Modeling cognitive learning of urban networks in daily activity-travel behavior

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Modeling Cognitive Learning of Urban Networks in Daily Activity-Travel Behavior

How people perceive and process the information they receive, and how they store it in their memories are essential factors of cognitive learning. In general, people learn through observation, ICT and imitating other people. Regardless of how people learn, their cognitive skills affect spatial learning. Cognitive skills such as attention, memory, visual and auditory processing, and reasoning carry vital importance to learning. Since people may have different cognitive skills and different interpretations to similar spatial experiences, individuals develop their own mental representation of an urban environment. This is why it is difficult, however very important to include cognitive learning in activity-travel models.

This dissertation presents a modeling approach to simulate spatial perception updating process through activity-travel patterns. An illustration of the model, numerical simulations designed to test the part of the model concerned with attribute learning and forgetting, and estimation of the model with real-world data are presented in this dissertation. The findings allow drawing conclusions that the development of spatial cognition is strongly related to interactions within the built environment. Better understanding of the development of spatial cognition of urban networks and the inclusion of the proposed modeling approach to the activity-based models of travel demand may provide new insights into urban and transport planning.
Modeling Cognitive Learning of Urban Networks in Daily Activity-Travel Behavior

PROEFSCHRIFT

ter verkrijging van de graad van doctor aan de Technische Universiteit Eindhoven, op gezag van de rector magnificus prof.dr.ir. C.J. van Duijn, voor een commissie aangewezen door het College voor Promoties, in het openbaar te verdedigen op maandag 18 november 2013 om 14:00 uur

door

Sehnaz Cenani Durmazoglu

geboren te Gaziantep, Turkije
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Modeling Cognitive Learning of Urban Networks in Daily Activity-Travel Behavior
to my beloved uncle
Jim Morrison defines *metamorphose*, in *The Lords and the New Creatures*, as “an object is cut off from its name, habits, associations. Detached, it becomes only the thing, in and of itself. When this disintegration into pure existence is at last achieved, the object is free to become endlessly anything”. Since February 2009, a lot has happened in my life and I metamorphosed, as some living things. I left my home, my family, my friends and my habits, and came to live in the Netherlands, which was one of my dreams since I came to Delft in 2007 as an exchange student. I metamorphosed into something new in Eindhoven—a being with a new home, new friends and new habits. I will always remember the years I spent in the Netherlands happily and will appreciate these years for adding me new layers, both figuratively and literally (during winters)!

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I started with Jim Morrison, and would like to end with another quote, which is from Albert Einstein: “anyone who has never made a mistake has never tried anything new”. I believe that if we are learning, we are going to (and should) make mistakes along the way, because we have to do things outside of our comfort zones. This dissertation is the result of a four-year out-of-comfort-zone journey, and I hope that it raises new questions and new possibilities for you, as it has risen for me.

Sehnaz CENANI DURMAZOGLU

Eindhoven, August 2013
CONTENTS

ACKNOWLEDGEMENTS

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1. Motivation

1.2. Research objectives

1.3. Outline

2. ACTIVITY-TRAVEL BEHAVIOR

2.1. Introduction

2.2. Modeling of activity-travel behavior
2.3. Dynamics of activity-travel behavior ........................................... 7
2.4. Conclusions .............................................................................. 9

3. SPATIAL BEHAVIOR ................................................................................... 11

3.1. Introduction ............................................................................ 11
3.2. Perception and cognition ......................................................... 12
3.3. Built environment and human behavior .................................... 12
3.4. Learning different urban forms ................................................. 13
3.5. Spatial knowledge acquisition ................................................... 15
3.6. Spatial memory ....................................................................... 18
    3.6.1. Path integration............................................................. 18
    3.6.2. Spatial memory of maps, built and virtual environments . 19
    3.6.3. Cognitive mapping......................................................... 20
3.7. Landmarks and spatial behavior ............................................... 21
    3.7.1. Definition ...................................................................... 22
    3.7.2. Classification of landmarks............................................ 23
3.8. Wayfinding and landmarks....................................................... 24
3.9. Navigation and landmarks .......................................................... 26
    3.9.1. Navigation in an unfamiliar environment .................... 27
    3.9.2. Navigation in a familiar environment .............................. 28
3.10. Conclusions ........................................................................... 28

4. COGNITIVE LEARNING MODEL ............................................................. 31

4.1. Introduction ............................................................................ 31
4.2. The conceptual framework ....................................................... 32
  4.2.1. Level-A and level-B representation ................................. 37
     Links ............................................................................. 38
     Nodes .......................................................................... 38
     Points .......................................................................... 38
     Neighborhoods ......................................................... 38
  4.2.2. Attributes ........................................................................ 39
4.3. Models .................................................................................... 39
  4.3.1. Learning through observation and vision ...................... 40
     Perception updating (the Bayesian model) ..................... 40
     Sensitivity of an observation ...................................... 41
     Saliency of a landmark ............................................. 42
  4.3.2. Memory retention .......................................................... 43
4.4. Illustration .............................................................................. 45
  4.4.1. Data .......................................................................... 45
  4.4.2. Results ........................................................................ 53
4.5. Conclusions ............................................................................ 62
5. MODEL ESTIMATION ................................................................................. 65
  5.1. Introduction ....................................................................... 65
  5.2. Experiment ........................................................................ 66
     5.2.1. Experiment set-up .................................................. 66
     5.2.2. Participants ......................................................... 69
     5.2.3. Materials ............................................................ 69
CONTENTS | ix

PUBLICATIONS ...................................................................................................................... 117
LIST OF FIGURES

Figure 2.1 Modeling individual’s daily dynamics (adapted from Schönfelder & Axhausen, 2010) ........................................................................................................8

Figure 3.1 Urban forms (from left to right): the concentric city, the lobe city, the linear poly-nuclear city, the concentric poly-nuclear city, the linear city, and the grid city (Snellen, Borgers, & Timmermans, 2002) .............................................13

Figure 3.2 The maps of New York, USA (left) and Amsterdam, the Netherlands (right) (www.maps.google.com) ........................................................................15

Figure 3.3 Stages (left side) and characteristics (right side) of spatial knowledge (Stern & Leiser, 1988) ........................................................................17

Figure 3.4 The sketch maps from a study by Wielens (2011) ..........................21

Figure 4.1 The development of spatial cognition ........................................33
Figure 4.2 Flowchart of the multi-agent model with cognitive learning component .................................................................................................. 36
Figure 4.3 Level-A (left) and level-B (right) representation ........................................ 37
Figure 4.4 Representation of neighborhoods surrounding anchor points .... 38
Figure 4.5 Experiment location ........................................................................ 46
Figure 4.6 Route choice behavior ....................................................................... 48
Figure 4.7 Relationship diagram ........................................................................ 51
Figure 4.8 Flow-chart of cognitive learning of an activity location ............... 54
Figure 4.9 Flow-chart of cognitive learning of a landmark ................................. 55
Figure 4.10 The most used links ................................................................. 57
Figure 4.11 The most observed activity locations ......................................... 58
Figure 4.12 The most observed landmarks ....................................................... 58
Figure 4.13 Perception updates of four shopping locations ......................... 59
Figure 4.14 Perception updates for three service locations during 12 weeks .. 61
Figure 4.15 Three sections of perception updates ........................................ 61
Figure 4.16 Perception updates of five landmarks .................................. 62
Figure 5.1 The map of Eindhoven showing two experiment locations red area: Route-A, blue area: Route-B. (www.maps.google.com) ................................. 68
Figure 5.2 Aerial views of the experiment locations (www.maps.google.com). 68
Figure 5.3 The number of participants ............................................................. 69
Figure 5.4 Tools used in the experiment: Navigon 2510 Explorer (www.navigon.com) and A4-size paper maps ......................................................... 70
Figure 5.5 Answer sheet for the landmark recollection task .................... 71
Figure 5.6 Landmarks on Route-A (left) and Route-B (right) ......................... 72
Figure 5.7 Answer sheet for the saliency task (Route-A) ............................. 74
**List of Tables**

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>Landmark classifications</td>
<td>24</td>
</tr>
<tr>
<td>4.1</td>
<td>Activity categories</td>
<td>49</td>
</tr>
<tr>
<td>4.2</td>
<td>Landmark categories</td>
<td>50</td>
</tr>
<tr>
<td>4.3</td>
<td>Initial probabilities related to the availability of activity locations</td>
<td>52</td>
</tr>
<tr>
<td>4.4</td>
<td>Parameter-set used in the illustration</td>
<td>57</td>
</tr>
<tr>
<td>5.1</td>
<td>Measurements regarding the landmarks on Route-A</td>
<td>76</td>
</tr>
<tr>
<td>5.2</td>
<td>Measurements regarding the landmarks on Route-B</td>
<td>77</td>
</tr>
<tr>
<td>5.3</td>
<td>Saliency of a landmark on Route-A and Route-B</td>
<td>79</td>
</tr>
<tr>
<td>5.4</td>
<td>Estimation results: binary recognition assumption (( J ))</td>
<td>82</td>
</tr>
<tr>
<td>5.5</td>
<td>Estimation results: continuous recognition assumption (( q ))</td>
<td>83</td>
</tr>
</tbody>
</table>
1.1. Motivation

The starting point of this research project was to explore how people gain spatial knowledge over time, in particular to study how they learn urban networks through their daily activity-travel behaviors, and then, to develop a modeling approach. As an example, consider an individual who just moved to Eindhoven, the Netherlands and therefore has limited knowledge about the city. Due to limited knowledge of activity locations and transport networks, this individual will learn the urban network through observation and external information sources such as social contacts (colleagues, friends, neighbors) or information and communication technologies (ICTs), (e.g., Internet, maps, electronic navigation devices, etc.). In the beginning, the individual only has a-priori knowledge about the layout of the cities in general. This means, he/she assumes that there is a higher probability of finding most things in the city center; for example, finding a supermarket, restaurant, post office, cinema, shopping locations or a drugstore. Over time, new activity locations, different
routes and neighborhoods surrounding activity locations will be learned, and then at the end, this individual will develop an advanced cognitive map of the city he/she lives in.

Cognitive learning is a powerful mechanism necessary to form an urban network as described in the scenario above. How people perceive and process the information they receive from the environment, and store it in their memories are essential factors of cognitive learning. People learn through observation, imitation, and repeated experience. However, regardless of how people learn, our cognitive skills affect learning. Cognitive skills such as attention, memory, visual and auditory processing, and reasoning are important for learning. Memory is the ability to store and recall information, and human beings cannot store everything in their memories; we select what to store, thus attention is essential as well as visual and auditory processing. Based on these skills, people make deductions and since different people may have different cognitive skills and interpretations of similar spatial experiences, each of us has our own cognitive representation of spatial environments, and that is why it is difficult, however very important, to include cognitive learning in activity-travel models.

An assessment of the related studies indicates that current activity-travel models do not include behavioral mechanisms and do not thoroughly contain the development of dynamic cognitive maps and their relationships with different aspects of activity-travel patterns. Although there are operational models to predict single day activity-travel patterns such as ALBATROSS (Arentze & Timmermans, 2004) and numerous studies on spatial knowledge acquisition (Golledge & Stimson, 1997; Heth, Cornell, & Alberts, 1997; Gärling & Golledge, 2000; Ishikawa & Montello, 2006; Schönfelder & Axhausen, 2010), there is not enough research on modeling cognitive learning of urban networks in daily activity-travel behavior. Therefore, developing applications of these models remains a challenging task, and the model described in this dissertation is an essential contribution to activity-travel models of transport demand.
1.2. Research objectives

In light of the motivations described above, the main aim of this project is to develop and test a modeling approach for cognitive learning of urban networks in daily activity-travel behaviors.

It should also be noted that this research project is a part of U4IA research program, which is funded by the European Science Foundation (section: Environment) and consists of six PhD projects (see Timmermans et al., 2010 for the research scope). All of these projects have their own objectives; however they are connected to each other from a broader point of view. In the future, they will be integrated into a multi-agent framework, which will be briefly explained in the following chapters.

Arentze and Timmermans (2005) developed a model based on Bayesian belief networks for representing mental maps and cognitive learning into micro-simulation models of activity-travel behavior. However, their study has not been integrated into a more comprehensive framework, and furthermore some aspects have not been considered in their study and have been left for future studies. Thus, this project aims to contribute to their research and further their study in unexplored terrain.

