making is neglected in utility models.

Because we are especially interested in this research in how recency and salience effects (with respect to both travel time experiences and travel time information) influence the updating of an expected travel time (learning), the mathematical advantages of expected utility models lead us to use this model type. In specifying the model we tried to minimize the effect of the potential drawbacks of expected utility models:

- By introducing salience into our model which makes it possible to give extra weight to very large travel times in updating the expected travel time we account for the fact that travellers are not risk neutral.
- By introducing a recency effect into our model we account for the fact that travellers do not remember all past experiences and information, a form of bounded rationality.
- By entering past choices into our model we account for the fact that habits can develop.

Concluding: the utility model we use is for us a means to an end, not an end on its own. If an attribute proves to be significant, we know that there is a statistical relation between the attribute and the modelled choice, i.e. the outcome of the choice process. We do not know if it is a causal relation and subsequently how the choice process works. If the end goal is to have a realistic model of the choice process, one would therefore need a different type of model based on a different type of experiment. The possible limitations of the model will be kept in mind when interpreting results and drawing conclusions.

#### 2.3.5 Role in the framework

The core of the conceptual framework is formed by the decision mechanism. This is where all inputs come together and are transformed into a route choice. One of the inputs is the traveller's estimate of the travel time (reliability) on a route. Other possible decision criteria include the route's scenery, number of gas stations along the route and road type. It depends on the traveller's preferences what criteria play a role in his route choice and how important each criterion is. It also depends on the traveller's cognitive abilities and the effort – accuracy trade off what type of decision mechanism is used. Emotions can influence the decision making process as well. Recent scientific research showed that while thinking about an alternative, various biological and neurological processes, simply referred to here as emotion, can influence the evaluation of the alternative (Shiv et al., 2005). Finally, the outcome of the decision mechanism constitutes the route choice.

Note that decision making process can be overruled by habitual behaviour, especially under conditions of cognitive load (Aarts and Dijksterhuis, 2000). More information on the development of habits and their effect on route choice behaviour is provided in section 6.1.

#### 2.4 Traffic information

Traffic information is one of the main topics of this thesis. The previous chapter gave a general introduction to the existing forms of traffic information. Two effects of traffic information were distinguished: a short-term and a long-term effect. The next section gives

some examples of these effects. It is followed by a discussion of the role of traffic information in the route choice framework we presented earlier.

#### 2.4.1 Short-term and long-term effect regarding travel time perceptions

We defined the short-term effect of traffic information to be the effect of traffic information on the traveller's current estimates. So if en-route information on a VMS tells a traveller that route A has a 10 minute delay and the traveller only expected 5 minutes delay, then the direct effect may be that the traveller increases his estimate of the current travel time on route A by 5 minutes.

Evidence that this short-term effect indeed occurs can be found among others in (Srinivasan and Mahmassani, 2003; Chatterjee and McDonald, 2004). The first two authors found in a simulator experiment that route switching behaviour was influenced by providing en-route information. The second two authors found in a survey that one-third of drivers regarded VMS information as useful in selecting a route for the rest of their journey and about half of the drivers found information useful even though they considered that there were no alternative route options.

The long-term effect of traffic information was defined to be the effect of traffic information on a traveller's long-term expectations. Even if a traveller does not choose route A from the previous example, he may use this information to adjust his overall expectation of the travel time on route A. Especially when he notices that route A often has long delays, he may increase his expectation. Ex-post information on non-chosen alternatives can also help a traveller to have a better overall expectation. An important difference with en-route information is that ex-post information is always correct, whereas en-route information provides estimates of travel times that will be encountered.

Although we encountered this long-term effect in some route choice models (Ben-Akiva et al., 1991; Jha et al., 1998), we did not find any empirical or experimental evidence in literature of its existence. This thesis will provide experimental evidence for this long-term effect. Note that there is experimental evidence for different long-term effects of traffic information. For example, if travellers learn in the long run that the provided information is unreliable, compliance with this information decreases (e.g. (Chen et al., 1999; Chen and Jovanis, 2003) Furthermore, compliance is increased if travellers learn from post-trip information that the provided advice turned out to be good (Chen et al., 1999).

#### 2.4.2 Other effects of traffic information

As this thesis focuses on the updating of travel times, the previous examples concerned travel time information and its effect on updating a traveller's expected travel time. Travel time information can also have another effect: it can increase a traveller's general knowledge of the traffic network and make him aware of the existence of alternative routes. In other words it can increase a traveller's subjective choice set. Choice set generation is outside the scope of this thesis. More information on choice set generation can be found in (Hoogendoorn-Lanser, 2005).

Various other types of traffic information are also not further studied in this thesis. For example information on road works and accidents. Obviously, things like these often have an effect on travel times as well.

#### 2.4.3 Role in the framework

Traffic information can be found in two places in the conceptual framework. These places represent the short-term and long-term effects from the previous section. The arrow from

'traffic information' (the box on top of the conceptual framework) to 'estimate current travel time' concerns the short-term effect of traffic information. Here, the current traffic information is combined with the longer term expectation to form an estimate of the current travel times. The long-term effect is represented by the box 'past information'. This can concern en-route traffic information on non-chosen routes, or ex-post information on nonchosen routes. In a learning process, the information is integrated with previous knowledge to form this new expectation. The expectation can concern both mean travel times and travel time reliability.

#### 2.5 Learning

Learning is besides traffic information and reliability an important topic in this thesis, because the repetitive nature of day-to-day route choice implies an opportunity for learning. Travellers can learn from travel experiences and from traffic information. Two types of learning can be distinguished: explicit learning and implicit learning. The first can lead to an expected travel time, whereas the second can ultimately lead to habit formation. The types will be discussed in the next sections. The role of learning in the conceptual framework is discussed next.

#### 2.5.1 Explicit learning

Explicit learning, also known as cognitive learning, concerns intentional learning, paying attention to the object. Through explicit learning people construct new knowledge and understanding based on what they already know and believe (e.g. (Cobb, 1994), (Piaget, 1977) and (Piaget, 1978)). Travellers can learn about many route characteristics. In this thesis, however, we concentrate on learning about a route's travel time and the reliability of this travel time. By explicit learning, we therefore mean the updating of the expected travel time by integrating newly obtained travel time knowledge (from experience or traffic information) with the current travel time expectation.

Memory is an important topic here, as learning from past experiences or information implies remembering them. At least two concepts have to be addressed here: recency and salience. Already in 1885 (Ebbinghaus) found that there was a (steep) exponential curve between time and memory, i.e. the more recent an event, the easier it can be remembered.

Salience relates to the extremeness of an event. Literature is not clear on how this salience effect could work. Familiarity is an important aspect in recognition memory (Mandler, 1980). Still, unfamiliar things, are sometimes remembered better (Gregg, 1976; Marmurek, 1984). As salience is related to familiarity, we think it may have an effect on memory strength. Alternatively, salient experiences may be easier to remember, because they draw attention. They may also provoke certain feelings that can bias the development of an expectation as well as a decision directly, as can be concluded from (Shiv et al., 2005).

Considering all, we hypothesize both salience and recency effects to influence the updating of the expected travel time (reliability).

#### 2.5.2 Implicit learning

Implicit learning comprises all kinds of learning where repetition of the relationship between stimulus and response patterns is stored in the neural system as memory (a mental representation) or automated behaviour. Two types are differentiated, classical conditioning and operant conditioning. Classical conditioning is typical for the situation when a stimulus is (immediately) followed by another stimulus or an event, often a positive token, which leads to a response. The classic example of this phenomenon is the Pavlov Reaction (Pavlov, 1927). Although Skinner became famous for operant conditioning, Thorndike described the basic principles of operant conditioning. Thorndike formulated the law of effect, saying that when a
response leads in a certain situation to a satisfying result, it is probable that in that situation this response will be given more often. And even if the result is not really satisfying, the mere exposure to it can increase a person's valuation of the response, solely because the person becomes familiar with it. This is known as the mere exposure effect (Zajonc, 1968). Reinforcement can ultimately lead to habitual behaviour implying automatic responses.

In our route choice situation, experiencing a relative short travel time should be regarded as positive reinforcement, whereas extremely long travel time is a case of negative reinforcement. Furthermore, repeatedly experiencing a route can produce a mere exposure effect. To conclude, choosing a route can, at least as long as it does not produce very bad outcomes, increase the perceived attractiveness of a route, bias further route choices and lead to habitual behaviour.

More insights from psychological learning theory, results from studies into learning in route choice situations and existing learning models are discussed in chapter 6.

## 2.5.3 Role in the framework

Learning is represented in the conceptual framework by the four boxes within the dashed line. Past experiences and information are input to the learning process, i.e. to the construction of the expected travel time. Both the recency and salience of the experience or information affect how well they are remembered. This memory strength affects the weight the experience or information has in constructing the expected travel time.

The salience of the experience or information can also trigger certain emotions. If a traveller experienced a very long travel time and consequently missed an important meeting, he may feel very frustrated, angry or stressed. These emotions can bias his expected travel time on that route. Following the somatic marker theory (Bechara and Damasio, 2004) as introduced in section 2.3.3, these emotions can also bias the decision mechanism directly by triggering similar negative emotions as soon as the route is considered.

Finally, past experiences can also lead to habits, which can overrule al other decision mechanisms. This is represented by a direct arrow between past experience and decision mechanism / habits.

Not all travellers have the same learning capacities. Therefore, their characteristics are also input to the learning process. The impact of traveller characteristics on learning and other processes form the topic of the next section.

## **2.6** Traveller characteristics

In the route choice framework, the traveller is the one who makes the choice. As not all travellers are the same, this section concentrates on the characteristics of travellers that can influence route choice. Two models are discussed that shed some light on how traveller characteristics may influence route choice behaviour: Ajzen's Theory of Planned Behaviour and the Triade model.

## 2.6.1 Theory of planned behaviour

Looking at route choice as behaviour, we can apply Ajzen's Theory of Planned Behaviour (Ajzen, 1985; Ajzen, 1991). The theory states that behaviour is the result of

- the attitude towards the behaviour, i.e. the degree to which performance of the behaviour is positively or negatively valued,
- a subjective norm regarding the behaviour, i.e. an evaluation of opinions from others about the desirability of the behaviour and

• perceived control of the behaviour, which refers to people's perceptions of their ability to perform a given behaviour.



Figure 7: Theory of Planned Behaviour (Ajzen, 1985; Ajzen, 1991)

In the route choice situation this means that if a traveller has a negative attitude towards highways, he will probably not choose a highway route. Aarts adapts the Theory of Planned Behaviour by adding 'habit', which can overrule intentions (Aarts and Dijksterhuis, 2000).

## 2.6.2 Triade model

The Triade model (Poiesz, 1999) can also be applied to predict (route choice) behaviour. It says that a specific behaviour can be predicted by looking at three factors:

- Motivation, the extent in which a person is interested in (the result of) the specific behaviour
- Capacity, the extent in which the person possesses the needed characteristics, power, skills and tools to perform the behaviour
- Opportunity, the extent in which time and circumstances enable the behaviour to occur.

An example of a factor that influences a traveller's motivation to make a good route choice is trip purpose. Arriving on time at the airport to catch a flight is probably more important than arriving on time at home for dinner. An example of the ability to make a good route choice is a traveller's intelligence. Finally, an example of opportunity is the available time. This can be an important factor as choices that are made en-route (that is, while driving) sometimes have to be made within a few seconds. The term *heterogeneity* is often used to describe the fact that these traveller characteristics can vary between travellers. More on heterogeneity can be found in (Srinivasan and Mahmassani, 2003).

The Triade model and the Theory of Planned Behaviour have some commonalities. Perceived behavioural control can be regarded as a combination of capacity and opportunity; attitude and subjective norm are comparable to motivation. We chose to use the terms of the Triade model in our framework because of their simplicity and ease of understanding.

### 2.6.3 Role in the framework

Traveller characteristics influence all processes from the conceptual framework that are performed by the traveller. Learning an expected travel time from travel experiences and traffic information is one of these processes. It is for example influenced by a traveller's learning abilities (intelligence, memory), his motivation to develop a good estimate (does he have to make the choice and suffer the consequences very often?) and the opportunity to learn. This opportunity can for example be enlarged by providing the traveller with ex-post information on all routes. A traveller's abilities, motivation and opportunity influence in a similar manner the way he combines traffic information with his expected travel time to form an estimate of the current travel time. The decision mechanism a traveller chooses is also dependent on his characteristics. A traveller, for example, cannot use a mechanism that is too complicated for him.

## 2.7 Alternative route choice frameworks

In this chapter we have presented a conceptual framework of day-to-day route choice under traffic information. Although alternative frameworks exist in literature, we chose to develop this new framework. The existing frameworks we found had a different focus and / or were not tested on any data and / or were not sufficiently comprehensive for the purpose of this study. An example of an alternative route choice scheme is the one by Bovy and Stern (1990). It decomposes the choice process into a relatively large number of steps. It provides a way of thinking about choice processes and defines a number of concepts. The authors, however, do not present evidence that the decision process indeed takes place the way they have presented it. Furthermore, the topic of learning, which is very important in this thesis, is not given much attention in their framework. This last remark also applies to the framework of (Chang and Mahmassani (1989). The model of Van Berkum and Van der Mede (1993) does give much attention to the topic of learning, but fails to include the traveller. Finally, the framework of Chorus et al. (2006) focuses on the decision to acquire information.

### 2.8 Conclusion

This chapter presented a conceptual framework of day-to-day route choice under traffic information integrating notions from traffic science, psychology (especially about various types of learning), neuroscience (about the role of emotions in decision making) and experimental economics (about risk behaviour). Some of these insights from other sciences, such as risk avoiding behaviour and recency effects in learning, have been used already in traffic science. The contribution is that they have been described here together in an interrelated way for a day-to-day route choice situation and that the framework is (partly) calibrated on experimental data.

The next chapter will show how we use the framework to develop a mathematical model. The estimation of this model and the interpretation of its results - which can be regarded as calibration of the conceptual framework - are discussed in chapters 5, 6 and 7.

# **3** Day-to-day route choice model

This chapter presents the day-to-day route choice model under traffic information. It is a utility model, meaning that the characteristics of a route are transformed into one overall value which is called utility. The route's utility expresses its attractiveness and determines the probability that the route is chosen. The model is based on the conceptual framework that was presented in the previous chapter. How the framework is 'translated' to the model is the topic of the first section. In the next section a basic introduction to utility theory and the main advantages and limitations of utility models. The elements from the model are discussed separately in the following sections. In these sections we concentrate on explaining the reasons why we modelled these elements as we did. Other existing ways to model them will be discussed in more detail in chapters 5, 6 and 7. The chapter ends with conclusions.

## **3.1** From conceptual framework to route choice model

In this section we first relate the mathematical model that is presented in this chapter to the elements from the conceptual framework that was presented in the previous chapter. When translating these elements from the conceptual framework to the mathematical model a number of assumptions and hypotheses were made. These are stated in the next section. finally, in section 3.1.3 a brief overview of the mathematical model is presented next.

## **3.1.1** Elements in the mathematical model

The conceptual framework comprises a number of elements that influence day-to-day route choice. In this section, we discuss the elements that are also included in the mathematical day-to-day route choice model: learning, reliability, traffic information and traveller characteristics.

## Learning: updating expected travel time and the role of habits

Two types of learning were distinguished in the conceptual framework: explicit and implicit learning. The first type of learning leads a traveller to have an expectation of travel time, which we refer to as his expected travel time. Our formulation of the expected travel time also takes into account travel time reliability. Implicit learning leads to a favouring of routes that have often been chosen in the past and can ultimately lead to habits. Therefore, both expected travel time and past choice behaviour are included in our model.

### Reliability

As was explained in sections 1.5.3 and 2.3.3, travel time reliability influences choice behaviour in a number of ways. First, some travellers prefer reliable routes even if they take longer on average. Second, salient travel times may be remembered differently which influences the updating of expected travel time (learning). Third, decision making under uncertainty can trigger emotions, as explained in the somatic marker theory (Bechara and Damasio, 2004). For these reasons it is important that travel time reliability is included in our route choice model. The model takes reliability into account by giving specific weights to salient travel times in updating a traveller's expected travel time.

### Traffic information

The direct effect of en-route traffic information helps travellers to improve their estimate of the current travel time. This effect is included in the model. The indirect effect helps travellers to improve their overall understanding of travel time distributions. We included the indirect effect of en-route traffic information with respect to updating a traveller's expected travel time. Indirect effects of ex-post information are not included as we did not design the model to analyze route choice under provision of ex-post information.

### Traveller characteristics

The motivation, ability and opportunity that travellers have to make a route choice all influence the outcomes of the choice. In the model, we only took a road type specific preference into account. The model, however, can be adapted to accommodate other traveller characteristics.

### Not included: Decision mechanism and traffic situation

The decision making mechanism is not included in the model. Rather, a mechanism is assumed beforehand: the expected utility rule / weighted additive rule. The advantages and limitations of this approach are discussed in sections 3.2.3 and 3.2.4.

The traffic situation is part of the conceptual framework as well. It is, however, outside the scope of this research and therefore not included in the route choice model.

### 3.1.2 Assumptions and hypotheses

The conceptual framework gives insight into how day-to-day route choice works. It explains what elements play a role and what relations exist between them. In order to build a mathematical model we have to be very precise about the exact nature of these relations. To this end, we need to make a number of assumptions and formulate some hypotheses. The reasons why we made these particular assumptions and hypotheses are given in the remainder of this chapter and in the chapters 5, 6 and 7 for the topics reliability, learning and traffic information respectively. The assumptions and hypotheses are presented here in relation to the elements in the model: explicit learning, reliability, implicit learning and traffic information. The first assumption, however, concerns a general one that affects the entire model.

### General

G1) Travellers can be modelled as utility optimizers.

### Explicit learning

EL1) The updating process of the expected travel time can be used as a proxy for explicit learning.

EL2) Travellers determine the expected travel time on a route by updating the current expected travel time with the newly experienced travel time. (In case the route was chosen.)

EL3) Travellers determine the expected travel time on a route by updating the current expected travel time with the newly received en-route travel time information. (In case the route was not chosen, but en-route traffic information was received for that route.)

EL4) The weight of a travel time in updating the expected travel time depends on the salience of this travel time and on the recency effect. If the recency effect is large the weight of the newly experienced / informed travel time will be large and the weight of the previous expected travel time will be low. If the recency effect is small, the opposite applies.

### Reliability

R1) There is a clear relation between salience and reliability. Large fluctuations can lead to salient travel times, which lead to less reliability.

R2) The weight of a travel time in updating the expected travel time depends among others on the salience of this travel time.

R3) Salience of a travel time can be modelled by the ratio of that travel time to the expected travel time.

R4) A very large travel time on a habitual route has a different, probably less negative, impact on a traveller's expected route travel time than a very large travel time on a non-habitual route.

### Implicit learning

IL1) The share of choices for a certain route during the past N days can be used as a proxy for implicit learning.

IL2) If the number of N is limited to 9, we do not need to account for any decay of past choices.

### Traffic information

TI1) En-route traffic information is used to improve the estimate of the current travel time (direct effect).

TI2) En-route traffic information is used to improve the expected travel time of a route that was not chosen (indirect effect).

### 3.1.3 Overall route choice model

The purpose of this section is to give a brief overview of the route choice model that is used in this thesis. Details on how utility models work in general, why we chose the individual components to be included in the model, why we modelled them the way we did and what mathematical implications this has are given later in this chapter and in chapters 5 through 7.

The route choice model that is developed in this thesis can be classified as a mixed logit model for panel data. The characteristics of this model type are given in 3.2.2. The model applies to the following situation:

- Repeated (day-to-day) route choices, i.e. a traveller can choose several times between the same routes. This is often the case for trips to work, trips to the gym, etc.
- En-route information concerning the predicted travel times on the routes.

By omitting the information variables, the model can also be applied to repeated route choices without any traffic information. The model is visualized in

Figure 8 and formalized in (3.1).



## Figure 8: Visualization of utility model

 $U_{\text{int}} = RoadType_n + \beta_{Info}TTInfo_{it} + \beta_{ETT}ETT_{\text{int}} + \beta_{choice_i}ChoiceFraction_i + \varepsilon$ (3.1)

Reading from left to right, we find the following components (the elements from the conceptual model that they relate to are given in brackets):

- The overall utility / value of a certain route for a certain traveller on a certain day,
- A road specific preference representing the fact that some travellers have an intrinsic preference for a route regardless of the values of other attributes *(traveller characteristics)*
- Traffic information as displayed on a variable message sign (en-route traffic information)
- Expected travel time (*explicit learning, reliability*)
- A habit / inertia component which reflects reinforcement of chosen alternatives (*implicit learning*)
- An error term containing everything that is not explained by the previous elements.

More details are provided in Table 1. In the remainder of this chapter the elements are discussed in more depth and terms from the table that may not be clear at this point (like 'Gumbel i.i.d.', or 'panel data') will be clarified.

Symbol	Definition	Explanation
U	Utility	Overall value of the route
i	Route index	Route 'name' (1, 2 or 3)
n	Traveller index	Unique number to define each traveller
t	Time index	Day number (1 to 40)
RoadType	Alternative (road type) specific	Gives the distribution of travellers' intrinsic
	constant ~ N( $\mu$ , $\sigma$ ) ; $\mu$ and $\sigma$ to be	preferences for a certain road type
	estimated	(accommodates panel data).
βInfo	Travel time information	Gives weight of travel time information in the
	parameter	total utility.
TTInfo	Travel time as displayed on VMS	Variable containing the travel time information
		in minutes on VMS.
βΕΤΤ	Expected travel time parameter	Gives weight of expected travel time in the
		total utility.
ETT	Expected travel time	Variable containing the travel time information
	_	in minutes on VMS.
βchoice	Inertia / habit parameter	Gives weight of inertia / habit in the total
		utility.
ChoiceFraction	Fraction of choices for a specific	Variable containing the fraction of choices for
	route over the past 9 days	a specific route over the past 9 days.
3	Error term ~ Gumbel i.i.d.	Random component

### Table 1: Elements in the utility model

## 3.2 Utility modelling

The route choice model in this thesis is a utility model, more specifically a mixed logit model for panel data. This section provides the basic concepts of utility theory in general followed by a discussion of the mixed logit model type. Limitations of utility models are discussed in the final subsection.

## 3.2.1 Basics of utility theory

Only the very basics of random utility theory are discussed here. More in-depth discussion and derivations can be found in among others (Ben-Akiva and Lerman, 1985) and (Hensher et al., 2005). Random utility models are based on the weighted average decision mechanism (refer to section 2.3). Utility is the numeric characteristic of a decision alternative that represents its value. It is made up by a systematic part and a random part. The systematic part is specified by the analyst. If the analyst thinks that a route's utility consists of the route's travel time and travel costs, the systematic utility of route i would be

$$V_i = \beta_1 TravelTime_i + \beta_2 TravelCost_i$$
(3.2)

The  $\beta$  values reflect the relative weight of travel time and travel cost. The analyst, however, can acknowledge that this may not be the route's 'true' utility. There may have been unobserved attributes (for example travel comfort), errors in the measurement of the observed attribute values, or unobserved variations in taste among the decision makers. To accommodate the fact that this systematic utility may not be correct, the analyst can add a random component, also referred to as disturbance or error. Then the random utility of route i is:

$$U_i = \beta_1 TravelTime_i + \beta_2 TravelCost_i + \varepsilon_i$$
(3.3)

The probability that route i is chosen from the subjective choice set  $C_n$  can easily be derived from (3.3) when we assume the errors for all routes to be independent and identically Gumbel distributed:

$$P_{n}(i) = \frac{e^{V_{in}}}{\sum_{j \in C_{n}} e^{V_{jn}}}$$
(3.4)

This formula is known as the *multinomial logit model (MNL)*. From choice data, specifying choices and the values of the attributes belonging to these choices, the  $\beta$  values and their statistical significance can be estimated using maximum likelihood estimation. The overall performance of the model is then expressed in terms of the log-likelihood or rho-square.

Finally, note that the attribute values are not always known in advance with certainty. In route choices for example, the exact travel time a traveller will encounter is often uncertain. In this case, we talk about decision making under uncertainty. Instead of applying utility theory, expected utility theory can then be applied. *Expected utility theory* uses the expected attribute values. That is, the travel time from formulation (3.2) would be replaced by the mean travel time. If travel cost is uncertain as well, this would be replaced by the mean travel cost. Refer also to section 2.3.3 and chapter 4 for a discussion of decision making under uncertainty.

### 3.2.2 Mixed logit models

The MNL model is only one of many logit model types. Since it assumes the error terms to be independent and identically distributed (i.i.d. assumption), it is not the ideal type for our route choice model. We will explain this now. The route choice model that is used in this thesis deals with day-to-day route choice, meaning that one individual makes several choices. The term that is used to describe data that contain several choice observations per individual is panel data. The choice that an individual makes on a given day can be related to the choice that he makes on another day due to persisting personal preferences. If these preferences are not completely incorporated in the systematic part of the utility specification, they will reside in the error term. The error terms are then related, violating the i.i.d. assumption which leads to statistical problems.

The mixed logit model for panel data is in our case a more suitable model type and is therefore used in this thesis. This model type differs from MNL models in that the  $\beta$ parameters are specified to follow a specified probability distribution, instead of having only one value. Furthermore, it is possible to specify the  $\beta$  parameters to vary across individuals, but to be constant per individual. Instead of estimating the  $\beta$  value, the parameters of the probability distribution have to be estimated. Besides the fact that it helps to prevent statistical problems like correlation, an advantage of this type of model is that it can accommodate taste variations. For example, a very busy and rich person may have a less negative  $\beta$ 2 in equation (3.3) than an unemployed person. In sum, compared to normal MNL models, a mixed logit model for panel data is in our case a more realistic way of modelling and helps to prevent statistical problems like correlation.

### 3.2.3 Limitations of utility models

Utility models have a number of limitations. We will discuss some of them here, without having the intention of being complete. One reason why utility models may be unrealistic relate to the remarks from section 2.3.4. As discussed there, the decision mechanism implied

by utility models may cost too much effort of the traveller, especially for less important decisions like route choice. In case of travel habit, the route choice is even completely automatic and no effort at all is spent on it. Furthermore, feelings can influence the evaluation of a route. This can be very hard to capture in a utility model in a systematic and comprehensive way. Of course, the error term can be seen as a representation of emotional factors in decision making, but it does not cover its systematic effects.

Another limitation concerns the compensatory nature of utility models, meaning that a 'bad' value of an attribute can be compensated by a 'good' value of one or more other attributes. This may not reflect reality, as decision makers can sometimes have a minimum aspiration level for an attribute. If the attribute doesn't meet this aspiration level, the decision maker may not consider the subsequent alternative anymore. An example is safety. If 50% of the flights of an airline end in a crash, the airline may not be considered as an alternative anymore; ticket prices can no longer compensate for the bad safety.

Note that these theoretical limitations can be circumvented practically. To give two examples: 1 Non-linear transformations of the attribute values can be used to make sure that some attribute values can practically not be compensated by other attribute values.

2 A penalty to make a different choice today than yesterday can express habitual behaviour.

### 3.2.4 Advantages of utility models

We want to mention four advantages of utility models here. First of all, the statistical significance of the beta parameters says something about the decision criteria of the travellers. If, for example in formula (3.3)  $\beta_1$  is found to be significant, this can be regarded as an indication that route choice decisions are influenced by travel time.

Second, the values of the beta parameters teach us something about the relative weight of the variables in the decision. The beta values from formula (3.3) for example can tell us how travel time is valued compared to travel cost.

Third, the performance of different models (in terms of the log-likelihood or rho-square value) tells something about which model explains the observed behaviour best. Suppose that in formula (3.3) travel time is raised to the power of two and that the resulting model outperforms the original formulation. This would indicate that travellers do not judge travel time linearly, but instead place relatively more weight on very large travel times. As such, the comparison of different models gives insight in the way travellers give value to attributes of the choices.

Finally utility theory is highly developed: numerous model types have been specified and documented, special software is available (sometimes even for free like the Biogeme package (Bierlaire, 2003)), courses are taught, etcetera. This makes utility models very practical for a researcher to use.

### 3.2.5 Conclusion

Random utility models have some important advantages and can help us to analyse and better understand route choice behaviour. Therefore, we chose to use them for our analysis. In specifying the utility function we will try to prevent possible drawbacks from occurring. However, as with all models, they simplify reality and for the estimation of the parameters some important assumptions have to be made about the character of the errors. When interpreting the results, their limitations and the implications of these limitations should be kept in mind.

# 3.3 Reliability

Travel times on routes usually fluctuate. This can be due to weather conditions, accidents, events, road works, behaviour of the travellers on the routes, etc. Reliability refers to the degree of fluctuation. If a route has always more or less the same travel time we call it very reliable; if a route always has completely different travel times we call it very unreliable. Obviously, there is a large domain between these two situations. In this thesis the term 'salience' is used in relation with reliability. Something is salient if it somehow stands out. If the travel time on a route is much longer on a certain day than expected, we call it salient. In other words, a large fluctuation can lead to a salient (long) travel time, which also indicates less reliability.

## 3.3.1 Existing reliability measures

In order to capture 'reliability' in our route choice model, we somehow have to operationalize the concept. There is no consensus, however, on what measure expresses reliability best. Van Berkum and Van der Mede (1993) use the standard deviation of the travel time in their route choice model. On the other hand, Lam and Small (2001) found in their study that reliability was best represented by the difference between the 90th percentile and its median instead of the standard deviation. Van Lint and Van Zuylen (2005) argue that besides the width of the travel time distribution, also skew (a measure for the asymmetry of the travel time distribution) must be considered a key indicator.

In deciding what measure for reliability to use in the route choice model, we also have to consider the relation between the mean travel time and its reliability. Both travel time characteristics have to be incorporated in the model, as they both influence route choice. They are highly correlated, though, as an extremely high travel time increases for example both the mean and the standard deviation of travel time. It becomes very difficult to estimate a model with such highly correlated variables.

## 3.3.2 Reliability in our route choice model: chosen approach

In the previous section two issues were mentioned that have to be dealt with when incorporating reliability into our model (namely what reliability measure to use and how to deal with correlation between mean and reliability measure). There is also a third issue: the mentioned reliability measures can hardly be calculated for our experimental data. Especially in the beginning of the experiment a traveller only has a few experiences for each route. After 15 days, for example, a traveller has at most<sup>4</sup> 5 experiences per route.

The formulation we propose, offers a solution for these three problems. It integrates the salience of a travel time (which is closely related to reliability) into the expected travel time. This is in line with psychological learning theories that state that not only the recency of an event but also its salience influence how well it is remembered.

The question then remains whether extremely high travel times should have a relatively high impact on the expected travel time, or a relatively low impact. Arentze and Timmermans (2003) suggest that the larger the deviation of a new event from the current expectation, the smaller the impact should be. However, if the deviation is very large and thus the event is very salient and remembered better, one could also argue that the impact should be larger.

Possibly, the answer to this question also depends on the habitual route of the traveller. Cognitive dissonance can arise when behaviour and cognition are dissonant (Festinger, 1957).

<sup>&</sup>lt;sup>4</sup> Only if a traveller has chosen each route exactly 5 times, he has 5 experiences for each route.

This can occur when the outcome of a person's behaviour is negative and the person is aware of this. An example is the habit of smoking cigarettes. Smokers usually know about the negative health consequences of this habit. In order to solve the cognitive dissonance, they can either change their behaviour, or change their cognition. An example of the first solution is to quit smoking; an example of the second solution is to tell themselves that the health risk cannot be too large, because their grand parents smoked and lived to be 90 years old.

Returning to the route choice situation, this line of reasoning leads us to the following hypothesis: a very large travel time on a habitual route has a different, probably less negative, impact on a traveller's expected route travel time than a very large travel time on a non-habitual route.

### 3.3.3 Reliability in our route choice model: used formulation

Before listing the formula's we developed, we have to make one critical remark: the proposed formulations are not the only possible formulations. They serve as a starting point to assess the potential of this research direction. And as this thesis will show, there is potential in this research direction.