Exposing the dynamics of spatial relations of an environment with its habitants can help us to observe and to solve the design problems of cities. It also helps us to gain insight in behavioral mechanisms of daily activity-travel patterns. Therefore, the following research questions will be addressed in this dissertation;

- how spatial cognition is developed over time
- how activity-travel behavior affects spatial learning
- why some places are better remembered than others
- how environmental features, such as landmarks are learned

In brief, the main research objectives of this dissertation are to better understand the development of spatial cognition in urban networks, and to develop and test a model of cognitive learning of urban networks.
1.3. Outline

This dissertation is organized into six chapters. After this introductory chapter, Chapter 2 reviews the state-of-the-art progress on activity-travel modeling. This chapter does not present a comprehensive review, but rather it briefly introduces the background of the activity-travel modeling, current models and their shortcomings. Furthermore, the reasoning behind the need of a more complex approach, namely dynamic activity-travel modeling, will be described in the same chapter. Chapter 3 explains human spatial behavior and presents a literature review on theoretical foundations of the dissertation. Theories on spatial knowledge and the findings of the empirical studies guide the current research project and help to form a base for the modeling approach. The aim of Chapter 4 is to introduce an approach for modeling of cognitive learning, to explain its components, and then to present the results of the numerical simulations. Chapter 5 reports an experiment and an additional survey, which are used in model estimation. Finally, the last chapter, Chapter 6, concludes this dissertation with suggestions for future work.
CHAPTER 2

ACTIVITY-TRAVEL BEHAVIOR

2.1. Introduction

The purpose of the current chapter is to present a historical background on activity-based models of travel demand, and also to provide examples of the state-of-the-art activity-travel models, to highlight the research gaps in current activity-travel behavior studies, and to show why it is important to include cognitive learning in these models.

The chapter is organized as follows: The following section explains the modeling of activity-travel behavior, and then the next section provides details on the dynamics of activity-travel behavior. Finally, the last section draws some conclusions and discusses the chapter.

2.2. Modeling of activity-travel behaviors

The implementation of activities in space and time is an important issue in analyzing and modeling activity-travel patterns. The urban planning and
transportation research communities have been developing and applying choice models to predict activity-travel patterns over the last decades. Theoretical developments and applications of activity-based models are the prominent outcomes of this research interest. Current models of activity-travel demand, including ALBATROSS (Arentze & Timmermans, 2004), which has been developed for the Dutch Ministry of Transportation, Bowman and Ben-Akiva model (Bowman & Ben-Akiva, 2001), which was one of the first, and is still important a model of activity-travel demand, MATSim (Balmer, Meister, Rieser, Nagel, & Axhausen, 2008), which is an open-source multi-agent travel demand simulation, and other models such as TASHA (Roorda, Miller, & Habib, 2008), CEMDAP (Bhat, Guo, Srinivasan, & Sivakumar, 2004), FAMOS (Pendyala, Kitamura, Kikuchi, Yamamoto, & Fujii, 2005), Aurora (Joh, Arentze, & Timmermans, 2006), and the ADAPTS model (Auld & Mohammadian, 2011) have been developed to predict activity-travel patterns. It should be noted that this list is simply a list of examples, and not an exhaustive list.

Activity-based models have achieved a growing interest in the transportation research community. The logic behind the traditional models differs from today’s modeling approach. Traditional models consider an approach of trip-based modeling (Hutchinson, 1974). These models do not model decisions on an individual level, which means that activity scheduling constraints, as well as individual variability cannot be taken into account. As a result of these shortcomings, activity-based modeling has started to receive attention. The ground-breaking theories of Hägerstrand (1970) and Chapin (1974) are the first to identify the value of space and time in urban planning and geography. The PESASP model (Lenntorp, 1978) and CARLA (Jones, Dix, Clarke, & Heggie, 1983) are the earliest examples of this modeling approach. At present, several activity-based models are operational (Arentze & Timmermans, 2004; Pendyala, Kitamura, Kikuchi, Yamamoto, & Fujii, 2005; Roorda, Miller, & Habib, 2008). A detailed review on activity-based travel demand modeling is presented in Ettema (1996) and the history of evaluation of activity-based travel analysis can be found in Kitamura (1988).

Activity-based models include individual mobility issues as well as activity patterns. These models predict individual activity-travel behaviors including a list of activities which are conducted, with descriptions for when, where, for how long, with whom, and the transport mode involved in each activity.
Activity-travel models focus on the interdependencies of choices such as activity generation, transportation mode, travel party, task allocation, duration of the activity, joint activity participation, destination, and route choice. All existing operational models are cross-sectional, which means that activity-travel patterns are predicted, or simulated, for an average or a typical day. This implies that plan assessment and predictions may be biased. These models rely on the assumption that observed relationships remain invariant over time. Yet, interactions between different individuals, needs, behavioral changes over time (e.g., rescheduling, adaptation) and environmental dynamics are not included in these models. These shortcomings reveal an evolution in the modeling approach; the development of dynamic activity-travel models. Auld and Mohammadian (2009) proposed an agent-based dynamic activity planning and travel scheduling (ADAPTS) model. In order to incorporate dynamics from short-term, mid-term and long-term, Timmermans et al. (2010) proposed a similar framework. Their main goal is to develop a comprehensive model of dynamic activity-travel patterns, expanding and integrating concepts and partial approaches that have been suggested over the last few years.

Dynamic activity-travel models, which focus on changes in activity-travel patterns along various time horizons, currently receive high attention on international research agendas, as these types of models have a greater degree of validity, sensitivity, and will therefore have greater relevance to a larger spectrum of policies, when compared to non-dynamic models. For these reasons, this dissertation aims to contribute to this novel research approach.

2.3. Dynamics of activity-travel behaviors

Figure 2.1 illustrates how Schönfelder and Axhausen (2010) model an individual’s daily dynamics. As can be seen from this figure, scheduling and rescheduling of agendas and updating of perceptions throughout networks are crucial actions that should be considered in the dynamic modeling approach.

In the short-term, it is important to realize that individuals are faced with a considerable amount of uncertainty, during their decision-making process. For example, because of the traffic congestion, travel times are not constant, and this leads to some uncertainty in the activity-travel schedules. It is thus assumed that individuals base their decisions on their beliefs, and on perception of the environment. If individuals do not consult any external
information sources (e.g., use of ICT), they may have limited information about an environment. They may or may not know some locations in an unfamiliar environment, and their knowledge about attributes of these locations and the urban network may be incomplete and partially incorrect (Cenani, Arentze, & Timmermans, 2010a).

As briefly explained in the previous section, earlier activity-travel models predict activity-travel patterns for a typical day; therefore, these models do not consider the interactions between activities across days (Hamed & Mannering, 1993). However, dynamics should be incorporated from multiple time horizons such as short-term (daily scheduling), mid-term (adjustments) and long-term (lifecycle adaptations). The impacts of short-term and mid-term dynamics on multi-day activity-travel patterns are important for this study, because modeling the cognitive learning of urban networks over time is the essence of this research. For example, moving into a new city or to a new location in the same city has an impact on an individual’s or a household’s daily activity-travel patterns. Individuals may have to change their transport mode, their route choices, and their activity locations. Due to unpredicted events such as changes in weather and traffic conditions, they may need to reschedule their activities or adapt to new conditions. Learning new activity locations and new routes, and adjusting to these drastic changes are a part of their lives. Therefore, focusing on a typical day is not enough for predicting learning processes over time. Our lives are not static; they change every minute of every
day. In order to capture these changes and to observe the learning process over time, multiple days of observations are needed. Exploring the development of spatial cognition of urban networks and their change over time, and modeling cognitive learning of urban networks in daily activity-travel behavior are important steps in developing dynamic activity-travel models of transport demand.

Long-term dynamics (e.g., lifecycle events) are also essential in activity-travel models. However, the impacts of lifecycle events such as getting married or having children on an individual’s activity-travel patterns are not in the scope of this dissertation. Even though long-term dynamics are just as important as others, and have an impact on learning processes, in order to limit the research framework, they are excluded.

2.4. Conclusions

This chapter has discussed earlier studies, and emphasized the importance of a new modeling approach regarding how development of spatial cognition of urban networks and perception updating should be incorporated in the activity-travel studies.

Limitations in current comprehensive activity-based models of travel demand, have led to the need of developing dynamic activity-travel models. Unlike current models, dynamic models will simulate how changes in personal and household characteristics, exogenous or endogenous changes in urban, transportation and institutional environment may trigger adaptation in activity-travel behavior. For modeling short-term dynamics, it is important to realize that individuals make decisions on the basis of their beliefs of their environment. These beliefs are not necessarily congruent with the physical world. Moreover, they change over time as people learn and forget. In the context of activity-based modeling, both cognitive learning of locations and of networks are important. Both topics have received little attention from a modeling perspective. As explained earlier in this chapter, an assessment of studies in this area indicates that current activity-travel models do not contain the development of dynamic cognitive maps and their relations with different aspects of activity-travel patterns. Research on modeling cognitive learning of urban networks is still limited to date. Therefore, exposing the dynamics of spatial relations of an environment with its habitants (Chapter 3), and
developing applications of these models are difficult tasks and thus, the modeling approach introduced in Chapter 4 is believed to be a vital contribution to such models.
CHAPTER 3

SPATIAL BEHAVIOR

3.1. Introduction

This chapter presents the state-of-the-art progress on spatial behavior, and is divided into ten primary sections. First, a distinction is made between the two concepts that are important to the present dissertation; perception and cognition, followed by a description of human behavior in the built environment. The following section explains the difference in spatial learning processes due to different urban forms. Then in the fifth section, theories of the development of spatial knowledge and how people acquire spatial knowledge are presented. The next section describes the characteristics of spatial memory. The seventh section gives details on landmarks and their impact on human spatial behavior. Sections 3.8 and 3.9 emphasize the differences and the similarities between navigation and wayfinding, and also describe their impact on spatial learning through landmarks. Section 3.8 briefly describes the topic of wayfinding. The ninth section explains navigation in the built environment, and the final section provides conclusions.
3.2. Perception and cognition

Lang (1987) defines perception as the physiological and psychological process of obtaining information from the environment. People make interpretations based on the information gathered from spatial environments, and then via cognitive processes, they form a cognitive representation of the built environment. Similarly, according to Golledge and Stimson (1997), perception is an interaction between an individual and an environment. They indicate that two individuals may perceive the same environment differently, as a result of the difference in information contents and in ability of individuals receiving the information messages.

Cognitive psychology deals with the acquisition, organization and storage of knowledge. Lang (1987) indicates that it concentrates on topics such as thinking, learning, remembering, feeling, and mental development. He also argues that “an understanding of the processes of cognition can make a major contribution to the understanding of environmental aesthetics and the choices people make in the use of the environment”.

Golledge and Stimson (1997) indicate that “cognition refers to the way information, upon reception, is coded, stored, and organized in the brain so that it fits in with a person’s accumulated knowledge and values, and thus, cognition is developmental”. Cognition includes concepts of sensory data, perception, imagination, retention and recollection, reasoning and making choices (Golledge & Stimson, 1997). Perceiving the location of your home is different than knowing the route between your home and work; the latter depends on cognitive organization of perceptions that are experienced while traveling frequently. The final product of perception and cognition is a cognitive map of the environment, which will be briefly explained later.

3.3. Built environment and human behavior

It is important to understand how people learn, remember, and interact with their environment, as all of these affect their decision-making processes and therefore their daily dynamics. There can be some emotional or psychological reasons behind their choices. As an example, an individual may consider a particular route more attractive or safer than other routes. In addition, some environments can be more challenging than others; for instance, when an
individual moves to a new city or he/she visits an unfamiliar environment. In these kinds of situations, people are forced to learn a new environment, and as a result they acquire spatial knowledge.

Experience is important for spatial learning. Experience leads to learning, since it improves orientation and wayfinding in an environment. As individuals spend more time in the environment, it becomes familiar to them, and they begin to learn more locations and routes in the environment. This results in the enlargement of their choice-sets. Bovy and Stern (1990) state that familiarity with the environment is related to either exposure (the length of the time spent in it) or experience (the amount of actual usage made of it). Familiarity obtained through exposure is usually influenced by an individual's residential location, while familiarity obtained through experience is due to the range of activities in the environment. After processing the experience gained from a previous trip, the choices with maximum utility are added to the choice-set for future trips. Accordingly, individual's spatial knowledge of the environment will be improved.

### 3.4. Learning different urban forms

People use different search strategies in different urban forms. Lynch (1960) has studied three American cities; Boston, Jersey City and Los Angeles, in order to understand the role of environmental images, and to develop and test the idea of *imageability*, and thus to suggest some principles for urban design. According to Lynch (1960), even though the grid network of Los Angeles makes it difficult for people to distinguish one route from another, because of the regularity of the city network system, the grid system also makes it easy to remember major routes in correct relation to each other.

![Urban forms](image)

*Figure 3.1 Urban forms (from left to right): the concentric city, the lobe city, the linear poly-nuclear city, the concentric poly-nuclear city, the linear city, and the grid city (Snellen, Borgers, & Timmermans, 2002)*
Snellen, Borgers, and Timmermans (2002) identify six different urban forms, as indicated in Figure 3.1. They describe the *concentric* city as a city form that is grown from a historic center with several radial roads. This city form is usually connected with a radial road network and generally, has a well-built center with several types of facilities. The *lobe* city is similar to concentric city. The major difference is that the city has developed between some radial roads and not between others. The *linear poly-nuclear* and *concentric poly-nuclear* cities are similar to each other. According to them, either a number of smaller settlements, located close to each other, start to function as one city or a city is actually designed as a poly-nuclear city. *Grid* cities have a rectangular shape and both grid and *linear* cities have a grid transport network. The grid and the concentric city forms are the most observed city forms in U.S.A. and in Europe, respectively. An example of a grid city (New York, USA) and a concentric city (Amsterdam, the Netherlands) can be seen in Figure 3.2. Radial pattern of Amsterdam is caused by the geographic features (e.g., canals) of the city. On the other hand, the city of New York has a distinctive grid city plan consisting of similar sized blocks, which makes it easier to learn.

Davies and Pederson (2001) argue that UK residents seem not to use the geo-directional features of grid layout of the city, which are in fact well accepted by USA residents. Therefore, they decided to investigate long-term residents’ mental models and behavior regarding wayfinding and spatial knowledge. Residents of two grid-pattern cities (Milton Keynes, UK and Eugene, Oregon, USA) performed a series of tasks including confidence ratings, sketch map drawing, verbal route directions, and pointing to non-visible landmarks. Their results show that the UK residents placed less emphasis on the central grid in their sketch maps, and showed an error in their pointing direction.

Montello (1991) examined the effect of route angularity on the spatial orientation of pedestrians navigating in an urban setting. His results show that environmental orientation depends on the angularity of route structure, the disorienting effect of tilted routes being caused by memory distortion or uncertainty related to tilted routes.
Based on these empirical evidences, it can be stated that due to different urban forms and road structures, spatial learning process may differ, and as a result, people may develop different cognitive maps.

3.5. Spatial knowledge acquisition

The model described in this dissertation has its foundations from the theories explained in this section. How these theories, particularly Siegel and White's (1975), Thorndyke's (1980) and Golledge's (1974; 1978), are integrated into the conceptual framework as well as the model itself will be further explained in Chapter 4.

If people visit the same location several times, their past experiences may help them to remember the relevant information about that location, and in this manner their next visit will become less time-consuming. As an example, regular customers of a shopping mall learn the locations of the shops over time. Thus, behavioral differences can be observed between new and regular customers. A study by Golledge et al. (1985) presents empirical evidence with regard to acquiring spatial knowledge after walking the same route multiple times. Their results indicate that the route seemed well-known, traveled with confidence and error free after the tenth trial.

The most widely known and accepted theory of the development of spatial knowledge is Siegel and White's theory (1975). According to this theory,
individuals first acquire *landmark knowledge*, and it is the base of other types of spatial knowledge. The intermediate phase is the *route knowledge*. Learning a route concerns the knowledge of sequences of landmarks and making decisions linked to these landmarks. The final phase, *survey knowledge*, is about learning Euclidean (straight line) distances and acquiring spatial relations between different locations, even if the individual has never traveled between these locations (e.g., a soldier can learn an area through a map). Survey knowledge is considered to be the most sophisticated type of knowledge obtained about an environment (Siegel & White, 1975). Similar to Siegel and White's (1975) theory, Thorndyke's (1980) research on military personnel indicates that human spatial learning develops in several steps. Based on his research, he defined a theory called *four levels of knowledge*. First, individuals learn set of landmarks that are easy to remember. Then, they begin to indicate their direction relative to their location. Next, individuals start to memorize sequences of locations. However, they are still unable to construct short-cuts between locations belong to different memorized sets. At the final step of learning process, individuals can associate different locations and routes, and develop a complete cognitive representation of their environment.

McNamara, Sluzenski, and Rump (2008) state that the abilities to construct efficient routes like learning a short-cut, to point directly to unseen locations, and to estimate Euclidean distances should be considered as the main indications of survey knowledge. Similar to McNamara and colleagues' statement, Worchel's (1951) study proves the existence of complex spatial behavior (in blind individuals). Worchel designed a test, which is called *triangle completion problem*. Each individual is given a task that consists of walking two legs of a triangle, and then returning to the origin without using the first two legs. This task can be completed by making a correct turn, estimating the correct distance, and then walking back to the origin. Therefore, the task involves an individual keep a representation of the origin in memory, and be able to update the locations of landmarks during the trip. In brief, as Worchel's study points out, learning a short-cut, which means an individual is able to associate different routes and therefore, concludes a more efficient route according to his/her needs, indicates a high level of spatial learning.

Stern and Leiser (1988) summarize the above-mentioned research in their study (Figure 3.3). They explore the difference in level of spatial knowledge
between non-professional and professional drivers (e.g., taxi and emergency vehicle drivers) in their study. Their results reveal that participants’ knowledge become stable at “route level”, but only professional drivers achieve “survey level”.

On the other hand, Golledge (1974; 1978) has suggested a slightly different approach to spatial knowledge acquisition, which is known as the anchor point theory. This theory emphasizes that the hierarchical order of locations, paths and areas in a spatial environment are based on the relative importance of these locations to the individual. As an example, home, work or frequently visited activity locations are anchor points for an individual. Individuals first learn the neighborhoods surrounding the anchor points, and then spatial knowledge expands with continuous interactions along paths in the network (Bovy & Stern, 1990). Empirical evidence to anchor point theory can be found in Golledge et al. (1985), and in a study by Couclelis, Golledge, Gale, and Tobler (1987).
These empirical studies has confirmed that during learning an environment, spatial knowledge improves both quantitatively and qualitatively, due to changes in cognitive organization of the knowledge as well as with increased experience.

The topic of spatial memory and acquiring spatial knowledge from different media will be discussed in more details in the next section.

3.6. Spatial memory

Spatial memory is fragmented (Lynch, 1960; Appleyard, 1970), distorted (Tversky, 1992), hierarchical (McNamara, Hardy, & Hirtle, 1989), and orientation dependent (McNamara, 2003). Spatial memories of familiar environments are used in spatial updating (orientation), wayfinding (see section 3.8), and navigation (see section 3.9).

In general, as an individual moves through an environment, he/she has to keep track of his/her location with respect to the objects in the environment, to unseen portions of the environment. The individual has to avoid obstacles, to remain oriented, and to navigate toward his/her destination. These processes are referred to as spatial updating (McNamara, Sluzenski, & Rump, 2008).

The concept of spatial reference objects (landmarks), which is a crucial part of the spatial memory, will be explained in the section “landmarks and spatial behavior”. In the following subsections, in order to better understand the human spatial memory with regard to spatial updating process, the concept of path integration and spatial memory of different media will be explained.

3.6.1. Path integration

The act of spatial updating is closely linked to one’s ability of spatial orientation in an environment. McNamara, Sluzenski, and Rump (2008) explain path integration (or dead reckoning) as navigation that depends completely on an individual’s history of self movement. An individual can calculate approximately his/her displacement from an origin location by integrating velocity or double integrating acceleration regarding time. Additionally, Scholl and colleagues (2000) define dead reckoning as “a method of orientation that does not rely on visual references, but instead as a mainly internally driven
process which keeps track of an individual's present position relative to his/her origin location using kinetic signals produced by the action of walking".

Worchel's (1951) study on complex spatial behavior has already been discussed in the previous section. Similarly, Loomis and colleagues (1993) tested a theory with a non-sighted path integration task. During this test, participants were guided through a route, and then had to return to the origin via the shortest linear route. They discovered that the time it took participants to initiate their return to the origin varied as a function of the complexity of the path navigated. This result suggests that a travel trajectory representation exists in spatial memory.

In general, these studies try to explain how the spatial structure of an environment is represented in memory, and how memories of an environment are used in navigation.

3.6.2. Spatial memory of maps, built and virtual environments

As stated in the previous section, people acquire spatial knowledge through direct experience in the environment or by viewing a map. Evidence shows that learning through maps and direct experience produce different cognitive representations (Evans & Pezdek, 1980; Thorndyke & Hayes-Roth, 1982). Learning from a virtual environment is similar to learning from direct experience, as the landmarks experienced during real and virtual navigation are comparable, and also the field-of-vision and the perspective of the observer are similar, if the level of details, the colors and so, are comparable for both environments.

To explore the difference between acquiring spatial knowledge by experiencing the environment or by viewing a map, Thorndyke and Hayes-Roth (1982) compared spatial learning via maps and navigation. Participants studied the layout of a building either by a map or by navigating in it. Their study showed that participants have a survey representation of the environment, after studying a map, and can estimate straight-line distances. Main downside of acquiring a spatial knowledge by viewing a map is explained as people's tendency to make more errors in pointing to unseen locations in a building, due to the difficulty of translating the perspective of a map to a horizontal one. In brief, their study confirmed that, with moderate exposure, map learning is
superior for judgments of relative location and straight-line distances among objects. Learning from navigation is superior for orienting oneself with respect to unseen objects and estimating route distances. With extensive exposure, the performance superiority of maps over navigation vanishes (Thorndyke & Hayes-Roth, 1982).

Richardson, Montello, and Hegarty (1999) claim the alignment effect is a prominent difference between mental representations constructed from different learning experiences. Levine, Marchon, and Hanley’s (1984) study supports Richardson and colleagues’ claim. Levine and colleagues (1984) state that when an individual learns an environment from a map, and is then tested in the environment, he/she is usually very accurate when aligned with the original orientation of the map. However, they observed poor performance when he/she is not aligned. These findings suggest that spatial learning via maps results in orientation-specific representations of the environment.

3.6.3. Cognitive mapping

In an unfamiliar environment, individuals gain spatial knowledge quickly; however, learning process slows down after being familiar with the environment, and at some point learning almost stops. Exposure to an unfamiliar environment causes individuals to build up a representation of their surroundings. This process is called cognitive mapping and the product is called a cognitive map, a term initially used by Tolman (1948).

Downs and Stea (1973) define cognitive mapping as “a process composed of series of psychological transformations by which an individual acquires, stores, recalls, and decodes information about relative locations and attributes of the phenomena in his everyday spatial environment”. Cognitive mapping is an essential process of spatial knowledge acquisition. Topographic maps represent the real world, whereas cognitive maps represent both personal and conceptual representations of the environment with some distortions. Cognitive maps, therefore, differ from individual to individual (Lang, 1987), and the image of a place is enriched and corrected through continual use (Steinitz, 1968). Two sketch maps drawn by two different individuals from a study of Wielens (2011) are presented in Figure 3.4, as an example of cognitive map development after one-time experience in an unfamiliar environment. The details of this study can be found in Chapter 5.
The level of familiarity with the environment affects both the amount and the accuracy of spatial information represented in cognitive maps. Appleyard (1970; 1976) compares the sketch maps of adults who have lived in a city for less than 6 months, for 6 to 12 months, for 1 to 5 years, and for more than 5 years. Individuals, who have lived in a city for one year or less, draw maps illustrating more routes. Appleyard classifies such map as a sequential dominant map. Long-term residents draw maps give emphasis to borders, neighborhoods and landmarks. He defines this type of map as a spatial dominant map. Additionally, in Devlin’s (1976) study, 2-week-long residents draw almost the same routes six weeks later in their maps, however they indicate more landmarks. Over time, routes in the maps become detailed with continuous experience. Briefly, it is safe to say that the extent of interaction with the environment as well as overall length of residence affect spatial knowledge, thus cognitive maps.

Landmarks have a critical function in spatial learning and therefore play a key role in the development of cognitive maps. They enable an individual to determine spatial relations between objects and routes, which consecutively make possible the development of a cognitive map of an area. The following section aims to clarify the impact of landmarks on spatial behavior.

3.7. Landmarks and spatial behavior

Learning a route or an environment require spatial decision-making processes, and during these processes, individuals use spatial references, which leads us to one of the important elements of the current study; landmarks. In this
section, first of all, a description of a landmark will be made, and then classification methods for landmarks will be explained.

3.7.1. Definition

A landmark can be defined as an object or feature of a city/landscape that is easily seen and recognized from a distance, and help individuals to be certain of their locations. Additionally, Lynch (1960) indicates that “a landmark is not necessarily a large object; it may be a doorknob as well as a dome”. However, the location of the landmark is critical. Landmark should be visible to the observer, or if it is small, then there should be an angle-of-view that the observer can perceive it and pay more attention than other objects. Lynch (1960) characterizes landmarks as external point references that are physical elements which may differ in size. He defines singularity and saliency as the essential features of a landmark. He links singularity to a clear shape; a landmark should generate a contrast with its background, and has a well-known location. Siegel and White (1975) indicate that landmarks have a critical function in cognitive map development. Additionally, Heth, Cornell and Alberts (1997) state that landmarks are imperative for navigation, since they are memorable reference points that are chosen along a route.

Appleyard (1969) describes the reasoning behind why some buildings are better known or recalled than others; it is related to form, visibility, and use and significance attributes. If a building has a distinct form, then it tends to stand out from its surrounding. As a result, buildings with distinct forms significantly noticed and recalled more easily. The visibility attributes are important too. For example, buildings on decision-points are likely to be noticed and recalled. A clear recognition of a building’s use is another essential reason of why some buildings are better known and recalled. As an example, a hospital, a religious building, a museum or a factory is expected to be noticed and recalled more easily. As Lynch (1960) points out, if powerful reinforcements such as historical or personal associations are attached to a certain object, its importance as a landmark increases.
3.7.2. Classification of landmarks

In general, there are two types of landmarks; global and local. Eiffel Tower and Statue of Liberty can be given as examples of global landmarks, whereas local landmarks are reference points for a specific city or a neighborhood, and are used as reference points by individuals for wayfinding.