Salience was defined as the degree to which something stands out. The word 'degree' implies that it is a relative term. To determine the salience of a travel time, we can therefore look at the relative deviation of the travel time from the current expected travel time. As our formulation serves as a starting point, we chose the simplest formulation that expresses this relative deviation:

$$s(TT_{\rm int}) = \frac{TT_{\rm int}}{ETT_{\rm int}}$$
(3.5)

With

s salience TT travel time ETT expected travel time i route index n traveller index t time index

The weight of an experienced travel time, used in modelling the new expected travel time, is dependent on both the recency effect and the salience. In this case, we also chose the simplest formulation we could think of. For non-habitual routes the weight can then become

$$w(TT_{int}) = s(TT_{int})r(TT_{int})$$
(3.6)

With

- w overall weight of an experience in updating the expected travel time, lies between 0 and 1
- r recency effect, impact of a new experience relative to the previous expected travel time, lies between 0 and 1
- s salience effect, a factor that gives extra or less weight to the new experience

This formulation is a way to give very large travel times a higher weight, as is hypothesized to be the case for non-habitual routes. For habitual routes, the opposite applies and the formulation becomes:

$$w(TT_{\rm int}) = \frac{1}{s(TT_{\rm int})} r(TT_{\rm int})$$
(3.7)

The weight needs to be in between 0 and 1, due to the way it is used in computing the expected travel time (this is explained further in the next section). Therefore, we add the following restriction:

if weight > 1 weight = 1; elseif weight < 0 weight = 0;

## 3.4 Learning

In the previous chapter two types of learning relevant in route choice situations were discerned: explicit and implicit learning. Therefore, the route choice model has to accommodate both types of learning. This section describes how this is done in our route choice model.

### 3.4.1 Explicit learning

### Chosen model type

Section 2.5.1 explains what is meant by explicit learning, also known as cognitive learning. It says that through explicit learning people construct new knowledge and understanding based on what they already know and believe (e.g. (Cobb, 1994), (Piaget, 1977) and (Piaget, 1978)). Constructing new knowledge based on existing knowledge and beliefs is analogous to the term 'updating' which is commonly used in travel behaviour research. Although travellers can learn explicitly about many different route characteristics, we concentrate in this thesis on explicit learning with respect to travel time, which results in a traveller's expectation of a route's travel time.

Several mathematical formulations have been developed to model the construction of an estimate of the travel time and the updating of it based on experienced travel times. These will be discussed in chapter 6. The conclusion of the discussion there is that experimental underpinning of the models is a highly neglected yet important task. Therefore, it is not possible to say what type of model best describes behaviour. We can only judge the models on for example how well they are in line with psychological learning theory on the one hand and how practical (in terms of number of parameters to be estimated and ease of interpretation) they are on the other hand.

An overview of how the various models perform on these two criteria is provided in 6.1.2. Here we only present its conclusion: a Markov process model representation, which represents an expectation as a convex combination of an earlier expectation with newly acquired information, is in our view the most appropriate type of model for three reasons. First of all it is in line with psychological research into memory decay in which an exponential curve was found. Second, it is in line with the contemporary view of learning which regards learning as integrating new information with existing knowledge. Third, it is

simple. It needs only few parameters, which facilitates both estimation of the model and interpretation of the estimation results. Although this last characteristic may not make a model good, it is very practical.

A general formulation of a Markov process model is given in equation (3.8):

$$Xi+1 = (1-\varphi)Xi + \varphi Y$$
(3.8)

In this formulation the variable X is updated using variable Y. The weight that Y has in this updating is given by  $\varphi$ . The value of  $\varphi$  lies between zero (Y has no weight and no updating takes place: X remains unchanged) and one (Y determines the new X completely). The subscript i is used as index.

#### **Used formulation**

Through explicit learning, the traveller develops an overall expectation of the travel time on a route. More specifically, we define the expectation individual *n* has of the travel time on route *i* at day *t* before receiving en-route travel information as  $ETT_{int}$ . Similarly, the expectation he had at the previous time interval (yesterday) is defined as  $ETT_{in(t-1)}$ . If he experienced a travel time on route *i* at the previous time interval,  $\delta_{in(t-1)} = 1$ , else  $\delta_{in(t-1)} = 0$ .

We assume the traveller to use his experience (instead of the provided en-route traffic information) for updating his expected travel time in case he chose a route. The reason for this assumption is that an experience is more intense and more reliable than information. In case he did not choose the route we assume the traveller to use the en-route traffic information.

As was explained in section 3.3 the salience of an experience is integrated in the formulation for the expected travel time. The following formulation for t > 1 results:

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTT_{in(t-1)}$$
 if  $\delta_{in(t-1)} = 1$  (3.9)

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTTInfo_{in(t-1)}$$
 if  $\delta_{in(t-1)} = 0$  (3.10)

With TT: true travel time TTInfo: travel time as given by the en-route info w: weight, as defined in (3.6) and (3.7)

The weight w can be regarded as the share of an experienced or informed travel time in deriving the expected travel time and can therefore be at least 0 (no influence) and at most 1 (completely determines new expected travel time). This is why we added the restriction that w needs to be between 0 and 1.

Note that formulations (3.5) through (3.7) are used both for experienced travel times (in case the route was chosen) and for informed travel times (in case the route was not chosen). Obviously, in the first case the experienced travel time has to be entered in (3.5) through (3.7) and in the second case the informed travel time.

The recency effect is captured in the model as follows:

•  $\lambda$  gives the weight of the most recent experienced travel time, it lies between 0 and 1

•  $\alpha$  gives the weight of the most recent informed travel time, it lies between 0 and 1 To be perfectly clear, the resulting formulations are given in (3.11) through (3.14).

$$w(TT_{int}) = \frac{TT_{int}}{ETT_{int}} \lambda TT_{int} \qquad \text{if } \delta in(t-1) = 1 \cap \text{chosen route} \neq \text{habitual route} \quad (3.11)$$

$$w(TT_{int}) = \frac{ETT_{int}}{TT_{int}} \lambda TT_{int} \qquad \text{if } \delta in(t-1) = 1 \cap \text{chosen route} = \text{habitual route} \quad (3.12)$$

$$w(TTInfo_{int}) = \frac{TTInfo_{int}}{ETT_{int}} \alpha TTInfo_{int} \qquad \text{if } \delta in(t-1) = 0 \cap \text{chosen route} \neq \text{habitual route} \quad (3.13)$$

$$w(TTInfo_{int}) = \frac{ETT_{int}}{TTInfo_{int}} \alpha TTInfo_{int} \qquad \text{if } \delta in(t-1) = 0 \cap \text{chosen route} = \text{habitual route} \quad (3.14)$$

The expected travel time appears in the route choice model as follows:

$$\beta_{ETT} ETT_{int}$$
 (3.15)

The parameters  $\beta_{ETT}$ ,  $\alpha$  and  $\lambda$  will be estimated from the data.

### 3.4.2 Implicit learning

Remember that implicit learning comprises all kinds of learning where repetition of the relationship between stimulus and response patterns is stored in the neural system as memory (a mental representation) or automated behaviour. Thorndike formulated the law of effect, saying that when a response leads in a certain situation to a satisfying result, it is probable that in that situation this response will be given more often. And even if the result is not really satisfying, the mere exposure to it can increase a person's valuation of the response, solely because the person becomes familiar with it. This is known as the mere exposure effect (Zajonc, 1968). Reinforcement can ultimately lead to habitual behaviour implying automatic responses.

In this way, past choices for a certain route can –probably apart from very negative experiences resulting from them- positively influence future choices for this route and even make it the habitual route. So, somehow, we want to integrate past choices into our route choice model. As far as we know, there are not many route choice models that take past choices in this way into account. Van Berkum and Van der Mede are an exception. Their approach and the difference with our approach is discussed in section 6.1.2. This section also presents some studies that take into account only one past choice. Most existing models, however, use past choices only for updating expected travel times, which we labelled and modelled as explicit learning. Of course, a very low travel time can be regarded as a satisfying result and as such can lead to implicit learning as well. We come back to this issue in the next section. First we describe how we integrated past choices in our route choice model.

One way is to enter the past choices into the model. When limiting the number of past choices to nine, an attribute expressing past choices for route i would result in:

$$\sum_{x=1}^{\min(9,t-x+1)} \beta_{choice_{i(t-x)}} \delta_{in(t-x)}$$
(3.16)

The drawback of this method is that it results in nine  $\beta$ 's for each route that have to be estimated. This makes the model difficult to estimate and makes interpretation of the results complex. Therefore, we decided to look at the fraction of choices for a certain route over the past nine choices, leading to the following formulation:

$$ChoiceFraction_{i} = \left(\frac{\sum_{x=1}^{\min(9,t-1)} \delta_{in(t-x)}}{\min(9,t-1)}\right)$$
(3.17)

This appears in the route choice model as

$$\beta_{choice_i} ChoiceFraction_i$$
 (3.18)

For more information on why we chose to use nine past choices and why we did not use any decay function to give recent choices more weight than older choices, refer to section 6.3.3

#### 3.4.3 A critical reflection of explicit and implicit learning models

Here we want to reflect on the proposed formulations for explicit and implicit learning. One point of attention has already been mentioned briefly. This concerns the fact that past choices that resulted in short travel times can have a positive impact both on the expected travel time (explicit learning formulation) and on the implicit learning formulation. As such, it is 'counted double' and could make it harder to separate the effects of implicit and explicit learning. However, we believe that it is impossible to make a model that perfectly separates the two learning types, as these learning mechanisms can coincide in reality as well: Positive rewards can both improve the way a person thinks about something (influencing cognition, explicit learning) and the way a person feels about something (implicit learning, possibly unconscious). And even if the mathematical formulations perfectly separated the two, it would be very hard to obtain valid data to estimate the model. The researcher can not know what a person feels and learned unconsciously and by asking about this the researcher would influence the person. Finally, note that many route choice models contain attributes that are related to each other. Examples include a model containing both travel time and travel distance, or a model containing both travel cost and travel distance.

A second remark concerns the fact that formulation (3.17) uses *all* past choices, irrespective of the desirability of the outcome. Due to the mere exposure effect in principle all past choices could increase a traveller's valuation of a route, but is questionable whether this is true for extremely negative past choices. Still, the formulation allows negative values for  $\beta$ , so if travellers do not like a certain route, this can be accommodated. If somehow the researcher can design an experiment in which he knows how a traveller feels about the result of a choice (without influencing him), a more complex, individual based implicit learning formulation would be worth exploring. However, this was beyond the scope of this research.

Finally, formulation (3.17) uses lagged dependent variables. This can lead to endogeneity issues which are discussed in appendix A.

# **3.5** Traffic information

The developed route choice model consists of a number of attributes. One of them is the provided en-route information. A short-term and a long-term effect of traffic information were discerned in the previous chapter. They are also present in Figure 8, the visualization of the route choice model. The short-term effect, meaning the direct effect of en-route information on the current route choice, is entered in the model rather straightforwardly. The used formulation is as follows:

$\beta_{Info}TTInfo_{it}$	(3.19)
---------------------------	--------

With	
TTInfo:	provided travel time information
$eta_{{\scriptscriptstyle Info}}$ :	parameter to be estimated

By long-term effect we refer to the effect of en-route traffic information on the long-term expectation of travel time. As we labelled this development of an expected travel time as explicit learning, this long-term effect was already described in section 3.4.1 on explicit learning. Equations (3.10), (3.13) and (3.14) show how this effect was captured in the model.

## 3.6 Alternative specific constant and error term

A traveller can have a certain preference for a route that is not captured by the variables specified in the model. An example is a preference for a certain type of road. By adding an alternative specific constant (ASC) to the model this phenomenon can be accommodated. Since our data contain multiple choices from one person (i.e. our data are 'panel data'), we set the ASC for each person-route combination fixed<sup>5</sup> and estimate a mean and standard deviation of all individual ASC's for each route. This construction leads to a mixed MNL model for panel data. The ASC is then specified as follows:

$$RoadType_n$$
 (3.20)

With RoadType<sub>n</sub> ~  $N(\mu,\sigma)$ ;  $\mu$  and  $\sigma$  to be estimated.

The last part of our model is the error term  $\varepsilon$ . We assume this to be Gumbel independent and identical distributed (i.i.d.) in order to be able to estimate the model. The validity of this assumption is discussed in Appendix A.

# 3.7 Conclusions

Based on the conceptual framework, from the previous chapter, this chapter formulated the mathematical route choice model. In contrast to most models, the model captures both explicit and implicit learning and will be estimated on experimental data. While this chapter gave a brief overview of the complete route choice model, chapters 5, 6 and 7 give a more thorough discussion of the model part relating to reliability, learning and traffic and the estimation outcomes on these topics. In the next chapter the data collection is discussed.

<sup>&</sup>lt;sup>5</sup> Remember that *evolving* preferences for a certain route are captured by the implicit learning component.

# **4** Data collection with the TSL

This chapter describes the collection of the data that are used in this thesis using the TSL (travel simulator laboratory), an interactive internet-based software tool. The data are needed to estimate the model from the previous chapter. The model estimation process and its results are given in appendix A. Conclusions drawn from these results are discussed for each of the three focus points of this thesis (reliability, learning and traffic information) separately in the next three chapters.

The chapter starts with a discussion of two different research methods: stated preference and revealed preference. Characteristics, advantages and limitations of both methods are given. Then it is explained that the TSL is a mixture of both types in an attempt to capture the advantages of both methods while avoiding their limitations as much as possible. The next section provides details of the TSL respondents: their recruitment and socio-economic characteristics. Then, the experimental design is discussed. An example with screenshots is given in section 4.4. This chapter ends with a discussion of the validity of the chosen approach.

# 4.1 Research methods: Stated Preference and Revealed Preference

Two different methods exist to gain insight into choice behaviour: RP (revealed preference) and SP (stated preference). As the names already tell, the first method observes real choice behaviour, as *revealed* in real life, whereas the second method presents people with described alternatives from which they can choose in a given situation and asks them to *state* what alternative they would choose. Both methods have their own advantages and limitations. Without the intention of being exhaustive, a number of these advantages and limitations will be discussed next. They are summarized in Table 2 at the end of this section.

## 4.1.1 Advantages and limitations of stated preference research

One of the main advantages of SP research is the controllability of the experiment. The researcher can exactly control what choice alternatives in what situations the respondent is presented with. In this way, the researcher can make sure that everything he is interested in is represented in the experiment in enough variation, so that later on (statistically significant) conclusions can be drawn. Even not yet existing choice alternatives can be analyzed.

Furthermore, it is easier to control the respondents' knowledge level before and during the experiment, track reaction times, etc.

Another main advantage is the cost-effectiveness of stated preference research. Especially when the experiment is carried out on a computer, many questions can be asked to large numbers of respondents and their answers can be automatically saved in the desired format to a file without the intervention of a researcher.

### 4.1.2 Limitations stated preference research

By far the most important limitation of SP research concerns its validity. Respondents have to *imagine* that they are in the choice situation described and face the described alternatives. Then, they have to choose what they *think* they would choose in that situation. At best, the SP research measures valid intentions. In terms of the theory of planned behaviour (Ajzen 1985; Ajzen 1991), this could occur when attitude, subjective norm and perceived behavioural control are all assessed correctly. Alternatively, in terms of the TRIADE model (Poiesz 1999), motivation, capacity and opportunity would all have to be assessed correctly by the respondent. And even if a respondent is able to truly assess his intentions, then there is still a gap between intentions and actual behaviour. A clear example concerns habitual behaviour, in which behaviour is automatic and can overrule any intentions. An extensive overview of validity issues of this kind in SP research is given in (Fujii and Gärling, 2003).

We want to mention two issues that play a role in travel behaviour research and that could cause stated preferences to be invalid. The first concerns consequences of choices which are difficult to convey in SP research. These consequences can evoke different emotions which in their turn affect choices. Refer to (Bonsall, 2004) for more information on the role of emotions in decision making. For example. in a route choice situation the consequence in real life of a disadvantageous choice could be arriving late and missing an important appointment, getting lost, wasting time in a traffic jam, etc. In SP research, there are in fact no real consequences unless the researcher includes this in the experiment, for example by awarding money for good choices and giving a fine for bad choices. But by doing this, the researcher influences the respondent by imposing what choices are good and what choices are bad, thereby reducing the validity of the research.

The second issue concerns vague concepts which somehow have to be conveyed to the respondent. An example is travel time reliability which has got something to do with probabilities. Many people experience difficulties understanding the concept of probability. The representation that the researcher chooses (for example a list of 10 possible travel times, or a histogram) can influence people considerably (Beaton et al., 1996; Urama and Hodge, 2006). And even if the researcher succeeds in conveying the probabilities correctly, a validity problem still exists, since in reality probabilities are never explicitly known by the traveller.

The prior all concerned theoretical drawbacks of SP research. Practical studies have been conducted to look at the discrepancy between stated preferences (in SP research) and revealed preference (in real life). Some studies show small discrepancies (e.g. (Fujii and Gärling, 2003), whereas others are less optimistic (e.g. (Bonsall, 2004)). Validity studies of other travel simulators conclude that they are sufficiently valid (refer to (Chorus et al., 2007) and (Bates et al., 2001)). The last reference, however, only uses 'face validity' arguments, so its conclusion is plausible but can be challenged.

The conclusion is therefore, that if one decides to conduct an SP research, special attention has to be paid to validity issues, both when designing the experiment and when analyzing and interpreting the results.

## 4.1.3 Advantages revealed preference research

While research validity is a limitation of SP research, it constitutes an important advantage of revealed preference research. People's choices are observed in real life. Consequences of choices and constraints are automatically captured in people's choice behaviour. There is no need for a researcher to intervene and thus no possibility for the researcher to 'accidentally' influence the observed people.

## 4.1.4 Limitations revealed preference research

Conducting RP research is often very expensive and time consuming. Furthermore, its poor controllability can cause some serious problems. These problems can be statistical in nature. An RP research into the valuation of travel time reliability, for example, is in an RP research not challenged by validity issues (like in an SP research), but can be difficult due to a lack of real choice situations with sufficient variation to allow statistically reliable estimates of the valuation of reliability (Bonsall, 2004). Furthermore, the researcher has no control over the knowledge levels of the respondents. This makes it hard to know the respondent's choice set, or to assess his learning behaviour. The last limitation we want to mention is the fact that it is not possible to study the attractiveness of not (yet) existing alternatives, as they can obviously not be chosen in real life.

	Stated Preference	Revealed Preference
Advantages	Controllability (of variables and	Good validity
	respondent)	
	Hypothetical choice alternatives	
	Cost effectiveness	
Disadvantages	Validity issues (e.g. hard to capture	Expensive and time consuming
	vague concepts)	
		Controllability (of variables and
		respondent)
		No hypothetical choice alternatives

### Table 2: Advantages and disadvantages of SP and RP research

## 4.1.5 Conclusion: choice of research method

The previous overview of RP and SP research showed that both methods have some specific strengths, but also some serious limitations. We therefore use a mix of both methods in an attempt to use the strengths of both methods while avoiding as much as possible their limitations. The next section presents the design of this enriched SP experiment, followed by an example including screenshots. Although these sections will implicitly discuss how the limitations of pure SP research are avoided / handled in our experiment, this topic is important enough to deserve its own section. Therefore, in the final section of this chapter, we provide a critical discussion of the strengths and limitations of our research method.

## 4.2 **Respondents in the TSL**

The travel simulator laboratory (TSL) of Delft University of Technology has been used for collecting the route choice data. The TSL is an interactive internet-based software tool to investigate travel choice behaviour, in this case route choice. In this section, the recruitment

process of the respondents is described. It is followed by an overview of the respondent characteristics.

## 4.2.1 Recruitment

Many car drivers in The Netherlands are members of the Netherlands organization of road users called ANWB. Therefore, recruiting among ANWB members provides a good opportunity of having a heterogeneous (in terms of profession, education, age, etc) set of respondents. The ANWB placed a call for respondents in their monthly magazine, which is sent to all their members. Furthermore, a number of active ANWB members received an email with an invitation to join the experiment. As an incentive to participate in the experiment, respondents were told that a navigation system would be awarded to one participant. This prize was randomly drawn among the participants, so there was no goal imposed on them (like minimize total travel time) that would influence their behaviour.

## 4.2.2 Characteristics of the respondents

Here are some characteristics of the respondents whose data are used in this research:

- 2500 people carried out the experiment in June 2005,
- 66 % male; 34 % female,
- nearly all between 20 and 60 years old, refer to Figure 9,
- various educational levels, as depicted in Figure 10,
- the majority liked driving and arriving a bit early,
- the majority disliked congestion and arriving late,
- 56% drove his / her car at least 21 days per month,
- they all lived in The Netherlands.



Figure 9: Histogram respondents' age



Figure 10: Histogram respondents' highest finished education

In sum, people from different genders, ages and educational levels are represented by our respondents.

## 4.3 Experimental design

The experiment is aimed at studying route choice behaviour under different information scenarios. First, the general design that is the same for all respondents is presented. This concerns the routes from which the respondents can choose and their characteristics in terms of travel time distribution and road type. Then, the design variables that are varied for different groups of respondents (like type of provided traffic information, travel goal, etc.) are explained. This is followed by an overview of how the possible values of these variables are used to form different experimental treatments. The method we used is known as full factorial design.

### 4.3.1 Provided info to respondents before start experiment

The respondents were provided with some basic instructions and information before the start of the experiment. Some static information about the routes was given. Originally, the routes were only characterized as route 1, 2 and 3, each being approximately 30 kilometres long. During the test phase it became clear that it was too abstract, and respondents needed more information to imagine they were in a route choice situation. Therefore, at the beginning of the experiment the respondents were not only told that the routes were approximately 30 kilometres long, but also that they were of the following road type:

- Route 1: Consists mainly of highway.
- Route 2: Consists mainly of rural roads.
- Route 3: Consists partly of highway and goes partly through a city centre.

The road types were chosen like this, because we wanted them to be very different in terms of travel time reliability. Without any congestion, route 1 is then the fastest as its speed limit is the highest. On route 2 there is hardly ever congestion, but its speed limit is much lower than route one's limit leading to reliable but long travel times. Route 3 consists of two components. The first, highway, can be very fast; the second can be reasonably fast, but can also be very slow, depending on traffic lights, accidents, etc. In sum, route 3 is very unreliable. More details on the travel time distributions can be found in the next section.

Other information that was given to the respondents before the start of the experiment concerned the travel goal (work meeting or job interview). The respondents were encouraged to imagine they were in the described situation and to act realistically. This also means that we did not impose any goal function (like minimize total travel time, or always arrive on time), as this can highly influence behaviour and hence make it invalid.

### 4.3.2 Routes and their travel time distributions

A respondent had to make 40 consecutive choices from three routes. In this way the respondent could learn about the travel time variations of each route, without being told in advance what the actual distribution was. Because one goal was to study the effect of travel time reliability on route choice, each route had a different travel time distribution (see Table 3).

More specifically, route 1 could be characterized as being usually (3 out of 4 days) quite fast, but sometimes very slow (1 out of 4 days). As Table 3 shows, the travel times were drawn from two Gumbel distributions. A Gumbel distribution was chosen because its shape is plausible for travel times (dense around the mean and tailed to the right only). Route 2 was by far the most reliable route, but also on average the slowest route. The travel time of route 3

was normally distributed with a large variance. Due to this distribution travel times could vary a lot, both below and above the mean, which results in low reliability. Route 1 also had a large variance, but this was due to a limited number of very long travel times. Usually, 3 out of 4 days, route 1 took between 33 and 36 minutes, whereas route 3 varied between 33 and 56 minutes. For this reason, route 3 can be regarded as the least predictable one. The travel times were sampled only once, which means that the travel times were the same for each respondent.

Table 3: The Travel Time Distributions of the Routes during the First 22 Days

Route	Description	Mean travel time (min)	Variance of travel time (min <sup>2</sup> )	10 <sup>th</sup> per- centile (min)	90 <sup>th</sup> per- centile (min)
1	30 draws are made from Gumbel (35, 1) 10 draws are made from Gumbel (70, 1) The resulting travel times are randomly distributed over the 40 days.	44	233	34	70
2	all draws are made from Gumbel (53, 1.25)	53	1	52	54
3	all draws are made from Normal (47, 12)	47	146	33	56

During the second half of the experiment, the travel time distribution of the route that was chosen most often during days 10 to 22 was changed. For some people it became slowly worse, for other people it became incidentally very bad and for some people it did not change. For the first group the sampled travel times were increased with one minute every day. For the second group the travel time was increased with 15, or 20 minutes once every four days. Within a group the travel times were the same. The numbers in Table 3 apply to the first 22 days of the experiment.

## 4.3.3 Design variables and levels

The above mentioned information and travel time distributions were the same for all respondents. Some things, which we refer to as design variables, were different for different groups of respondents. A combination of values, also called levels, for all these design variables is called treatment. That is, different groups of respondents received different experimental treatments. By analyzing differences in behaviour among groups who received different treatments, insight can be gained in the effect of design variables on behaviour. The various design variables and their levels are given in Table 4. In the next sections their meaning is clarified.

Design		En-route	info	Ex-post info			
variable						Number	Travel times
				Number	Best route	of past	2 <sup>nd</sup> half
	Travel goal	Presentation	Content	of routes	marked	days	experiment
Possible	meeting						
levels	with						slowly
	colleagues	VMS	km	all routes	no	one	worse
							incidentally
	job	FCIP	min	chosen			bad
	interview	nothing	nothing	route	yes	all	no change

Table 4: Design variables and their levels

## En-route traffic information: content, presentation and accuracy

There were three possibilities for the content of the en-route information:

- no en-route traffic information at all,
- en-route traffic information about queue lengths in kilometres on the three routes, or
- en-route traffic information about expected travel times in minutes on the three routes.

If there was any en-route information, it was presented on either a VMS (variable message sign), or an FCIP (full colour information panel). An example of the first is given in Figure 11; an example of the second is given in Figure 12.





Figure 11: Example of a VMS

Figure 12: Example of an FCIP

The travel times provided by the en-route information were set in advance by the researcher and were for all respondents the same. The provided travel times were based on the true travel times and were most of the time very accurate: they deviated in 85% of the days at most 2 minutes from the real travel time. In the other 15% they deviated approximately 10 to 30 minutes from the real travel time, usually underestimating the real travel time.. The 15% large deviations, were spread randomly across the 40 days of the experiment.

These design choices enable us to analyze differences in behaviour as a function of information content and presentation. Furthermore, we can analyze what happens when people received a very inaccurate message on the VMS or FCIP.

## Ex-post traffic information: content and presentation

Ex-post information refers to information given directly after a route choice. The information could concern the realized travel time of either the chosen route only, or all three routes. Furthermore, the information was given for only the last day, or for all previous days. Additionally, the shortest travel time was in some treatments marked green. This possibly makes it easier to recognize the route that is usually fastest.

## Travel goal

Before starting the experiment the respondents were told what the goal of their trip was. Two goals were used:

- A meeting at work with colleagues starting at 9 o'clock, or
- A job interview starting at 9 o'clock.

We chose these travel goals to be able to gain insight in the effect of importance of arriving on time, as most people find it probably much more important to arrive on time at a job interview than at a meeting with colleagues.

## Travel time habitual route second half of experiment

During the experiment, travellers possibly develop a habitual route choice. We wanted to analyze what happens if this habitual route becomes worse. Is their habit so strong that they keep choosing it? Or do they not even notice that the route becomes worse? Three different situations were designed:

- The habitual route becomes slowly worse
- The habitual route becomes incidentally very bad (25% of the days)
- The habitual route does not change

The habitual route was defined to be the route that was most chosen during days 10 to 22. In case of a tie between two routes, the habitual route was the one (from these two) that was chosen most recently. The reason for not including days 1 to 9 is that at the beginning of the experiment respondents probably try different routes and get used to the experiment. There is no real habit yet. The last 18 days are needed to have enough observations to analyze any change in behaviour. Maybe 15 days would have been enough as well, but we had to make a choice, and chose 18.

### **Design of experiment**

The levels of the design variables lead to 180 possible unique combinations. As we used a full factorial design, we defined 180 different treatments. The first 90 treatments all had 'meeting with colleagues' as their travel goal; the last 90 all had 'job interview' as travel goal.

Because we did not know how many respondents would engage in the experiment, we decided to we used the following scheme to assign a respondent to a treatment. The first respondent was assigned to treatment 1. As soon as there were 20 respondents who completed at least 35 of the 40 'days', we assigned the next respondent to scenario 2. As soon as there were 20 respondents who had completed at least 35 of the 40 'days' we moved on to scenario 3, and so on. This way, we were sure not to end up with only 2 respondents per scenario (which would make statistical analysis hard / impossible).

As many respondents joined the experiment, data were gathered for 112 treatments.

## 4.4 Example

In Figure 13 an example is given of the experiment.



Figure 13: Screenshots of the experiment

# 4.5 Discussion: validity of followed methodology

Section 4.1 highlighted some potential drawbacks concerning the validity of SP research. To prevent these drawbacks from occurring we developed an enriched SP research. Looking back, we can make the following positive remarks concerning the validity of our method:

- In pure SP studies travel time characteristics of route alternatives are described. Even vague concepts like reliability have to be operationalized. This is completely different from real life and leads to serious validity problems, as discussed earlier. These kind of problems did not occur in our experiment, as respondents had to learn the route characteristics from experiences and traffic information.
- We did not impose any goal function, as this influences behaviour. We merely asked the respondents to act realistically.
- The experiment could be completed within 15 minutes to prevent fatigue.
- The development and testing of the TSL in cooperation with ANWB members (instead of only fellow scientists) improved the clarity of the experiment. In this way, we increased the likelihood that our target group of respondents also interpreted the experiment correctly.
- Results of the analyses described throughout this thesis seem plausible, as they can be explained by results found earlier in psychology and traffic engineering research.
- Validity studies of other travel simulators conclude that they are sufficiently valid (refer to (Chorus et al., 2007) and (Bierlaire, 2003)). The last reference, however, only uses 'face validity' arguments, so its conclusion is plausible but can be challenged.

Still, we realize that route choice in real life is still different from route choice in the TSL. Three major differences include the lack of consequence of bad choices in the TSL, the time horizon (40 'days' in 15 minutes) and the intensity. The lack of consequence could decrease people's motivation to make a good choice and learn from their mistakes. It can also lead people to take more risk than in real life.

The short time horizon will influence memory and thus learning. In real life, we can only remember experiences from 40 days ago when they are stored in long-term memory.

Experiences during the experiment can be retrieved from short-term memory. Still, in real life people are probably more motivated to remember experiences, or (the consequence of) the experience was so intense that it becomes easy to remember.

In sum, the positive remarks lead us to conclude that the outcomes of the experiment are valuable. And looking at the fact that as far as the topic of learning is concerned, earlier studies have hardly used any data at all, our outcomes are even more valuable. Yet, we cannot ignore the critical remarks. Therefore, we think the results have to be interpreted with some caution. Parameter estimates, for example, have to be treated as rough estimates instead of exact truth. To acquire more exact estimates, one of our recommendations for future research is to carry out an RP study as well. Of course, this study will suffer the drawbacks of RP studies, but the results of the two types of studies can be combined and will give a thorough understanding of travel behaviour.

# 5 Reliability: effect on route choice and learning

In the previous chapters we introduced the topic of this thesis and its three focus points: reliability, learning and traffic information. The conceptual framework was described in which these three points were related to each other. The mathematical model, that is based on this framework, and the collection of the data, to estimate this model and answer our research questions, were also described. This chapter is dedicated to one of the three focus points: reliability.

First, an overview of literature is given in section 5.1. Both travel behaviour research and other sciences (psychology, experimental economics, neuro-science) show that people are not risk neutral. Hence, travel time reliability has to be taken into account as an influential factor in route choice. The literature overview also led to a number of issues we want to contribute to. These are summed at the end of section 5.2.

One of the ways to contribute to these issues is by developing a route choice model, estimating it on our experimental data and interpret the results. The route choice model, i.e. the part that relates to reliability, is described in section 5.3. The estimation results are interpreted in section 5.4, the section that describes the analysis of our experimental data with respect to the effect of reliability on route choice.

Besides the results of our route choice model, this last section also looks at an aggregate level on how route choices evolve over time. Different reliability measures are compared to shed some light on what measure explains behaviour best in our experimental situation. The effect of travel information and travel goal on the risk averseness of route choices is also discussed in this section. The chapter ends with overall conclusions.

## 5.1 Literature overview

In this section we take a top-down approach and start with a discussion of the theories on choice behaviour under uncertainty from psychology and experimental economics that most influenced travel behaviour research. Then, in section 5.1.2 we show how these ideas have been applied in travel behaviour research and what conclusions were drawn from this. In section 5.1.3 we further focus on how uncertainty and similarly reliability can be operationalized and measured for travel behaviour research. This section ends with a discussion challenges when doing research into the effects of reliability.

## 5.1.1 Decision making under uncertainty

In chapter 2 it was argued that the type of decision which we are interested in

- is discrete (as opposed to continuous),
- entails some degree of uncertainty (as travel times can not be known for certain),
- is operational,
- often has to be made under time pressure and
- offers opportunities for learning and habit development.