Landmarks can also be classified according to their locations. In the previous studies (Denis, 1997; Denis, Pazzaglia, Cornoldi, & Bertolo, 1999), landmarks have been defined as choice point (decision point) or non-choice point landmarks. Lovelace, Hegarty, and Montello (1999) make a distinction between landmarks that are located at potential turning points but are not used on the route being described (potential choice point landmark), and landmarks that are located at choice points and are used in route description (choice point landmark). Furthermore, they divide non-choice point landmarks into en-route landmarks (along the path of travel, but not at a potential or a used choice point) and off-route landmarks (not neighboring to the path followed, but has some orientation value, such as mountains, ocean, or out-of-view buildings). To sum up, Lovelace, Hegarty, and Montello (1999) describe four landmark variables (choice point, potential choice point, en-route, and off-route), and three choice point variables (the number of turn statements, the number of choice points at which landmarks are mentioned, and the number of turn statements for which a landmark is used).

According to Klippel and Winter (2005), landmarks can be distant from the route (distant landmarks), somewhere along the route segments (segment landmarks), or at specific route nodes (node landmarks). Furthermore, Lynch (1960) classifies landmarks in two categories; “trigger cues” indicate turning decisions, and “reassuring cues” confirm an individual in decisions already made.

Based on the above-mentioned studies, a classification is made in a study by Cenani and Timmermans (2011). According to this classification, it is assumed that there are three types of landmarks: en-route landmarks, off-route (distant) landmarks and decision-point landmarks (located on a choice point). En-route and off-route landmarks can be classified under non-choice point landmarks. The purpose of these landmarks is similar to Lynch’s “reassuring cues”. All
referred studies are summarized in Table 3.1. How these landmark classes are used in the data collection is explained in Chapter 5.

Table 3.1 Landmark classifications

<table>
<thead>
<tr>
<th>Authors, Year</th>
<th>Classification</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Denis, Pazzaglia, Cornoldi, &amp; Bertolo, 1999</td>
<td>choice point, non-choice point</td>
<td>choice point, potential choice point, en-route, off-route</td>
</tr>
<tr>
<td>Lovelace, Hegarty, &amp; Montello, 1999</td>
<td>choice point, potential choice point</td>
<td>en-route, off-route</td>
</tr>
<tr>
<td>Klippel &amp; Winter, 2005</td>
<td>node, segment</td>
<td>distant</td>
</tr>
<tr>
<td>Lynch, 1960</td>
<td>trigger</td>
<td>reassuring</td>
</tr>
<tr>
<td>Cenani &amp; Timmermans, 2011</td>
<td>decision-point</td>
<td>en-route, off-route</td>
</tr>
</tbody>
</table>

In the following section, empirical research on wayfinding will be presented and then the impacts of landmarks on wayfinding will be clarified.

3.8. Wayfinding and landmarks

According to Gärling and Golledge (2000), if a new route is tried, or a portion of an old route is forgotten, the traveler is wayfinding. It is easy to use known routes over wayfinding. Known routes minimize cognitive effort; processes of wayfinding become simplified and automatic as a result of the repeated sequence of environmental events and associated actions (Gärling & Golledge, 2000). McNamara, Sluzenski, and Rump (2008) define wayfinding as “navigation that depends jointly on an enduring external or internal spatial representation-a map or a cognitive map, respectively- and the observation of objects whose locations are specified in the spatial representation”. The key feature of wayfinding, according to them, is that an individual uses a representation of the design of an environment as well as his/her perception of the objects in that environment to orient with respect to unobserved objects.

The rest of this section will discuss the empirical research on wayfinding, in particular, giving and following wayfinding descriptions. According to Lawton and Kallai (2002), there are two main types of wayfinding strategies: orientation strategies and route strategies. Orientation strategies (survey perspective) involve cardinal directions, while route strategies (route perspective) involve landmarks and left-right turns. A route perspective involves a first-person spatial perspective, for instance, assuming the
perspective of the traveler as reference point (e.g., turn left and the elementary school is in front of you). On the other hand, a survey perspective involves a third-person spatial perspective, which is similar to see the entire environment at once, as on a map. Cardinal directions, such as north, south, and so forth, involve distances (e.g., meter, mile). In the route perspective, landmarks are usually described relative to the traveler who is moving through the environment. This means that route descriptions contain viewer-related terms like “you”, “your”. Whereas, in the survey perspective, the narrator takes an external point of view, and describes the route from a bird’s eyes view point, like a map.

Various studies have shown that men are more likely to state survey perspectives (e.g., cardinal directions and distances), while women are more likely to describe route perspectives (e.g., landmarks) (Montello, Lovelace, Golledge, & Self, 1999; Sholl, Acacio, Makar, & Leon, 2000). According to Lawton’s research (2001), men include significantly more cardinal directions (survey perspective) than women do, while women include significantly more left-right turns and landmarks (route perspective) than men do. Furthermore, Hund and colleagues (2008) support Lawton’s findings; similar gender differences emerge both when giving and following wayfinding directions.

In addition to the above-mentioned findings about gender differences in wayfinding strategies, Fontaine and Denis’ (1999) study shows that an individual navigating through an environment has personal preferences when choosing landmarks. The topic of landmark has already been discussed in the previous section. However, personal preferences on landmark choices during wayfinding have not been discussed yet. According to Fontaine and Denis (1999), women are inclined to select more three-dimensional objects like buildings or monuments, whereas men appear to prefer two-dimensional features like streets or squares. It is also possible that the age, social and cultural background of the individual have an impact on the choice of landmarks. Furthermore, different transport modes will naturally lead to different selection of landmarks. Millonig and Schechtner (2007) stated that car drivers choose mostly neighboring objects belonging to the street furniture, due to their accelerated speed. On the other hand, pedestrians, who travel slower compared to car drivers, perceive more details and can notice objects located in greater distances, like distant landmarks.
The study of Lovelace, Hegarty, and Montello (1999) shows that landmark references are evenly distributed in wayfinding descriptions; however, Allen (1997) suggests that references to landmarks should be more frequent at decision points and should increase toward the end of the route. Similarly, Denis and colleagues (1999) state that in route directions, landmark distribution is not random. They indicate that long route segments can be reported without mention of landmarks; while at decision-points, mention of landmarks increases, it is likely as a result of the necessity of reorientation. These studies are in-line with previously mentioned landmark categories in section 3.7.2.

3.9. Navigation and landmarks

The topic of navigation has already been introduced in this dissertation; it is used to describe “path integration” in a section on spatial memory, followed by the definition of “landmark” in section 3.7, and then, in the previous section to define “wayfinding”. Therefore “navigation”, in general, can refer to any skill or study that involves the purpose of position, direction, and orientation (Hofmann-Wellenhof, Legat, & Wieser, 2003).

According to Golledge (1999), the process of guiding travel is called navigation. Similarly, Montello (2005) defined navigation as “coordinated and goal-directed movement through the environment by organisms or intelligent machines”. The description of a successful navigation consists of three steps, according to Ishikawa, Fujiwara, Imai, and Okabe (2008); first of all, individuals need to know where they are, and in which direction they are facing. Then, they need to plan a route towards the destination, and finally, they execute the planned route.

An important difference between navigating in an unfamiliar and familiar environment is the importance of landmarks. Landmarks and their impact on spatial behavior are already introduced earlier. In addition to this, the role of landmarks in navigation has been investigated in several studies (Sorrows & Hirtle, 1999; Klippel & Winter, 2005). Landmark knowledge can be considered as a special class of object knowledge. Landmarks help individuals to identify their locations. Additionally, landmarks can indicate certain locations of changes of direction, such as turning points or intersections, and they can be used to maintain a course (McNamara, Sluzenski, & Rump, 2008). Individuals
need some reference points (landmarks) in an unfamiliar environment, in order to remember the route for the next trip. However, in a familiar environment people do not need landmarks to navigate. When people use navigation devices or maps to navigate in an environment, especially in an unfamiliar environment, point-of-interests (i.e., landmarks) become essential.

The following two subsections will briefly describe how individuals navigate in unfamiliar and familiar environments, and will present a short review of current knowledge on the topic of navigation.

3.9.1. Navigation in an unfamiliar environment

An assessment of the related literature suggests that there are many studies focusing on navigation in an unfamiliar environment (Book & Gärling, 1981; Iachini & Logie, 2003), in a familiar environment (Evans, 1980) or in both types of environment (Lovelace, Hegarty, & Montello, 1999).

In an unfamiliar environment, Golledge (1999) points out that individuals’ learning strategies are based on search and exploration according to some rules or heuristics such as collecting information from maps, sketches, verbal descriptions, photographs, or experiencing the environment through navigation or exploration using path integration to sustain knowledge of a home base, retrace the origin of the trip.

The most important feature of navigating in an unfamiliar environment is to maintain the spatial orientation. It means that an individual should be able to pinpoint his/her location relative to other buildings such as landmarks, as well as re-orient himself/herself while interacting with the environment. Spatial orientation is the process of establishing a link between spatial perception and spatial knowledge that is stored in one’s cognitive map or spatial knowledge acquired from a regular map (Peruch & Lapin, 1993). Millonig and Schechtner (2007) denote that people navigate through familiar environments using their cognitive maps. In view of that, the following section briefly explains how individuals navigate in a familiar environment.
3.9.2. Navigation in a familiar environment

If an individual is familiar with the environment, he/she does not need any landmarks for navigation or any source to consult. Therefore, navigating in a familiar environment is rather easier than in an unfamiliar environment.

As Millonig and Schechtner (2007) indicate, route knowledge and landmark knowledge are both egocentric. Familiarity with the environment leads to the development of survey knowledge. Survey knowledge is allocentric and enables an individual to estimate spatial relations between random locations within the familiar environment. Basically, familiarity is a result of repeated experience. Experience leads to learning, and improves spatial orientation and wayfinding in a given environment. As the environment becomes familiar, it will be easier to recognize more locations. Over time, repeated experiences turn into habits. This relates to the statements and empirical findings explained earlier in sections 3.3 and 3.5.

3.10. Conclusions

This chapter briefly reviewed the existing literature on human spatial behavior and the development of spatial cognition. Although it was hard to divide the topics described in this chapter into different sections, an effort is put into highlighting both differences and mutual relationships in human spatial behavior. First of all, the fundamental concepts of spatial behavior are described. Furthermore, empirically based theories of the development of spatial knowledge are presented. These theories form a base to the conceptual framework of the current research. Section 3.5 explains theories on spatial learning, whereas section 3.6 focuses on the cognitive mechanisms underlying spatial learning. Additionally, an attempt is made to present some basic definitions and characteristics of landmarks in section 3.7. Landmarks are building blocks of our spatial knowledge; they are an important part of our spatial memory. Therefore, they play an important role on the development of spatial cognition, wayfinding, navigation, and also on the modeling approach presented in the following chapter. It is essential to emphasize the difference between navigation and wayfinding, since both of them are important for spatial learning. They both affect route choices, and route choices affect spatial learning. Furthermore, in the future, the proposed model will be extended to include wayfinding (exploration) behavior.
Evans (1980) indicates that the study of environmental cognition is an important area of psychology that provides potentially main conceptual links among environmental psychology, cognitive psychology, urban planning, and geography. Amount of experience in an environment is an important variable in environmental cognition research. It is obvious that people gain spatial knowledge with constant exposure. Today, more is known about how physical variables affect spatial cognition. For example, landmarks are important in learning new environments and in the development of cognitive maps. Furthermore currently, researchers know significant amount of information on the development of spatial knowledge and how this information is processed. Therefore this chapter examined the state-of-the-art research on human spatial behavior. The next chapter describes a model of how spatial information is processed in human beings and presents the design of a modeling approach for cognitive learning of urban networks in daily activity-travel behavior.
CHAPTER 4

COGNITIVE LEARNING MODEL

4.1. Introduction

From the point of view of the activity-based modeling framework, the importance of modeling cognitive learning of urban networks in daily activity-travel behavior was emphasized in Chapter 2. It was also stressed that the existing models do not pay enough attention to spatial cognition and that research on modeling cognitive learning of urban networks is still restricted. On the other hand, Chapter 3 reviewed the state-of-the-art studies on human spatial behavior. The reviewed literature presents important theories of how individuals gain spatial knowledge, and provides empirical findings on the development of spatial cognition over time. The present chapter, therefore, targets to link these studies of environmental and cognitive psychology with the studies of urban planning and geography, from a modeling perspective.

The main aim of this chapter is to introduce a modeling approach for cognitive learning of urban networks in daily activity-travel behavior. Arentze and Timmermans (2005) developed a model that is derived from existing Bayesian
theories of belief updating, and following their study, in this chapter, a modeling approach to simulate perception updating based on individual observations in the built environment is described.

In this chapter, first, the conceptual framework is described with the inclusion of some basic notions and concepts. This section gives details on the attributes of the model, and also on level-A and level-B representation in the modeling approach. The next section introduces the models, which are derived from the reviewed literature in the previous chapter. The following section shows an illustration of the modeling approach. This section presents the data and the results of the numerical simulations designed to test the face validity of the part of the model concerned with attribute learning. Finally, the last section draws some conclusions.