While chapter 2 gave an introduction to decision making in general, we focus in this chapter on the role of uncertainty in decision making, the second item in the list above. This is done by addressing he following topics:

- Expected utility theory and uncertainty modelling
- Somatic marker theory
- Examples of deviations from expected utility theory
- Cognitive dissonance
- Non-expected utility theory

## Expected utility theory and uncertainty modelling

A large body of literature that focuses on decision making under uncertainty can be found in economic sciences. There, it was for a long time described and modelled according to the rules of expected utility maximization. Based on the ideas of Bernoulli (Bernoulli, 1738) and later translated to English in (Bernoulli, 1954) expected utility theory was first formally described by Von Neumann and Morgenstern (1947). The rules of expected utility theory state that in uncertain environments, decision makers use the objective (i.e. mathematical) expected attribute values to derive the expected utility of the choice alternative. As an example, suppose a traveller chooses a route based on its travel time. Typically, travel times are uncertain. The expected utility of the route would then consist of the expected (mean) travel time and an error term, as given in equation (5.1).

$$U_i = \beta E(TravelTime_i) + \varepsilon_i$$

(5.1)

For more details on utility theory in general and the role of error terms refer to section 3.2.1.

## Somatic marker theory

Perhaps the most fundamental shortcoming of expected utility theory is the negligence of the role of emotions in decision making. Bechara and Damasio (2004) point to this missing role of emotions in the way economists (and this applies also to most behavioural modellers in transportation) explain choice behaviour. They conclude with respect to decision making in uncertainty that

- knowledge and reasoning are not sufficient for making decisions that are good for the decision maker and that the role of emotions should be recognized,
- the process of rationally considering different options is slow, the decision behaviour is in practice much faster and apparently not fully conscious,
- emotions form a good mechanism in decision making when they are related to the task (and can be disruptive when they are not related, examples follow),
- decision making under certain conditions and uncertain conditions involve different neural circuitry.

Examples of emotions related to risk and uncertainty are anxiety and fear. Consider two examples of the mechanisms described under C. When deciding to neglect a red traffic light because your late for work, the mere thought of having an accident will trigger somatic states

relating to fear. These somatic states are related to the decision-making task at hand and will bias the decision in an advantageous manner. An example of a disruptive emotion is receiving a cell phone call about someone dying in the family while driving.

Bechara and Damasio (2004) base their opinion on well known cases of persons with brain damage who repeatedly make bad decisions in uncertain situations. Though these persons are intellectually normal, their brain damage affects their emotions. More specifically, the control mechanism of bodily states related to emotions does not work properly due to the lost functions in the brain.

Emotions appear to have an important role as a mechanism to take decisions: certain stimuli (e.g. the presence of certain choice options) induce in the brain and later in the body an emotional state and this somatic (bodily) state prepares a state in the brain that influences certain actions. Such inducers can be direct, primary inducers, because a person learns from the direct experience that such inducers cause pain or pleasure, or they can be secondary inducers of emotions, like memories or thoughts.

To give a very clear example: the mere thought of spending all your money on a risky yet highly profitable bet (secondary inducer) will cause most people to sweat, have a higher blood pressure and pulse rate (bodily states). Even though the expected utility of the bet may be very high, most people will decide not to engage in it. Hence, the rules of expected utility theory will be violated. The next section gives two famous examples of deviations.

### Examples of deviations from expected utility theory

The somatic marker theory says something about the reason people do not behave according to the rules of expected utility theory. The fact that they do not behave that way was already known long before. Allais was probably the first to publish about this in an elaborate article (Allais, 1953). The basic ideas are that there exists a distinction between monetary and psychological values and that there is a distortion of objective probabilities and the appearance of subjective probabilities. An example is the later called Allais paradox which is now illustrated. Imagine there are three lotteries a1, a2 and a3, each having the characteristics as given in Figure 14.



Figure 14: Lotteries and winning chances



Figure 15: Lotteries and winning chances

Allais found that most people prefer a 1 over a 2 in the first pair and a 3 over a 4 in the second pair. This implies the following inconsistent inequalities, with U(x) as the utility of x

U(\$1M) > 0.10U(\$5M) + 0.89U(\$1M) + 0.01U(\$0)	→	0.11U(\$1M) > 0.10(\$5M)
0.10U(\$5M) + 0.90U(\$0) > 0.11U(\$1M) + 0.89U(\$0)	→	0.11U(\$1M) < 0.10(\$5M)

Kahneman and Tversky (1979) also found that people do not always follow the rules of expected utility maximization in economic choices, but rather have a perception of the probability of a certain outcome and the value of that outcome which may not always be representative of the actual probability. They noticed a non-linearity in the relationship between the objective and the perceived probability, as described in their prospect theory. Furthermore, they found that people's attitude towards risk depends on whether the choice is framed as a loss or a gain (Tversky and Kahneman, 1981). Their ideas have later been applied to route choice situations, as will be discussed in section 5.1.2.

In one of the experiments by Kahneman and Tversky (1979), inspired by Allais, people could choose between the pairs of lotteries described in figure 15. Here, most people preferred b2 over b1 and b3 over b4, which also leads to inconsistent inequalities of utility. They also found that when the gains in figure15 were replaced by losses (so a \$6000 gain becomes a \$6000 loss), people's preferences were reversed (Tversky and Kahneman, 1981).

### **Cognitive dissonance**

The previous theories all said something about risk behaviour and how outcomes and probabilities can be changed by individuals. The theory of cognitive dissonance gives another view on distortion. Cognitive dissonance can arise when behaviour and cognition are dissonant (Festinger, 1957). Remember the example about smoking that was given in section 3.3. If the individual solves his cognitive dissonance by adapting his cognitions (instead of his behaviour) this leads to an adapted view of reality. Returning to the route choice situation, cognitive dissonance could arise when a traveller habitually chooses a route that is not very good, e.g. because it is unreliable. In order to solve his cognitive dissonance, a traveller may adapt his cognitions: he may perceive the unreliability of his habitual route in a much more positive way than the unreliability of his non-habitual route. Our route choice model, which is discussed in section 5.3, takes this idea into account.

### Non-expected utility theory

Though the previous sections gave many examples of the unrealistic behavioural assumptions of expected utility theory, the theory and the extensive mathematical literature on it still offers great analytical advantages. In an attempt to retain this analytical and mathematical power of expected utility theory and to accommodate the found behavioural deviations from expected utility theory, non-expected utility theory was created. In fact, the already mentioned prospect theory (Kahneman and Tversky, 1979) can be regarded as one of many possible implementations of non-expected utility. The idea is to adapt the objective mathematical probabilities and outcome values in such a way that they better reflect the individuals' perceived subjective probabilities and outcome values. These subjective probabilities and outcome values and the utility formulations.

### Conclusion

The main conclusion from the previous sections is that individuals are not risk neutral and do not behave according to the rules of expected utility theory. Instead they exhibit different kinds of risk behaviour in different situations. For our route choice situation this means that simply entering the mean travel time in a route's utility formulation will not suffice. Somehow, travel time reliability will have to be taken into account.

### 5.1.2 Impact of reliability on route choice behaviour

The notions on risk behaviour discussed in section 5.1.1 have found their way into travel behaviour research. Especially the ideas of Tversky and Kahneman have been adopted by travel behaviour scientists. Katsikopoulos et al. (2002) found in a route choice experiment the risk attitude of people to be in line with the theory of Tversky and Kahneman. In their experiment people could choose between a reference route (for which they had to imagine that it was their habitual route) and an alternative route. They varied the range of the route, range being defined as the longest travel time minus the shortest travel time. In this way four different risk categories can be distinguished, see Table 5.

#### Table 5: Risk behaviour in different categories

	More risk: $rA > rR$	Less risk: $rR > rA$
Loss: $E(TA) > E(TR)$	1 Risk seeking, increasing in rA	2 Risk averse, decreasing in rA
Gain: $E(TA) < E(TR)$	3 Risk averse, increasing in rA	4 Risk seeking, decreasing in rA

R: reference route

A: alternative route

 $E(T_i)$  = expected value of the travel time on route i

Range = longest travel time minus shortest travel time of the alternative route

 $r_A$  = range of the alternative route

 $r_R$  = range of the reference route

Bogers and Van Zuylen (2004) did some experiments which involved route choice situations in all four risk categories. They asked truck drivers about the preferred routes. As for categories two and three of Table 5, 50 to 80 % of the truck drivers were indeed risk averse when they could choose between a short and uncertain alternative and a longer but more certain alternative. A highly significant linear relation (rho-square = 0.9) was found between the difference in range between the two routes and the number of truck drivers making a risk averse choice, i.e. choosing the on average longer but more reliable route, refer to Figure 16.

As for categories one and four they found that only 10 to 20 % of the truck drivers opted for the route with highest expected travel time and highest risk. This risk seeking attitude did not clearly seem to increase with the range of the risky route. Avineri and Prashker (2005) also carried out route choice experiments. They came to the conclusion that the higher the variance in travel time is, the lower the traveller's sensitivity to differences in average travel time. They refer to this as the payoff variability effect. They also found that in some cases, increasing travel time variability of a less attractive route could increase its perceived attractiveness. Looking at the findings of Katsikopoulos et al. in risk categories one and four this comes as no surprise.

Most authors, however, found a negative valuation of unreliability. Brownstone and Small (2005) found that unreliability, expressed in terms of the travel time variance, is highly negatively valued, although there exists a high heterogeneity among travellers concerning how negatively exactly unreliability is valued. Liu et al. (2004) came in their study to a similar conclusion. Other examples can be found in Bates et al. (2001).

Summarizing, the value of unreliability is in most cases negative, but is in some cases found to be positive. Tversky & Kahneman and Avineri & Prashker explain this positive valuation

by a subjective perception of probabilities and outcomes relative to a reference point and the payoff variability effect respectively. In our view, cognitive dissonance theory could provide an explanation for the different valuation of reliability as well, as explained in the previous section.



Figure 16: The fraction of risk averse truck drivers in category 3 plotted against the difference in range

The impact of reliability on route choice can be influenced. Traffic information and travel goal for example can influence risk behaviour. Ben-Elia et al. (2008) found that providing traffic information enhances initial risk seeking behaviour. Perhaps the explanation is that people are willing to accept a specific level of uncertainty. Information can reduce uncertainty. Choosing a riskier route with information may result in the same level of uncertainty as choosing a less risky route without information.

### 5.1.3 Measures of reliability

In order to investigate and measure the valuation of reliability, the concept 'reliability' has to be operationalized. However, as was discussed in section 3.3.1, there is no consensus on what measure expresses reliability best.

Various reliability measures are proposed in literature. Some measures found their origin in statistics, whereas other measures take the viewpoint from the traveller. Table 6 and Table 7 list a number of measures, which are discussed next.

Name and description	Formula
Standard deviation	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(TT_i - \mu(TT))}$
Variance	$\sigma^2$
<i>Reliability ratio</i> : extra mean travel time a traveller would be prepared to incur for a minute less variance	$\frac{\mu(TT)}{\sigma(TT)}$
Difference between the 90th percentile and median	p90(TT) - p50(TT)
<i>Percentage variation</i> : size of standard deviation compared to mean	$\frac{\sigma(TT)}{\mu(TT)}$ 100%
$\lambda^{var}$ : range of possible travel times compared to the median	$\frac{p90(TT) - p50(TT)}{p50(TT) - p10(TT)}$
$\lambda^{skew}$ : a measure for the asymmetry of the travel time distribution	$\frac{p90(TT) - p10(TT)}{p50(TT)}$

### Table 6: Reliability measures (statistics oriented)

### Table 7: Reliability measures (traveller oriented)

Name and description	Formula
Misery index: relative delay of 20% worst trips.	$\frac{\mu(TT_{20\%worst}) - \mu(TT)}{\mu(TT)}$
<i>Buffer time index</i> : relative amount of extra time needed to be 95% on time	$(p95(TT) - \mu(TT))$ *100%

Lam and Small (2003) found in a study that travel time was best represented by its median instead of its mean and reliability by the difference between the 90th percentile and its median instead of the standard deviation. Black and Towriss (1993) define the reliability ratio which expresses the relative valuation of reliability and travel time, i.e. how many minutes of extra travel time a traveller would be prepared to incur for a minute less of variance. Bates et al. (2001) conclude from an elaborate literature review that most studies provide a value for this measure between 1.1 and 2.2. Again another study claims the three best measures for reliability are the percentage variation, the misery index, which focuses on the delay of the worst trips and the buffer time index, the relative amount of extra time that should be allowed for by the traveller to be 95% on time (Lomax et al., 2003). Van Lint and Van Zuylen (2005) argue that besides the width of the travel time distribution, also skew (a measure for the asymmetry of the travel time distribution) must be considered a key indicator and introduces two new measures:  $\lambda^{skew}$  and  $\lambda^{var}$ , refer to Table 6 for definitions (px = x<sup>th</sup> percentile of the travel time distribution). The larger  $\lambda^{skew}$ , the more the travel time distribution is skewed to the left, which implies a small amount of trips incur travel times which are much higher than the vast majority of trips.  $\lambda^{var}$  reaches 0 if the range in possible travel times is small compared to the median.

Van Lint and Van Zuylen (2007) furthermore show that the choice of reliability measures (e.g.  $\lambda^{skew}$ , misery index, standard deviation) strongly determines the outcome. Put simply: the same situation can be labelled 'reliable' by one reliability measure and 'unreliable' by another. As an example, consider the relation between the misery index and the buffer time index (calculated on the same data set) in Figure 17.



Figure 17: Scatter plot of misery index versus buffer index on same travel time dataset

We argue that there is not one best measure, as reliability measure that is most appropriate is contingent upon the goal that has to be reached. The following example will further illustrate this view. Suppose that the government wants an important airport to be reachable with very high reliability, so that travellers will not (easily) miss their flights. A brief survey among our faculty staff shows that most people plan their trip to the airport in such a way that even in a worst case scenario, they still catch their flights. As such, only decreasing the delay of the worst trips would effectively improve the required departure time for these travellers. Therefore, the misery index (which focuses on the delay of the worst trips) would in this case be the most effective reliability measure. When going to work, however, travellers may be content arriving on time in a percentage of the cases, which would make the buffer time index (which focuses on the relative amount of extra time that should be allowed for by the traveller to be 95% on time) a more appropriate measure.

Note that if skewness is thought to be relevant for explaining behaviour, variance (and therefore also standard deviation) is not very appropriate. The reason is that a high variance can be the result of both a symmetrical distribution with a large range in possible travel times and a skewed distribution. Although the idea of contingent reliability measures is generally acknowledged in travel behaviour research, the contingency view has not been formulated formally before in travel time reliability research.

## 5.1.4 Reliability in route choice models: research methods, modelling and estimation

Two different research methods exist to gain insight into how people deal with reliability of travel times in route choice: RP (revealed preference) and SP (stated preference). In RP
research real choices are observed, whereas in SP studies respondents are asked to make a hypothetical choice between a number of given alternatives. More details on SP and RP research can be found in section 4.1.

Studying responses to reliability by means of SP research is quite challenging. As the respondents are very much influenced by the representation of reliability that is used by the researcher in SP studies, a typical validity problem arises (Bonsall, 2004). Especially the representation of probability, a concept that is for many people not very clear, can influence people considerably. And even if the researcher succeeds in conveying the probabilities correctly, a validity problem still exists, since in reality probabilities are never explicitly known by the traveller.

With RP research, however, there are serious problems of finding real choice situations with sufficient variation to allow statistically reliable estimates of the valuation of reliability (Bates et al., 2001). Furthermore, RP is often very expensive and time consuming.

In an attempt to overcome the aforementioned problems of RP and SP research, we decided to conduct an enriched SP experiment. Though the experiment is conducted by means of a computer, the characteristics of choice alternatives are not described, but have to be learned. More details on the design of the experiment can be found in chapter 4.

Another way to overcome some limitations of RP and SP research, is to conduct both types of experiments and analyse the data simultaneously. Pooling SP and RP data (data fusion) has several mathematical implications. Hensher and Louviere (1979) for example report on the need of scaling and Cherchi and Ortúzar (2006) treat the problem of fitting alternative specific constants in models estimated on RP / SP data. Ahern and Tapley (2008) argue that only data from SP studies that closely mirror real-world situations can be combined with RP data.

Closely related to the discussion on measures for reliability is the modelling of reliability in route choice models, as the measures can be used as an explaining variable in the model. Usually, the standard deviation is used, as introduced by Jackson and Tucker (1982). Research on the valuation is then often done by SP research. Two very fundamental issues are addressed here. First, it is not at all clear if standard deviation is the best measure to use, (refer to the previous section). Second, the validity problems concerning SP research can further make the results somewhat doubtful. Using the standard deviation on RP data presents another challenge: usually there are not enough data to allow a statistically sound estimate of its valuation. We will further explain this in section 5.3 and show how we solved this problem for our data, which are enriched SP data.

# 5.2 Synthesis

Based on the literature review we identified a number of topics that we further want to investigate and contribute to. These are:

- valuation of reliability on habitual versus non-habitual routes,
- integration of reliability in route choice model,
- longer-term effect of reliability and
- effect of traffic information and travel goal on the risk averseness of route choices.

The first topic concerns the different valuation of reliability on habitual and non-habitual routes. We hypothesize that – compared to regular travel times - very bad travel times are given extra weight on non-habitual routes and less weight on habitual routes. We come to this hypothesis by applying cognitive dissonance theory. Cognitive dissonance could arise when a traveller habitually chooses a route that is not very good, e.g. because it is unreliable. In order to solve his cognitive dissonance, a traveller may adapt his cognitions: he may perceive the unreliability of his habitual route in a more positive way than the unreliability of his non-

habitual route. We will analyze the data of our experimental research in order to accept or reject this hypothesis. The results are given in section 5.4.1.

The second topic we want to contribute to can be found in the integration of reliability in our route choice model. As discussed, there are many different reliability measures. Problems relating to statistics and data availability arise when integrating these measures in our route choice model and estimating it on our data. Section 5.3 will provide a simple solution for these problems.

Besides the integration of reliability in our individual route choice model, we start the analyses in section 5.4.2 by looking at a more aggregate level on how route choices evolve over time. This approach is less limited by data availability and statistical issues. It allows us to compare different reliability measures and shed some light on what measure explains behaviour best in our experimental situation. This constitutes our third contribution.

The fourth contribution concerns an assessment of the effect of travel information and travel goal on the risk averseness of route choices using the aforementioned aggregate analyses.

Finally, a contribution in itself concerns the fact that all these four topics have been analyzed using data from an enriched SP experiment, which are probably more valid than data from a plain SP experiment.

# 5.3 Modelling: Impact of reliability on expected travel time

This section describes how reliability was modelled inside the route choice model. This model has been introduced in a complete form in chapter 3. The notation section at the beginning of this thesis provides a short overview of all formulas and symbols. The results of the estimation of this model – as far as they are related to salience - are discussed next.

#### 5.3.1 Introduction

As discussed in section 5.1.4 reliability is usually modelled by entering the standard deviation of travel time into the route's utility function. We do not follow this method for two reasons. First, a fairly large number of observations are needed to allow for a good estimate of the standard deviation. For reasons discussed in chapter 4, we limited the number of observations per individual to 40. As there are three routes to choose from, the number of choices per route is especially in the beginning of the experiment very limited. Second, the expected travel time at day t and the standard deviation at day t are highly correlated. If for example a traveller experiences a very long travel time, both his expected travel time and his estimate of the standard deviation will increase. This high correlation can cause estimation problems.

The formulation we propose offers a solution for both problems. Furthermore, it takes into account the idea that not only the recency of an experience, but also its salience (which is closely related to reliability as will be clarified later) influence memory strength. Finally, we use the formulation to test whether, due to cognitive dissonance, long travel times on habitual routes are in fact weighted less than long travel times on non-habitual routes.

One critical remark has to be made: the proposed formulation is not the only possible formulation. It serves as a starting point to assess the potential of this research direction. As this chapter will show, there is potential in this research direction.

#### 5.3.2 Hypotheses and assumptions

A number of assumptions and hypotheses were made in deriving the formulation for salience that is used in our model. They are summed here.

#### *R1) There is a clear relation between salience and reliability.*

Large fluctuations can lead to salient travel times, which lead to less reliability.

*R2)* The weight of a travel time in updating the expected travel time depends among others on the salience of this travel time.

Literature is not clear on how this salience effect could work. Familiarity is an important aspect in recognition memory (Mandler, 1980). As salience is related to familiarity, we think it may have an effect on memory strength. Still, unfamiliar things are sometimes remembered better. Gregg (1976) found that low-frequency words in a list are recalled better than high-frequency words in a list. Marmurek (1984) presented respondents with a description of a peron's personality in order to give the respondents an expectation of that person's personality. Then, he presented them with 12 sentences about that person's personality. He found that respondents could remember the sentences that were inconsistent with the expectation better than the sentences that were consistent with it.

Alternatively, salient experiences may be easier to remember, because they draw attention. They may also provoke certain feelings that can bias the development of an expectation as well as a decision directly, as can be concluded from (Shiv et al., 2005).

*R3)* Salience of a travel time can be modelled by the ratio of that travel time to the expected travel time.

Salience was defined as the degree to which something stands out. The word 'degree' implies that it is a relative term. To determine the salience of a travel time, we therefore look at the relative deviation of the travel time from the current expected travel time. As our formulation serves as a starting point, we chose the simplest formulation that expresses this relative deviation: the ratio of the travel time to the expected travel time.

R4) A very large travel time on a habitual route has a different, probably less negative, impact on a traveller's expected route travel time than a very large travel time on a non-habitual route.

The reasoning underlying this hypothesis, involving cognitive dissonance theory, is given in section 5.2.

# 5.3.3 Salience: used formulation

The expected travel time is one of the attributes in our route choice model. Other attributes are road type, en-route traffic information, the fraction of choices for the route in the past and an error term. The expected travel time is made up by previous experiences, or earlier received information. We use the following formulas (for an in-depth discussion refer to chapter 6):

$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTT_{in(t-1)}$	if $\delta_{in(t-1)} = 1$	(5.2)
$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTTInfo_{in(t-1)}$	if $\delta_{in(t-1)} = 0$	(5.3)

With

TT	travel time
ETT	expected travel time
TTInfo	travel time as displayed on VMS
W	weight experienced / informed travel time in updating expected travel time
i	route index
n	traveller index
t	time index
$\delta_{int}$	choice dummy, equals 1 if route i was chosen by individual n at day t

Also in chapter 6, we argue that the weight of a single experienced or informed travel time depends on recency and salience. Salience refers to the degree to which something stands out. We therefore define the salience of a travel time as the degree to which it stands out from the current expected travel time. This definition also presents the relation with reliability [R1]<sup>6</sup>. A highly reliable route will always have more or less the same - not salient - travel time, whereas a highly unreliable route can have travel times which are very different from the current expectation and are hence very salient.

The word 'degree' in the definition means that salience is a relative term. To assess the salience of a travel time, we therefore look at the relative deviation of the travel time from the current expected travel time. As the analysis serves as a staring point, we choose the simplest mathematical formulation that can express this [R3]. Therefore, the following formulation for the salience of experienced travel times results:

$$s(TT_{\rm int}) = \frac{TT_{\rm int}}{ETT_{\rm int}}$$
(5.4)

For travel times that are provided by the en-route traffic information and are not experienced, the experienced travel time has to be replaced by the informed travel time *TTInfo* in equation (5.4).

#### 5.3.4 Weight of a travel time: used formulation

The weight of a travel time, used in computing the new expected travel time, is dependent on recency and salience effects [R2]. For non-habitual routes we hypothesize the weight to be larger for very large travel times. As the analysis serves as a staring point, we choose the simplest mathematical formulation that can express this. The following formulation results:

$$w(TT_{int}) = s(TT_{int})r(TT_{int})$$
(5.5)

With

- w overall weight of an experience in updating the expected travel time, lies between 0 and 1
- r recency effect, impact of a new experience relative to the previous expected travel time, lies between 0 and 1
- s salience, a factor that gives extra or less weight to the new experience

For habitual routes, we hypothesize the opposite mechanism to apply, i.e. very large travel times have less weight [R4]. The formulation can then become:

$$w(TT_{\rm int}) = \frac{1}{s(TT_{\rm int})} r(TT_{\rm int})$$
(5.6)

To compute the weight of an informed travel time *TT* is replaced by *TTInfo* in the equations above.

As the weight needs to be in between 0 and 1 (as explained in chapter 6), we add the following restriction:

<sup>&</sup>lt;sup>6</sup> The numbers in brackets refer to the assumptions and hypotheses from the previous section.

if weight > 1
weight = 1;
elseif weight < 0
weight = 0;</pre>

#### 5.3.5 Habitual route: used definition

The habitual route is defined to be the route that is chosen most over the past 10 days. We chose to use 10 past days for the following reasons. If one uses much more than 10 days, fundamental changes in behaviour (due to learning dynamics) would not be reflected in the habitual route. When using much less than 10 days, incidental changes would have too much effect on the habitual route. Ten days is used as a compromise. For the first 10 days, we define the habitual route to be the route that is chosen most over all past days. In case of a tie, we define the habitual route to be the same as the day before.

# 5.4 Data analysis

The data analysis comprises two parts. First, the route choice model is estimated and its outcomes, as far as they are related to reliability, are discussed. The route choice model specifies the route's utility for a traveller on a given day. As such, it can be regarded as a micro analysis. Macro analysis were also carried out. The experimental data were aggregated to gain insight in the attractiveness of routes, how this evolves during the experiment and how this depends on provided traffic information or imposed travel goal. This aggregate analysis and its outcomes are discussed in section 5.4.2.

#### 5.4.1 Model outcomes salience

First, the followed estimation procedure is discussed. The results are given next. We conclude with a discussion on whether to accept or reject the hypothesis that reliability is valued differently on habitual routes than on non-habitual routes.

#### **Estimation procedure**

To analyze whether the salience formulations improve model performance, we estimated our route choice model using the following salience treatments:

- 1. Without taking account of any salience effects, so  $w(TT_{int}) = r(TT_{int})$
- 2. Calculating the weight for experiences / provided traffic information on both habitual and non-habitual routes as in equation (5.5).
- 3. Calculating the weight for experiences / provided traffic information on both habitual and non-habitual routes as in equation (5.6).
- 4. Calculating the weight for experiences / provided traffic information on habitual routes as in equation (5.6) and on non-habitual routes as in equation (5.5).
- 5. Calculating the weight for experiences / provided traffic information on habitual routes as in equation (5.5) and on non-habitual routes as in equation (5.6).

For each salience treatment, the optimal values of the recency parameters were determined. These optimal values were then used in estimating the route choice model. In this way, only the best models for each salience method are estimated. The estimation was done for the beginning, middle and end period and for two different information scenarios. The first is the scenario in which travellers received en-route information about the expected travel time in minutes and did not receive ex-post information on realized travel times on all routes. The second is the scenario in which travellers did not receive any en-route information and did not receive ex-post information on realized travel times on all routes either.

### Outcomes

The rho-square values of the best model for each salience method are listed in Table 8. Details of the best performing model for each period and each information scenario are provided in appendix A.

Salience method $\rightarrow$		1	2	3	4	5
No info	Beginning	0.208398	0.208973	0.206240	0.209468	0.207077
	Middle	0.375916	0.374984	0.374630	0.373858	0.374349
	End	0.464846	0.461715	0.464562	0.460830	0.464080
Info	Beginning	0.349461	0.352625	0.346786	0.355682	0.345711
	Middle	0.406407	0.407815	0.404711	0.411049	0.403195
	End	0.456687	0.458301	0.455499	0.456437	0.456672

<b>Fable 8: Rho-square</b>	values for	best model of	f each salience method
----------------------------	------------	---------------	------------------------

As the table shows, method 4 is clearly the best in beginning and middle period of the info scenario and slightly the best in the beginning period of the no info scenario. This is the method by which long travel times on habitual routes are weighted less and on non-habitual routes are weighted more than normal travel times. In other words, it is the method that is in line with our hypothesis on cognitive dissonance.

For the later periods method 1 for the no info scenario and method 2 for the info scenario are found to be slightly better than the other methods. This doesn't necessarily mean that for these periods our hypothesis is wrong. Since the expected travel time for the beginning periods has been computed by method 4, it is objectively seen too low for the habitual routes and too high for the non-habitual routes. Remember that the expected travel time for the next period is an update of the expected travel time from the previous period. Using method 1, the expected travel time *remains* therefore from an objective viewpoint too low for the habitual routes and too high for the non-habitual routes (though the discrepancy from the objective expected travel time is not *further* increased).

# **Conclusions model outcomes**

Including salience into our model taking into account our hypothesis on cognitive dissonance sometimes improved model performance. Therefore, the hypothesis is partly confirmed by this analysis. Further research is necessary, however, to draw stronger conclusions.

# 5.4.2 Analysis of evolution of route choice behaviour

This paragraph will start with an overview of the routes' performance on various travel time reliability measures. Then, the evolution in route choice behaviour will be presented and related to these routes' performance on travel time reliability measures. This will tell us something about what reliability measure explains behaviour best in our experiment. The next section zooms into the results from the previous section by disaggregating the data on behalf of received traffic information and imposed travel goal. We end with some overall conclusions.

#### **Evolution reliability measures**

We start with an overview of a number of the travel time (reliability) measures that were introduced earlier. As explained in chapter 4, the travel times during the second half were

changed for some respondents. As a result, travel times could differ between respondents. Therefore, the mean, variance, standard deviation,  $10^{th}$  percentile,  $50^{th}$  percentile,  $90^{th}$  percentile,  $\lambda^{skew}$  and  $\lambda^{var}$  of the actual travel times for each route had to be calculated for each respondent individually. Finally, the mean of all these individual values was computed. Table 9 summarizes the values. It gives the values calculated over all 40 days, over the first 10 days, the second 15 days and the last 15 days. Refer to Table 6 for an explanation of the various measures.

One more remark has to be made about the values in the table. Due to the small sample sizes (10, 15 and 15 observations), it is problematic to calculate the percentile values. Having 15 observations, it is straightforward to calculate the  $67^{\text{th}}$  percentile (=10/15<sup>th</sup> percentile) and the 73<sup>rd</sup> percentile (=11/15<sup>th</sup> percentile). However, calculating the 70<sup>th</sup> percentile requires interpolation. To avoid discussions on what interpolation method to use (linear, or following the probability distribution which is not known to the traveller), we decided to list the 13<sup>th</sup>, 53<sup>rd</sup>, 67<sup>th</sup>, 73<sup>rd</sup>, and 93<sup>rd</sup> percentiles for the 15 day periods and the 10<sup>th</sup>, 50<sup>th</sup>, 70<sup>th</sup>, 75<sup>th</sup> and 90<sup>th</sup> percentiles for the 10 day period.

Table 9: The	routes a	nd the	mean of	individual	values	for a	number	' of	travel	time
(reliability) m	easures									

Route			1			,	2			3		
			11	26		1	11	26			11-	26-
days	all	1-10	-25	-40	all	-10	-25	-40	all	1-10	25	40
mean	45	46	45	45	53	53	53	54	47	43	51	47
											15	
var	235	296	252	201	10	0	4	19	156	138	8	160
stdev	15	17	16	14	3	1	2	4	13	12	13	13
$\lambda^{skew}$	15	24	16	14	4	1	1	5	2	4	1	2
$\lambda^{var}$	1	1	1	1	0	0	0	0	1	1	1	1
p10 / p13 *	34	35	34	35	52	52	52	52	33	33	34	33
p50 / p53 *	37	36	36	38	53	53	53	53	44	39	49	45
p70 / p67 *	42	54	42	42	53	53	53	53	52	44	60	51
p75 / p73 *	57	70	62	42	53	53	53	56	57	47	64	53
p90 / p93 *	71	72	71	71	57	53	54	59	66	64	67	66

\*  $13^{th}$ ,  $53^{rd}$ ,  $67^{th}$ ,  $73^{rd}$ , and  $93^{rd}$  percentiles relate to the two 15 day periods and the  $10^{th}$ ,  $50^{th}$ ,  $70^{th}$ ,  $75^{th}$  and  $90^{th}$  percentiles to the 10 day period.

Without having discussed yet what reliability measure is best, it becomes immediately clear from Table 9 that route 2 is very reliable, since all reliability measures agree on this. It is also clear that route 2 is on average the slowest. Route 1 and 3 perform on most measures relatively similar. On  $\lambda^{skew}$ , however, they are extremely different. This measure reflects the very different shape of the travel time distributions of route 1 and route 3 best. The percentiles p70 / p67 are also quite different for routes 1 and 3. Possibly, travellers are satisfied with arriving 70% of the cases on time and choose the route that has the best value for p70. As argued, we are looking for a measure that describes behaviour best. This is the topic of the next section.

#### **Evolution route choice behaviour**

Table 10 shows how often (in percentages) each route is chosen during the first 10 days of the experiment, the second 15 days and the last 15 days. On a high level it shows how the preferences for a route evolve as the respondents gain more experience with the route's

characteristics. A critical remark has to be made here. We realize that we do not know the individual's perception of the reliability of each route. However, due to the large number of route choices made (2500 respondents each made 40 route choices resulting in 100,000 route choices), we do believe that we can draw some meaningful conclusions from Table 10.