4.2. The conceptual framework

Siegel and White's (1975) and Thorndyke's (1980) theories on the development of spatial knowledge and Golledge's (1974; 1978) anchor point theory play an important role in the development of the conceptual framework of the current study. As reported in the previous chapter, both Siegel and White (1975) and Thorndyke (1980) state that spatial knowledge develops step by step; first, landmark knowledge, then route knowledge, and finally survey knowledge. In addition to these studies, Golledge (1974; 1978) argues that an individual's spatial knowledge develops based on the relative importance of activity locations (anchor points), paths (routes) and areas (neighborhoods) in a given environment. The empirical findings are consistent with both approaches, and they form a base for the current study. The specific theories and models will be explained later.

The development of spatial cognition by means of the cognitive processes involved in an individual's daily activity-travel behavior is illustrated in Figure 4.1. As in the anchor point theory (Golledge, 1974; 1978), dark blue points represent the anchor points such as home, work, shopping and social activity locations; other circles with shades of blue correspond to the learned neighborhoods over time; large and irregular blobs (neighborhoods) symbolize the overall spatial knowledge over time. Furthermore, the weights of the links (route segments) differ as a result of the frequency of the use of the links. Based on the reviewed literature in the previous chapter and the exploratory
study reported by Cenani, Arentze and Timmermans (2010b), these routes and activity locations can be learned through personal observation (exploration), the use of ICT and social networks. Links will be further discussed later. Additionally, it is assumed that individuals have a-priori knowledge about the layout of a city in general and they know how to find basic facilities in a city. First, only the base locations -a number of “anchor points” and several landmarks- are known. Eventually, they learn new activity locations and routes between these locations. As a result, they acquire “survey knowledge” and thus, develop a mental representation of the city, as specified in Siegel and White’s (1975) and Thorndyke’s (1980) studies. Because of memory loss and perception updating processes, activity-travel patterns evolve and the cognitive map of the individual enhance over time.

Figure 4.1 The development of spatial cognition

Until now, concepts that shape the modeling approach are discussed. Hereafter, how spatial learning is integrated into the framework will be discussed. A prerequisite of all the foregoing processes is that an individual has a-priori knowledge about the layout of a city. Initially, when there is no knowledge at all, only the base locations are known (as in the anchor point
Activity schedules to be implemented by an individual define the trips that need to be made. Each time, for a given trip, the individual searches the existing cognitive map for determining a route. This will fail in case only base locations are known, meaning that the individual will consult external sources, such as a map of the city, information services or other people. During the implementation of the trip, the individual will gain spatial knowledge. The following elements of learning processes are assumed:

- Links that were not known yet are added and links that did have a representation in the cognitive map have their memory strength increased (reinforcement of the memory trace),
- Probabilities regarding attributes of links are updated (for the newly added ones as well as the existing ones) based on observation,
- Sequences of links traveled are grouped as chunks and added (when not yet existed) or reinforced (when already existed),
- Landmarks are identified as anchor points and added or reinforced,
- Neighborhood borders are defined or revised.

There are two types of learning in the framework: object learning and attribute learning. Object learning is about the formation of memory traces in terms of yes/no existence of a point or a link. Attribute learning concerns learning attributes of objects (links or points), such as the presence of stores of particular type, presence of an entrance to a park, or presence of parking places, in short, all attributes that are important for conducting activities. A special attribute is landmarks. A landmark is not necessarily important for activities, but plays a key role in navigation, i.e. identifying a link (knowing where one is) and remembering routes. A landmark can be anything but is to some extent extraordinary and unique. For example, seeing a particular church on the side of the street might confirm an individual's notion that it is on a particular known link. Whenever an individual is traveling on a link, it is making observations and these observations result in updating the perceptions about that link.

In this dissertation, an agent represents an individual in a city. The behavior of an agent is modeled as a series of decisions such as destination choice, activity choice, route choice and transport mode choice. An agent may not always make all these choices, if the purpose of the trip is exploration or
wayfinding. As an example, in retail environments, destination choice may change rapidly depending on the attractors and the attention of an individual (e.g., Dijkstra, Timmermans, & de Vries, 2012).

The model proposed here is one of the layers of a large-scale multi-agent model (Figure 4.2) that is capable of handling short-term, mid-term and long-term dynamics (Timmermans, et al., 2010), and simulates dynamic activity-travel patterns of individuals and households. Daily scheduling decisions are dependent on the state of the agent and, at the same time, implementing a schedule can change an agent’s state. After having implemented the schedule, an agent updates its knowledge about the transport network, transport modes and route network, and develops habits for implementing these activities (e.g., habitual routes). At the beginning of each day, the agent generates a schedule and during the day, it executes the schedule in space and time. When there is an unexpected event, the agent will make adaptations to its schedule (within-day re-planning). At any decision moment during the implementation process, memory will receive perception results of the observations made so far and probabilities will be updated. Also, at the end of the day, probabilities will be updated according to the observations made during traveling and conducting activities at locations, simulating learning especially through exploration and/or encountering unexpected events during the day. As a design decision, each component of the main agent-based model receives and updates the information, and then sends it to the main agent-based model at the end of each day.
Figure 4.2 Flowchart of the multi-agent model with cognitive learning component
The following subsections will briefly explain the representation of different knowledge levels in the framework and attributes of the objects at these levels.

4.2.1. Level-A and level-B representation

It is assumed that there are two levels in the framework. In the remainder of the dissertation, the terms level-A and level-B are used to refer to the high and low level representation, respectively.

In Figure 4.3, a representation of level-A (left) and level-B (right) can be seen. The illustration on the right side shows a closer look to the marked area on the left side. The route between home and work is actually a combination of several links that may or may not contain several types of landmarks. As Figure 4.3 illustrates, level-A is the summary information of level-B objects on the same dimension. Objects at both levels include points (activity locations and landmarks), links (route segments) and nodes (decision points on the road network).

Memory decay involves loss of what has been learned in the past. An important note here is that the decay processes run independently at level-A and level-B. This may have a consequence that an entity on level-A still exists, whereas entities at level-B that it represents have been lost. For example, an individual may discover that a route on level-A has no longer a representation on level-B. In other words, the individual knows there is a route, but does not remember anymore how to find it exactly, which is a realistic feature of the model. For now, only level-B representation is considered in the current numerical simulations.
**Links**
At level-A, a link is not a single route on a road network, but rather a major route; so, level-A links are routes consisting of sequences of level-B links. Level-A links are formed by a learning process that is called *chunking* (Rosenbloom & Newell, 1987).

**Nodes**
Nodes serve the technical purpose of defining how links are interconnected. They are decision points such as an intersection or a corner on the road network. The nodes on level-A are the locations where routes intersect, in the same way nodes on level-B are the locations where links are interconnected.

**Points**
At level-A (the high level), the points represent the major activity locations, which are called *anchor points* (Golledge, 1974; 1978). Anchor points include at least the base locations (home and work locations) as well as landmarks, which are important for spatial orientation. The detailed information about point objects is stored on level-B.

**Neighborhoods**
Points on level-A are at the same time central points of neighborhoods. As illustrated in Figure 4.4, for an individual, a neighborhood represents the direct environment of an anchor point. Neighborhoods do not overlap and as the cognitive map of the individual expands, ideally they will cover the whole area of a city. In other words, neighborhoods refer to a zoning system – a way for an individual to categorize space in meaningful areal units.

![Figure 4.4 Representation of neighborhoods surrounding anchor points](image_url)
In principle, a neighborhood is a group of nodes and links. This grouping establishes the (one-to-many) correspondence relationships between level-A objects and level-B objects. In sum, where chunks are single-link representations of sequences of level-B links, anchor points are single-point representations of neighborhoods which are partitions of an entire network.

4.2.2. Attributes

Links, nodes and points are described in terms of a set of attributes. Link objects store most of the information. Following attributes are considered in this study:

- Geometric features:
  - Distance: Straight-line distance from the object to the road network
  - Direction: Angle between the observer and the observed object
  - Shape: Saliency of the object
  - Position: Location in the coordinate system

- Morphological features:
  - Obstacle: Open or blocked vision (field-of-vision)

- Functional features:
  - Availability of facilities (e.g., store, parking place)

Extension such as adding a functional attribute regarding the type of the road (transport mode) et cetera is possible in the future improvement of the model.

4.3. Models

So far, basic theoretical concepts and notions that have impacts on the conceptual framework, integration of spatial learning into the framework, representation of different knowledge levels in the framework and attributes of the objects at these levels are explained in the previous sections. In this part of the chapter, technical details of the modeling approach; particularly learning through observation and vision, and memory retention will be elaborated. Afterward, an illustration of the part of the model concerned with attribute learning will be described.
4.3.1. Learning through observation and vision

Arentze and Timmermans (2005) developed a model that is derived from existing Bayesian theories of belief updating, and following their study, current and the following sections will describe a modeling approach for simulating probabilities based on observation and vision while implementing an activity-travel schedule. The proposed approach consists of two main parts: learning (through observation and vision) and forgetting (memory retention). The latter will be described in the next section.

**Perception updating (the Bayesian model)**

Given that an observed state does not have to be identical to the true state, Arentze and Timmermans (2005) represent an observation of some attribute of some link \( X = \{x_1, x_2, ..., x_n\} \) by a separate variable \( Y = \{y_1, y_2, ..., y_n\} \), where \( y_1, y_2, ..., y_n \) denote observed states. They indicate that uncertain observations means that the probability of \( Y = y_s \) given that \( X = x_s \) is not necessarily one and the probability of \( Y = y_s \) given that \( X \neq x_s \) is not necessarily zero. When some observation \( Y = y_u \) is made, the belief in \( X = x_s \) is updated according to the Bayesian method (Arentze & Timmermans, 2005):

\[
P(x_s | y_u) = \frac{P(y_u | x_s)P(x_s)}{\sum_{x_{s-1}}^{n} P(y_u | x_{s-1})P(x_{s-1})}
\]

(1)

where \( P(x_s) \) is the initial probability for \( x_s \); \( P(x_s | y_u) \) is the updated probability after observation \( Y = y_u \); \( P(y_u | x_s) \) is the probability of observation \( Y = y_u \) given \( X = x_s \); \( n \) is the number of possible values of \( X \) and \( Y \). According to the equation above, the updated probability, \( P(x_s | y_u) \), becomes the initial probability in the next observation, which means learning process is incremental. Equation (1) assumes that initial (conditional) probabilities, \( P(y_u | x_s) \), are known and considered by the agent in perception updates.

Arentze and Timmermans (2005) suggested a technique to identify the initial probability of an observation as a function of the state of the agent and variables of the field of vision that is applicable here as well. Their method assumes that observation accuracy is composed of two factors: sensitivity and bias, and they suggest a logit model:
where $\beta_{us}$ is observation-bias parameter and $\theta$ is the observation-sensitivity variable. If sensitivity is constant, and $\beta_{us}$ increases, then there is a higher probability of observing $u$ while $s$ is the case. If, $\beta_{uu} > 0, \forall u$, and $\beta_{us} = 0, \forall s \neq u$, then observation-bias will not be present.

As sensitivity sets the scale of the parameters, a zero-one scale for the bias parameters is used, whereby $\beta_{uu} = 1$ and $\beta_{us} = 0$ for states $x_u$ and $x_s$ that are considered to be the least easily confused with each other for the measured attribute.

**Sensitivity of an observation**

It is assumed that the sensitivity is a function of series of factors:

\[
\theta_{jk} = f(A_{jk}, V_{jk})
\]

\[
A_{jk} = \gamma_0 + \gamma_1 E_j + \gamma_2 C_{jk}
\]

\[
V_{jk} = \sigma_0 + \sigma_1 D_{jk} + \sigma_2 R_{jk} + \sigma_3 B_{jk}
\]

where $jk$ is some attribute $k$ of link $j$, $A_{jk}$ is the amount of attention the agent pays to attributes of type $k$, and $V_{jk}$ is the visibility of the object from the current position of the observer (see also sections on visibility and attention in Chapter 5). $D_{jk}$ is the shortest (straight-line) distance between position of the observer and the observed object on link $j$, $E_j$ is a binary variable indicates that it is a decision point on link $j$ or not, $c_{jk}$ is the measure of saliency of a landmark on link $j$, $R_{jk}$ is the direction of the object on link $j$, $B_{jk}$ is blockage (i.e., obstacles) between the observer and the observed object on link $j$, $\gamma_0$ and $\sigma_0$ are constant.

McNamara and colleagues (2008) indicate that people recall and recognize spatial relations among objects more efficiently from some perspectives than others. There is evidence that spatial memories may also be viewpoint-dependent (Waller, 2006; Valiquette & McNamara, 2007).
As Lynch (1960) stated, paths (or routes) have directional quality: one direction of the street can easily be distinguished from the reverse. Consequently, an individual may not easily find his/her way during the return trip; even though he/she uses the same route (see Vandenberg & Kuse, 1978, for spatial memory tests). A landmark's location is, therefore, essential for spatial learning and also for the proposed model.

The observed object may be situated on a different link than the link the observer is on, which can mean that the object is viewed from a distance. As an example, sensitivity is higher if attention for the attribute is high, distance is short, and the view is not blocked by a building. In addition, it is assumed that the relation between the purpose of the trip and the attribute type has a possible effect on the amount of attention. For example, sensitivity will be high for landmarks, if the purpose of the trip is exploration or wayfinding (e.g., agent is lost). As another example, when the trip purpose is shopping, attention will be high for attributes related to presence of stores. This extension will be included in the future improvement of the modeling approach.

**Saliency of a landmark**

As indicated in Chapter 3, the presence of landmarks plays a special role in wayfinding and in spatial learning. An individual who has limited knowledge about a city is particularly sensitive for landmarks, given their importance for wayfinding. However, not all landmarks are equally discriminating. The extent to which landmark is discriminating depends on the degree of saliency. For example, a school building may be less salient than a cathedral. The degree of saliency can be modeled as follows:

\[
\begin{align*}
    c_{jk} &= \frac{N^{-k}}{N-1} \\
    \end{align*}
\]

where \(N\) is the total number of links and \(N^{-k}\) is the number of links where a landmark \(k\) is not present. So, if the landmark is salient for the link, then \(N^{-k} = N - 1\) and \(c_{jk} = 1\). If the landmark appears on every link, then \(N^{-k} = 0\) and \(c_{jk} = 0\). It is assumed that if an agent is searching for the right route or is exploring the city, the amount of attention for a landmark, \(A_{jk}\), will be proportional to saliency \((c_{jk})\) and \(E_j\) (see Equation 3). As another example, the
agent will not pay attention to the landmarks after frequently traveling on the same route, in view of the fact that the agent becomes familiar with the route. Hence, attention will be low for landmarks, which in return will affect sensitivity (see Equations 2 and 3).

4.3.2. Memory retention

Forgetting processes run in the opposite direction as perception updating processes. Three cases of memory retention need to be distinguished here:

- link/point attributes that have discrete states (categorical variables)
- link/point attributes that have values on a continuous scale
- point and link objects

Categorical attributes include binary attributes such as yes/no presence of a particular function (e.g., a store, a parking place, a church, etc.) as well as multinomial attributes such as the type of street, type of neighborhood, and so on. Continuous variables include in particular geometric attributes such as position, orientation, length and the like. A memory of attributes of objects supposes a memory of the object. This means that when an object is forgotten, all attribute associations with the object will be lost as well.

Following above notions, forgetting is modeled as a step-wise return to initial probabilities (Arentze & Timmermans, 2005):

\[ P_{jkts}^{t+1} = P_{jkts}^t + \alpha'_{jk} \left( P_{kis}^0 - P_{jkts}^t \right) \]  

(5)

where \( P_{jkts}^t \) is the probability that attribute \( X_k \) has value \( s \) at time \( t \), \( P_{kis}^0 \) is the initial probability, and \( \alpha'_{jk} \) is a step-size parameter for memory retention. After the memory decay, the probabilities return to their initial values, so that entropy returns to the value it had before learning.

Following argument is applicable for all abovementioned cases of memory retention. Anderson (1983) argues that the following memory retention function is consistent with empirical evidence:

\[ S = T^{-b} \]  

(6)
where $S$ is the strength of a memory trace and the time $T$ is measured from the point at which the trace was created and exponent $b$ has a value on the interval $0$ and $1$. The closer $b$ is to zero, the smaller the speed of forgetting. So, $b$ reflects the retentiveness of the system. For a trace that had multiple strengthening, Anderson (1983) argues that the total strength is the sum of the strengths remaining from an individual strengthening:

$$S = \sum_i T_i^{-b}$$

where $T_i$ is the time since the $i$-th strengthening. In a generalized function, sensitivity of an observation is taken into account and necessary subscripts are added as follows:

$$S'_{jk} = \sum_{i \in O_{jk}} \theta_{jk} T_i^{-b}$$

where $O_{jk}$ is the set of observations of $jk$ before time $t$ and $\theta_{jk}$ is the sensitivity of an observation. For objects, the memory strength is defined similarly as:

$$S'_j = \sum_{i \in O_j} \theta_j T_i^{-b}$$

where $j$ is a link or a point object, $O_j$ is the set of all observations of $j$ before time $t$ and $\theta_j$ is the sensitivity of the observation. Clearly, there should be some relationship between the sensitivity of an observation on link and attribute level. One possible assumption is:

$$\theta_j = \sum_k \theta_{jk}$$

implying that the strength of memory of an object will be as large as the strength of memory of attribute associations with that object.

As indicated previously, alpha represents the memory loss in one time step, and hence can be computed as:
\[
\alpha = S_j^{t+1} - S_j^t
\]
\[
\alpha = \sum_{i \in \mathcal{I}_j} \theta_{ijk} T_{ijk}^{-b} - \sum_{i \in \mathcal{I}_j} \left( \theta_{ijk} \left[ T_{ijk} + 1 \right] \right)^{-b}
\]
\[
\alpha = \sum_{i \in \mathcal{I}_j} \left[ \theta_{ijk} T_{ijk}^{-b} - \left( \theta_{ijk} \left[ T_{ijk} + 1 \right] \right)^{-b} \right]
\]

Note that this function, at the same time, determines the effect of reinforcement of a memory trace when an observation is made.

Memory strength determines the recollection of an object from the memory. A threshold value can be applied to determine an all-or-nothing recollection, in the future application of the model. When fallen below this level, the object concerned can be removed from the memory.

4.4. Illustration

Validation is essential for every simulation model. Law (2005) defines validation as “the process of determining whether a simulation model is an accurate representation of the system, for the particular objectives of the study”. Designing a proper method to validate a model is crucial. There are different types of validation, such as empirical validation, statistical validation, conceptual model validation, operational validation, structural validation or process validation (Klügl, 2008). Klügl (2008) indicates that “face validity shows that processes and outcomes are reasonable and plausible within the frame of theoretic basis and implicit knowledge of system experts or stakeholders”. She also states that face validation may be applied from the early phases of the simulation study under the context of conceptual validations, which is called plausibility checking.

In order to validate the model, face validity is performed. Artificial data is used in the numerical simulations. The details of the data used in the illustration will be explained in the next section.

4.4.1. Data

Only attribute learning and limited forgetting (Equations 1-5) are considered in the illustration. The attributes considered are attributes of points and concern
the (yes/no) presence of particular facilities (e.g., a store) or landmarks (e.g., a church). Attributes of landmarks (e.g., saliency, distance) affect sensitivity of an observation, which in return, affect the perception updating processes.

The calibration and the validation of the model are done with artificial data. The activity-travel schedule of a fictional newcomer is designed for illustration purposes. For the purpose of illustration, the first consecutive 12 weeks of a fictional newcomer was taken into consideration. Figure 4.5 shows the map of the study area. It is assumed that the fictional newcomer is male, 36 years old, married with one child and lives in Eindhoven, the Netherlands. Furthermore, his activity-travel schedule for the 12 weeks is given. As a result, the type of the activities conducted daily and the sequence of the stores visited are known.

According to his activity-travel schedule, he works five days a week (full-time job), and every day before and after work, he goes to the day-care center to drop-off and pick-up his child. Once a week, on Wednesdays after work, he conducts grocery shopping. Friday nights, after work, he goes to non-grocery
shopping or to a restaurant, or participates in some social activities. On Saturdays, he goes to grocery shopping and conducts several recreational, leisure and social activities. The first Sunday of each month is called “Shopping Sunday” in the city; therefore sometimes on Sundays, he goes to the city center for several activities. On weekends, he usually participates in recreational activities, has guests at home, visits friends, or sometimes stays at home. Activity-travel schedule of each day starts at home and ends at home.

The route choice behavior is illustrated in Figure 4.6. Based on the preferences (e.g., want to explore, want to optimize the trip, feeling unsatisfied), there are four choices. If the individual does not know any route or unsatisfied with the existing route choice, he may consult an external information source. If there are multiple known routes, a conscious choice can be made. Depending on the preferences (e.g., want to explore), he may choose a random route, otherwise he may choose his habitual route.

For illustration purposes, it is assumed that he travels with his private vehicle. Route choice is not in the scope of this study and is assumed that he consults a navigation system and chooses the shortest route between origin and destination points. It should be emphasized that destination (activity location) choice and transport mode choice are also managed elsewhere in the model system.

Tables 4.1 and 4.2 show respectively, activity and landmark categories. Each activity location is located in one of the six land-use types (i.e., industry, residential, commercial, green, mixed commercial and residential, other), and initial probabilities related to the availability of specific facilities are dependent on these land-use types. Individuals frequently use activity locations as landmarks, therefore for the illustration, landmarks are chosen from activity locations in the given activity-travel schedule. However, there are some additional categories that can be considered as landmarks, such as parking and storage facilities, industrial and transportation structures and so on.
Figure 4.6 Route choice behavior
<table>
<thead>
<tr>
<th>ID</th>
<th>Main category</th>
<th>Subcategory</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>home</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>work</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>volunteering</td>
<td>-</td>
</tr>
<tr>
<td>4</td>
<td>education</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>grocery shopping</td>
<td>clothing or footwear</td>
</tr>
<tr>
<td></td>
<td></td>
<td>drugstore items</td>
</tr>
<tr>
<td></td>
<td></td>
<td>electronics</td>
</tr>
<tr>
<td></td>
<td></td>
<td>household items</td>
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<tr>
<td></td>
<td></td>
<td>flowers</td>
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<td></td>
<td></td>
<td>books</td>
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<td></td>
<td></td>
<td>other</td>
</tr>
<tr>
<td>6</td>
<td>non-grocery shopping</td>
<td>bank</td>
</tr>
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<td></td>
<td></td>
<td>post office</td>
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<td></td>
<td></td>
<td>hairdresser</td>
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<tr>
<td></td>
<td></td>
<td>healthcare</td>
</tr>
<tr>
<td>7</td>
<td>service</td>
<td>-</td>
</tr>
<tr>
<td>8</td>
<td>pick-up/drop-off family members</td>
<td>eat out</td>
</tr>
<tr>
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<td></td>
<td>cinema</td>
</tr>
<tr>
<td></td>
<td></td>
<td>theater</td>
</tr>
<tr>
<td>9</td>
<td>leisure</td>
<td>bar, café, disco</td>
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<td></td>
<td>museum</td>
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<tr>
<td></td>
<td></td>
<td>concert, show</td>
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<tr>
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<td></td>
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<td>walk the dog</td>
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<td></td>
<td></td>
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<td>walking in the forest</td>
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<td></td>
<td></td>
<td>beach</td>
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<tr>
<td>11</td>
<td>social</td>
<td>having guests</td>
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<td></td>
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<td></td>
<td></td>
<td>church</td>
</tr>
<tr>
<td>12</td>
<td>helping family</td>
<td>-</td>
</tr>
<tr>
<td>13</td>
<td>waiting</td>
<td>-</td>
</tr>
<tr>
<td>14</td>
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<td>-</td>
</tr>
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<td>Subcategory</td>
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<tr>
<td>4</td>
<td>education</td>
<td></td>
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<tr>
<td>5</td>
<td>grocery store</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>non-grocery store</td>
<td>clothing or footwear, drugstore, electronics, household items, flower shop, bookstore, other</td>
</tr>
<tr>
<td>7</td>
<td>service</td>
<td>bank, post office, hairdresser, healthcare</td>
</tr>
<tr>
<td>8</td>
<td>pick-up/drop-off members</td>
<td>day-care center</td>
</tr>
<tr>
<td>9</td>
<td>leisure</td>
<td>restaurant, cinema, theater, bar, café, disco, museum, concert, show, sports game</td>
</tr>
<tr>
<td>10</td>
<td>recreation</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>social</td>
<td>church</td>
</tr>
<tr>
<td>161</td>
<td>parking &amp; storage</td>
<td>indoor bicycle park</td>
</tr>
<tr>
<td>162</td>
<td></td>
<td>outdoor bicycle park</td>
</tr>
<tr>
<td>163</td>
<td></td>
<td>indoor car park</td>
</tr>
<tr>
<td>164</td>
<td></td>
<td>outdoor car park</td>
</tr>
<tr>
<td>165</td>
<td></td>
<td>storage/depot</td>
</tr>
<tr>
<td>17</td>
<td>industrial structure</td>
<td></td>
</tr>
<tr>
<td>181</td>
<td>transportation/infrastructure</td>
<td>bridge</td>
</tr>
<tr>
<td>182</td>
<td></td>
<td>bus stop</td>
</tr>
<tr>
<td>183</td>
<td></td>
<td>traffic light</td>
</tr>
<tr>
<td>184</td>
<td></td>
<td>intersection</td>
</tr>
<tr>
<td>191</td>
<td>historical monument</td>
<td>castle</td>
</tr>
<tr>
<td>192</td>
<td></td>
<td>statue</td>
</tr>
<tr>
<td>201</td>
<td>geographical landmark</td>
<td>mountain</td>
</tr>
<tr>
<td>202</td>
<td></td>
<td>hill</td>
</tr>
<tr>
<td>203</td>
<td></td>
<td>lake</td>
</tr>
<tr>
<td>204</td>
<td></td>
<td>canal</td>
</tr>
<tr>
<td>205</td>
<td></td>
<td>sea</td>
</tr>
<tr>
<td>211</td>
<td>temporary landmark</td>
<td>bazaar</td>
</tr>
<tr>
<td>212</td>
<td></td>
<td>carnival/fair</td>
</tr>
</tbody>
</table>
In the current illustration, a node is a decision (choice) point on the road in a transport network (e.g., intersections on a road); a point is an activity location or a landmark in an urban area, and a link is a transport link between any two nodes in a transport network. The transport network consists of 90 links in the illustration. Each link is defined by a start node and an end node, and can be traveled in both directions. Some activity locations can be located close to each other or on the same link. Similarly, more than one landmark can be located on the same link. For instance, some links have three landmarks, some have only one and some links do not have any landmarks at all. Similarly, a link can accommodate one or more activity locations. For the current scenario, transport mode is same (i.e., private vehicle) for all links on the road network. The relationship diagram between entities is shown in Figure 4.7. Four of the tables indicate four entities (link, landmark, point, and activity) and their attributes. The rest of them are input and output tables related to these entities.