<b>Travel goal</b>	Meet	ing with colle	agues	Job interview			
Days							
Route	1-10	11-25	26-40	1-10	11-25	26-40	
1	45.4%	43.1%	51.1%	42.3%	39.6%	46.8%	
2	19.7%	34.3%	30.3%	21.2%	37.2%	33.7%	
3	34.8%	22.6%	18.7%	36.6%	23.2%	19.5%	

T٤	abl	<b>e</b> 1	10:	Evo	lution	of	Route	Cho	oices	duri	ing	the	Ex	perime	nt
											_				

We conclude from Table 10 that the respondents have learned to dislike route 3. Furthermore, it is clear that route 1 is preferred most. To put it differently, route 1 has got something that travellers like and route 3 has got something they do not like. Remember from the previous section that route 1 and route 3 perform similarly on most travel time (reliability) characteristics, except on  $\lambda^{skew}$ . This might be seen as an indication that  $\lambda^{skew}$  is an important reliability measure when one tries to explain route choice behaviour in this context. Apparently, people prefer a route that is usually fast, accepting that it is sometimes very slow, over a route that can have any travel time within a long range with more or less the same probability. In a way route 1 is more predictable, i.e. when predicting route 1 to take approximately 35 minutes, this will be correct in 75% of the cases. For route 3 it is impossible to predict any specific travel time with a chance of being right 75% of the time.

Another possible explanation for this finding can be found in psychology. Route 1 usually has a very short travel time. Choosing route 1 therefore often leads to being *rewarded* with a short travel time. However, sometimes it is *punished* with a long travel time. Psychological research has found that behaviour that is often rewarded, but sometimes punished is strongly reinforced. It is even stronger reinforced than behaviour that is always rewarded and never punished (Skinner, 1938).

One more critical remark that is related to the first one – saying that we do not know the individual's perception of the reliability of each route – concerns the length of the experiment. It may be possible that it takes longer to learn the unreliability of a route and adapt ones perception of unreliability the skewer the travel time distribution is, since in that case very long travel times occur only rarely. However, observing a long travel time on route 1 is in the experiment not extremely rare (25% probability). Still, in line with the contingency view, one should be careful when translating the findings from this study to very different situations.

Furthermore, Table 10 shows that travellers going to a job interview choose the reliable route 2 slightly more than travellers going to a meeting with colleagues. Still, the majority of travellers going to the job interview choose the less reliable routes 1 or 3. We expect this to be less the case in reality, since the consequences of arriving late at the job interview are far more severe in reality than in the experiment. The provision of information may also have stimulated choosing the unreliable routes. This is the topic of the next section.

#### Influence of traffic information and travel goal

En-route travel information allows the traveller to have a better estimate of the current travel time. The en-route information in the TSL experiment was most of the time very accurate: it deviated in 85% of the days at most 2 minutes from the real travel time. In the other 15% it deviated approximately 10 to 30 minutes from the real travel time, usually underestimating the real travel time.

Without en-route information route 3 is much less and route 2 is much more chosen than with en-route information, see Table 11. Apparently, travellers find route 3 too unreliable to choose without having any indication how it will perform on the current day. Without this information they rather choose the reliable, albeit longer, route 2. This is especially true for the job interview scenario. Note that by this behaviour, the amount of risk remains more or less the same, which can be explained by the theory of risk homeostasis.

Travel g	oal	Meeting with colleagues									
	Info	Ν	o en-route in	fo	En-route info						
	Days										
	Route	1-10	11-25	26-40	1-10	11-25	26-40				
	1	60.3%	46.3%	44.4%	41.7%	42.4%	52.7%				
	2	22.2%	37.5%	40.4%	19.1%	33.5%	27.7%				
3		17.4%	16.2%	15.1%	39.2%	24.2%	19.6%				
Travel g	oal	Job interview									
	Info	No en-route info En-route info									
	Days										
	Route	1-10	11-25	26-40	1-10	11-25	26-40				
	1	53.7%	43.2%	39.7%	40.0%	38.9%	48.2%				
	2	27.6%	40.5%	48.3%	20.0%	36.6%	30.9%				
	3	18.7%	16.3%	12.1%	40.0%	24.5%	20.9%				

#### Table 11: Evolution of Route choice percentages with and without en-route information

Another goal of this research is to see whether ex-post travel information on non-chosen routes can change the perception of travel time reliability. It is assumed that the perception of reliability influences the route choice. Table 12 shows route choice percentages for travellers with ex-post information on non-chosen routes; table 5 shows these percentages for travellers without ex-post information on non-chosen routes. Comparing the tables one can see that the provision of ex-post information does not have a large influence on route choice percentages for people who also receive en-route information. However, for travellers who do not receive en-route information, the provision of ex-post information enlarges the share of route 1 and decreases the share of route 2. Probably, the provision of en-route information and / or ex-post information changes travellers' perception and makes them realize better that route 1 is only sometimes very bad. Table 13 also shows that the reliable route 2 has the largest share (51.9%) among travellers who did not receive en-route information nor ex-post information and had to go to a job interview. This seems rather plausible as this scenario represents maximum uncertainty (no information) and maximum costs of arriving late (job interview).

#### **Conclusions aggregate analysis**

Aggregate analysis on our experimental data showed that people prefer a route that is usually fast, accepting that it is sometimes very slow, over a route that can have any travel time within a long range with more or less the same probability. Further analysis of this result showed that

travel goal and travel information influenced route choice. The largest difference in choosing the most reliable route 2 can be found between the following two scenarios:

- No en-route information, no ex-post information on non-chosen routes and going to a job interview (maximum uncertainty, maximum costs of arriving late)
- En-route information, ex-post information on non-chosen routes and going to a meeting with colleagues (minimum uncertainty, minimum costs of arriving late)

In the first case the reliable route 2 is chosen most, in the latter case it is chosen least, refer to Table 13. The 90<sup>th</sup> percentile would be more explanatory in the first case, whereas the 70<sup>th</sup> percentile would be a more suitable reliability measure in the second case. This is an indication of the appropriateness of the contingency view, saying that the appropriateness of a reliability measure depends on the specific situation.

#### Table 12: Route Choice Percentages for People with Ex-post Information

		Meeting with colleagues										
		No en-	route info			En-rout	e info					
		d	ays			day	/S					
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total				
1	60.8%	46.5%	46.2%	50.0%	42.3%	42.4%	53.0%	46.3%				
2	22.7%	36.8%	39.2%	34.2%	19.0%	33.2%	26.9%	27.3%				
3	16.5%	16.7%	14.6%	15.8%	38.6%	24.4%	20.1%	26.4%				
				Job int	erview							
		No en-	route info			En-rout	e info					
		D	ays			day	'S					
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total				
1	81.1%	69.6%	74.1%	74.2%	43.0%	42.4%	48.1%	44.7%				
2	5.6%	15.6%	20.7%	15.0%	15.2%	31.6%	29.0%	26.5%				
3	13.3%	14.8%	5.2%	10.8%	41.8%	26.0%	22.9%	28.8%				

# Table 13: Choice Percentages for People without Ex-post Information

	Meeting with colleagues										
		No en-r	oute info			En-rout	te info				
		da	ays			day	/S				
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total			
1	59.4%	45.7%	40.7%	47.2%	40.5%	42.3%	52.2%	45.5%			
2	21.3%	39.0%	43.0%	36.1%	19.3%	33.9%	29.5%	28.6%			
3	19.4%	15.3%	16.3%	16.7%	40.2%	23.8%	18.4%	25.9%			
				Job in	terview						
		No en-r	oute info			En-rout	te info				
		da	ays		days						
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total			
1	50.1%	39.7%	35.2%	40.6%	38.6%	37.1%	48.2%	41.7%			
2	30.4%	43.8%	51.9%	43.5%	22.3%	39.0%	31.9%	32.2%			
3	19.4%	16.5%	12.9%	15.9%	39.1%	23.8%	19.9%	26.2%			

# 5.5 Conclusions reliability

A review of literature from psychology, economics and neuro-science led to the conclusion that people exhibit specific types of risk behaviour. In this light, not only mean travel times, but also travel time reliability plays an important role in travel behaviour. Reviewing literature from travel behaviour research showed that travel time reliability indeed is taken into account. Nevertheless, we identified a number of topics to contribute to.

The first topic concerns the different valuation of reliability on habitual and non-habitual routes. We found that – compared to regular travel times - very bad travel times are sometimes given extra weight on non-habitual routes and less weight on habitual routes. We explained this by applying cognitive dissonance theory.

Second, we integrated reliability in our route choice model. The method is also feasible on data not acquired through SP research. The first contribution (different valuation of reliability on habitual and non-habitual routes) is the result of estimating this model.

Furthermore, different reliability measures were tested. We found that there is not one best measure in terms of explaining route choice behaviour. High-level analysis showed that people prefer a route that is usually fast and sometimes very slow over a route that can have any travel time within a long range with more or less the same probability. As such, a measure incorporating skewness is appropriate. Travel goal and travel information were found to influence route choice.

Finally, a contribution in itself concerns the fact that all these topics have been analyzed using data from an enriched SP experiment, which are probably more valid than the often used pure SP data.

# 6 Learning

Learning is a very important topic in day-to-day route choice, as the repetitive nature of dayto-day route choice offers ample opportunities for learning. This chapter is dedicated to the topic of learning and is organized as follows. First, a review of relevant literature is given. Basic insights from psychological learning theory are described. We conclude that both explicit learning (related to the updating of an expected travel time) and implicit learning (related to inertia and habit formation) are important in route choice. The second part of section 6.1 contains a review of current approaches to modelling learning in day-to-day route choice. Section 6.2 is a synthesis of the previous and compares the insights from psychological learning theory to current modelling approaches. We conclude that existing models seldom capture both types of learning and that their parameters are hardly estimated on experimental or empirical data. Therefore, section 6.3 focuses on developing a model that does capture both types of learning. In section 6.4 the results of estimating the model's parameters on experimental data are presented.

# 6.1 Literature overview

This section presents an overview of basic insights from psychological learning theory and of the current approaches to modelling learning in day-to-day route choice.

# 6.1.1 Psychological learning theory

Many theoretical issues with respect to learning and memory, which is pertinent to learning, can be found in specific psychology literature. Two relevant types of learning in a route choice context are described here: *implicit* (reinforcement) learning versus *explicit* (cognitive) learning (Johnson and Proctor, 2004). Implicit learning occurs without intention, the learner or operator is often not even aware of what is learned, while explicit learning is based on intentional learning, paying attention to the object. The respective forms of memory are implicit memory, which is in principle non-declarative, unconscious, and explicit memory, which is declarative and conscious (refer to (Gray, 2002)). A short remark on other relevant memory characteristics is made at the end of this section.

#### **Implicit learning**

Implicit learning comprises all kinds of learning where repetition of the relationship between stimulus and response patterns is stored in the neural system as a memory trace (a mental representation), leading to automated behaviour. Two main types are differentiated, classical and operant conditioning. Classical conditioning is typical for the situation when a stimulus is (immediately) followed by another stimulus or an event, often a positive token, which leads to a response. The classic example of this phenomenon is the Pavlov Reaction (Pavlov, 1927). Pavlov discovered this reaction in the behaviour of dogs. When a bell rang, food was presented to a dog. Every time the bell rang, the dog's mouth started to water, even when the food was not presented. Although Skinner became famous for operant conditioning, Thorndike described the basic principles of operant conditioning. Thorndike (1898) found out that when he locked a cat in a box, the cat discovered by coincidence that when it pushed a handle, the box opened. Every time the cat was put in the box again, it took less time for it to escape. Thorndike formulated the law of effect, saying that when an action, a response leads in a certain situation to a satisfying result, it is likely that in that situation this response will be given more often. And even if the result is not really satisfying, the mere exposure to it can increase a person's valuation of the response, solely because the person becomes familiar with it. This is known as the mere exposure effect (Zajonc, 1968). Reinforcement can ultimately lead to habitual behaviour implying automatic responses.

In this way, reinforcement learning (automation) may also determine route choice. An overview of findings concerning the role of habit in travel choices is given in (Garling and Axhausen, 2003). Note that when the characteristics of the transport system change, the habitual route choice may not lead to the result that is optimal for the traveller anymore (Jager, 2003). Experiencing a relative short travel time should be regarded as positive reinforcement, whereas extremely long travel time is a case of negative reinforcement. Furthermore, repeatedly experiencing a route can produce a mere exposure effect. To conclude, choosing a route can, at least as long as it does not produce very bad outcomes, increase the perceived attractiveness of a route, bias further route choices and lead to habitual behaviour.

#### **Explicit learning**

People are also very well able to learn intentionally. After decades of studying reinforcement learning, psychology started to study explicit or cognitive learning. The contemporary view of learning is that people construct new knowledge and understanding based on what they already know and believe (e.g. (Cobb, 1994), (Piaget, 1977) and (Piaget, 1978). Examples of explicit learning include learning through written or verbal instruction and learning through observation and imitation. This last type of learning is also known as social learning and described in detail in (Miller and Dollard, 1941) and (Bandura, 1977).

This view on learning is deemed especially relevant for studying the effect of travel information in route choices, as the information itself does not induce any reinforcement, but does allow for constructing new knowledge about the routes. Furthermore, in the case that a traveller had only received positive reinforcement with respect to a route, phenomena like choosing an unknown route for the sake of gaining information and seeking novelty (as described by (Arentze and Timmermans, 2005) and (Chorus et al., 2006)) can be explained by this view of learning. Finally, since a traveller is seldom alone in traffic, there is an opportunity to learn by observing other travellers. This lies, however, outside the scope of this thesis. As far as explicit learning is concerned, we focus on expected travel time: how it is developed and updated.

#### Memory

Learning from past experiences implies remembering them. A huge body of literature exists on memory. Here we only want to note the most basic issues.

#### Memory and time

For the relation between time and memory a (steep) exponential curve was found by Ebbinghaus (Ebbinghaus, 1885). This means that the more time has past since an event, the less well it is remembered and that forgetting is fast at the beginning and slow at the end. An example of the shape of the forgetting curve is given in Figure 18.



Figure 18: Example of the forgetting curve

Similarly, recent events are remembered better. This is referred to as recency effect. Later research showed that besides this recency effect, there is also a primacy effect (Murdock Jr, 1962). This means that the first item in a series is often remembered relatively well.

The explanation for the primacy and recency effect, together called the serial positioning effect, may lie in the different types of memory. Two important memory types are the shortterm working memory and the long term memory. The short term memory can store a limited amount of information, perhaps four to seven items, for several seconds. This memory is sufficient to remember a telephone number as long as it is dialled, but it fades away in a few seconds. Short term memory, or working memory, is supposed to control the execution of operations and decision making. The long-term memory is a more or less permanent store of knowledge and information. Information storage and retrieval in long-term memory is rather slow and requires effort and attention (Atkinson and Shiffrin, 1968). Much knowledge and information is stored in a way that combinations of knowledge items can be used to (re)produce new knowledge which is essential to learning. Information is better stored and retrieved if it has a structure that can be semantically organized. Coming back to the serial positioning effect, one can argue that the first item in a list attracts full attention and can be rehearsed shortly without distraction before attention is diverted by the next item. As such, it can be stored more effectively in long-term memory than the following items. The last item in the series is likely to be still present in working memory.

Many more phenomena that influence memory have been found. On Wikipedia for example, 40 of these so called memory biases are described (Wikipedia). As we are mainly interested in

how travel times in a series are remembered and recency and primacy relate to how items in a series are remembered, we limited the discussion here to these two memory effects.

#### Memory and function

In the introduction to this section it was written that explicit learning is related to explicit, in principle declarative memory, while implicit learning is related to implicit, in principle non-declarative memory. The first type concerns our factual conscious memory; the second type is also called procedural memory and is subconscious. Habits are stored in procedural memory. Research has shown that the types reside in different parts of the brain (Squire, 1992). Declarative memory relies on a medial temporal lobe system, whereas habit learning relies on the striatum (Cohen and Eichenbaum, 1993) Declarative and habit learning compete to mediate task performance; distraction biases this competition in favour of habit learning (Foerde et al., 2006). As there can be much distraction in traffic, this finding can mean that the role of habit is very important in travel behaviour.

#### Salience

Besides recency and primacy, we also want to mention salience here. Literature is not clear on how this salience effect could work. Familiarity is an important aspect in recognition memory (Mandler, 1980). As salience is related to familiarity, we think it may have an effect on memory strength. Still, unfamiliar things are sometimes remembered better. Gregg (1976) found that low-frequency words in a list are recalled better than high-frequency words in a list. Marmurek (1984) presented respondents with a description of a peron's personality in order to give the respondents an expectation of that person's personality. Then, he presented them with 12 sentences about that person's personality. He found that found that respondents could remember the sentences that were inconsistent with the expectation better than the sentences that were consistent with it.

Alternatively, salient experiences may be easier to remember, because they draw attention. They may also provoke certain feelings that can bias the development of an expectation as well as a decision directly, as can be concluded from (Shiv et al., 2005).

#### Conclusion

Research has described different types of learning and memory: implicit and explicit. It has been shown that these types reside in different parts of the brain. Recency, primacy and salience of the event influence how well it is remembered and learned. Based on this, we conclude that route choice models should at least accommodate both types of learning. Preferably, recency, primacy and salience have to be taken into account as well.

To illustrate how the previous conclusions can be applied in route choice, we give an example: As a result of certain route choices travellers experience consequences (arriving late, arriving early, standing in queue, etc.). These can be positive or negative. If the link between choice and outcome is stored in memory it can positively or negatively influence future choices. A positive outcome of choosing a certain route can for example reinforce future choices for this route, even if the traveller is not aware of this mechanism: the traveller has learned implicitly. If the traveller does realize that the experienced travel time was better than the travel times on the alternative routes and this observation is stored in memory, the traveller learned explicitly. The extent to which an experience is stored in memory depends on its recency, primacy and salience.

#### 6.1.2 Modelling learning in route choice

Most approaches to model learning in route choices focus on explicit learning through which a mental representation of the travel time characteristics of a route is built, often referred to as expected travel time, or travel time estimate. Although much research has been carried out on the role of habit in travel choices *in general* (refer to (Garling and Axhausen, 2003)), implicit learning (i.e. reinforcement learning and habit formation) is often not accounted for *in route choice models*.

Note, however, that part of this implicit learning is probably captured indirectly in the expected travel time when one regards short travel times as rewards and long travel times as punishments. An overview of different model types is provided in this section.

#### Weighted Average of Travel Costs

One of the first to use a weighted average approach was Horowitz (1984). He formulates the expected generalized travel cost of route i at time t as follows:

$$\hat{C}_{it} = \sum_{k=1}^{t-1} w_k C_{ik} + \varepsilon_{it}$$
(6.1)

where  $C_{ik}$  is the measured travel cost on link i in time period k,  $\varepsilon$  is a random variable and  $w_k$  is a weight at time k. Various functions can be used to compute the weights. Because of memory decay, recent experiences typically have a higher weight than older experiences. Chang and Mahmassani (1988) use this type of model. One of their conclusions is that especially the latest day's experience is used for making an expectation of the travel time. Experiences from two days ago are hardly used and experiences from more than three days ago are insignificant in making an expectation of the travel time.

Oh et al. (2003) use the method of successive averages. The updated estimation of the travel time is given by:

$$T_{t+1}^{'} = (tT_{t}^{'} + T_{e,t})/(1+t)$$
(6.2)

where  $T'_{t+1}$  is the updated expected travel time after the trip on day t and  $T_{e,t}$  is the experienced travel time during the trip on day t. Some critical remarks can be made on this model. First, they have no empirical data to test their model. Second, when t is large, new experiences hardly have any weight when using this formula. Because of memory decay on the one hand and possibly changing characteristics of the route on the other hand, this may not be a proper way of modelling.

#### **Myopic Models**

The myopic models described here can be regarded as a special type of a weighted average model, namely with a weight of one for the most recent experience and a weight of zero for all other experiences. Although this may have computational advantages, it is not in line with the notions on memory (refer to section 6.1.1) and probably not very realistic. Mahmassani and Chang (1986) formulated their model of myopic adjustment as follows:

$$T'_{i,t+1} = T_{i,t} + a_i \gamma^e_{i,t} E_{i,t} + b_i \gamma^l_{i,t} E_{i,t}$$
(6.3)

- $T'_{i,t+1}$  trip time estimate by user i for day (t+1)
- T<sub>i,t</sub> actual trip time experienced by user i on day t
- $E_{i,t}$  actual schedule delay of user i on day t
- $\gamma_{i,t}^{e}$  binary variable such that  $\gamma_{i,t}^{e} = -1$  if user i is early on day t and 0 otherwise

 $\gamma^{l}_{i,t}$  binary variable such that  $\gamma^{l}_{i,t} = 1$  if user i is late on day t and 0 otherwise

a, b parameters

Other articles that use myopic adjustment in their route choice model include (Mahmassani and Liu, 1999) and (Srinivasan and Guo, 2004).

#### **Markov Process Representation of Learning**

Ben-Akiva et al. (1991) state that a driver can update his historical travel time estimate by combining it with yesterday's experience and information. In order to model this day-to-day learning, they use an exponential Markov process of order  $1^7$  with the following rules:

$$tt_{r^*,t^*}^h(w) = (1-q^x)tt_{r^*,t^*}^h(w-1) + q^x tt_{r^*,t^*}^x(w-1)$$
(6.4)

$$tt_{r,t}^{h}(w) = (1 - q^{E})tt_{r,t}^{h}(w - 1) + q^{E}tt_{r,t}^{E}(w - 1)$$
(6.5)

$$(r,t) \neq (r^*,t^*)$$
 (6.6)

Where  $tt_{rt}^{h}(w)$  constitutes the individual's travel time estimate at the beginning of day w for travel pattern (r,t). His or her update is a function of the previous historical estimate  $tt_{tr}^{h}(w-1)$  and the information acquired either by personal experience  $tt_{t*r*}^{h}(w-1)$ , or by exogenous information  $tt_{tr}^{E}(w-1)$ . Note that this formulation allows also for updating estimates for travel patterns that were not chosen. The authors have no data to estimate their model, nor extensive argumentation for the correctness of this type of model.

Reddy et al.(1995) and De Palma and Marchal (2002) use similar formulations to model the updating of the expected travel time. They have no empirical data either to estimate their model and assume the weight of a new experience to be 0.05 (resulting in a weight of 0.95 for the historical expected travel time).

Like myopic models, this type of model has the advantage of requiring only a small number of parameters that have to be estimated. An advantage over myopic models, however, is that it does not assume upfront that experiences of two or more days ago are irrelevant. Furthermore, it incorporates the exponential memory decay curve from Ebbinghaus (1885) and is in line with the contemporary view on learning saying that people construct new knowledge and understanding based on what they already know and believe (e.g. (Cobb, 1994), (Piaget, 1977) and (Piaget, 1978)).

#### **Bayesian Updating**

Jha et al. (1998) model the learning of the routes' mean travel time by regarding it as a Bayesian updating process. Before a route choice, the expected travel time is updated by combining it with the received travel information. After experiencing the resulting route travel time, post-trip updating occurs. Through Bayesian updating the old expected travel time is combined with the new experienced travel time. Advantages of this kind of modelling are that

<sup>&</sup>lt;sup>7</sup> A Markov process is a stochastic process in which the distribution of future states depends only on the present state and not on how it arrived in the present state. Order 1 models only need one piece of historical information: tomorrow is dependent on today; information about yesterday is not needed.

information from various sources can be combined and that the reliability of these sources can also be modelled. The idea of updating and giving different weights to different sources is comparable to the Markov process representation of learning. The required number of parameters is, however, much larger.

#### Classification

Ettema, Timmermans and Arentze (2003) contribute to the modelling of learning by taking into account both recency and representativeness of experiences. The weight of an experience in their model is dependent on them. The traveller learns by classifying the experiences. Experiences made under similar conditions are put into one class and for each experience the mentioned recency and representativeness are stored. It is not explained how from these classes of experiences a traveller comes to an expected travel time. The authors have no empirical data to validate their model.

### **Combined Explicit and Implicit Learning Models**

Camerer et al. (2002) integrate habit formation and cognitive learning. They model the attractiveness of an alternative as a function of the number of times chosen in the past and the expected attractiveness (calculated using Bayesian updating). As the number of times the alternative had already been chosen increases, the attractiveness of the alternative increases as well. Viti et al. (2005) have successfully applied their model to a route choice situation. Mahmassani and Liu (1999) include in their model some kind of inertia by assuming that a traveller only switches to another route if this is significantly faster. Srinivasan and Mahmassani (2000) also include an inertia component based on the most recent choice. Note that these ways of modelling are myopic, as only one past choice is considered. A long-term learning process, or the building up of habitual behaviour cannot be modelled this way.

Van Berkum and Van der Mede (1993) also integrate both types of learning in their route choice model. The cognitive learning part is a Markov process model and is the same as given in equation (3.9); the implicit learning part is given in (6.7):

$$PIN_{irt} = \frac{\gamma PIN_{ir,t-1} + \delta_{ir,t-1}}{\gamma + \delta_{i,t-1}^r}$$
(6.7)

With

PIN probability that a route is chosen out of habit

 $\gamma$  speed with which PIN increases after the route has been chosen once more

 $\delta_{irt}$  equals 1 if route r was chosen at day t by individual i and 0 else

They estimated their model on empirical data obtained from a motorway system around Amsterdam. Drivers could choose between two routes there and during the experiment a VMS was introduced which provided queue lengths on both routes. Around 400 drivers recorded during four two-week periods their route choices, observed VMS information, experienced congestion and arrival time at the VMS and at their destination. Besides the mentioned explicit and implicit learning attributes, the expected standard deviation of travel time and queue length information appears in their model. The results indicate that habit is by far the dominant decision rule and that providing information only slightly decreases the influence of habit. In our approach we do not use a decay parameter to model implicit learning. The reasons for this are discussed in section 6.3.1.

Their model and experiment are very relevant for our study. Note, however, that the respondents in their experiment are drivers who were already very familiar with the situation.

As such, their results may not shed much light on the total learning process, from beginning until the end, the type of learning in which we are interested. Also note that their experiment was conducted in a time when travellers were not used yet to VMS's. At present travellers are used to all sorts of dynamic traffic information, like VMS, navigation systems, etc. Their reactions to dynamic traffic information may therefore be very different. Indications that reactions are indeed influenced by the familiarity of travellers with the information service are found in (Emmerink et al., 1996; Abdel-Aty and Abdalla, 2006).

Finally, we want to mention a study that includes only an implicit learning part in their model (an left out an explicit learning part). Adler and McNally (1994) model route switching behaviour and use data from a laboratory experiment to estimate the model's parameters. The familiarity with the current street and the number of previous trips on the current link (which can be regarded as a proxy for implicit learning) were found to decrease the probability of switching to another route.

# 6.2 Synthesis

Based on the literature review we hypothesize that both explicit and implicit learning play a significant role in route choice. Modelling efforts in route choice have concentrated on explicit (cognitive) learning. Habit formation or reinforcement of alternatives that have been chosen frequently in the past is often not modelled at all. Only Camerer et al. (2002) and Van Berkum and Van der Mede (1993) - and to some extent Mahmassani and Liu (1999) and Bogers et al. (2005) - incorporate this as well in their model. The results obtained by Van Berkum and Van der Mede (1993), however, are not very recent (travellers were not used to VMS information then) and do not involve the entire learning process as the respondents were already familiar with the traffic situation.

The literature review also showed that experimental underpinning of the models is a highly neglected task. Therefore, it is not possible to say what type of model best describes behaviour. Important for our study is how well a model is in line with psychological learning theory on the one hand and how practical (in terms of number of parameters to be estimated and ease of interpretation) it is on the other hand. An indication of how the models perform on these criteria is provided in Table 14.

The table shows that the Markov process model representation is the model that performs well on more criteria that are important for our research than the other model types. It is relatively simple and (partly) in line with psychological research into memory decay and the contemporary view of learning which regards learning as integrating new information with existing knowledge. It does not comprise, however, implicit learning. We will use the Markov process model representation therefore to model explicit learning. Note that we do not say that the other models are not good in general. It all depends on the criteria that are used to judge them and the goal the researcher has in using them.

Based on the previous, this chapter will contribute in the following ways:

- A model specification is proposed that captures both explicit learning (using a Markov process model representation) and implicit learning.
- The model will be estimated on experimental data.
- The estimation will be done in such a way that we gain insight in the complete learning process, from the beginning where the respondents know nearly nothing about the situation until they become more or less familiar with it.

Related to the modelling of learning is the influence of different types of travel information on the learning process. This will be analyzed partly in this chapter and partly in the next chapter.

Finally, remember that the influence of salience on learning was discussed in the previous chapter.

	In line with psychological theory on	In line with contemporary view of	Includes explicit learning?	Includes implicit learning?	Easy to estimate and interpret?
Model type	memory decay?	learning?			
Weighted	у	У	у	n	y / n *
Average of					
<b>Travel Costs</b>					
Successive	n	n	у	n	у
averages			-		-
<b>Myopic Models</b>	n	n	у	n	у
Markov Process	у	у	у	n	у
Representation			-		-
of Learning					
Bayesian	у	у	у	n	n
Updating			-		
Classification	y **	y / n **	y **	n **	n **
Combined	***	***	***	у	***
Explicit and				-	
Implicit					
Learning Models					

# **Table 14: Comparison learning models**

(y = yes; n = no)

\* Ease of estimation depends on data availability. Ease of interpretation depends on the number of estimated parameters and the degree to which there is a structure in their values.

\*\* Since the article on classification (Ettema et al., 2003) did not provide the mathematical details, the 'scores' in the table are only indicative.

\*\*\* Depends on the model type used for explicit learning modelling.

# 6.3 Model formulation

As argued in the previous section, the model has to incorporate both explicit and implicit learning. A number of assumptions and hypotheses were made in formulating the model. These are summed first. In the next subsection the modelling of developing an expected travel time (explicit learning) is described. Then, the modelling of reinforcement of chosen routes (implicit learning) is described. Refer to chapter 3 for a description of the complete model, or to the notation section after at the beginning of this thesis for a brief overview of formulas and symbols.

# 6.3.1 Hypotheses and assumptions

# **Explicit learning**

*EL1)* The updating process of the expected travel time can be used as a proxy for explicit learning.

*EL2)* Travellers determine the expected travel time on a route by updating the current expected travel time with the newly experienced travel time. (In case the route was chosen.) The contemporary view of learning is that people construct new knowledge and understanding based on what they already know and believe. The term 'updating' is in line with this view.

*EL3)* Travellers determine the expected travel time on a route by updating the current expected travel time with the newly received en-route travel time information. (In case the route was not chosen, but en-route traffic information was received for that route.)

As experiences are more intense than information and information can be inaccurate, we give experiences priority over information in our model.

*EL4)* The weight of a travel time in updating the expected travel time depends on the salience of this travel time and on the recency effect. If the recency effect is large the weight of the newly experienced / informed travel time will be large and the weight of the previous expected travel time will be low. If the recency effect is small, the opposite applies.

The underlying argumentation is provided in section 6.1.1.

#### **Implicit learning**

*IL1)* The share of choices for a certain route during the past N days can be used as a proxy for implicit learning.

Implicit learning is about the repetition of stimulus – response patterns and the resulting outcomes. The share of choices in the past provides information on how often the stimulus – response pattern was repeated. A positive outcome of choosing a certain route can reinforce future choices for this route and lead to habituation. Due to the mere exposure effect even negative outcomes can reinforce future choices.

# IL2) If the number of N is limited to approximately 9, we do not need to account for any decay of past choices.

While explicit learning relates to conscious memory ('route A took 50 minutes yesterday'), implicit learning relates to subconscious non-declarative memory. The fact that the link between stimulus, response and outcome is *repeated* is more crucial than an exact memory. Therefore we do not use any decay of past choices. An earlier version of our route choice model in which decay was accommodated, did not show any decay effects (Bogers et al., 2007). The number 9 is used as a compromise: if one uses much more than 9 choices, fundamental changes in behaviour (due to learning dynamics) would hardly be reflected anymore. When using much less than 9 days, incidental changes would have too much effect. Nine days is used as a compromise.

# 6.3.2 Explicit learning

In a previous section we concluded that - from all discussed model types - the Markov process model representation was the most appropriate one to model explicit learning. Still, like all models, it is just a simplified representation of reality. Many other representations of reality are possible. Because we concluded the Markov model to be the most appropriate one, we base our model on this type. The exact formulations are presented next.

#### Updating the expected travel time: used formulation

Let us define the expectation individual *n* has of the travel time on route *i* at day *t* before receiving en-route traffic information as  $ETT_{int}$ . Similarly, the expectation he had at the previous time interval (yesterday) is defined as  $ETT_{in(t-1)}$ . If he experienced a travel time on route *i* at the previous time interval,  $\delta_{in(t-1)} = 1$ , else  $\delta_{in(t-1)} = 0$ . The proposed model defines the expected travel time as a convex combination between the expected travel time at the previous time interval and either the travel time actually experienced at the previous time

interval, or the travel time provided by the en-route information interval [EL1, EL2, EL3]<sup>8</sup>. Furthermore, it takes into account the salience of the experience or travel information in the way described in chapter 4. The following formulation for t > 1 results:

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTT_{in(t-1)}$$
 if  $\delta in(t-1) = 1$  (6.8)

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTTInfo_{in(t-1)}$$
 if  $\delta in(t-1) = 0$  (6.9)

With

TT: actual travel time TTInfo: travel time as given by the en-route info w: weight of the most recent experience / information

The weight w can be regarded as the share of an experienced or informed travel time in deriving the expected travel time and can therefore be at least 0 (no influence) and at most 1 (completely determines new expected travel time). This is why we added the restriction that w needs to be between 0 and 1.

#### Weight: used formulation

As discussed in this chapter and in the previous one, we hypothesize the weight of an experienced travel time to be a function of the recency and salience effects [EL4]. The analyses in the previous chapter found that including salience effects slightly increased model performance compared to not accounting for salience effects and letting the weight only depend on the recency effect. For non-habitual routes salience was best represented as the travel time divided by the current expected travel time. For habitual routes we found the opposite: representing salience as the current expected travel time divided by the travel time slightly increased model performance. Formula (6.10) gives the resulting formulation for the weight of a travel time in updating the expected travel time on a non-habitual route.

$$w(TT_{\rm int}) = \frac{TT_{\rm int}}{ETT_{\rm int}} r(TT_{\rm int})$$
(6.10)

Note that formulation (6.10) is used both for experienced travel times (in case the route was chosen) and for informed travel times (in case the route was not chosen). Obviously, in the first case the experienced travel time has to be entered in (6.10) and in the second case the informed travel time. We now define two parameters that we expect to be able to assess the impact of recency:  $\lambda$  represents the effect of the most recent experience and  $\alpha$  represents the effect of the most recent informulations are given in (6.11) through (6.14).

$$w(TT_{int}) = \frac{TT_{int}}{ETT_{int}} \lambda TT_{int} \qquad \text{if } \delta in(t-1) = 1 \cap \text{chosen route} \neq \text{habitual route} \quad (6.11)$$

$$w(TT_{int}) = \frac{ETT_{int}}{TT_{int}} \lambda TT_{int} \qquad \text{if } \delta in(t-1) = 1 \cap \text{chosen route} = \text{habitual route} \quad (6.12)$$

<sup>&</sup>lt;sup>8</sup> The numbers in brackets refer to the assumptions and hypotheses from the previous section.

$$w(TTInfo_{int}) = \frac{TTInfo_{int}}{ETT_{int}} \alpha TTInfo_{int}$$

if 
$$\delta in(t-1) = 0 \cap chosen route \neq habitual route (6.13)$$

$$w(TTInfo_{int}) = \frac{ETT_{int}}{TTInfo_{int}} \alpha TTInfo_{int} \qquad \text{if } \delta in(t-1) = 0 \cap \text{chosen route} = \text{habitual route} \quad (6.14)$$

We did not introduce another parameter for primacy. Instead, the model is estimated for three different periods: beginning, middle and end. Changes in the estimated values for  $\lambda$  and  $\alpha$  will say something about a primacy effect.

The expected travel time appears in the route choice model as  $\beta_{ETT} ETT_{int}$ . The parameters  $\beta_{ETT}$ ,  $\alpha$  and  $\beta$  will be estimated from the data.

#### 6.3.3 Implicit learning

Past choices can, possibly as long as their consequences were not too negative, increase the perceived attractiveness of a route [IL1]. A simple way of modelling the effect of past choices is to enter them into the model. When limiting the number of past choices to N, this would for route i result in:

$$\sum_{x=1}^{\min(N,t-x+1)} \beta_{choice_{i(t-x)}} \delta_{in(t-x)}$$
(6.15)

The drawback of this method is that it results in N  $\beta$ 's for each route that have to be estimated. Depending on the value of N this can make the model difficult to estimate (long estimation time and many insignificant parameter estimates) and makes interpretation of the results complex.

Therefore, we decided to look at the fraction of choices for a certain route over the past N choices, leading to the following formulation:

$$ChoiceFraction_{i} = \left(\frac{\sum_{x=1}^{\min(N,t-1)} \delta_{in(t-x)}}{\min(9,t-1)}\right)$$

This appears in the route choice model as  $\beta_{choice_i}$  ChoiceFraction<sub>i</sub>.

We chose to look at the past 9 days (N=9). Furthermore, we did not use any decay parameter for past choices, i.e. the impact of a nine day old choice is the same as the impact of a one day old choice. The reasons for these two choices are given in [IL2].

#### 6.3.4 Critical reflection explicit and implicit learning models

Implicit and explicit learning are related to each other. Experiencing a good travel time has a positive effect on both the expected travel time and on the number of experiences on that

route. This is true in reality and in the proposed model formulation. We refer to chapter 3 for a discussion on this issue. In that chapter a discussion is also provided on serial correlation and endogeneity issues that can arise from entering previous choices in a model.

# 6.4 Model estimation outcomes

This section presents the outcomes of the estimation of the formulations from section 6.3, i.e. the values for  $\beta_{ETT}$ ,  $\beta_{choice}$ ,  $\alpha$  and  $\lambda$ . (An overview of all parameters and formulations is also provided on page viii.) The estimation has been carried out on two selections of the data.

The first selection, which we refer to as 'No info scenario', concerns data of respondents who

- had as travel goal a meeting with colleagues,
- did not receive any en-route information and
- did not receive ex-post information on non-chosen routes.

The second selection, which we refer to as 'Info scenario', concerns data of respondents who

- had as travel goal a meeting with colleagues,
- received en-route information about the expected travel time on the three routes in minutes
- did not receive ex-post information on non-chosen routes.

The results are presented in sections 6.4.1 and 6.4.2 respectively. The complete results of the model estimation (including t-values and standard errors) and details on the estimation procedure are listed in Appendix A.

# 6.4.1 No info scenario

In Table 15 a summary of the estimation results is given. The parameter estimates are standardized with respect to  $\beta_{ETT}$  for ease of comparison. Note that the estimates for  $\beta_{ETT}$  and most estimates for  $\beta_{choicei}$  are statistically significant. This means that there is a proven statistical relation between the chosen operationalization of implicit and explicit learning and the respondents' behaviour in the experiment. Though this can be regarded as an indication that implicit learning and explicit learning occurred more or less in the way they were modelled, it is not a proof of a causal relation.

In the next two sections the main results concerning explicit and implicit learning that follow from the table are discussed.

# Explicit learning

The estimates for  $\beta_{ETT}$  are statistically significant. Furthermore, the found values for  $\lambda$  are fairly reliable, as model performance clearly worsens for slightly higher or lower values of  $\lambda$  and the standard deviation of  $\lambda$  is reasonably small. (Refer to Appendix A for the model performance graphs and the calculation of the standard deviations.)

When interpreting the values, the high values of  $\lambda$  are striking: in the end period it is equal to its maximum. This means that in this period the expected travel time is completely determined by the most recent experience. Although this result has been found more often in travel behaviour studies (refer to the literature review earlier in this chapter) it may seem strange for three reasons:

- Human memory capacities allow people usually to remember more than one experience.
- The primacy effect would lead to lower values later on in the experiment.

• The  $\lambda$  values for the info scenario, which are presented in the next section, are considerably lower.

Considering these two arguments, a possible explanation for the high  $\lambda$  values may lie in the experiment. Possibly, people find it hard to recognize any structure in it having 'only' 40 choices, no further travel time information and no real incentive to make an effort. The construction of an expected travel time based on more than one experience may then be a bridge too far. As we did not ask the respondents about this, we do cannot know this with any certainty.

Table	15 :	Summ	nary	of	route	choice	model	estimation	results	for	no	info	scenario
standa	rdize	d wrt f	З <sub>ЕТТ</sub> (	nu	mbers	in italic	s are in	significant	at the 95	5% I	evel	)	

Name	Value Beginning	Value Middle	Value End		
$\beta_{choice1}$	4.04E-01	5.72E+00	1.04E+01		
$\beta_{choice2}$	-2.79E+00	4.71E+00	6.85E+00		
$\beta_{choice3}$	2.78E+00	2.67E+00	4.50E+00		
$\beta_{ETT}$	-1.00E-01	-1.00E-01	-1.00E-01		
City	-3.51E+00	<i>-1.62E+00</i>	1.16E+00		
Highway	0.00E+00	0.00E+00	0.00E+00		
Provincial	-1.77E+00	6.84E-01	2.42E+00		
σ	-2.23E+00	-3.27E+00	-1.85E+00		
Optimal $\lambda$	0.66	0.86	1.00		
Rho-					
square	0.21	0.38	0.46		
Salience	Habitual route: large travel times less weight Non-habitual routes: large travel times extra weight	No effect	No effect		

#### **Implicit learning**

Regarding implicit learning Table 15 shows that the combined effect of the  $\beta_{choice}$  parameters increases during the course of the experiment. Note that after the begin period all values are positive. This is in line with the ideas discussed earlier in this chapter that previous choices (possibly unless their consequences are very negative) are reinforced. Apparently, people become more and more habit driven in their route choices. This is not surprising as habits usually grow stronger over time. Furthermore, note that the estimates for the  $\beta_{choice3}$  parameters are lower than for the other two  $\beta_{choice}$  parameters. This is in line with the previous chapter that showed that the share of route choices for route 3 decreases over time. It was argued there that this may be due to the reliability characteristics of route 3.

# 6.4.2 Info scenario

In Table 16 a summary is given of the estimation results. The parameter estimates are standardized with respect to  $\beta_{ETT}$  from the beginning period of the no info scenario for ease of comparison. The comment about statistical and causal relations that was made in 6.4.1 applies here as well.

In the next two sections the main results concerning explicit and implicit learning that follow from the table are discussed.

Name	Value Beginning	Value Middle	Value End			
$\beta_{choice1}$	-1.01E+00	8.19E+00	6.67E+00			
$\beta_{choice2}$	9.94E+00	1.43E+01	1.12E+01			
$\beta_{choice3}$	-2.15E+00	1.56E+00	4.38E+00			
$\beta_{ETT}$	-1.00E-01	-1.00E-01	-1.00E-01			
$\beta_{Info}$	-2.32E-01	-4.33E-01	-3.28E-01			
City	-2.62E-01	4.51E+00	1.72E+00			
Highway	0.00E+00	0.00E+00	0.00E+00			
Provincial	-2.81E+00	3.91E+00	2.29E+00			
σ	-2.05E+00	Not applicable: MNL	Not applicable: MNL			
Optimal $\lambda$	0.52	0.64	0.25			
Optimal a	0.41	0.00	0.00			
Rho- square	0.36	0.41	0.46			
Salience	Habitual route: large travel times less weight Non-habitual routes: large travel times extra weight	Habitual route: large travel times less weight Non-habitual routes: large travel times extra weight	Both habitual and non- habitual routes: large travel times extra weight			

Table	16	:	Summary	of	route	choice	model	estimation	results	for	info	scenario
standa	rdiz	zed	l wrt β <sub>ΕΤΤ</sub>									

# Explicit learning

Like in the no-info scenario, the estimates for  $\beta_{ETT}$  are statistically significant. Furthermore, as the graphs in appendix A show, the found optimal values for  $\lambda$  are probably rather accurate, i.e. model performance decreases clearly for higher or lower values than the optimum. This is even stronger the case for the found optimal values for  $\alpha$ .

The values for  $\lambda$  and  $\alpha$  for the three periods as depicted in Table 16 show that

- The (combined) influence of the latest experience / information on the expected travel time becomes smaller as time goes by.
- Travel information is used for updating the expected travel time only in the beginning  $(\alpha_{middle} \text{ and } \alpha_{end} \text{ are } 0.00).$

The first observation seems rather logical, since at the beginning people have only few past experiences and the initial expected travel times as set by the researcher may not reflect an individual's expectation. One extra experience therefore increases an individual's true experience relatively much. Going from 2 to 3 past experiences is an increase of past experiences by 50%. At the end, however, people have more past experiences. Going from 10 to 11 past experiences is then an increase of only 10%. A lower influence of this 11<sup>th</sup> experience on ETT than in the previous example may then be appropriate. Note that - due to the high value of lambda at the beginning – the first experiences have a relatively high weight. This may indicate the existence of a primacy effect.

The values for  $\alpha$  are smaller than for  $\lambda$  and even reach zero in the middle and end periods. Possibly, due to bounded rationality and limited cognitive resources travellers may (unconsciously) choose to neglect travel information for updating and solely focus on real experiences once they have obtained a satisfactory expectation of travel time.

Finally, as pointed out earlier, the values for  $\lambda$  are very different than in the no info scenario. Even though  $\alpha$  equals zero after the beginning period, the presence of travel information apparently allows travellers to have a less myopic (and more realistic) expectancy of travel time.

# Implicit learning

As the observations regarding implicit learning in the no info scenario apply to the info scenario as well, we refer the reader to 6.4.1 for a discussion of the results.

# 6.4.3 Conclusions

The developed model was estimated on two selections of the experiment data: the info scenario and the no info scenario. In this chapter we concentrated on the learning part of the model. The estimation results showed that both the parameters regarding implicit learning and the parameters regarding explicit learning were significant for both the info and the no info scenario.

For the no info scenario it was found that people are very myopic in developing an estimate of the expected travel time, i.e. the recency effect is large. The role of implicit learning increased as the experiment evolved. The info scenario showed different results. The (combined) influence of the latest experience / information on updating the expected travel time became smaller as time goes by. Information only played a role in updating at the beginning. The recency effect is smaller here than in the no info scenario and there may have been a primacy effect. Like in the no info scenario, the weight of implicit learning became stronger during the experiment.

Comparing the results of both information scenarios we can conclude that the presence of travel information apparently allowed travellers to have a less myopic (and more realistic) expectancy of travel time.

# 6.5 Summary and Conclusions

Learning is a very important topic in day-to-day route choice, as the repetitive nature of dayto-day route choice offers ample opportunities for learning. This chapter was dedicated to the topic of learning.

From a review of relevant, mainly psychological, literature we concluded that both *implicit* (reinforcement) and *explicit* (cognitive) learning are likely to be present in route choice under traffic information. Therefore, both forms of learning have to be present in a route choice model as well. The psychological literature also showed that the recency, primacy and salience of experiences play an important role in explicit learning.

The review of 'modelling literature' showed that current approaches to modelling learning in day-to-day route choice focus only on explicit learning and are hardly calibrated on empirical or experimental data. From the reviewed model types, we found the Markov process model representation the most appropriate one to use for modelling explicit learning. The reasons are that it is relatively simple and (partly) in line with psychological research into memory decay and the contemporary view of learning (which regards learning as integrating new information with existing knowledge).

Based on this, we contribute to the existing scientific knowledge in two ways. First, we specified a model that captures both explicit learning (using a Markov process model representation and accounting for recency and salience) and implicit learning. Second, we estimated its parameters using experimental data to gain insight in how travellers learn in day-to-day route choice. We estimated the model for three different periods (beginning, middle and end) to be able to gain insight in the learning *process* and in the occurrence of primacy effects.

The estimation led to a number of insights. For the no info scenario it was found that people are very myopic in developing an estimate of the expected travel time, i.e. the recency effect is large. The role of implicit learning increased as the experiment evolved. The info scenario showed different results. The (combined) influence of the latest experience / information on updating the expected travel time became smaller as time goes by. Information only played a role in updating at the beginning. The recency effect is smaller here than in the no info scenario and there may have been a primacy effect. Like in the no info scenario, the weight of implicit learning became stronger during the experiment. Comparing the results of both information scenarios we can conclude that the presence of travel information apparently allowed travellers to have a less myopic (and more realistic) expectancy of travel time.

# 7 Dynamic traffic information: effect on learning, perception of reliability and route choice

In this chapter effects of dynamic traffic information on travel behaviour are discussed. The focus is on learning and reliability. To be more precise: we are interested in how traffic information influences learning and the perception of reliability and how this affects *individual* route choice behaviour. We do not discuss effects of traffic information on system performance as a whole. Issues like overreaction, penetration grade and consistency of predictive information are therefore not discussed.

We start with an overview of literature in section 7.1. based on this literature review we conclude in section 7.2 that a substantial amount of literature exists on traffic information, but only a small part focuses on our topics of interest and uses experimental or empirical data to test its hypotheses. Therefore, this chapter contributes among others by providing insights, based on our experimental data, into the effect of traffic information on learning and perception of reliability.

The experimental data are used to estimate our route choice model. The role of information in the route choice model and the relation with the conceptual framework is described in section 7.3. This section also presents the part of the route choice model that relates to traffic information. In section 7.4 the outcomes of the estimation of the route choice model are discussed. A number of statistical analyses are also performed and analyzed in this section. At this point all outcomes relating to reliability, learning and traffic information have been discussed in this thesis. This was done for each topic separately in chapters 5, 6 and the current one respectively. In section 7.5 they are related to each other to gain insight into their relative impact on route choice. This chapter ends with overall conclusions.

# 7.1 Literature overview

In this section we present insights from literature into the effect of dynamic traffic information on route choice. We start with a general introduction on types of traffic information, which will help the reader to interpret the remainder of this chapter.

Then a number of findings regarding the effectiveness of ATIS are presented in section 7.1.2. In section 7.1.3 we focus on our main topic of interest: the effect of ATIS on a traveller's perception of travel times and their reliability. Two effects were discerned in chapter 2: the

short-term and the long-term effect. The *short-term effect* takes place when the traveller updates his estimate of the current travel time using the provided information. The *long-term effect* takes place when the traveller updates his overall expected travel time using the provided information. This last type of updating can be classified as explicit learning, as defined in the previous chapter.

# 7.1.1 Information types: En-route and ex-post traffic information

In section 1.2 a general introduction on Advanced Traveller Information Systems (ATIS) was given. It was described how ATIS works, what actors are involved in enabling and using the system and what their respective goals are and what types of ATIS exist. In this section we limit ourselves to describe two types of ATIS that are considered in this chapter: en-route and ex-post information.

En-route traffic information concerns information that is provided to a traveller while he is en-route, so after he left his origin and before he will arrive at his destination. A typical example is a Variable Message Sign (VMS). A VMS is located at the side of a road, or above the road, refer to Figure 19 for an example.





Source (above): www.vanAnaarBeter.nl Source (left): www.datadisplayuk.com

# Figure 19: Examples of Variable Message Signs

Ex-post traffic information concerns information that is provided to a traveller after he has completed his trip. The information can contain the travel time of the route the traveller just finished, or travel times of alternative routes.

# 7.1.2 The effectiveness of traffic information

Many studies agree that traffic information influences route choice. In this section we focus on studies that base their conclusions on 'real' data (as opposed to simulated data), obtained by surveys, laboratory experiments, or empirical research empirical.

The first study we like to mention is a survey that was carried out on nine different European locations. It showed that about one-third of drivers found VMS information useful in selecting a route for the rest of their journey and about half of the drivers found information useful even

though they considered that there were no alternative route options (Chatterjee and McDonald, 2004). Emmerink et al. (1996) found that women and commuters are less likely to be influenced by ATIS. Women were also found to be less influenced by ATIS in a study by Vaughn et al. (1993). The probability that travellers divert from their habitual route can be increased by ATIS (Khattak et al., 1996; Abdel-Aty and Abdalla, 2006). Not only characteristics of the travellers influence the effect of ATIS. Information attributes like the nature of the information (i.e. descriptive vs prescriptive information), its correctness and completeness, the availability of feedback information and some generic information effects like under- and overestimation errors all proved to have significant effects on route switching behaviour (Srinivasan and Mahmassani, 2003).

Another study analyzed traffic before and after the installation of a number of Variable Message Signs. It was conducted in Rotterdam, The Netherlands by the research company Transpute (1997). The VMS installations proved to influence route switching and to reduce traffic congestion. More specifically:

- A difference of one kilometre queue length on two alternative routes leads to approximately 1% change in split percentage. If, for example, 30% of the car drivers usually choose route 1 and 70% route 2 and the VMS says '1 km queue on route 1 and 3 km queue on route 2', this leads to 32% of the car drivers choosing route 1 and 68% choosing route 2.
- A reduction of the number of traffic jams can be realized by introducing VMS. The number of traffic jams was reduces by 10 to 15%. It was not completely clear, however, if this reduction was completely due to the VMS introduction, because other traffic measures had been introduced simultaneously.

With respect to learning about ATIS itself it has been found that if travellers experience that the provided information is unreliable, they comply less with the provided advice (e.g. (Chen et al., 1999; Chen and Jovanis, 2003) Furthermore, compliance is increased if travellers learn through post-trip information that the provided advice was indeed good (Chen et al., 1999). Compliance with the provided ATIS advice decreases when the familiarity of travellers increases. Familiar travellers exhibit stronger taste preferences that may not be in line with the ATIS advice (Adler and McNally, 1994; Lotan, 1997).

The above suggests that ATIS can indeed influence travel behaviour. Conquest et al. (1993) found that 75% of the travellers who completed a survey on their travel behaviour were willing to change one or more aspects of their travel behaviour. Still, we should not be too optimistic. Some travellers do not even notice the information (Chatterjee and McDonald, 2004). And since part of the travellers are influenced by ATIS, this also means that the other part is not.

# 7.1.3 Short-term and long-term effect of traffic information

The previous section gave some indirect evidence that the short-term effect of traffic information indeed exists, as ATIS was found to influence the current route choice. As far as we know, there is no empirical or experimental knowledge on how ATIS exactly influences the current estimate of travel time. We found one article that comes close to this topic. It concerns a survey among car divers in which they were asked how they interpreted the provided VMS travel time information (Zhao and Harata, 2001). It was found that their perception of the VMS information is a linear function of the provided travel time plus a constant. The role of previous travel time expectations (in this thesis called 'expected travel time') in forming this perception is not studied.

Literature review showed that there is not much known either on how information supplied by ATIS influences explicit learning, by which we mean expected travel time updating. Two studies were found that directly address this topic: one by Ben-Akiva et al. (1991) and one by Jha et al. (1998). Both studies have neither used empirical nor experimental data to estimate their models on, so it is hard to judge the value of their contributions.

There are a number of empirical / experimental studies that indirectly show that ATIS has a long-term effect, for example the study by Van Berkum and Van der Mede (1993). As described in section 6.1.2 they defined a traveller's expected travel time to be a convex combination of his recent experience and his previous expected travel time. The formula is repeated in (7.1)

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTT_{in(t-1)}$$
(7.1)

Van Berkum and Van der Mede found that before introducing en-route information on a VMS, travellers hardly updated their expected travel time: the most recent experience only determined 1% of the updated expected travel time (i.e. w = 0.01 in formula (7.1)); the other 99% was determined by the previous expected travel time. Furthermore, travellers chose mostly out of habit instead of out of minimizing expected travel time. After introducing enroute information on a VMS, travellers started to choose less out of habit and gave more weight to the most recent experience in updating their expected travel time. These results, however, may not be in line with present travel behaviour, because they were obtained 15 years ago. Travellers were not yet used to VMS information which may have affected their response to it. Indications that reactions are indeed influenced by the familiarity of travellers with the information service are found in (Emmerink et al., 1996; Abdel-Aty and Abdalla, 2006). Furthermore, in the study only the effect of travel time *experiences* on updating the expected travel time is modelled, not the effect of travel time *information* on updating the expected travel time.

The provision of ATIS does not only influence learning about expected travel times. Travellers can also learn about travel time reliability, or about the quality of the information itself. Ex-post information, for example, can influence the perception a traveller has of a route's reliability. Avineri and Prashker (2003) studied the influence of providing dynamic ex-post information about the realized travel time on one of two possible routes, neither routes, or on both routes. When there is no travel information on the better, but less reliable route, it tends to be chosen less often than when there is information on this route. They explain this by introducing the term sequential sampling process. This means that if the sample of outcomes is small (which is the case for the route of which there is no information) then the route, which is usually fairly good, but is occasionally very poor is likely to be interpreted as worse than it is. An important critical remark about the experimental set-up has to be made: the experiment concerns a simulation in which mathematical models are used instead of real people. If people behave in the exact manner as in the simulation remains uncertain.

# 7.2 Synthesis

Though a substantial amount of literature exists on traffic information, only a small part of it focuses on our topics of interest (learning and reliability) and uses experimental or empirical data to test its hypotheses. The question raised in chapter 1 (How does the provision of traffic information influence both the updating of the expected travel time (learning) and choice

behaviour?) therefore still needs to be addressed in our own research. To be more precise, the remainder of this chapter will contribute by answering the following research questions:

- How does en-route traffic information influence learning in terms of updating expected travel times?
- How does en-route traffic information influence route choice behaviour?
- How does ex-post traffic information influence route choice behaviour?

The questions will be addressed by performing and interpreting some simple statistical analysis of the experimental data obtained in the TSL experiment and by interpreting the outcomes of the route choice model that was introduced in chapter 3. That chapter presented the complete route choice model as a whole; the next section discusses the place of traffic information inside this route choice model.

# 7.3 Model formulation

In line with the results of the literature study from the previous section, we think traffic information can have a short-term and a long-term effect. The short-term effect can take place right before a route has to be chosen and enables a traveller to have a better estimate of the current travel time on the routes. The long-term effect refers to the updating of the overall expected travel time and / or to the estimation of a route's reliability and can take place after a route choice was made. We highlighted these effects in the route choice model presented in Figure 20. The two effects are further discussed in the next sub sections.

# 7.3.1 Hypotheses and assumptions

A number of hypotheses and assumptions are made in deriving the model. The ones that relate to traffic information are listed here.

# *TI1)* En-route traffic information is used to improve the estimate of the current travel time (short-term effect).

A number of studies found that en-route traffic information influenced route choice, refer to section 7.1.2 for an overview of these studies. As the information contains an estimate of the travel time, it is logical that the effect on route choice was caused by an effect on a traveller's estimate of the current travel time.

*TI2)* En-route traffic information is used to improve the expected travel time of a route that was not chosen (long-term effect).

Even if a traveller does not choose a route, he can see the en-route information about that route's travel time. And if he sees it, he could use it.

*EL2)* Travellers determine the expected travel time on a route by updating the current expected travel time with the newly experienced travel time. (In case the route was chosen.)

*EL3)* Travellers determine the expected travel time on a route by updating the current expected travel time with the newly received en-route travel time information. (In case the route was not chosen, but en-route traffic information was received for that route.)

As experiences are more intense than information and information can be inaccurate, we give experiences priority over information in our model.

#### 7.3.2 Short-term effect of traffic information

Directly before a route choice has to be made the traveller receives en-route information concerning traffic conditions at that moment. Together with the overall expected travel time a traveller already had before receiving the information, this allows him to develop a new travel time estimate for that moment. The overall expected travel time has a weight of  $\beta_{ETT}$  in the route's utility; the en-route information has a weight of  $\beta_{Info}$  in the route's utility. The relations are visualized in Figure 20 and formalized in equation (7.2).

 $U_{\text{int}} = RoadType_n + \beta_{Info}TTInfo_{it} + \beta_{ETT}ETT_{\text{int}} + \beta_{choice}ChoiceFraction_i + \varepsilon$ (7.2)

with	
U	Utility
i	route index
n	traveller index
t	time index
RoadType	road type specific constant ~ $N(\mu,\sigma)$ ; $\mu$ and $\sigma$ to be estimated
β <sub>Info</sub>	travel time information parameter
TTInfo	travel time as displayed on VMS
$\beta_{ETT}$	expected travel time parameter
ETT	expected travel time
β <sub>choice</sub>	inertia / habit parameter
ChoiceFraction	Fraction of choices for a specific route over the past 9 days

We can compare  $\beta_{ETT}$  to  $\beta_{Info}$ . If, for example,  $\beta_{Info}$  is much larger than  $\beta_{ETT}$  this could mean that the traveller highly trusts the provided information. The model outcomes and statistical analysis will show how  $\beta_{Info}$  and  $\beta_{ETT}$  relate to each other in our experiment.



Figure 20: visualization of utility model
#### 7.3.3 Long-term effect of traffic information

The en-route information the traveller received before making the route choice can also be used to update the expected travel time. For this case we assumed that a traveller only uses the provided traffic information for non-chosen routes. That is, if a traveller has chosen a route, he uses his experienced travel time to update the expected travel time for the next day for that route rather than the provided traffic information. The reason for this assumption is that the traveller's experience is more recent and probably also more reliable and intense than the enroute information. The formulas used in our route choice model to describe this long-term effect of en-route information have already been discussed in the previous chapter. For completeness, they are repeated here in equations (7.3) through (7.7).

$$ETT_{int} = (1 - w)ETT_{in(t-1)} + wTTInfo_{in(t-1)} \quad \text{if } \delta in(t-1) = 0$$
(7.3)

$$w(TTInfo_{int}) = s(TTInfo_{int})r(TTInfo_{int})$$
 if  $\delta in (t-1) = 0 \cap chosen route \neq habitual route (7.4)$ 

$$w(TTInfo_{int}) = \frac{1}{s(TTInfo_{int})} r(TTInfo_{int}) \qquad \text{if } \delta in(t-1) = 0 \cap \text{chosen route} = \text{habitual route} \quad (7.5)$$

$$s(TTInfo_{int}) = \frac{TTInfo_{int}}{ETT_{int}}$$
(7.6)

$$r(TTInfo_{int}) = \alpha \tag{7.7}$$

With

w weight

- r recency effect: relative impact of most recent travel time experience / information in updating the expected travel time
- s salience effect: factor which gives a travel time experience / information, depending on its salience, more or less weight in updating the expected travel time

 $\alpha$  recency parameter concerning traffic information

 $\delta_{int}$  choice dummy, equals 1 if route i was chosen by individual n at day t

Not only en-route information can play a role after a route choice: Ex-post traffic information informs a traveller about the realized travel time on the non-chosen routes after a route choice was made. A traveller can use this information to update the expected travel time on those routes and to get a better idea of the probability distribution of the travel times on those routes. The route choice model from this thesis, however, has not been developed to analyze situations with ex-post information. Therefore, this effect of ex-post information is not included in the model.

## 7.4 Model outcomes and statistical analysis

The results relating to route choice in general are presented first. Then, the influence of traffic information on learning is discussed. Finally, the influence of traffic information on the perception of, or reaction to reliability is the topic of the last sub section. Details on the model estimation procedure and outcomes are provided in appendix A.

#### 7.4.1 Introduction: Short-term effect and influence on route choice

To gain insight into the influence of traffic information on route choice, we looked at the weight of traffic information in our route choice model as given in formula (7.2). In

comparison to the other weights, this can teach us something about the relative importance of information in making a choice.

Table 16 gave a summary of the parameter estimates of the route choice model. It is repeated in the left part of Table 17. A first look at the table shows that the traffic information weight seems quite large. To ease interpretation some elasticities of these weights were computed. To be precise, the disutility that comes from one extra minute travel time as shown on the VMS is computed. Then, for each variable we computed the required change that gives rise to the same disutility. The results are shown in Table 17. The most striking result concerns the high weight of en-route traffic information compared to the weight of the expected travel time. Apparently, the travellers place much trust in the information and / or have little faith in the accuracy and applicability of their expected travel time for the current moment. Note that this says something about the strength of the short-term effect of traffic information. Put differently: the effect of traffic information on updating the expected travel time with the provided information to form an estimate of the current travel time is very large. What happens when the information is wrong and does not warn a traveller for an extremely long travel time, is one of the topics of section 7.4.3.

	Parameter	Parameter	Parameter	Required change in attribute value for same amount of disutility as 1 min extra travel time on VMS				
Nama	Destinute	Middle	End	Designing	Middle			
Iname	Beginning	Middle	End	Beginning	Middle	End		
$\beta_{choice1}$	-1.006	8.193	5.889	-0.231	0.053	0.049		
$\beta_{choice2}$	9.938	14.332	10.526	0.023	0.030	0.029		
$\beta_{choice3}$	-2.150	1.558	3.978	-0.108	0.278	0.075		
$\beta_{ETT}$	-0.100	-0.100	-0.100	-2.324	-4.331	-3.280		
$\beta_{Info}$	-0.232	-0.433	-0.311	1	1	1		

Table 17: Elasticities with respect to 1 minute extra travel time on VMS

(The numbers in italics are insignificant at the 95% level.)

## 7.4.2 Influence on learning

To assess the influence of traffic information on learning, two things are considered. First, the weight of the most recent information in the updating of the expected travel time is discussed. This tells us something about explicit learning. Second, travel time savings (a possible consequence of learning) are analyzed for various types of provided traffic information.

#### Influence on updating of expected travel time

Though this topic was already addresses in section 6.4, it is repeated here, because we feel it cannot be omitted in this chapter on traffic information. The estimation results for the recency parameters  $\lambda$  and  $\alpha$  are given in Table 18. While  $\alpha$  refers to the weight of the most recent enroute traffic information,  $\lambda$  refers to the weight of the most recent experience.