![Figure 4.7 Relationship diagram](image-url)
As an example, Table 4.3 indicates arbitrary values of the initial probabilities related to the availability of each activity location in six land-use types. The specification of each probability is based on the assumption that the agent has accurate knowledge about conditional probabilities. These initial probabilities (see also Equation 2) reflect the case of an individual who just moved into a new city, yet has enough information through a map or a navigation device, of how the area is structured in terms of land-use types. For instance, an agent has a-priori knowledge that a grocery store can be found with a higher probability in a commercial area than in a residential area. Also, the agent knows that it is almost impossible to find a grocery store in an industrial area. Therefore, the values on Table 4.3 represent a-priori knowledge of a newcomer. Since, individuals may have different assumptions about how urban areas are structured, because of their experiences or occupations; this a-priori knowledge may be different for other individuals and cities.

Table 4.3 Initial probabilities related to the availability of activity locations dependent on land-use types

<table>
<thead>
<tr>
<th>Activity location</th>
<th>Probability (Yes)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Industry</td>
</tr>
<tr>
<td>Grocery store</td>
<td>0</td>
</tr>
<tr>
<td>Non-grocery store</td>
<td>0</td>
</tr>
<tr>
<td>Service</td>
<td>0</td>
</tr>
<tr>
<td>Leisure</td>
<td>0</td>
</tr>
<tr>
<td>Recreation</td>
<td>0</td>
</tr>
<tr>
<td>Social</td>
<td>0</td>
</tr>
</tbody>
</table>

A newcomer’s knowledge about a city evolves over time. In the beginning, a newcomer cannot be familiar with all landmarks in the city. In this study, landmarks are sub-categories of activity locations. When a newcomer learns a new activity location, it is assumed that this activity location will become a landmark too. The city will certainly change over time and new activity locations and new landmarks will be added to the memory and consequently to the activity-travel schedule. In this context, initial probabilities of landmarks are not defined on land-use types as in activity locations; they are computed by using Equation (12). It is assumed that individuals have accurate a-priori
knowledge about presence of landmarks. Following equation is used to compute initial probabilities of observing a landmark of type $k$ on any given link:

$$P_{ks} = \frac{TNL_k}{TNL}$$

(12)

where $P_{ks}$ is the initial probability that attribute $X_k$ has value $s$, $TNL$ is the total number of landmarks on all links and $TNL_k$ is the total number of landmark of type $k$ on all links. For example, consider landmarks like an indoor bicycle parking place or a bridge. In this illustration, the total number of landmarks across all links ($TNL$) is 137, and there are four links with the first landmark type (i.e., indoor bicycle parking place) and six links with the second landmark type (i.e., bridge) in the study area. Therefore, initial probability of observing an indoor bicycle parking place on any given link is $4/137=0.03$ and initial probability of observing the second landmark, bridge, on any given link is $6/137=0.04$. Then, these values are used as initial values in Equation (1) to compute perception updates with regard to the landmarks.

The initial state of the cognitive map of an agent assumes that it knows the land-use type of each activity location. It is assumed that an individual, who is not an expert in urban studies, can have such level of information. As implied by Equation (5), if no observations are made for a long time, the probabilities will return to their initial values.

Until now, the details of the illustration are explained. In the following section, results of the numerical simulations designed to test the face validity of the part of the model concerned with attribute learning will be explained.

4.4.2. Results

Currently in the illustration, only attribute learning and limited forgetting of activity locations (Figure 4.8) and landmarks (Figure 4.9) are considered. It is assumed that an agent is traveling on a road network and making observations about attributes of activity locations and of landmarks.
Figure 4.8 Flow-chart of cognitive learning of an activity location
Figure 4.9 Flow-chart of cognitive learning of a landmark
For illustration purposes, a basic specification is used for the function used to predict sensitivity. Equations (13) and (14) are special settings of the parameters of Equation (3), and are used in the perception update processes of activity locations and landmarks, respectively:

\[
\begin{align*}
\theta_{jk} &= z - (b \times D_{jk}) \\
\theta_{jk} &= (z - (b \times D_{jk})) \times c_{jk}
\end{align*}
\]

For current illustration, it is assumed that all activity locations and landmarks are visible \((V_{jk})\) at all times (visible=1, not visible=0) and attention \((A_{jk})\) is fixed, meaning that sensitivity of observations decrease only with increase of distance \((D_{jk})\). The sensitivity function is a linear function of distance, where \(z\) is a constant and \(b\) is slope. Parameters of the sensitivity function are set as \(b = 0.01\) and \(z = 5\) in Equation (13) and Equation (14). Thus, during the implementation of the activity-travel schedule, the agent acquires spatial knowledge in terms of attributes of activity locations and landmarks. The initial probabilities for activity locations are taken from Table 4.3. On the other hand, initial probabilities for landmarks are calculated by using Equation (12). Briefly, attribute learning of activity locations (perception updating of each visible point) is computed by means of calculating the sensitivity using Equation (13), and Equation (14) for landmarks, and then deriving the initial probabilities using Equation (2). A basic setting for the logit model (Equation 2) is used to calculate the initial probabilities for a given observation; all \(\beta_{us}\) are assumed zero for off-diagonal cells \((u \neq s)\) and one for the diagonal cells \((u = s)\). Finally, the probabilities are updated using Equation (1). In addition to these steps, if an agent does not make any observation about the attributes of activity locations, then the forgetting is computed using Equation (5) \((\alpha = 0.01)\). Table 4.4 shows the parameters used in the illustration.
Table 4.4 Parameter-set used in the illustration

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visibility</td>
<td>1</td>
</tr>
<tr>
<td>Distance</td>
<td>Activity-travel schedule</td>
</tr>
<tr>
<td>Attention</td>
<td>1</td>
</tr>
<tr>
<td>$b$</td>
<td>0.01</td>
</tr>
<tr>
<td>$z$</td>
<td>5</td>
</tr>
<tr>
<td>$\beta_{sa}, \beta_{su}$</td>
<td>0</td>
</tr>
<tr>
<td>$\beta_{sr}, \beta_{sw}$</td>
<td>1</td>
</tr>
<tr>
<td>Initial probability</td>
<td>Table 4.3</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Figure 4.10 represents graphically the frequency of use of links indicated in the activity-travel schedule of the fictional newcomer. As shown, respectively L04, L25, L23 and L24 are the most used links. These links are part of his habitual routes between home, day-care center and work. As a result, the individual frequently uses these links.

Similarly, Figure 4.11 shows the frequencies related to the observation of activity locations. Based on this graph, it can easily be seen that the most observed three activity locations are P1 (home), P2 (day-care center) and P3 (work), respectively. This is very straight-forward, since these are the most visited activity locations according to the agent's activity-travel schedule. In the same way, Figure 4.12 indicates the frequencies linked to observation of a landmark on the related link. Derived from this graph, the most observed
landmarks are k184, k183, k182 and k181. When these landmarks are compared with the information on the given activity-travel schedule, it appears that these landmarks are located on the most observed links.

Figure 4.11 The most observed activity locations

Figure 4.12 The most observed landmarks
In parallel with these three graphs, as expected, the results of the perception updates (Figures 4.13 and 4.16) indicate that the most observed activity locations and landmarks have the highest probabilities, which means that these activity locations and landmarks are kept in the memory longer than the others.

Figure 4.13 shows the perception updates of four shopping locations during 12 consecutive weeks. The difference between the updated probability and initial probability for an activity location represents the level of knowledge about that activity location. In Figure 4.13, initial probabilities for all shown shopping locations are 0.5 (see Table 4.3). If there is an observation, the values increase. On the other hand, if there is no observation, as a result of the forgetting process, a small amount of memory decay occurs for each day without observation. Forgetting is linked to time, because memories degrade with the passage of time. This is simply a result of the storage limit of human memory. Therefore, if individuals have a gap in between their observations, their perception values drop. This does not mean that they completely forget the information. As long as it is above the threshold level, it will stay in the memory. For example, the agent does not go to work or to day-care center at weekends; as a consequence of Equation (5), forgetting takes place, yet the agent does not completely forget the unobserved activity locations. Then again, if the agent never visits an activity location after the first observation (e.g., P11 in Figure 4.13), due to Equation (5), the agent will start to forget this activity location, and the value will eventually go back to its initial state. The same point (i.e., activity location or landmark) can be visible from multiple links, which means that there can be multiple observations of the same point on the
same day. If there are multiple observations of the same point, the distance between the point and the agent \( D_{jk} \), visibility of the activity location \( V_{jk} \), and the sensitivity will be different for each link which the observation is made on. Furthermore, when an agent actually visits an activity location (e.g., a store) rather than seeing it from a distance, the sensitivity will be significantly large, so the agent will know with certainty that there is a store. These behaviors will be modeled in the future. In Figure 4.13, after the first observation of a shopping location, an increase is noticed, and then a decrease is observed as a result of memory decay. Later, the values increase again, which means he starts to make observations again. In the case of shopping location P11; the agent makes an observation about this location only once in 12 weeks, therefore the value constantly decreases after the last observation and in long-term, will return to its initial state. For P4 (grocery store), the values are always close to 1, which means that he makes observation regularly; as a result, memory decay is slower than the others. On the other hand, the frequency of the rise-and-falls of the probabilities for P67 (clothing store) is less than P4 (grocery store), and this indicates that the agent makes fewer observations for P67. The perception updates of P81 (drugstore) show a stable situation until the last week of the schedule, which indicates the agent makes its first observation on the last week.

In Figure 4.14, perception updates of three service locations are shown. According to the graph, there is only one observation for each service location in 12 weeks. P14 (hair dresser) is the first observed service location and P13 (post office) is the last observed. All service locations have the same a-priori values (0.5). After the first observation of each service location, a sharp increase is observed. After that day, no observations are made; therefore, continuous decrease is monitored, due to forgetting. At some point in the future, probabilities will return to their initial values (see Equation 5).
In Figure 4.15, three sections which are taken from the activity-travel schedule can be seen. These sections belong to day-7 (end of the first week), day-42 (end of the sixth week) and day-84 (end of the 12th week). If the perception updates of two drugstores (P6 and P81) are compared during 12 weeks, a slight decrease of probability for P6, and a sharp increase of probability for P81 are detected. The observed fluctuations show that each week the agent makes an observation about the drugstore (P6) less than the previous week, and in the last month of the schedule, it makes an observation about a new drugstore (P81). Until that time, the initial value (0.5) of P81 stays unchanged. This new drugstore may be discovered as a result of exploration or may be a suggestion from a social contact. Similar results are also seen for P35, P36, P37, P66, P67 and P82. The graph shows no observations in the beginning, then the agent starts to make observation and they become a part of its routine.
Figure 4.16 Perception updates of five landmarks

Figure 4.16 shows the perception updates for five landmarks. The interpretation of Figure 4.16 is similar to Figure 4.13; however, there are some differences in the computational processes. The sensitivity of a landmark is affected by the saliency of a landmark ($c_{ij}$), and also initial probabilities are not linked to land-use types as in activity locations. They are computed by using Equation (13). Nevertheless, as long as the agent makes an observation about the attributes of the landmarks, memory decay is slower than the case of not making an observation, and the values remain close to 1. As an example, at the end of 12th week, k181 (bridge) has the highest value, which means that the agent frequently makes an observation about this landmark and uses the link it is located on.

4.5. Conclusions

In this chapter, first, the conceptual framework and the motivation behind the modeling process are explained, and then the key mechanisms of a model of cognitive learning of urban networks in daily activity-travel behavior are described, and finally an illustration of the model and the results of the numerical simulations designed to test the face validity of the part of the model concerned with attribute learning and limited forgetting are presented.

To illustrate the model, it is assumed that activity-travel schedule and route choices are given (i.e., handled by another model). According to this model, an agent travels with a private vehicle, consults a navigation system and uses the shortest path between origin and destination points.