#### Table 18: estimation results for the recency parameters $\lambda$ and $\alpha$

	Beginning	Middle	End
Optimal $\lambda$ – no info scenario	0.66	0.86	1.00
Optimal $\lambda$ – info scenario	0.52	0.64	0.25
Optimal α – info scenario	0.41	0.00	0.00

The values show that

- The (combined) influence of the latest experience / en-route traffic information on the expected travel time becomes smaller as time goes by.
- En-route traffic information is used for updating the expected travel time only in the beginning ( $\alpha_{middle}$  and  $\alpha_{end}$  are 0.00).

The values for  $\alpha$  are smaller than for  $\lambda$  and even reach zero in the middle and end periods. Possibly, due to bounded rationality and limited cognitive resources travellers may (unconsciously) choose to neglect en-route traffic information for updating and solely focus on real experiences once they have obtained a satisfactory expectation of travel time.

Finally, as pointed out earlier, the values for  $\lambda$  are very different than in the no info scenario. Even though  $\alpha$  equals zero after the beginning period, the presence of travel information apparently allows travellers to develop a less myopic (and more realistic) expectancy of travel time.

#### **Travel time savings**

Not only en-route traffic information can lead travellers to have a 'better' expectancy of travel time. Ex-post information can also enable travellers to better learn the travel time characteristics of the three routes. This may lead to 'better' route choices. The word 'better' is put in parenthesis, because a good route choice is something subjective. Therefore, the researcher cannot say whether a traveller has made a good choice. Still, assuming that most people prefer short travel times, we can say that travel time savings are good.

Table 19 shows the mean experienced travel times for all respondents for all days, for four different information scenarios. The most striking result is that providing en-route information leads to approximately 4 to 5 minutes of travel time savings. The provision of ex-post information also has a positive effect, though not very large.

	En-route info	No en-route info
Ex-post info	44,84 <i>(N=48417)</i>	48,98 <i>(N=11160)</i>
No ex-post info	45,12 <i>(N=31626)</i>	49,52 <i>(N=7800)</i>

 Table 19: mean experienced travel time per information scenario

In the next section, route choices in relation to traffic information are further analyzed.

#### 7.4.3 Influence on reaction to reliability

Accurate en-route traffic information can make unreliable routes (i.e. routes that do not always lead to approximately the same travel time) very predictable. In this light, en-route traffic information could increase the attractiveness of unreliable routes. Whether this is the case in our route choice experiment, is the topic of the first section. In the second section we focus on route choice behaviour after extremely bad experiences (i.e. experiencing a travel time of over 65 minutes) and analyze how this affects route choice behaviour. The analysis is done in three cases: correct traffic information, wrong information, or no information at all. The aim is to assess the importance of accuracy.

#### **Route choice percentages**

To assess the influence of traffic information on route choice we analyzed route choice percentages for the various information scenarios. The analyses are summarized in Table 20 through Table 22. Table 20 shows that without en-route information route 3 is much less and route 2 is much more chosen than with en-route information. As route 1 and 3 have similar

mean travel times, but very different reliability characteristics, we can conclude that it is likely that travellers find route 3 too unreliable to choose without having any indication how it will perform on the current day. Without this information they rather choose the reliable, albeit longer, route 2. This is especially true for the job interview scenario. Ex-post traffic information could also have an effect on route choice.

Table 21 shows route choice percentages for travellers with ex-post information on nonchosen routes; Table 22 shows these percentages for travellers without ex-post information on non-chosen routes. Comparing the tables it is clear that the provision of ex-post information does not have a large influence on route choice percentages for people who also receive enroute information. For travellers who do not receive en-route information, however, the provision of ex-post information enlarges the share of route 1 and decreases the share of route 2. Probably, the provision of en-route information and / or ex-post information changes travellers' perception and makes them realize better that route 1 is only sometimes very bad. Table 22 also shows that the reliable route 2 has the largest share (51.9%) among travellers who did not receive en-route information nor ex-post information and had to go to a job interview. This seems rather plausible as this scenario represents maximum uncertainty (no information) and maximum costs of arriving late (job interview).

Travel goal: Meeting with colleagues								
Info		No en-i	route info		En-route info			
Days								
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total
1	60.3%	46.3%	44.4%	49.1%	41.7%	42.4%	52.7%	46.1%
2	22.2%	37.5%	40.4%	34.8%	19.1%	33.5%	27.7%	27.7%
3	17.4%	16.2%	15.1%	16.1%	39.2%	24.2%	19.6%	26.2%
Travel g	oal: Job i	nterview						
Info		No en-i	route info			En-r	oute info	
Days								
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total
1	53.7%	43.2%	39.7%	44.5%	40.0%	38.9%	48.2%	42.7%
2	27.6%	40.5%	48.3%	40.2%	20.0%	36.6%	30.9%	30.3%
3	18.7%	16.3%	12.1%	15.3%	40.0%	24.5%	20.9%	27.0%

Table 20: Evolution of Route choice percentages with and without en-route information

		Meeting with colleagues								
		No en-	route info		En-route info					
	days					day	'S			
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total		
1	60.8%	46.5%	46.2%	50.0%	42.3%	42.4%	53.0%	46.3%		
2	22.7%	36.8%	39.2%	34.2%	19.0%	33.2%	26.9%	27.3%		
3	16.5%	16.7%	14.6%	15.8%	38.6%	24.4%	20.1%	26.4%		
				Job int	erview					
		No en-	route info		En-route info					
		d	ays			day	'S			
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total		
1	81.1%	69.6%	74.1%	74.2%	43.0%	42.4%	48.1%	44.7%		
2	5.6%	15.6%	20.7%	15.0%	15.2%	31.6%	29.0%	26.5%		
3	13.3%	14.8%	5.2%	10.8%	41.8%	26.0%	22.9%	28.8%		

Table 21: Route Choice Percentages for People with Ex-post Information

## Table 22: Choice Percentages for People without Ex-post Information

		Meeting with colleagues							
		No en-r	oute info		En-route info				
		da	iys			day	/S		
Douto	1 10	11.25	26 40	total	1 10	11.25	26.40	total	
Roule	1-10	11-25	26-40		1-10	11-25	20-40		
1	59.4%	45.7%	40.7%	47.2%	40.5%	42.3%	52.2%	45.5%	
2	21.3%	39.0%	43.0%	36.1%	19.3%	33.9%	29.5%	28.6%	
3	19.4%	15.3%	16.3%	16.7%	40.2%	23.8%	18.4%	25.9%	
				Job in	terview				
		No en-r	oute info		En-route info				
		da	iys		days				
Route	1-10	11-25	26-40	total	1-10	11-25	26-40	total	
1	50.1%	39.7%	35.2%	40.6%	38.6%	37.1%	48.2%	41.7%	
2	30.4%	43.8%	51.9%	43.5%	22.3%	39.0%	31.9%	32.2%	
3	19.4%	16.5%	12.9%	15.9%	39.1%	23.8%	19.9%	26.2%	

#### Extremely bad experiences with or without accurate traffic information

The previous section showed that route choice behaviour was strongly influenced by the type (en-route / ex-post) of traffic information that was provided. Furthermore, it turned out that the more elaborate the provided information was, the more travel time savings were realized. Earlier, the route choice model estimation results also showed that travellers place high weight on traffic information in their route choice. In sum, the effects of traffic information seem very positive. Previous research, however, showed that en-route traffic information needed to be highly accurate to have positive effects. In our experiment, the en-route information was usually rather reliable, but sometimes it was wrong. In the next analysis we look at what happens to a traveller's route choice behaviour after experiencing an extremely long travel time under correct en-route information, wrong en-route information, or without en-route information.

In the analysis an experience is classified as extremely bad when the experienced travel time was at least 65 minutes. En-route information is called inaccurate, when it underestimates the travel time by at least 10 minutes.

For each extreme experience on a route, the percentage of choices for this specific route after the extreme experience took place has been compared with the percentage of choices for this specific route before the extreme experience took place. The number of days before was set to be 10 and the number after was set to be 5. This was done for each individual. Figure 21 gives the histograms of the difference in percentage for 5 days after and 10 days before the extreme experience, for each of the three different information settings.

A number of conclusions can be drawn from Figure 21:

- When correct en-route information warned for an extremely long travel time on a route and people chose this route after all, this had not much impact in the choice percentage for that route after the extreme experience. Apparently, people do not loose confidence in the route. Rather they may blame themselves for choosing a route ignoring the warning from the travel information.
- Without en-route information, most people choose the route on which they had an extreme experience a slightly less frequent. Remarkably, there are also people who choose a route more often.
- The largest effect can be seen for people who had received incorrect en-route information. This means that the en-route traffic information did not warn them for the extremely bad travel time. People who choose it less frequently may realize that an extreme travel time can occur on the particular route and that they cannot rely on the information to warn them for it. They do not want to experience the same thing again and decide to choose the route less often. There are, however, also people who choose the route more often after an extreme experience under wrong information. Though we do not understand why this happens, we do understand that accuracy of information is important if one wants to prevent such unforeseeable reactions.



Figure 21: histograms of the difference in percentage choice for a route for 5 days after and 10 days before the extreme experience on that route, for each of the three different information scenarios. So, if a person chose 2 times route 1 in the five days after an extreme experience on that route and 6 times in the ten days before the extreme experience, the difference in percentage is (2/5 - 6/10) \* 100% = -20%

## 7.4.4 Summary

We can conclude from all our analyses in this chapter that traffic information has a large influence on route choice. Summarizing, the following conclusions were drawn:

- In the route choice model, the en-route traffic information has a high weight compared to the weight of the expected travel time.
- En-route traffic information does not seem to have a large influence in developing an expected travel time (explicit learning), as the values for  $\alpha$  (recency parameter information) are smaller than for  $\lambda$  (recency parameter experience) and even reach zero in the middle and end periods. Still, the values for  $\lambda$  are very different than in the no info scenario. Even though  $\alpha$  equals zero after the beginning period, the presence of travel information apparently allows travellers to develop a less myopic (and more realistic) expectancy of travel time.
- The more information provided, the higher the travel time savings. Providing en-route and ex-post information compared to not providing any information at all leads to 5 minutes (10%) savings.
- Providing en-route traffic information increases the share of an on average fast but unreliable route (route 1) at the expense of a reliable but slow route (route 2). This is especially true for the job interview scenario.
- The provision of ex-post information does not have a large influence on route choice percentages for people who also receive en-route information. For travellers who do not receive en-route information, however, the provision of ex-post information enlarges the share of route 1 and decreases the share of route 2.
- Travellers who suffered a very long travel time on a route but were not warned for this long travel time due to inaccurate traffic information, demonstrated highly diverging reactions. Some chose the route less often after this experience, some chose it with the same frequency and some chose it more often. Though we do not understand why this happens, we do understand that accuracy of information is important if one wants to prevent such unforeseeable reactions.

# 7.5 Relative influence learning, reliability and information on day-to-day route choice

The outcomes relating to reliability, learning and traffic information have been presented for each topic separately in the previous two chapters and the current one respectively. In this section we look at their relative impacts on route choice. The analysis is done for the two experimental scenarios on which the route choice model was estimated.

## 7.5.1 Relative influence in 'en-route traffic information scenario'

The relative influence of reliability, learning and traffic information can be assessed by comparing the parameter estimates from the utility model to each other. To do so, we return to the analysis of elasticities that was provided in section 7.4.1. The elasticities are defined as the change in attribute value that leads to the same amount of disutility as one extra minute expected travel time (ETT). In Table 23 the parameter estimates and the elasticities are given.

The most striking result concerns the high weight of en-route traffic information compared to the weight of the expected travel time (explicit learning): the weight of traffic information equals two to four times the weight of the expected travel time. Apparently, the travellers place much trust in the information and / or have little confidence in the accuracy and applicability of their expected travel time for the current moment. Note that this says something about the strength of the short-term effect of traffic information. Put differently:

the effect of traffic information on updating the expected travel time with the provided information to form an estimate of the current travel time is very large.

The implicit learning parameters,  $\beta_{choice}$ , relate to the fraction of choices for a certain route during the past 9 days. Choosing route i one extra time during the past nine days could increase this fraction by 0.11. Note that for route 1 in the middle period, a change of 0.012 is required to compensate 1 minute extra ETT. So choosing route 1 in the middle period 1 extra time can compensate approximately 10 minutes extra expected travel time (0.012 \* 10  $\approx$  0.11), or 2.5 minutes on the VMS. This means that always choosing route 1 compared to choosing route 1 half of the time leads to a difference of approximately 10 minutes on the VMS, or 40 minutes expected travel time that can be compensated. Remember that the average travel time is approximately 40 minutes. This simple calculation shows three things:

- The weight of en-route traffic information is relatively large compared to the weight of explicit learning;
- the weight of implicit learning is relatively large compared to the weight of explicit learning;
- the weight of implicit learning is not extremely small or large compared to the weight of en-route traffic information.

	Parameter estimate	Parameter estimate	Parameter estimate	Required change in attribute value for same amount of disutility as 1 min extra ETT			
Name	Beginning	Middle	End	Beginning	Middle	End	
$\beta_{choice1}$	-1.006	8.193	5.889	-0.099	0.012	0.015	
$\beta_{choice2}$	9.938	14.332	10.526	0.010	0.007	0.009	
$\beta_{choice3}$	-2.150	1.558	3.978	-0.047	0.064	0.023	
$\beta_{ETT}$	-0.100	-0.100	-0.100	1	1	1	
$\beta_{Info}$	-0.232	-0.433	-0.311	-0.430	-0.231	-0.305	

Table 23: Elasticities with respect to 1 minute extra expected travel time in info scenario

(The numbers in italics are insignificant at the 95% level.)

## 7.5.2 Relative influence in 'no en-route traffic information scenario'

The analysis that was done for the info scenario can – obviously apart from the effect of traffic information – also be done for the no info scenario. In Table 24 the elasticities for the no info scenario are listed. (The numbers in italics are insignificant at the 95% level.) The elasticities of the  $\beta_{choice}$  parameters of this no info scenario are similar to ones of the info scenario. We can therefore draw the same conclusion as in the info scenario: the weight of implicit learning is relatively large compared to the weight of explicit learning. Since there is no traffic information that can also influence route choice, the influence of implicit learning on route choice is very large in this scenario.

	Parameter estimate	Parameter estimate	Parameter estimate	Required change in attribute value for same amount of disutility as 1 min extra ETT			
Name	Beginning	Middle	End	Beginning	End		
$\beta_{choice1}$	4.04E-01	5.72E+00	1.04E+01	0.248	0.017	0.010	
$\beta_{choice2}$	-2.79E+00	4.71E+00	6.85E+00	-0.036	0.021	0.015	
$\beta_{choice3}$	2.78E+00	2.67E+00	4.50E+00	0.036	0.037	0.022	
$\beta_{ETT}$	-1.00E-01	-1.00E-01	-1.00E-01	1	1	1	

Table 24: Elasticities with respect to 1 minute extra expected travel time in no info scenario

(The numbers in italics are insignificant at the 95% level.)

## 7.6 Conclusions

Literature study showed that en-route traffic information has a clear effect on the route choice that has to be made directly after receiving this information. We labelled this the short-term effect of traffic information. Less is known on the long-term effect. A number of findings from our experiment prove the existence of both this long-term effect and the short-term effect.

As for the short-term effect, we found that en-route information has a large weight in making a route choice. Its relative impact is much larger than the impact of a traveller's expected travel time (explicit learning). Its relative impact is not extremely small or large compared to the weight of implicit learning.

Regarding the long-term effect, it was found that en-route information helped travellers in developing a long-term expected travel time. Furthermore, ex-post information can increase the perceived attractiveness of an unreliable yet fast route for travellers who do not receive en-route information.

Finally, some findings can be caused by the short-term and the long-term effect. For instance, the share of an on average fast but unreliable route was increased by providing en-route traffic information. Furthermore, larger travel time savings were realized by providing more elaborate information.

These findings can have several implications. First of all, they demonstrate the importance of providing traffic information. It allows travellers to develop a more accurate long-term expectation and current estimate of travel time and results in travel time savings. It also increases the use of routes which are otherwise thought as too unreliable. Travel time savings are not only beneficial to individual travellers. It also means that total car hours are reduced, leading to less traffic and hence less damage to the environment. Another implication is that the provided information has to be accurate. Otherwise unforeseeable reactions can occur which make it hard to manage and plan traffic. Thirdly, the finding that travellers' perceptions of routes (and therefore route choices) can be influenced by ex-post traffic information, may be an interesting mechanism in dynamic traffic management.

## 8 Conclusions and recommendations

In this chapter we look back upon the research described in this thesis. First a brief summary of the research is given in section 8.1. Then, the main findings are discussed. Conclusions based on these findings are discussed in section 8.3. The implications that these may have on policy and practice are the topic of the following section. In section 8.5 we present our reflections on the research. Some of them lead to recommendations for future research, which are discussed in the final section of this chapter.

## 8.1 Summary of research

In this section a brief overview of the research described in this thesis is provided. The goal is to provide the reader with knowledge on the research that is necessary to interpret the findings and conclusions that follow later in this chapter.

## 8.1.1 Research topic and research questions

This dissertation research focussed on day-to-day route choice under uncertainty and the impact of traffic information. Many trips are made on a (nearly) daily basis, e.g. going to work, or bringing children to school. Each day the traveller is faced with the same route choice situation. And each day he can experience the result of his choice. In this situation there is an opportunity to *learn* about the characteristics of the available routes (explicit learning) or to form habitual behaviour (implicit learning). The traveller can learn about their normal travel times and about the *reliability* of these travel times. This will probably play a role in his route choice. *Traffic information* can also influence the route choice, both directly and indirectly by influencing the learning process. Finally, as the route choice is made repetitively, there is also a possibility of habit formation. How learning, reliability and traffic information in day-to-day route choice under traffic information.

A number of research questions have been formulated on these three topics. As for *reliability* the questions focus on how reliability of travel times influence on the one hand the perceived attractiveness of a route and on the other hand the traveller's expected travel time of a route. We refer to this updating of an expected travel time with the term *explicit learning*. Explicit

learning, also known as cognitive learning, concerns intentional learning, paying attention to the object. The research questions that were formulated on explicit learning concern the effect of the recency, salience and primacy of an experienced or informed travel time in updating the expected travel time. Recent experiences are remembered better than old ones. The same applies to first experiences and may apply to salient experiences, i.e. experiences that stand out, and to. This is what is meant by recency, primacy and salience effects.

Besides explicit learning, *implicit learning* is also considered in this research. Implicit learning comprises all kinds of learning where repetition of the relationship between stimulus and response patterns is stored in the neural system as memory. It can lead to habits and inertia. Our research questions focuses on the relative influence of implicit learning on route choice compared to explicit learning. Finally, the effect of *traffic information* on the current route choice and on updating the expected travel time are topics of interest.

#### 8.1.2 Conceptual framework

Based on knowledge from literature, we have developed a conceptual framework. The framework gives insight into the various elements that play a role in day-to-day route choice under traffic information and the relations between those elements. As such, it is a first and important step in answering the research questions. The framework is given in Figure 22.



#### Figure 22: Conceptual framework of route choice

In the centre of the framework we find the box 'decision mechanism / habit'. All inputs come together here and are mapped onto our dependent variable of interest: route choice. More specifically, depending on:

- preferences of the traveller
- his personal characteristics that do or do not allow him to make a 'good' choice
- estimates of the travel times on the routes that he can choose from and
- emotions he holds regarding the (travel time reliability) of the alternative routes

he decides what route choose. Note that in case the traveller has a strong habit, this entire decision making process may be skipped and he may automatically 'choose' his habitual route. The route choice affects the traffic situation.

The estimates of the current travel times on all alternative routes are one of the inputs of the decision making process. The estimate is a combination of the en-route traffic information, which gives information on current traffic conditions on the routes, and the expected travel time, by which we mean a more or less long-term expectation that a traveller holds of the travel time on a route.

The expected travel time is the result of a learning process. The traveller can combine past experiences and past information to form an expectation of travel time. The recency of the experience (referring to how long ago it took place) and the salience of the experience (referring to how much it stands out from earlier experiences and expectations) influence how well it is remembered and hence how well it is used in this learning process. The same can be said about the recency and salience of past information.

Note that past information can have various meanings. It can be the en-route information of previous days, but it can also be ex-post information which gives the realized travel times on all routes of the previous days.

## 8.1.3 Discrete choice modelling

To answer the research questions, an interactive choice experiment was carried out. In this section the mathematical model that was used to analyze the data from this experiment is presented. This discrete choice model is based on the conceptual framework. The basic structure of the model is discussed below. For an overview of the used mathematical formulations, we refer to page viii.

## Hypotheses and assumptions

A number of hypotheses and assumptions had to be made to 'translate' the conceptual framework into the mathematical model. The most important ones being:

- Travellers can be modelled as utility optimizers.
- The updating of the expected travel time can be used as a proxy for explicit learning.
- The fraction of choices for a route in the past can be used as a proxy for implicit learning.
- Salience can be used to express reliability.

## Elements of the route choice model

The route choice model, which expresses the overall utility / value of a certain route for a certain traveller on a certain day, consists of a number of components:

- A road specific preference representing the fact that some travellers have an intrinsic preference for a route regardless of the values of other attributes *(traveller characteristics)*
- Traffic information as displayed on a variable message sign (en-route traffic information)
- Expected travel time *(explicit learning, reliability)*

- A habit or inertia component. This term reflects reinforcement of routes that were chosen relatively much in the past *(implicit learning)*
- An error term containing everything that is not explained by the previous elements.

## Updating the expected travel time

Today's expected travel time for a route is defined as yesterday's expected travel time updated with today's experienced travel time on that route. If the weight of today's experienced travel time is high in updating the expected travel time, we say that the recency effect is large. When today's experienced travel time is very different from yesterday's expected travel time, we say that it is very salient.

## Estimating the model

The route choice model was estimated for three periods: beginning (days 1-10), middle (days 11-25) and end (days 26-40). This allows us to gain insight into the evolution of parameters. This can help to make inferences about the existence of a primacy effect.

## 8.1.4 Experimental set-up and data collection

For our data collection, we used the Travel Simulator Laboratory. This is an internet-based tool in which respondents can make a route choice and are provided with feedback on their choice. In chapter 4 it was concluded that SP (stated preference) and RP (revealed preference) research each have advantages and disadvantages. The TSL can be regarded as a mixture of both methods. In this way we attempt to use the strengths of both methods while avoiding as much as possible their limitations.

At the beginning of the experiment a respondent was told that he had to make 40 consecutive choices from three hypothetical routes. The *route types* were:

- Route 1: Consists mainly of highway.
- Route 2: Consists mainly of rural roads.
- Route 3: Consists partly of highway and goes partly through a city centre.

Most respondents were given a meeting with colleagues as *travel goal*; some were told to imagine they had to go to a job interview.

Besides the travel goal, the type of traffic information that was provided also differed between respondents (*not* within a respondent). Some respondents received *en-route information* which gives an (uncertain) indication of the current travel time or kilometres queue on the routes. The information was usually quite accurate. Some respondents were (also) provided with *ex-post information* on non-chosen routes.

As a respondent received feedback regarding the realized travel time of the route he had chosen, he could learn about the *travel time characteristics of the routes*. The routes can be characterized as follows: One route was usually (3 out of 4 days) quite fast, but sometimes very slow (1 out of 4 days). Another route was by far the most reliable route, but also on average the slowest route. The travel time of the third route was normally distributed with a large variance. Its mean was slightly higher than the mean of route 1.

The *response* to this experiment was good: In total 2500 persons from different genders, ages and educational levels completed the experiment.

## 8.2 Main findings

In this section, we summarize the main findings of the dissertation research. We focus on the aspects reliability, learning, and information respectively.

## 8.2.1 Reliability

We analyzed the influence of travel time reliability on explicit learning and route preferences. Traffic information and travel goal can modify this influence of reliability. The findings on these topics are listed below.

## Salience effect in updating expected travel time (explicit learning)

The performance of our route choice model, measured in terms of the log-likelihood value, improved slightly by accounting for salience effects when updating the expected travel time. The salience effect for habitual routes was found to be opposite to the salience effect for non-habitual routes. More specifically, the salience formulation by which long travel times on habitual routes are weighted less and on non-habitual routes are weighted more than normal travel times, was found to be the best in the beginning and middle period of the info scenario and in the beginning period of the no info scenario.

## Evolving route preferences

The discrete choice model models individual route choices. We also looked at all choices from all respondents and the way they developed during the course of the experiment. The analysis showed that the share of choices for a route that is usually fast and sometimes very slow increased during the course of the experiment by approximately 5%. Similarly, the share of choices for a route that can have any travel time within a long range with more or less the same probability decreased with approximately 15%. The share of the reliable route increased with approximately 10%.

## Traffic information and travel goal

We also studied the fraction of choices for a certain route in relation to the traveller's travel goal and received traffic information. It was found that travel goal and traffic information influenced route choice in the following ways:

- For the travel goal 'meeting with colleagues' the route with an unreliable symmetrical travel time distribution is much more and the route with a very reliable but on average long travel time distribution is much less chosen with en-route information than without en-route information. The unreliable route has a route choice share of 16% without versus 26% with en-route information. The shares for the reliable route are 35% and 28% respectively.
- The previous finding applies even stronger to the job interview scenario. In this scenario the unreliable route has a share of 15% without versus 27% with en-route information. The shares for the reliable route are 40% and 30% respectively.
- The provision of ex-post information does not have a large influence on route choice percentages for people who also receive en-route information. However, for travellers who do not receive en-route information, the provision of ex-post information enlarges the share of the route with an unreliable skewed travel time distribution (from 45% to 51%) and decreases the share of the reliable yet on average slow route (from 39% to 34%).
- The reliable, yet on average slow route reaches its largest share (51.9%) among travellers who did not receive en-route information nor ex-post information and had to go to a job interview.

## 8.2.2 Learning

In this section, our finding related to explicit learning and implicit learning are discussed respectively.

## Explicit learning

For the no info scenario it was found that the weight of the most recent experience in updating the expected travel time (representing the 'recency effect') was increasingly large. In the beginning period it determined the expected travel time for 66%; in the middle for 86% and at the end for 100%.

The 'en-route information' scenario showed different results. The recency effect is smaller here than in the no info scenario and is decreasing. In the beginning period the most recent experience determined the expected travel time for 52%; in the middle for 64% and at the end for 25%. For the most recent received en-route information these percentages are 41, 0 and 0 respectively. The combined influence of the latest experience / information on updating the expected travel time therefore becomes smaller as time goes by. Note that information was found to play a role in updating the expected travel time only in the beginning period.

Besides this recency effect, a salience effect was also found to be present in updating the expected travel time. As discussed in the previous subsection on reliability, very large travel times have extra weight in updating the expected travel time for non-habitual routes and less weight for habitual routes.

## Implicit learning

The role of past choices (which is used to model implicit learning and habit formation) compared to the role of the expected travel time (which is used to model explicit learning) was found to be relatively large in the route choice process. Furthermore, it is increasing for both the 'no information' and the 'en-route information scenario' as the experiment evolved. To give an example: choosing route 1 in the middle period 1 extra time can compensate approximately 10 minutes extra expected travel time.

## 8.2.3 Traffic information

A number of results related to this question were found in our research. Some of them are related to reliability and learning and were discussed in the previous two subsections. For the sake of completeness they are discussed here as well.

## Travel time savings

The more traffic information that was provided to travellers, the higher the travel time savings that were realized. The most elaborate information scenario (en-route and ex-post information) for example leads to 5 minutes (10%) savings compared to the least elaborate information scenario (no information at all).

## Relative effect on route choice

In the route choice model, the en-route traffic information was found to have a high weight compared to the weight of the expected travel time: its weight equals two to four times the weight of the expected travel time.

## Reliability characteristics of chosen routes

Providing en-route traffic information increases the share of an on average fast but unreliable route (route 1) at the expense of a reliable but slow route (route 2). This is especially true for

the job interview scenario. The provision of ex-post information does not have a large influence on route choice percentages for people who also receive en-route information. For travellers who do not receive en-route information, however, the provision of ex-post information enlarges the share of route 1 and decreases the share of route 2.

#### Bad travel time experiences and accuracy of information

The route choice behaviour before and after an extremely bad travel time experience was analyzed. It was found that when correct en-route information warned for an extremely long travel time on a route and people chose this route after all, this had not much impact in the choice percentage for that route after the extreme experience. Without en-route information, most people choose the route on which they had the extreme experience a slightly less frequent. The largest effect can be seen for people who had received incorrect en-route information. They demonstrated highly diverging reactions. Some chose the route less often after this experience, some chose it with the same frequency and some chose it more often.

#### *Learning – updating of expected travel time*

In case a traveller did not choose a route, but did receive en-route information on the travel time, he may use this information to update the expected travel time for that route. This effect was only found to be present in the beginning period. To be precise: in the beginning period the most recent received en-route information determined the expected travel time for 41%.

## 8.3 Conclusions

After having presented the main findings of this dissertation research, the main conclusions which can be drawn based on these findings will be presented in the ensuing. This is done for the aspects reliability, learning, and information. The last subsections are dedicated to conclusions regarding the conceptual framework, our discrete choice model and the experimental set-up & data collection.

#### 8.3.1 Reliability

#### Habitual route perceived different than non-habitual route

It was found that sometimes very large travel times on non-habitual routes have extra weight in updating the expected travel time. The opposite holds for habitual routes. A plausible explanation can be found in cognitive dissonance theory. A traveller may not want to acknowledge that the route he chooses most is actually very bad. He can solve this cognitive dissonance by changing his cognition, for example by telling himself that the route is indeed very good and that the bad travel time is the exception that proves the rule. And, as he regards the bad travel time as an exception, he gives it less weight in updating the expected travel time. A good travel time, on the other hand, will strengthen his idea that the habitual route is good and deserves extra weight. The opposite line of reasoning may apply to non-habitual routes.

#### Skewed travel times preferred over broad-range travel times (when means are equal)

Another finding concerned the fact that people developed a preference for a route with a skewed travel time distribution at the expense of a route with a broad symmetrical travel time distribution. This may be explained by the fact that the skewed route was more predictable in a way. When predicting the travel time to be approximately 35 minutes, one would be right in 75% of the cases (and very wrong in 25%). For the other route, however, it is impossible to make a prediction that is right as often as 75%. A similar explanation is that the difference between the  $70^{\text{th}}$  percentile values of the two routes is quite large (10 minutes). If being on

time in 70 percent of the cases is enough, then choosing the skewed route saves 10 minutes a day.

#### Provision of traffic information increases attractiveness of less reliable routes

When en-route information is provided, unreliable symmetrically distributed is chosen more at the expense of the reliable long route. With ex-post information, the unreliable skewed route is chosen more at the expense of the reliable long route.

Although the ex-post information does not say anything about the current traffic conditions, it does help the traveller to get a better understanding of a route's travel time distribution. Apparently, this results in an increased attractiveness of the skewed route. This leads to the same conclusion as the previous one: travellers prefer a route with a skewed travel time distribution more than a broad symmetrical travel time distribution (assuming that the mean travel times of both routes are equal).

The route belonging to this last distribution, however, profits most from en-route information. Perhaps this can also be explained by assuming that travellers find this route least predictable. The relative increase in predictability that is derived from the en-route information is then large.

#### Important travel goal increases attractiveness of reliable routes

The reliable but on average longest route is chosen more when travellers have to go to a job interview than when they have to go to a meeting with colleagues. So, the travel goal that represents the highest importance of arriving on time leads to less risky route choices.

#### 8.3.2 Learning

## Travellers are very myopic without en-route information

For the no info scenario it was found that people are very myopic in developing an estimate of the expected travel time. This increases during the course of the experiment. In the end period the expected travel time is even completely determined by the most recent experience. Although this result has been found more often in travel behaviour studies (refer to the literature review earlier in this chapter) it may seem strange for two reasons:

- Human memory capacities allow people usually to remember more than one experience.
- The primacy effect would lead to lower values later on in the experiment.

Considering these two arguments, a possible explanation may lie in the experiment. Possibly, people find it hard to recognize any structure in it having 'only' 40 choices, no further travel time information and no real incentive to make an effort. The construction of an expected travel time based on more than one experience may then be a bridge too far.

#### En-route information helps travellers to have a more realistic travel time expectancy

The info scenario showed different results. The recency effect is smaller here than in the no info scenario. Apparently, the presence of traffic information allowed travellers to have a less myopic (and more realistic) expectancy of travel time. Possibly, the provided information helped the travellers to recognize a structure in the travel times and to acknowledge that travel times vary. In this way, travellers may understand that an expectation based on only the latest experience is not very accurate.

#### Experience more important than information in updating expected travel time

In contrast to travel time experiences, travel time information only played a role in updating the expected travel time in the beginning period. Possibly, due to bounded rationality and limited cognitive resources travellers may (unconsciously) choose to neglect travel information for updating and solely focus on real experiences once they have obtained a satisfactory expectation of travel time. Even if the travel time information is only used in the beginning period to update the expected travel time, it did help the traveller throughout the experiment to develop a less myopic expectancy of travel times. Refer for possible explanations to the previous conclusion.

#### Primacy effect perhaps present in the info scenario

Considering that experiences have a higher weight in updating the expected travel time in the info scenario during the beginning period than during the middle and end periods, a primacy effect was perhaps present. A counter argument can be made. The mathematical formulation used to express the updating of the expected travel time required the researcher to set an initial value for the expected travel time. The high weight at the beginning may therefore also be explained as a correction of this initial value.

#### Implicit learning determines route choice more than explicit learning

We found that the role of past choices (which is used to model implicit learning and habit formation) compared to the role of the expected travel time (which is used to model explicit learning) in making a route choice is large. Furthermore, it is increasing for both the no info and the info scenario as the experiment evolved. This may indicate habit formation.

#### 8.3.3 Traffic information

## Traffic information leads to travel time savings

The more traffic information that was provided to travellers, the higher the travel time savings that were realized. This has been discussed in the findings on traffic information.

#### Accuracy of information very important

When travellers experienced a very long travel time and the en-route information failed to warn for it, very diverging reactions follow. Though we do not understand why these diverging reactions happen, we do understand that accuracy of information is important if one wants to prevent such unforeseeable reactions.

*Provision of traffic information increases attractiveness of less reliable routes* This has been discussed in the conclusions on reliability.

*En-route information helps travellers to have a more realistic travel time expectancy* This has been discussed in the conclusions on learning.

#### 8.3.4 Conceptual framework

Most part of the framework was translated into the route choice model. Estimation of the model showed that all elements from the route choice model were significant and logical in sign. This leads us to conclude that the conceptual framework provides a useful way to describe day-to-day route choice behaviour under traffic information.

#### 8.3.5 Experimental set-up and data collection

We conclude that the data from the experiment were very usable. We were able to carry out a number of relevant statistical analyses on the data and we were able to estimate the discrete choice model on them. Most results were significant, could be explained and increased our understanding of route choice behaviour.

## 8.3.6 Discrete choice model

In this thesis we proposed a discrete choice model to model day-to-day route choice behaviour under traffic information. We conclude that the model worked well, since the model could be estimated on our data and the parameter estimates were significant and logical in sign.

## 8.4 Implications for policy and practice

The above findings and conclusions have several implications for policy makers, consultants and traffic managers. The ones we think are important are listed below.

## Traffic information

- Keep providing en-route information. It allows travellers to develop a more accurate long-term expectation and current estimate of travel time and results in travel time savings. It also increases the use of routes which are otherwise thought as too unreliable. Travel time savings are not only beneficial to individual travellers. It also means that total car hours are reduced, leading to less traffic and hence less damage to the environment.
- Make sure the en-route traffic information is accurate. Otherwise unforeseeable reactions can occur which make it hard to manage and plan traffic.
- Use the fact that travellers' perceptions of routes (and therefore route choices) can be influenced by ex-post traffic information as one of the mechanisms in dynamic traffic management. Perhaps this mechanism can also be used to increase use of public transport.

## Habits

• Despite the above, acknowledge that it is hard to change habits. Habits can be strong and automatically determine behaviour. Furthermore, travellers are possibly much more forgiving for bad experiences on habitual routes than on non-habitual routes. When combined with the previous remark, one should make it very explicit in the expost info which routes are best. The traveller should no longer be able to be unaware of the bad characteristics of the habitual route.

## Reliability

- Invest in increasing reliability of routes. Especially when the routes lead to important goals (like the airport) and / or no traffic information is available, travellers prefer reliable routes over slightly faster but less reliable routes.
- Do not limit yourself to variance when measuring reliability, but incorporate skewness as well. The nature of unreliability is important for travellers and their travel behaviour. Only looking at variance may therefore lead to wrong inferences regarding travel behaviour.

## 8.5 **Reflections on the research**

Most findings presented in this thesis are based on three interrelated things: the conceptual framework, the experiment and the mathematical model. The mathematical model was based on the insights from the conceptual framework. It was estimated on the data obtained from the experiment. Our reflection on the research therefore concentrates on the validity of the conceptual framework, the mathematical model and the experiment.

#### Conceptual framework

The conceptual framework was constructed using insights from various sciences. We think it concerns rather uncontroversial insights. They were found in numerous studies by numerous authors. The reader does have to be aware of the scope of the framework and the situation it applies to. It doesn't say anything about the way people construct routes (spatial recognition) and what routes are in their choice sets. It is, however, very well applicable to the route choice situation in our experiment.

#### Discrete choice model

The most critical remark concerning the mathematical model is probably about the model type, a utility model. Various shortcomings of this type of model were discussed in the text. Our approach was to use the model as a means to an end, not an end on its own. The fact that all attributes proved to be significant, means that there is a statistical relation between the attribute and the modelled choice, i.e. the outcome of the choice process. Many findings from all kinds of scientific research are based on finding such a significant statistical relation. Therefore, we find that the model was a good means to an end. Nevertheless, we do not know if it is a causal relation and subsequently how the choice process works. If the end goal is to have a realistic model of the choice process, one would therefore need a different type of model based on a different type of experiment.

#### Data collection

The data were obtained by an enriched research in an attempt to enjoy the advantages of SP research while avoiding their shortcomings. Compared to pure SP research, the fact that we did not have to operationalize vague concepts like reliability, but rather let respondents experience it themselves and that we did not impose a goal function in our view increased validity. The lack of any real consequences of choices and the time horizon of the experiment were not good in terms of validity. Some scientists carried out validity studies of other travel simulators and reported positively on the result. To conclude, the positive remarks lead us to think that the outcomes of the experiment are valuable. And looking at the fact that as far as the topic of learning is concerned, earlier studies have hardly used any data at all, our outcomes are even more valuable. Yet, we cannot ignore the critical remarks. Therefore, we think the results have to be interpreted with some caution. In our conclusions we treated parameter estimates, for example, as rough estimates instead of exact truth.

## 8.6 Recommendations for future research

Some recommendations follow directly from the reflections described in the previous section.

First, we recommend to carry out true RP research. Although we tried to avoid as much as possible the typical disadvantages of SP research by enriching our research, it is still different from true RP research. Combining our results with the ones that can be obtained from RP research, will lead to more valid conclusions. Furthermore, the RP research results can be used to study the validity of SP research. Note that RP research has been done in earlier studies, for example (Van Berkum and Van der Mede, 1993; Emmerink et al., 1996; Chatterjee and McDonald, 2004) in which surveys were held with respect to real encountered traffic situations. The scope and research questions, however, were different in those studies.

Second, we recommend to use biometrical tools like fMRI, skin conductance and heart rate in studying route choice behaviour. In this thesis the outcomes of the choice process were used to understand what attributes may have been used in what way in this choice process. As such, only statistical relations instead of causal relations can be proven. Alternatively it would

be interesting to analyze the process itself. Biological measures such as heart rate and skin conductance (sweaty hands) can be used as a proxy for anxiety. Due to recent advances in brain research, it is also possible to measure what part of the brain is used during the various phases of a choice process. The technology used for this is called fMRI. With fMRI research it is for example possible to measure to what extent a person consults his memory when making a route choice, or whether he feels emotions like frustration after a disadvantageous route choice. These examples could shed more light on recency and salience effects. Possibly this technique can also be used to do research into the diverging reactions after a bad experience under inaccurate traffic information, a finding in this thesis that we could not explain.

Finally, we found indications that reliability is perceived differently for habitual routes than for non-habitual routes. More research is needed to transform these indications into strong conclusions.

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## **Appendix A - Model estimation: procedure and** outcomes

This appendix presents all results from the estimation of the mixed logit model for panel data which is presented throughout this thesis. Only the results in terms of graphs and tables are presented. Discussion and interpretation of the results is done in the regular chapters of this thesis.

The model has been estimated on two selections of the data. The first selection, which we refer to as 'No info scenario', concerns data of respondents who

- had as travel goal a meeting with colleagues,
- did not receive any en-route information and •
- did not receive ex-post information on non-chosen routes.

The second selection, which we refer to as 'Info scenario', concerns data of respondents who • had as travel goal a meeting with colleagues,

- received en-route information about the expected travel time on the three routes in minutes
- did not receive ex-post information on non-chosen routes. •

The results of both estimations are presented in the sections A.3 and A.4 respectively. First, the procedure followed to estimate the models and estimation issues concerning endogeneity and serial correlation are explained in the next sections respectively.

## A.1 Estimation procedure

As mentioned before the model is estimated for different time periods to gain insight in the development of learning and choice behaviour as travellers gain more experience. Estimation of the model, however, proved to be an impossible task due to the higher order terms for  $\lambda$ and  $\alpha$  that arise when expanding formulations (6.8) and (6.9). Therefore, we estimated the MNL version of the model for fixed values of  $\lambda$  and  $\alpha$  and determined what values of  $\lambda$  and  $\alpha$ gave the best rho-square. This procedure is explained in detail in the next subsection. It is followed by a subsection on how the variance of the found optimal values of  $\lambda$  (and  $\alpha$ ) was determined.

## A.1.1 Estimating $\lambda$ and $\alpha$

## <u>Step 0</u>

The data are divided into three periods: route choices made at days 1 to 10, choices from days 11 to 25 and choices from days 26 to 40.

## Step 1

The initial values for ETT were set to 35, 40, and 45 minutes for routes 1, 2 and 3 respectively. Then, ETT was computed for a certain value of  $\lambda$  and, in the info scenario, also for a certain value of  $\alpha$ .

## <u>Step 2</u>

The computed values for ETT were used during the estimation of the MNL version of the model with the software package Biogeme (Bierlaire, 2008), (Chen et al., 2004). We constrained  $\beta_{ETT}$  to be non-positive to assure logical estimation results. The resulting log-likelihood value of the model was stored.

## Step 3

A grid search is performed. That is, step 1 and 2 are repeated in the info scenario for all 121 possible combinations of  $\lambda$  (values 0.0, 0.1, ... 0.9, 1.0) and  $\alpha$  (values 0.0, 0.1, ... 0.9, 1.0) and step 1 and 2 are repeated in the no info scenario for all 11 values of  $\lambda$ . As steps 1 and 2 are quite fast, a grid search doesn't cost much time and has the advantage of giving a complete picture of the behaviour of the log-likelihood as a function of  $\lambda$  and  $\alpha$ .

## Step 4

A more detailed grid search is performed around the parameter value(s) that gave the best rhosquare value and all resulting log-likelihood values are stored.

## Step 5

The parameters belonging to the best rho-square value from the previous step are fixed and used to compute ETT for the current period. We go back to step 1 to estimate the parameters for the next period until all 3 periods have been done.

## Step 6

The found optimal values of  $\lambda$  (and  $\alpha$ ) are used to compute ETT and the original model, i.e. the mixed MNL for panel data, is estimated.

## A.1.2 Estimating the variance of the found optimal values of $\lambda$ (and $\alpha$ )

The standard deviation of lambda and alpha are computed using the Cramér-Rao bound. The Cramér-Rao bound is given in (A.1) and (A.2).

$\operatorname{var}(\hat{\theta}) \ge B^{-1}$	(A.1)
$B = -E[\nabla^2 LL]$	(A.2)

With  $\theta$  the unbiased estimator of  $\lambda$  and  $\alpha$  $\nabla^2 LL$  the Hessian of LL with respect to  $\theta$ 

To be able to calculate (A.1), we have to determine the Hessian of the log-likelihood around the optimal point  $(\alpha^*, \lambda^*)$ . The following method was used to do so:

We recall the Taylor series expansion of the log-likelihood function around the optimum:

$$L(\alpha,\lambda) = L(\alpha^*,\lambda^*) + (\alpha - \alpha^*)\frac{\partial L}{\partial \alpha} + (\lambda - \lambda^*)\frac{\partial L}{\partial \lambda} + \frac{1}{2}(\alpha - \alpha^*)^2\frac{\partial^2 L}{\partial \alpha^2} + (\alpha - \alpha^*)(\lambda - \lambda^*)\frac{\partial^2 L}{\partial \alpha \partial \lambda} + \frac{1}{2}(\lambda - \lambda^*)^2\frac{\partial^2 L}{\partial \lambda^2}$$
(A.3)

The main step in the approach is fitting the following multivariate polynomial function to the available data:

$$f(\alpha, \lambda) = b_{1} + (\alpha - \alpha^{*})b_{2} + (\lambda - \lambda^{*})b_{3} + \frac{1}{2}(\alpha - \alpha^{*})^{2}b_{4} + (\alpha - \alpha^{*})(\lambda - \lambda^{*})b_{5} + \frac{1}{2}(\lambda - \lambda^{*})^{2}b_{6}$$
(A.4)

In fitting this function to the data, we only use data in the neighbourhood of the optimum. In doing so, we establish the optimal parameters  $b_1$  to  $b_6$ . Comparing Eq. (A.3) to Eq. (A.4), we see that  $b_4$  to  $b_6$  respectively denote estimates of the second derivatives of L, i.e.:

$$\Delta \mathbf{L} = \begin{pmatrix} \frac{\partial^2 \mathbf{L}}{\partial \alpha^2} & \frac{\partial^2 \mathbf{L}}{\partial \alpha \partial \lambda} \\ \frac{\partial^2 \mathbf{L}}{\partial \alpha \partial \lambda} & \frac{\partial^2 \mathbf{L}}{\partial \lambda^2} \end{pmatrix} = \begin{pmatrix} \mathbf{b}_4 & \mathbf{b}_5 \\ \mathbf{b}_5 & \mathbf{b}_6 \end{pmatrix}$$
(A.5)

Filling out the result of (A.5) in (A.2) gives us *B*. Entering *B* in (A.1) gives us the variance of  $\lambda$  and  $\alpha$ .

Note that the outlined procedure requires data in the neighbourhood of the optimum. In other words, it can only be applied if data are available around the optimal value of a parameter. If the optimal value of a parameter lies on the border of its range, it is not possible to estimate its variance. In our experimental situation, for example, the optimal  $\alpha$  was found to equal 0 in the middle and end period. Its variance can therefore not be determined in these periods. The variance for  $\lambda$  can be approached by inverting  $b_6$ .

#### A.2 Estimation issues: endogeneity and serial correlation

As discussed in the previous section, we assume the error term in our model to be Gumbel independent and identical distributed (i.i.d.) to be able to estimate the model. This may, however, not reflect reality completely. Although we added individual random effects (3.20) and tried to capture most (implicit and explicit learning) dynamics in the systematic part of the route's utility, we realize that there may still be some correlation left between the error terms belonging to one individual. This would also mean then that the lagged choices, which are used in the model to specify the implicit learning part, can be correlated with the current error term, which could lead to endogeneity problems. To be able to estimate the model, however, we need to assume the error terms to be i.i.d..

## A.3 Estimation results: no info scenario

A summary of the results is listed in Table 25. The more detailed results are presented for the three different periods separately in the next sections.

Table	25:	Summary	of	route	choice	model	estimation	results	for	no	info	scenario
standa	rdiz	ed wrt β <sub>ET1</sub>	· (nı	umbers	s in itali	cs are ii	nsignificant	at the 9	<b>5%</b> I	leve	l)	

Name	Value Beginning	Value Middle	Value End		
$\beta_{choice1}$	4.04E-01	5.72E+00	1.04E+01		
$\beta_{choice2}$	-2.79E+00	4.71E+00	6.85E+00		
$\beta_{choice3}$	2.78E+00	2.67E+00	4.50E+00		
$\beta_{\text{ETT}}$	-1.00E-01	-1.00E-01	-1.00E-01		
City	-3.51E+00	<i>-1.62E+00</i>	1.16E+00		
Highway	0.00E+00	0.00E+00	0.00E+00		
Provincial	-1.77E+00	6.84E-01	2.42E+00		
σ	-2.23E+00	-3.27E+00	-1.85E+00		
Optimal $\lambda$	0.66	0.86	1.00		
Rho-					
square	0.21	0.38	0.46		
Salience	Habitual route: large travel times less weight Non-habitual routes: large travel times extra weight	No effect	No effect		

#### A.3.1 Beginning

In Figure 23 the results of the optimization with respect to  $\lambda$  are shown. The optimal  $\lambda$  value is used in the estimation of the mixed logit model. The results of this are given in Table 26 and Table 27.



Figure 23: -Loglikelihood values for different values of  $\lambda$  (beginning, no info scenario)

Model:	Mixed Multinomial Logit for panel data	Final log-likelihood:	-1094.29
Number of draws:	1000	Likelihood ratio test:	579.914
Number of estimated parameters:	7	Rho-square:	0.209468
Number of observations:	1260	Adjusted rho-square:	0.204411
Number of individuals:	126	Final gradient norm:	0.00786606
Null log-likelihood:	-1384.25	Variance covariance:	from finite difference
Init log-likelihood:	-1384.25	variance-covariance.	hessian

Table 26: Descriptive statistics for model estimation (beginning, no info scenario)

Table 27	': Parameter	estimates	for model	(beginning.	no info scenar	io)
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Name	Value	Std. err.	t-test		Robust Std. err.	Robust t-test	
$\beta_{choice1}$	1.47E-01	1.73E-01	8.54E-01	*	1.80E-01	8.17E-01	*
$\beta_{choice2}$	-1.02E+00	4.29E-01	-2.37E+00		4.43E-01	-2.30E+00	
$\beta_{choice3}$	1.01E+00	4.68E-01	2.16E+00		6.06E-01	1.67E+00	*
$\beta_{ETT}$	-3.65E-02	7.57E-03	-4.82E+00		8.35E-03	-4.37E+00	
City	-1.28E+00	2.02E-01	-6.35E+00		1.84E-01	-6.97E+00	
Highway	0.00E+00	fixed					
Provincial	-6.46E-01	1.96E-01	-3.29E+00		1.93E-01	-3.34E+00	
σ	-8.15E-01	1.13E-01	-7.20E+00		1.28E-01	-6.38E+00	

#### A.3.2 Middle

In Figure 24 the results of the optimization with respect to  $\lambda$  are shown. The optimal  $\lambda$  value is used in the estimation of the mixed logit model. The results of this are given in Table 28 and Table 29.



Figure 24: -Loglikelihood values for different values of  $\lambda$  (middle, no info scenario)

Table 20. Descriptive statistics for model estimation (initiality, no	Table 28	: Descriptive	statistics for	<sup>•</sup> model estimatior	i (middle, no	info scenario)
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Model:	Mixed Multinomial Logit for panel data	Final log-likelihood:	-1295.83
Number of draws:	1000	Likelihood ratio test:	1561.09
Number of estimated parameters:	7	Rho-square:	0.375916
Number of observations:	1890	Adjusted rho-square:	0.372544
Number of individuals:	126	Final gradient norm:	0.0034926
Null log-likelihood:	-2076.38	Variance covariance:	from finite difference
Init log-likelihood:	-2076.38	variance-covariance.	hessian

Table 29: Parameter estimates for model (middle, no info scenario)

Name	Value	Std. err.	t-test		Robust Std. err.	Robust t-test	
$\beta_{choice1}$	1.94E+00	3.48E-01	5.58E+00		3.45E-01	5.63E+00	
$\beta_{choice2}$	1.60E+00	4.24E-01	3.77E+00		5.73E-01	2.79E+00	
$\beta_{choice3}$	9.07E-01	4.70E-01	1.93E+00	*	4.94E-01	1.84E+00	*
$\beta_{ETT}$	-3.39E-02	4.28E-03	-7.92E+00		5.92E-03	-5.73E+00	
City	-5.51E-01	3.06E-01	-1.80E+00	*	2.45E-01	-2.25E+00	
Highway	0.00E+00	fixed					
Provincial	2.32E-01	3.11E-01	7.46E-01	*	3.03E-01	7.66E-01	*
σ	-1.11E+00	1.31E-01	-8.45E+00		1.70E-01	-6.52E+00	
#### A.3.3 End

In Figure 25 the results of the optimization with respect to  $\lambda$  are shown. The optimal  $\lambda$  value is used in the estimation of the mixed logit model. The results of this are given in Table 30 and Table 31.



#### Figure 25: -Loglikelihood values for different values of $\lambda$ (end, no info scenario)

|--|

Model:	Mixed Multinomial Logit for panel data	Final log-likelihood:	-1111.18	
Number of draws:	1000	Likelihood ratio test:	1930.39	
Number of estimated	7	Rho-square.	0.464846	
parameters:	7	Kilo-square.	0.404040	
Number of	1800	A divisted the square:	0.461475	
observations:	1090	Adjusted mo-square.	0.401473	
Number of individuals:	126	Final gradient norm:	0.00679504	
Null log-likelihood:	-2076.38	Variance covariance:	from finite difference	
Init log-likelihood:	-2076.38	variance-covariance.	hessian	

Name	Value	Std. err.	t-test		Robust Std. err.	Robust t-test	
$\beta_{choice1}$	3.60E+00	3.00E-01	1.20E+01		3.83E-01	9.40E+00	
$\beta_{choice2}$	2.37E+00	3.36E-01	7.07E+00		5.26E-01	4.51E+00	
β <sub>choice3</sub>	1.56E+00	4.82E-01	3.23E+00		7.88E-01	1.98E+00	
$\beta_{ETT}$	-3.46E-02	4.32E-03	-8.02E+00		6.31E-03	-5.48E+00	
City	4.01E-01	2.32E-01	1.73E+00	*	2.77E-01	1.45E+00	*
Highway	0.00E+00	fixed					
Provincial	8.39E-01	2.74E-01	3.06E+00		3.59E-01	2.34E+00	
σ	-6.40E-01	1.19E-01	-5.39E+00		2.24E-01	-2.86E+00	

#### A.4 Estimation results: info scenario

A summary of the results is listed in Table 25. The more detailed results are presented for the three different periods separately in the next sections.

Table	32:	Summary	of	route	choice	model	estimation	results	for	info	scenario
standa	rdize	ed wrt $\beta_{ETT}$									

Name	Value Beginning	Value Middle	Value End
$\beta_{choice1}$	-1.01E+00	8.19E+00	6.67E+00
$\beta_{choice2}$	9.94E+00	1.43E+01	1.12E+01
$\beta_{choice3}$	-2.15E+00	1.56E+00	<i>4.38E+00</i>
$\beta_{\text{ETT}}$	-1.00E-01	-1.00E-01	-1.00E-01
$\beta_{Info}$	-2.32E-01	-4.33E-01	-3.28E-01
City	-2.62E-01	4.51E+00	1.72E+00
Highway	0.00E+00	0.00E+00	0.00E+00
Provincial	-2.81E+00	3.91E+00	2.29E+00
σ	-2.05E+00	Not applicable: MNL*	Not applicable: MNL*
Optimal $\lambda$	0.52	0.64	0.25
Optimal α	0.41	0.00	0.00
Rho- square	0.36	0.41	0.46
Salience	Habitual route: large travel times less weight Non-habitual routes: large travel times extra weight	Habitual route: large travel times less weight Non-habitual routes: large travel times extra weight	Both habitual and non- habitual routes: large travel times extra weight

\*Because  $\sigma$  turned out to be insignificant, we estimated the model as an MNL model.

#### A.4.1 Beginning

In Figure 26 the results of the optimization with respect to  $\lambda$  and  $\alpha$  are shown. The optimal  $\lambda$  and  $\alpha$  values are used in the estimation of the mixed logit model. The results of this are given in Table 33 and Table 34.



Figure 26: -Loglikelihood values for different  $\lambda$  and  $\alpha$  (beginning, info scenario)

Table 33: Descriptive statistics for model estimation (beginning, info scenario)

Model:	Model: Mixed Multinomial Logit for panel data		-1734.25	
Number of draws:	1000	Likelihood ratio test:	1914.71	
Number of estimated parameters:	8	Rho-square:	0.355682	
Number of observations:	2450	Adjusted rho-square:	0.35271	
Number of individuals:	245	Final gradient norm:	0.0101665	
Null log-likelihood:	-2691.6	Variance covariance:	from finite difference	
Init log-likelihood:	-2691.6	variance-covariance.	hessian	

Table 34: Parameter estimates for model (beginning, info scenario)

Name	Value	Std. err.	t-test		Robust Std. err.	Robust t-test	
$\beta_{choice1}$	-4.83E-01	2.10E-01	-2.30E+00		1.91E-01	-2.53E+00	
$\beta_{choice2}$	4.77E+00	4.43E-01	1.08E+01		5.60E-01	8.52E+00	
$\beta_{choice3}$	-1.03E+00	2.54E-01	-4.07E+00		2.44E-01	-4.22E+00	
$\beta_{ETT}$	-4.80E-02	6.39E-03	-7.52E+00		5.47E-03	-8.77E+00	
$\beta_{Info}$	-1.12E-01	6.18E-03	-1.80E+01		8.77E-03	-1.27E+01	
City	-1.26E-01	1.55E-01	-8.11E-01	*	1.39E-01	-9.04E-01	*
Highway	0.00E+00	fixed					
Provincial	-1.35E+00	2.72E-01	-4.97E+00		2.70E-01	-5.01E+00	
σ	-9.86E-01	1.21E-01	-8.14E+00		1.37E-01	-7.22E+00	

#### A.4.2 Middle

In Figure 27 the results of the optimization with respect to  $\lambda$  and  $\alpha$  are shown. The optimal  $\lambda$  and  $\alpha$  values are used in the estimation of the mixed logit model. The results of this are given in Table 35 and Table 36.



Figure 27: -Loglikelihood values for different  $\lambda$  and  $\alpha$  (middle, info scenario)

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Model:	Multinomial Logit	Final log-likelihood:	-2137.14
Number of draws:	1000	Likelihood ratio test:	2983.16
Number of estimated parameters:	7	Rho-square:	0.411049
Number of observations:	3303	Adjusted rho-square:	0.40912
Number of individuals:	3303	Final gradient norm:	0.00574141
Null log-likelihood:	-3628.72	Varianza aquarianza:	from finite difference
Init log-likelihood:	-3628.72	variance-covariance.	hessian

Table 36: Parameter estimates	for model	(middle, info	scenario)
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Name	Value	Std. err.	t-test		Robust Std. err.	Robust t-test	
$\beta_{choice1}$	2.66E+00	2.31E-01	1.15E+01		2.17E-01	1.22E+01	
$\beta_{choice2}$	4.65E+00	2.18E-01	2.13E+01		2.30E-01	2.02E+01	
$\beta_{choice3}$	5.06E-01	2.66E-01	1.90E+00	*	2.58E-01	1.96E+00	*
$\beta_{ETT}$	-3.25E-02	4.15E-03	-7.83E+00		4.19E-03	-7.75E+00	
$\beta_{Info}$	-1.41E-01	4.57E-03	-3.08E+01		4.92E-03	-2.86E+01	
City	1.46E+00	1.98E-01	7.40E+00		1.98E-01	7.40E+00	
Highway	0.00E+00	fixed					
Provincial	1.27E+00	1.67E-01	7.63E+00		1.64E-01	7.74E+00	
σ	Not applicat	ole; model es	timated as MN	IL, t	because $\sigma$ turned out	to be insignifica	nt.

#### A.4.3 End

In Figure 28 the results of the optimization with respect to  $\lambda$  and  $\alpha$  are shown. The optimal  $\lambda$  and  $\alpha$  values are used in the estimation of the mixed logit model. The results of this are given in Table 37 and Table 38.



Figure 28: -Loglikelihood values for different values of  $\lambda$  and  $\alpha$  (end, info scenario)

Model:	Multinomial Logit	Final log-likelihood:	-1075.97	
Number of draws:	1000	Likelihood ratio test:	1820.64	
Number of estimated	7	Pho square:	0.458301	
parameters:	1	Rho-square.		
Number of	1808	A divisted the square:	0.454777	
observations:	1000	Aujusieu mo-square.		
Number of individuals:	1808	Final gradient norm:	0.0027443	
Null log-likelihood:	-1986.29	Variance covariance:	from finite difference	
Init log-likelihood:	-1986.29	variance-covariance.	hessian	

Table 37: Descriptive statistics for model estimation (end, info scenario)

Table 38: Parameter estimates for model (end	l, info scenario)
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Name	Value	Std. err.	t-test		Robust Std. err.	Robust t-test	
$\beta_{choice1}$	2.81E+00	2.69E-01	1.05E+01		2.75E-01	1.02E+01	2.81E+00
$\beta_{choice2}$	4.71E+00	3.19E-01	1.48E+01		3.50E-01	1.35E+01	4.71E+00
$\beta_{choice3}$	1.85E+00	4.42E-01	4.18E+00		4.56E-01	4.05E+00	1.85E+00
$\beta_{ETT}$	-4.21E-02	6.64E-03	-6.35E+00		6.72E-03	-6.27E+00	-4.21E-02
$\beta_{Info}$	-1.38E-01	6.44E-03	-2.15E+01		6.79E-03	-2.03E+01	-1.38E-01
City	7.27E-01	2.41E-01	3.02E+00		2.57E-01	2.82E+00	7.27E-01
Highway	0.00E+00	fixed					0.00E+00
Provincial	9.67E-01	2.44E-01	3.96E+00		2.52E-01	3.83E+00	9.67E-01
σ	Not applicable; model estimated as MNL, because $\sigma$ turned out to be insignificant.						

# Appendix B - fMRI research concerning day-to-day route choice

#### This appendix gives excerpts from the paper

Zuylen, H.J. van & E.A.I. Bogers (2008), <u>A Neuro-Psychological Approach of Route Choice</u> <u>in Uncertainty</u>, presented at the 87th Annual Meeting of the Transportation Research Board, January 13-17, 2008, Washington D.C

#### Abstract

Modeling decision processes of travelers is often done by describing it in mathematical terms. The limitations of that approach are that only descriptive (and often even only normative) and no explanatory models are developed. The decision behavior of travelers in uncertain conditions appears to have features that are difficult to catch in the usual mathematical framework based on the utility concept. This paper proposes another approach: to model the decision process in neural functions in the body and the brain. The modeling in terms of neural processes is derived from research in literature on the behavior of persons in comparable situations executing tasks that are similar to the decisions of choosing routes and departure time in uncertain travel conditions. Brain activities and emotions appear to be related. This is represented in the *somatic marker model*. This model is a suitable framework to describe how people choose between uncertain options using limited information. The emotional state influences the decision process by making certain choices more probable.

The paper describes the hypotheses and a research plan how to validate these by using neuroimaging techniques. Brain scans with functional Magnetic Resonance Imaging (fMRI) are planned for the measuring of brain activities during and after the decision processes and emotions will be measured by monitoring heart frequency and skin resistance.

#### **The Somatic Marker Theory**

Bechara and Damasio [1] point to the missing role of emotions in the way economists (and this applies also to most behavioral modelers in transportation) explain choice behavior. They conclude with respect to decision making in uncertainty that

1. knowledge and reasoning are not sufficient for making good decisions and that the role of emotions should be recognized,

- 2. the process of rationally considering different options is slow, the decision behavior is in practice much faster and apparently not fully conscious,
- 3. emotions form a good mechanism in decision making when they are related to the task (and can be disruptive when they are not related),
- 4. decision making under certain conditions and uncertain conditions involve different neural circuitry.

They base their opinion on well known cases of persons with a brain damage who are not able to learn from experiences and take bad decisions if they make choices with uncertain outcomes, even though these persons are intellectually normal. The brain damage appeared to have influenced their ability to express and experience feelings. The control mechanism of bodily states related to emotions does not work properly due to the lost functions in the brain. The perception of certain choices with a recognizable consequence (e.g. if one of the choices has a big chance to give a loss on the long term) does not create the bodily emotion that is present by normal people. This lack of emotion gives a choice behavior that is suboptimal.

That means that if they have to choose between alternatives, they spend a lot of time in deliberating the pros and cons, are not able to decide quickly and they are not able to integrate the experiences of the past in the decision. Emotions appear to have an important role as a mechanism to take decisions: certain stimuli (e.g. the presence of certain choice options) induce in the brain and later in the body an emotional state and this somatic (bodily) state prepares a state in the brain that facilitates certain actions.

Such inducers can be direct, primary inducers, because a person learns from the direct experience that such inducers cause pain or pleasure, or they can be secondary inducers of emotions, like memories or thoughts. People can imagine the situation that will occur after a certain choice and this mental image can give rise to a bodily state that also occurs when the direct experience would be present. The generation of secondary inducers goes well as soon as the primary inducers are established, e.g. if the experience of pain in a certain situation will generate the primary inducer, later the thought of such a situation will be sufficient to create an emotion that gives the wish and action to avoid that situation.

The process of the formation of the primary inducers to the secondary inducers have been investigated in neuro psychology. Other parts of the brain are involved. These brain activities can be made visible e.g. with fMRI. This makes it possible to see a brain with all its structures and to identify which parts of the brain are active for certain functions.



Figure 1: MRI scanner. The testee is moved with his/her head inside the cylinder after which the magnetic field is switched on and off to parallelize odd valence atoms and to find their positions from the specific radiation pattern



Figure 2: fMRI scan of a part of the brain

MRI scanners generate a very high magnetic field which parallelizes the rotation axis of hydrogen atoms and (other atoms of uneven valence). When the magnetic field is turned off, these atoms emit electromagnetic radiation that can be measured. The origin of the radiation can be identified and this makes the spots visible of accumulation of these atoms. If these images are made for different brain activities, the differences of the images shows where the brain activities are located. That technique is known as function Magnetic Resonance Imaging.

#### Functions of the brain areas relevant for route choice

The brain has different areas with different functions and many complex structures. This paper is not the place to describe the full anatomy of the brain. In fact we just want to make a mapping of the route choice process on activities in the brain and we will limit the description of the brain to those areas and functions that are important for that process.

First of all the recognition of routes in the brain is based on two mechanisms: the development of place dependent responses (e.g. 'turn right at the second side road') and the development of cognitive maps. Both functions interact with each other and defects in one of the functions can be compensated by the other one [2]. The formation of place – appropriate responses leads to habitual behavior. The brain area that is active for this is the *caudate nucleus*, a spot in the center of the brain. The declarative representation of routes is developed in the area with the name *hippocampus*. This is located in the middle lower part of the brain.

It is likely that during the TSL (Traffic Simulation Laboratory) experiment the activities of both parts of the brain will occur at different moments: in the beginning the development of responses in the caudate nucleus is most likely, while the activities of the hippocampus will increase if during the experiment unexpected travel times occur, e.g. when the pre-trip information appears to be inconsistent with the experienced travel time. This difference in brain activity can be identified from the neuron-imaging technique.

The decision making in the case that travel times are unknown is a task in which the stimulus is formed by the request to choose a route and in some cases also by information about queue lengths or travel times on the three routes. The direct flexible response to external conditions is localized in the frontal brain. When this part of the brain is damaged, people can still function well, but the skills in social and emotional sense of these patients are not acting properly. This is located in the part of the brain that forms the primary inducers for emotions [1]. The *amygdala*, a structure lower in the brain, is also active to create a bodily state of emotion. Further structures in the brain that are effective are the parts that active for effectuating the bodily state, under control of the cortex and the amygdala, and the sensory structure that feels the state of the body. We could say that the emotional state of the body is a 'shadow' of the state of parts of the brain and that other parts of the brains can perceive the state of the body and thus of the part of the brain that generates the emotion. The bodily state acts as an intermediate in the communication of one part of the brain to other parts. The generated somatic state facilitates the response to the stimulus that activated the inducers of the state.



Figure 3: A schematic representation of the brain

There are two important aspects of this process that makes them often difficult to identify directly. First of all, the perception of the bodily states needs not to be perceived consciously in order to influence the behavior. Even when a person is not aware of her/his bodily state, the decision taken is influenced by the emotion. The second aspect is that the perception of the

emotionally state might be possible without the detour through the body: the sensors of the brain can directly perceive the signals to the body even when the body does not react yet: this is the 'as if body loop' [1]. That means that the body is not brought in the emotional state but the effect that this the emotion would have still comes in the brain and influences the decision process. This appears to happen in cases of choices that have often been made and that have a certain result.

The somatic marker theory becomes especially important in decision making in uncertainty. In that case the direct way (as if body loop) is less important and the bodily state plays a most important role in the response to a choice task where the outcomes are uncertain.

The fMRI technique has been applied already to study the functions of the brain and recently experiments are done to investigate which parts of the brain are active in decision making in uncertainty.

Apart from the somatic marker hypothesis, Bechara and Damasio also point to the fact that people taking decisions with uncertain outcomes and with limited information can use the foremost part of their frontal brain to process complicated information. This mental process is slow, requires much energy and needs skills and experience. This might be a key to the explanation of the difference of highly educated testees, who take more experiences into account and the persons with less education who are more myopic. The first group may be more experienced in using the foremost part of the brains and this might be visible in an fMRI scan.

Another important aspect of decision making in uncertainty is that people try to make choices that gives them the best feelings and that this is strongly influenced by information. Predictions are felt as solutions that elicit good feelings [3]. This will mean that the availability of travel information will reduces the stress of the route choice task. Such decision making task gives another pattern of the activities in the brain and the body than route choice without information.

#### Hypotheses for route choice making in uncertainty

In the experiment in the TSL the participants have to take 40 times a route and departure time and just as happens in reality the travel times are uncertain and the result of the route choice might be unexpected due to random variations of the travel time. The distribution of the travel times has been predetermined in the experiment as given in figure 4.

We can now give the following hypotheses about the decision process and the corresponding brain and body activities:

- 1. in the beginning of the experiment the stimulus-responses are developed as an activity of the frontal brain and the caudate nucleus,
- 2. later in the experiment the participants will develop a mental map with activities of the hippocampus,
- 3. the decision making will be involve changes in the bodily state that can be measured by changes in skin resistance and heart frequency,
- 4. testees with a higher education will use the frontal part of the cortex more than people with a lower education and this will also be seen as less or more myopic choice behavior,
- 5. after an unexpected travel time the hippocampus will be activated,
- 6. after an unexpected travel time, the body loop will be stronger activated, which will be visible by the activity of the amygdala,
- 7. the difference in choice behavior as reaction to unexpected long travel times can be observed in brain activities: persons who change their route choice after such an

experience will show a stronger activity in the hippocampus while they change their mental map,

8. the provision of information to the participants will reduce their stress, which will be measurable as a lower activity of the body loop.



Figure 4: Statistical distributions of the travel times on the three routes

The verification of these hypotheses can lead to a more sophisticated choice model. It can still be interpreted as a utility model but it will be based now on an explanatory background. Probably the utility function that can be calibrated will depend on the bodily state. This will provide a generic framework for decision making under different conditions, which can be seen as a generalization of the existing models for decision making, e.g. as the cumulative prospect theory. The value for practice will be that the choice of explanatory variables can be better structured than in the way it is done now.

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# **Summary - Traffic Information and Learning in Day-to-Day Route Choice**

Day-to-day route choice under uncertainty and the impact of traffic information is the topic of this dissertation research. Travellers who make the same trip several times, like commuters, business travellers, or truck drivers, form a large part of daily travel demand. Because many of them use their car during peak hours for these trips, they are both 'cause' and 'victim' of congestion.

In the situation as illustrated above, there is an opportunity to *learn* about the characteristics of the available routes. Drivers can learn what their normal travel times is and what the *reliability* is of these travel times. This will probably play a role in their route choice. *Traffic information* can also influence the route choice, both directly and indirectly by influencing the learning process. Finally, as the route choice is made repetitively, there is also a possibility of habit formation. Literature review showed that it is not exactly known how these processes work and that the experimental underpinning of proposed model specifications is a highly neglected task.

Therefore, this research contributes to scientific knowledge by

- Describing effects of learning, traffic information and reliability in day-to-day route choice in an interrelated way in a conceptual framework
- Formulating a mathematical model that captures the effects of learning, traffic information and reliability on route choice
- Calibrating the model on experimental data

The practical relevance pertains to the implications of the experimental knowledge on travellers' reactions to traffic information that has been acquired in this thesis.

#### **Research direction**

A number of research questions are formulated on the topics learning, reliability and traffic information. As for learning, we discern two types: explicit (cognitive) learning and implicit

(reinforcement) learning. Through *explicit learning*, a traveller forms an expectation of travel time. Travellers can learn both from their experienced travel times and from traffic information provided to them. To learn from them, they have to be stored in memory. The recency effect means that more recent events have a stronger presence in memory than older ones. The salience effect means that events that stand out may have a distinctive effect on memory. There is a relation between salience and reliability: Large travel time fluctuations can lead to salient travel times, which lead to less reliability. The research questions focus on the recency and salience effects in updating the expected travel time.

*Implicit learning* comprises all kinds of learning where repetition of the relationship between stimulus and response patterns is stored in the neural system as memory. It can lead to habits and inertia. Our research questions concern the relative influence of implicit learning on route choice compared to explicit learning.

Regarding *reliability*, the questions focus on how reliability of travel times influence the perceived attractiveness of a route. The questions also focus on the salience effect, i.e. the influence of salient travel times on the traveller's expected travel time.

Finally, the effect of *traffic information* on the current route choice and on updating the expected travel time (explicit learning) is a topic of research.

#### **Research** approach

The research questions are answered in five steps:

#### 1 Conceptual framework

Based on knowledge from literature, we have developed a conceptual framework. The framework gives insight into the various elements that play a role in day-to-day route choice under traffic information and the relations between those elements.

#### 2 Mathematical model

Based on the conceptual framework, a discrete-choice model was formulated. It is a mixed MNL model for panel data.

#### 3 Data collection

To be able to estimate the route choice model, we collected data using the Travel Simulator Laboratory (TSL). This is an internet-based tool in which respondents can make a route choice and are provided with feedback on their choice. Respondents could choose 40 times from three routes, having distinctive reliability characteristics. In total 2500 persons from different genders, ages and educational levels completed the experiment.

#### 4 Model estimation

Using the software package Biogeme, the route choice model was estimated on the TSL data for three periods: beginning, middle and end of the experiment. This allows us to gain insight into the evolution of parameters.

### 5 Model interpretation and calibration of conceptual framework

The significance, sign and value of the parameter estimates were used in answering the research question and calibrating the conceptual framework.

#### **Experimental findings and their interpretation**

The following knowledge has been developed with respect to learning, reliability and traffic information:

#### Learning

#### Explicit learning - Travellers are very myopic without en-route information

For the no information scenario we found that the weight of the most recent experience in updating the expected travel time (representing the 'recency effect') was increasingly large. In

the beginning period it determined the expected travel time for 66%; in the middle for 86% and at the end for 100%.

Although this result has been found more often in travel behaviour studies it may seem strange as human memory capacities allow people usually to remember more than one experience and the primacy effect would lead to lower values later on in the experiment.

A possible explanation for our finding may lie in the experiment. Possibly, people find it hard to recognize any structure in it having 'only' 40 choices, no further travel time information and no real incentive to make an effort. The construction of an expected travel time based on more than one experience may then be a bridge too far.

#### En-route information helps travellers to have a more realistic travel time expectancy

The 'en-route information' scenario showed different results. The recency effect is smaller here than in the no-information scenario and is decreasing. In the beginning period the most recent experience determined the expected travel time for 52%; in the middle for 64% and at the end for 25%. For the most recently received en-route information these percentages are 41, 0 and 0 respectively. Therefore, the combined influence of the latest experience / information on updating the expected travel time becomes smaller as time goes by.

#### Experience more important than information in updating expected travel time

In contrast to travel time experiences, travel time information only played a role in updating the expected travel time in the beginning period. Possibly, due to bounded rationality and limited cognitive resources travellers may (unconsciously) choose to neglect travel information for updating and solely focus on real experiences once they have obtained a satisfactory expectation of travel time. Still, travellers with traffic information had a less myopic expectancy of travel times than travellers without traffic information.

#### Implicit learning determines route choice more than explicit learning

The role of past choices (used to model implicit learning and habit formation) compared to the role of the expected travel time (used to model explicit learning) was found to be relatively large in the route choice process. Furthermore, it is increasing for both the 'no information' and the 'en-route information scenario' as the experiment evolved.

#### Reliability

#### Salience effect in updating expected travel time different for habitual and non-habitual route The performance of our route choice model improved slightly by accounting for salience effects when updating the expected travel time. The salience effect for habitual routes was found to be opposite to the salience effect for non-habitual routes. More specifically, the salience formulation by which long travel times on habitual routes are weighted less and on non-habitual routes are weighted more than normal travel times, was found to be the best in the beginning and middle period of the info scenario and in the beginning period of the no info scenario.

A plausible explanation can be found in cognitive dissonance theory. A traveller may not want to acknowledge that the route he chooses most is actually very bad. He can solve this cognitive dissonance by changing his cognition, for example by telling himself that the route is indeed very good and that the bad travel time is the exception that proves the rule. As such, he gives it less weight in updating the expected travel time.

#### Skewed travel times preferred over broad-range travel times (when means are equal)

The share of choices for a route that is usually fast and sometimes very slow increased during the course of the experiment by approximately 5%. Similarly, the share of choices for a route that can have any travel time within a long range with more or less the same probability decreased with approximately 15%. The share of the reliable yet on average slowest route increased with approximately 10%.

This may be explained by the fact that the skewed route was more predictable in a way. When predicting the travel time to be approximately 35 minutes, one would be right in 75% of the cases (and very wrong in 25%). For the other route, however, it is impossible to make a prediction that is right as often as 75%. A similar explanation is that the difference between the  $70^{\text{th}}$  percentile values of the two routes is quite large (10 minutes). If being on time in 70 percent of the cases is enough, then choosing the skewed route saves 10 minutes a day.

#### Provision of traffic information increases attractiveness of less reliable routes

- For the travel goal 'meeting with colleagues' the route with an unreliable symmetrical travel time distribution is much more and the route with a very reliable but on average long travel time distribution is much less chosen with en-route information than without en-route information.
- The previous finding applies even stronger to the job interview scenario.
- The provision of ex-post information does not have a large influence on route choice percentages for people who also receive en-route information. However, for travellers who do not receive en-route information, the provision of ex-post information enlarges the share of the route with an unreliable skewed travel time distribution and decreases the share of the reliable yet on average slow route.
- The reliable, yet on average slow route reaches its largest share among travellers who did not receive en-route information nor ex-post information and had to go to a job interview.

The underlying explanation may be that the relative increase in predictability that is derived from the en-route information is larger for unreliable routes than for reliable ones.

#### **Traffic information**

#### Traffic information leads to travel time savings

The more traffic information that was provided to travellers, the higher the travel time savings that were realized. The most elaborate information scenario (en-route and ex-post information) for example leads to 5 minutes (10%) savings compared to the least elaborate information scenario (no information at all).

#### Relative effect traffic information on route choice large

In the route choice model, the en-route traffic information was found to have a high weight compared to the weight of the expected travel time: its weight equals two to four times the weight of the expected travel time.

#### Accuracy of information very important

When travellers experienced a very long travel time and the en-route information failed to warn for it, very diverging reactions follow. Though we do not understand why these diverging reactions happen, we do understand that accuracy of information is important if one wants to prevent such unforeseeable reactions.

#### Provision of traffic information increases attractiveness of less reliable routes

Travellers were found to choose less reliable routes more often when they were provided with traffic information. Details on this finding were given in the previous section.

#### En-route information helps travellers to have a more realistic travel time expectancy

Whereas travellers who did not receive en-route traffic information based their expected travel time mainly on the most recent experience only, travellers with en-route information used more previous experiences to come to an expected travel time. Exact findings are provided in the section on learning.

#### Conclusions

This PhD research contributed to scientific knowledge by providing a framework of day-today route choice integrating knowledge from traffic science, experimental economics, psychology and neuroscience. The mathematical model comprises learning and traffic information and incorporates reliability in an innovative way. In contrast to most learning models, not only explicit learning, but also implicit learning is accommodated. As the model is estimated on experimental data, the research adds to the limited amount of experimentally underpinned models.

From a practical point of view, this PhD research has shown that it is good to provide en-route information. It helps travellers in developing a more accurate long-term expectation and current estimate of travel time and results in travel time savings. It also increases the use of routes which are otherwise thought as too unreliable. Travel time savings are not only beneficial to individual travellers. It also means that total car hours are reduced, leading to less traffic and hence less damage to the environment. The en-route traffic information has to be accurate. Otherwise unforeseeable reactions can occur which make it hard to manage and plan traffic. Decreasing environmental damage and increasing (perceived) reliability are in line with current traffic policy goals. Therefore, we encourage policies aimed at increasing the provision of traffic information and its reliability.

Ex-post information was shown to influence travellers' perceptions of routes. This insight can be used as one of the tools in dynamic traffic management. Perhaps this mechanism can also be used to increase use of public transport. Despite the above, one should acknowledge that it is hard to change habits. Habits can be strong and automatically determine behaviour. Furthermore, as our research indicated travellers may be much more forgiving for bad experiences on habitual routes than on non-habitual routes.

# Samenvatting- Verkeersinformatie en leren in dagelijkse routekeuzes

Dagelijkse routekeuze onder onzekerheid en de invloed van verkeersinformatie is het onderwerp van dit promotie-onderzoek. Reizigers die dezelfde reis herhaaldelijk maken, zoals forensen en vrachtwagenchauffeurs, vormen een groot deel van de dagelijkse verkeersvraag. Aangezien velen van hen de de auto tijdens de spitsuren gebruiken voor deze ritten, zijn zij zowel een 'bron' als een 'slachtoffer' van congestie.

In bovenstaande situatie doet zich de mogelijkheid voor om te *leren* wat de eigenschappen van de mogelijke routes zijn. Automobilisten kunnen leren wat de gebruikelijke reistijden zijn en wat de *betrouwbaarheid* daarvan is. Dit speelt waarschijnlijk een rol in hun routekeuze. *Verkeersinformatie* kan de routekeuze ook beïnvloeden, zowel rechtsstreeks als via beïnvloeding van het leerproces. Tenslotte kan de reiziger gewoontegedrag ontwikkelen, aangezien de routekeuze herhaaldelijk wordt gemaakt. Literatuuronderzoek wees uit dat het niet precies bekend is hoe deze processen werken en dat voorgestelde modelspecificaties vaak niet worden onderbouwd aan de hand van experimentele data.

Derhalve draagt dit onderzoek bij aan de wetenschappelijke kennis door

- De invloeden van leren, verkeersinformatie en betrouwbaarheid op dagelijkse routekeuze op een integrale manier in een conceptueel kader te beschrijven
- Een wiskundig model te formuleren dat de effecten van leren, verkeersinformatie en betrouwbaarheid op dagelijkse routekeuze omvat
- Het model te calibreren op experimentele data

De praktische relevantie behelst de implicaties van de experimentele kennis die in dit proefschrift is verworven.

#### Onderzoeksrichting

Op de onderwerpen leren, betrouwbaarheid en verkeersinformatie zijn een aantal onderzoeksvragen geformuleerd. Wat betreft leren onderscheiden we twee soorten: expliciet (cognitief, bewust) leren en impliciet (al doende, onbewust) leren. Door *expliciet leren* vormt de reiziger een verwachting van de reistijd. Hierbij kan zowel van ervaren reistijden als van ontvangen informatie geleerd worden. Deze moeten dan wel in het geheugen zijn opgeslagen. Met het 'tijdseffect' bedoelen we dat recente gebeurtenissen sterker in het geheugen aanwezig zijn dan oudere gebeurtenissen. Met het 'opvaleffect' bedoelen we dat gebeurtenissen die opvallen / anders zijn een bepaald effect op de geheugensterkte hebben. Er bestaat een verband tussen opvallen en betrouwbaarheid: grote reistijdfluctuaties kunnen tot opvallend lange of korte reistijden leiden, hetgeen tot verminderde betrouwbaarheid leidt. De onderzoeksvragen richten zich op deze twee geheugeneffecten.

*Impliciet leren* omvat alle soorten leren waarbij herhaling van de relatie tussen stimulus en respons wordt opgeslagen als herinnering. Het kan tot gewoontegedrag leiden. Onze onderzoeksvragen hebben betrekking op de invloed van implciet leren op routekeuze in vergelijking met die van expliciet leren.

Wat betreft *betrouwbaarheid* richten onze vragen zich op hoe reistijdbetrouwbaarheid de waargenomen aantrekkelijkheid van een route beïnvloedt. Ook richten ze zich op het opvaleffect, dat wil zeggen, op de invloed van opvallende reistijden op de door de reiziger verwachte reistijd.

Tenslotte vormt het effect van *verkeersinformatie* op de huidige routekeuze en op het bijstellen van de verwachte reistijd (expliciet leren) een onderzoeksrichting.

#### Onderzoeksaanpak

De onderzoeksvragen worden in vijf stappen beantwoord:

#### 1 Conceptueel kader

Op basis van kennis uit de literatuur hebben we een conceptueel kader ontwikkeld. Het kader verschaft inzicht in de verschillende elementen die een rol spelen in dagelijkse routekeuze onder verkeersinformatie en de relaties tussen deze elementen.

#### 2 Wiskundig model

Gebaseerd op het conceptuele kader, is een discreet-keuzemodel geformuleerd. Het is een gemengd MNL model voor paneldata.

#### 3 Dataverzameling

Om het routekeuzemodel te kunnen schatten hebben we data met de TSL (Travel Simulator Laboratory, 'reissimulator') verzameld. Via internet konden respondenten een routekeuze maken. Het resultaat van die keuze werd teruggekoppeld. Respondenten konden 40 keer uit dezelfde drie routes kiezen, elk met een eigen reistijdbetrouwbaarheid. In totaal hebben 2500 personen van verschillend geslacht, leeftijd en opleidingsniveau het experiment afgerond.

#### 4 Modelschatting

Met behulp van het programma Biogeme, is het routekeuzemodel op de TSL data geschat voor drie verschillende periodes: begin, midden en eind van het experiment. Hierdoor kunnen we inzicht krijgen in het verloop van de parameterwaardes.

#### 5 Modelinterpretatie en calibratie conceptueel kader

Het significantieniveau, teken en de waarde van de parameterschattingen zijn gebruikt om de onderzoeksvragen te beantwoorden en het conceptuele kader te calibreren.

#### Experimentele bevindingen en interpretatie

De volgende kennis is ontwikkeld op de gebieden leren, betrouwbaarheid en verkeersinformatie:

#### Leren

#### Expliciet leren – reizigers zijn erg kortzichtig zonder en-route informatie

Voor het 'geen-informatiescenario' bleek het gewicht van de meest recente ervaring in het bijstellen van de verwachte reistijd (het tijdseffect) steeds groter te worden. Op het begin bepaalde het de verwachte reistijd voor 66%; in de middenperiode voor 86% en op het eind voor 100%.

Hoewel dit resultaat in eerdere reisgedragonderzoeken is gevonden, lijkt het enigszins vreemd. Het menselijk geheugen stelt mensen normaliter in staat om meer dan één ervaring te onthouden en de allereerste ervaring wordt soms extra goed onthouden, hetgeen tot steeds kleinere in plaats van steeds grotere gewichten zou leiden. Een mogelijke verklaring kan in het experiment liggen. Wellicht vonden mensen het moeilijk om structuur in de reistijden te ontdekken, omdat ze 'slechts' 40 keuzes hadden zonder extra reistijdinformatie en zonder een echte stimulans om hun best te doen.

#### En-route informatie helpt reizigers een realistischere reistijdverwachting te ontwikkelen

Het en-route-informatiescenario' liet andere resultaten zien. Het tijdseffect is in dit scenario kleiner dan in het 'geen-informatiescenario' en neemt af in de loop van het experiment. Op het begin was het gewicht van de meest recente ervaring in het bijstellen van de verwachte reistijd 52%; in de middenperiode 64% en op het eind 25%. Voor de meest recent ontvangen reistijdinformatie zijn deze percentages respectievelijk 41, 0 en 0. De totale invloed van de meest recente ervaring plus de meest recente informatie neemt dus af in de loop van het experiment.

#### Ervaring belangrijker dan informatie bij bijstellen verwachte reistijd

In tegenstelling tot reistijdervaringen, speelde reistijdinformatie alleen een rol bij het bijstellen van de verwachte reistijd op het begin van het experiment. Wellicht door rationele beperkingen, kiezen reizigers - als ze eenmaal een voldoende idee van de verwachte reistijd hebben - (onbewust) om de informatie te negeren en zich op echte ervaringen te richten. Desalniettemin hebben reizigers met verkeersinformatie een minder kortzichtige reistijdverwachting dan reizigers zonder verkeersinformatie.

#### Impliciet leren beïnvloedt routekeuze sterker dan expliciet leren

De rol van eerdere keuzes (gebruikt om impliciet leren en gewoontevorming te modelleren) is in vergelijking met de rol van de verwachte reistijd (gebruikt om expliciet leren te modelleren) relatief groot in het routekeuzeproces. Bovendien bleek de invloed van eerdere keuzes toe te nemen gedurende het experiment.

#### Betrouwbaarheid

#### Opvaleffect bij bijstellen verwachte reistijd verschillend voor gewoonte- en nietgewoonteroute

Ons routekeuzemodel presteerde iets beter wanneer het opvaleffect wordt meegenomen bij het bijstellen van de verwachte reistijd. Het opvaleffect voor gewoonteroutes bleek tegenovergesteld aan het opvaleffect bij niet-gewoonteroutes. Anders gezegd, de formulering waarbij lange reistijden op gewoonteroutes minder zwaar en op niet-gewoonteroutes extra zwaar worden meegenomen bij het bijstellen van de verwachte reistijd gaf de beste resultaten in de begin- en middenperiode van het informatiescenario en in de beginperiode van het geen-informatiescenario.

Een aannemelijke verklaring hiervoor kan in de cognitieve-dissonantietheorie worden gevonden. Een reiziger wil wellicht niet onder ogen zien dat de route die hij het vaakst kiest eigenlijk erg slecht is. Hij kan deze cognitieve dissonantie kwijtraken door zijn cognitie te veranderen, bijvoorbeeld door zichzelf voor te houden dat de route juist wel heel goed is en de slechte reistijd de uitzondering is die de regel bevestigt. Op deze manier geeft hij de reistijd minder gewicht bij het bijstellen van de verwachte reistijd.

# Scheve reistijdverdelingen aantrekkelijker dan brede reistijdverdelingen (bij gelijk gemiddelde)

Het aandeel van keuzes voor een route die gewoonlijk snel is en soms erg langzaam nam in de loop van het experiment met ongeveer 5% toe. Het aandeel van keuzes voor een route die binnen een grote bandbreedte met ongeveer dezelfde kans een willekeurige reistijd oplevert, nam met ongeveer 15% af. Het aandeel van de betrouwbare doch gemiddeld langzaamste route nam met ongeveer 10% toe.

Het voorgaande zou verklaard kunnen worden door het gegeven dat de scheve route op een bepoaalde manier meer voorspelbaar is. Een voorspelling van een reistijd van ongeveer 35 minuten, zou in 75% van de gevallen juist zijn (en in 25% heel fout). Voor de brede route is het echter onmogelijk om een reistijd te voorspellen die zo vaak juist is. Een vergelijkbare verklaring is dat het verschil van de  $70^{ste}$  percentielwaarden tussen beide routes erg groot is (10 minuten). Als de reiziger genoegen neemt met in 70% van de gevallen op tijd zijn, kan de scheve route 10 minuten tijdswinst per dag opleveren.

*Het verschaffen van verkeersinformatie vergroot de aantrekkelijkheid van minder betrouwbare routes* 

- Met en-route informatie wordt voor het reisdoel 'vergadering met collega's' de route met een onbetrouwbare symmetrische reistijdverdeling veel meer en de route met een heel betrouwbare maar gemiddeld lange reistijd veel minder gekozen dan zonder en-route informatie.
- Het voorgaande geldt nog sterker voor het reisdoel 'sollicitatiegesprek'.
- Het verschaffen van ex-post informatie heeft niet veel invloed op routekeuzepercentages voor reizigers die ook en-route informatie ontvangen. Voor reizigers die echter geen en-route informatie ontvangen, wordt door het verschaffen van ex-post informatie het aandeel keuzes voor de route met een onbetrouwbare scheve reistijdverdeling vergroot en het aandeel keuzes voor de route met betrouwbare maar gemiddeld lange reistijden verkleind.
- De betrouwbare maar gemiddeld langzame route wordt het vaakst gekozen door reizigers die noch en-route informatie noch ex-post informatie ontvingen en naar een sollicitatiegesprek moesten.

De onderliggende verklaring kan zijn dat en-route informatie de voorspelbaarheid van onbetrouwbare routes relatief meer doet toenemen dan die van betrouwbare routes.

#### Verkeersinformatie

#### Verkeersinformatie leidt tot reistijdbesparing

Hoe meer verkeersinformatie de reizigers ontvingen, hoe groter de reistijdbesparingen waren. Het uitgebreidste informatiescenario (en-route en ex-post informatie) leidde bijvoorbeeld tot 5 minuten (10%) besparing vergeleken met het minst uitgebreide scenario (geen informatie).

#### Invloed verkeersinformatie op routekeuze relatief groot

De en-route informatie bleek in ons routekeuzemodel een groot gewicht te hebben in vergelijking met de verwachte reistijd: ongeveer twee tot vier maal zo groot.

#### Betrouwbaarheid informatie essentieel

Als reizigers een erg lange reistijd hadden ervaren en de en-route informatie hen daar ten onrechte niet voor had gewaarschuwd, reageerden zij erg divers. Hoewel wij deze verschillende reacties niet begrijpen, begrijpen wij wel dat het belangrijk is om betrouwbare informatie te verschaffen om zodoende onvoorspelbare reacties te voorkomen.

*Het verschaffen van verkeersinformatie vergroot de aantrekkelijkheid van minder betrouwbare routes* 

Reizigers kiezen vaker voor onbetrouwbare routes als zij verkeersinformatie ontvangen. In de vorige paragraaf is deze bevinding nader toegelicht.

*En-route informatie helpt reizigers een realistischere reistijdverwachting te ontwikkelen* Terwijl reizigers zonder en-route informatie hun verwachte reistijd op met name de meest

recent ervaren reistijd baseren, gebruiken reizigers met en-route informatie meer ervaringen om tot een reistijdverwachting te komen. Details hierover zijn beschreven in de paragraaf over leren.

#### Conclusies

Dit promotie-onderzoek heeft bijgedragen aan de wetenschappelijke kennis door een conceptueel raamwerk van dagelijkse routekeuze te ontwikkelen dat kennis uit de verkeerskunde, experimentele economie, psychologie en neurowetenschappen integreert. Het wiskundige model omvat leren en verkeersinformatie en op een innovatieve manier ook betrouwbaarheid. In tegenstelling tot de meeste leermodellen is niet alleen expliciet leren maar ook impliciet leren opgenomen. Doordat het model is geschat op experimentele data draagt dit promotie-onderzoek bij aan de beperkte hoeveelheid experimenteel onderbouwde modellen.

Meer praktisch gezien heeft dit promotie-onderzoek aangetoond dat het goed is om en-route informatie te verschaffen. Het helpt reizigers om een betere lange-termijn reistijdverwachting en schatting van de huidige reistijd te ontwikkelen en leidt tot reistijdtijdbesparingen. Het vergroot ook het gebruik van routes die zonder informatie als te onbetrouwbaar worden ervaren. Reistijdbesparingen zijn niet alleen voor de individuele reiziger van belang. Ze leiden ook tot een vermindering van het totaal aantal voertuiguren, met minder verkeer en minder milieubelasting als gevolg. De en-route informatie moet wel betrouwbaar zijn. Anders kunnen onvoorziene reizigersreacties optreden die het verkeersmanagement bemoeilijken. Het verkleinen van de milieubelasting en het vergroten van de (gepercipieerde) betrouwbaarheid past goed in de doelen van het huidige verkeersbeleid. Wij moedigen dan ook beleid aan dat is gericht op het vergroten van de hoeveelheid en betrouwbaarheid van verkeersinformatie.

Ex-post informatie bleek de reizigersperceptie van routes te beïnvloeden. Dit inzicht kan gebruikt worden binnen het dynamisch verkeersmanagement. Misschien kan het bovendien aangewend worden om het gebruik van het openbaar vervoer te stimuleren. Ondanks het bovenstaande moet men zich realiseren dat het moeilijk is om gewoontegedrag te veranderen. Gewoontes kunnen sterk zijn en gedrag automatisch bepalen. Bovendien heeft ons onderzoek laten zien dat reizigers slechte ervaringen op hun gewoonteroute misschien makkelijker vergeten dan op niet-gewoonteroutes.

### About the author

Enide A.I. Bogers was born in 1977 in Leiderdorp, The Netherlands. In 1995 she started her studies Industrial Engineering & Management at Twente University and finished in 2000. After a short stay in Spain to learn Spanish, she started in 2001 at TNO as consultant logistics and transport.

A few years later she went to Delft University of Technology, section Transport & Planning to conduct her PhD research on day-to-day route choice under traffic information. The research was part of the NWO-Connekt research program AMICI (Advanced Multi-agent Information and Control for Integrated multi-class traffic networks). For her research she worked together with among others the ANWB, EVO and EPFL in Lausanne, Switzerland.

Next to her research she managed the development of a new version of the TSL (Travel Simulator Laboratory). She was also involved in several teaching activities, like computer laboratories, lectures, post academic courses and supervising students. Furthermore, she organized a workshop on reliability. Finally, she established contacts with Leiden University which lead to a joint research project involving an fMRI study on route choice behaviour.

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