A valid model is able to produce reliable results within its framework. The results of the face validation revealed that (as it should be) frequently observed activity locations retain in the memory longer than less observed activity locations (see Figure 4.13). This finding is also valid for landmarks; frequently
observed links and landmarks on these links have higher perception values (see Figure 4.16) and consequently, retain in the memory for a longer period of time. These findings support that the face validity is enabled and that processes and outcomes are reasonable and plausible within the framework of theoretical basis. However, in order to ensure the empirical validity, the parameters of the sensitivity function should be empirically estimated with real-world measurements, which will be explained in Chapter 5. After that, the model will be valid enough for testing with a larger sample and integrating into the multi-agent model.

It should be emphasized that the current numerical simulations are based on one scenario concerning a newcomer; for that reason, the initial probabilities are resulting from the beliefs of a newcomer. The socioeconomic situation of an individual affects the activity-travel schedule. For example, activity-travel schedule of a single person is different than a married person with a child. Similarly, the activity-travel schedule of an elderly is different than a teenager's. Therefore, when this model is integrated into the main multi-agent model framework, different types of agents will be represented in the system, and it will be possible to compare various perception updating processes.
5.1. Introduction

The aim of this chapter is to empirically test the validity of the modeling approach and to estimate the parameters of the sensitivity function (see Equation 3) using data specifically collected. An experiment and an additional survey are reported in this chapter. The experiment is originally designed and conducted by Wielens, Cenani, Kemperman, and Borgers (2011). Information with regard to this experiment can be found in the following section. Section 5.3 describes an additional survey in connection with the experiment, and is carried out to collect additional data needed to carry out the estimation method. This is followed by a section about the estimation method and then the results. Finally, the chapter is completed by a conclusion section with a discussion of the main findings.
5.2. Experiment

The experiment is conducted in the context of the study by Wielens, Cenani, Kemperman, and Borgers (2011). The goal of that study was to measure the effect of different navigation aids on spatial knowledge acquisition while walking through an unfamiliar environment. To that effect, several recollection and recognition tasks are implemented. Landmark, route and survey knowledge are measured via these tasks. The task explained in this section is one of the (landmark) recognition tasks. Recognition data alone does not suffice for estimation of the proposed Bayesian perception updating model. The Bayesian model to be estimated is about perception updating after an observation. This means that in addition data about initial probabilities (beliefs before an observation) are needed. Thus, two data sources are combined. In order to use the data about recognition to estimate a model of perception updating, it is assumed that the extent to which an individual recognizes a landmark after walking the route gives a scale about the individual’s belief of the presence of that landmark (after an observation). Then in the complementary survey, a new scale is used to measure the saliency of a landmark before an observation. As a result, additional data is collected and will be further explained in Section 5.3. In this section, the experiment is briefly described. In the next section, the complementary survey and estimation method will be discussed.

5.2.1. Experiment set-up

The experiment took place between November 2010 and January 2011 in Eindhoven, the Netherlands. Two circular routes were chosen in Eindhoven, the Netherlands. Both routes consisted of the same number of turns (10 turns), same length (1.6 km) and same land-use type (mostly residential buildings along with commercial buildings). Each participant walked one of the two predetermined routes, either with a paper map or an electronic navigation device, during daytime. Two experimenters carried out the whole experiment. One of them was responsible for the route task in the field, and the other experimenter was in charge of the cognitive task at the university.

The map of Eindhoven indicating two experiment locations can be seen in Figure 5.1, and aerial views of both experiment locations with routes are shown in Figure 5.2.
The experiment consisted of two parts: route (in-field) and cognitive tasks. After the completion of the route task, participants came to the university, where the cognitive tasks took place. The following tasks were performed by the participants:

Route (in-field) tasks:
- walking the route
- pointing out the three landmarks from the start point (after walking the route)

Cognitive tasks:
- sketching a map of the experiment location
- giving written wayfinding directions
- drawing the walked route on a map
- marking salient objects (e.g., landmarks) on a map
- landmark recollection using photographs
- ordering photographs of landmarks in the right sequence
- placing landmarks on a map
- the Santa Barbara Sense-of-Direction (SBSOD) scale test (Hegarty, Richardson, Montello, Lovelace, & Subbiah, 2002)

All participants did the tasks individually. Prior to scheduling of the experiment, all participants were asked a series of screening questions to ensure minimal experience with the experiment locations.
Figure 5.1 The map of Eindhoven showing two experiment locations
red area: Route-A, blue area: Route-B. (www.maps.google.com)

Figure 5.2 Aerial views of the experiment locations (www.maps.google.com)
5.2.2. Participants

Sixty undergraduate students (40 male and 20 female) from the Department of the Built Environment, Eindhoven University of Technology participated in the experiment and received partial course credit for their participation. The mean age of participants was 21.1 years (SD = 3.99). Thirty (20 male and 10 female) participants were randomly allocated to each experiment location. Then, these 30 participants were divided into two groups. One of the groups navigated through the environment with an electronic navigation device and the other group performed the same task with a paper map.

<table>
<thead>
<tr>
<th>Route-A (30)</th>
<th>Route-B (30)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paper map (15)</td>
<td>Paper map (15)</td>
</tr>
<tr>
<td>Electronic navigation device (15)</td>
<td>Electronic navigation device (15)</td>
</tr>
</tbody>
</table>

Figure 5.3 The number of participants

Participants did not have prior knowledge about both experiment locations as well as the tasks they performed. The experiment groups and the number of participants of each group are shown in Figure 5.3.

5.2.3. Materials

*NAVIGON 2510 Explorer* was given to the electronic navigation device group. The reason for choosing this device was the pedestrian navigation feature with e-compass; the map was automatically oriented to the direction the individual facing. This was an important difference from paper maps, because participants did not need to orient the map themselves. As a result, navigating should be less time consuming, making a cartographic mistake should be minimal and the most important, the need for landmarks to navigate and to orient should be less in electronic navigation device users.

The participants used the electronic navigation device in pedestrian mode. The route was uploaded beforehand and in order to limit the visibility of the experiment location, map display on the screen was fixed in advance; consequently they could not zoom-in or zoom-out. During the experiment, all
features of the device except for the street names and the North-arrow were turned off. On the screen, participants could only see an orange line that indicates the untraveled route, a green line which indicates traveled route, and an arrow that shows the current location. The tools used in the experiment can be seen in Figure 5.4.

![Tools used in the experiment: Navigon 2510 Explorer (www.navigon.com) and A4-size paper maps](image)

A printed paper map, which was taken from www.maps.google.com, was given to the other experiment group. The Google map was chosen because of the accuracy of the route information and the popularity of this service among young people. The route, the North-arrow and the street names were indicated on the map. However, the rest of the information such as landmarks was deleted (Figure 5.4).

5.2.4. Method

As indicated previously, the experiment includes a route (in-field) task and cognitive tasks. One of the cognitive tasks is the *landmark recollection task* and this task is used to get the updated probabilities (beliefs after an observation) about the landmarks.

After the route task, participants were given an envelope with 24 randomly numbered and placed cards at the university. These cards included photographs of landmarks that were taken from the experiment locations. Participants were asked whether they recognized these landmarks or not.
Furthermore, they were requested to indicate how sure they were about their choices on a scale ranging from 1 (i.e., very unsure) to 5 (i.e., very sure). The answer sheet containing the explanation of the task and the questions can be seen in Figure 5.5.
Figure 5.6 Landmarks on Route-A (left) and Route-B (right)

Figure 5.6 shows the locations of the landmarks on both routes as well as the walking direction. The following types of landmarks are used in the experiment:

- en-route landmarks (ERL)
- off-route (distant) landmarks (ORL)
- decision-point landmarks (DPL)
- street façades

In the following section, an additional study in connection with this experiment will be explained.

5.3. Survey

This section describes an additional study with regard to the previously mentioned experiment. It is conducted in October 2012 in Eindhoven, the Netherlands. The goal of this survey is to collect additional data needed to get the initial probabilities (beliefs before an observation) and the real-world measurements concerning the landmarks for the sensitivity function. Then, data gathered from both studies are used in the estimation, which will be explained in Section 5.4.

5.3.1. Context

The additional study consists of two parts: 1) data about saliency and 2) data about attributes of the landmarks involved. Data about saliency is collected via
5.3.2. Participants

A group of colleagues from Eindhoven University of Technology and acquaintances (in total 30 people) were sent an invitation to the survey via email, and 20 of them (10 female and 10 male) accepted to be a participant. All participants except one were unfamiliar with the experiment locations. Only one participant indicated that she was slightly familiar with two landmarks from Route-A. Since she was slightly familiar with only two landmarks from only one of the experiment locations, her responses were not removed.

5.3.3. Materials and method

The participants were given the maps of the experiment routes (Route-A and Route-B) indicating the locations of the landmarks, and the landmark cards (same as the cards used in the experiment) with the following explanation:

“Assume that you walked the marked route on the map. You are given 24 cards, which are arranged in the order of walking direction. Some of the pictures are taken at decision points (270° corner views), and the others are pictures of landmarks or 180° street views along the walked route.

Please indicate whether the location on the card is salient by specifying how strongly you agree are with the statement. Salient implies prominent, it may refer to the state or quality of an item that stands out relative to neighboring items. Salient objects have prominent features in the environment that are unique or contrast with their neighborhood. Consequently, salient objects are very useful for wayfinding; they can be used as recognition points (landmarks) for wayfinding (e.g., when the route has to be walked again).

In order to complete this task, please circle a number from 1 to 5, where 1 stands for "I am strongly disagree with this statement", 5
represents “I am strongly agree with this statement” and 3 is “I am neither agree nor disagree with this statement”.

*23 and 24 are not indicated on the map, as they belong to the other experiment location.”

Figure 5.7 Answer sheet for the saliency task (Route-A)

Participants state their opinions about the saliency of the location on the card, by specifying how strongly they agree with the given statement (i.e., this location is salient) on a scale ranging from 1 to 5. As an example, the two-page answer sheet for Route-A is shown in Figure 5.7. The first page includes a map of the experiment location indicating the route and the landmarks, and the second page consists of the explanation of the task and the question.

5.3.4. Visibility

As Equation (3) indicates, sensitivity of an observation depends on visibility and attention. In Equation (3), $V_{jk}$ represents the visibility of the object (i.e., landmark) from the current position of the observer on link $j$. $A_k$ is the amount of attention the observer pays to attributes of type $k$ on link $j$. Tables 5.1 and 5.2 show real-world measurements regarding the landmarks on Route-A and
Route-B, respectively. Visibility of a landmark has three attributes; distance ($D$), direction ($R$) and blockage ($B$). Following sections will further explain these attributes. Attention and its attributes will be described later.

**Distance**
In order to calculate the sensitivity of an observation, the shortest (straight-line) distance between the observer and the observed object (i.e., landmark) on each link is measured (Tables 5.1 and 5.2).

**Direction**
Direction of each landmark towards destination is measured and shown in Tables 5.1 and 5.2. It is assumed that forward-facing direction of the observer is north (e.g., the landmark is in front of the observer), thus observers facing north will have south behind them (e.g., the landmark is located behind the observer), east on their right (e.g., the landmark is on the right-hand side of the observer), and west on their left. For example, Landmark 1 on Route-A is located on north-west of the observer while facing the destination.

**Field-of-vision** is the entire area that a person is able to see with a fixed eye position. Humans have an almost 180° forward-facing horizontal field-of-vision. In the data set, direction ($R$) is either 1 or 0. If landmarks are situated on west, north-west (NW), north, north-east (NE) or east, then they are considered as in the field-of-vision of the observer ($R = 1$). On the other hand, if landmarks are situated on south-west (SW), south or south-east (SE), then it is assumed that these landmarks are outside the field-of-vision of the observer ($R = 0$).
<table>
<thead>
<tr>
<th>Landmark ID</th>
<th>Distance (m.)</th>
<th>Direction (towards destination)</th>
<th>Blockage (1=open view; 0=closed view)</th>
<th>Landmark type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landmark1</td>
<td>2</td>
<td>NW</td>
<td>1</td>
<td>DPL*</td>
</tr>
<tr>
<td>Landmark2</td>
<td>15</td>
<td>East</td>
<td>0.2</td>
<td>ERL*</td>
</tr>
<tr>
<td>Landmark3</td>
<td>2</td>
<td>NW</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark4</td>
<td>2</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark5</td>
<td>2</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark6</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark7</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark8</td>
<td>5</td>
<td>NW</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark9</td>
<td>2</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark10</td>
<td>6</td>
<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark11</td>
<td>8</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark12</td>
<td>8</td>
<td>North</td>
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<td>street façade</td>
</tr>
<tr>
<td>Landmark13</td>
<td>4</td>
<td>East</td>
<td>0.2</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark14</td>
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<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark15</td>
<td>2</td>
<td>NE</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark16</td>
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<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark17</td>
<td>30</td>
<td>SW</td>
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<td>ORL*</td>
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<tr>
<td>Landmark18</td>
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<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark19</td>
<td>2</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark20</td>
<td>2</td>
<td>NW</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark21</td>
<td>10</td>
<td>East</td>
<td>0.9</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark22</td>
<td>95</td>
<td>North</td>
<td>0.5</td>
<td>ORL</td>
</tr>
<tr>
<td>Landmark23</td>
<td>6</td>
<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark24</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
</tbody>
</table>

*DPL: decision-point landmark; ERL: en-route landmark; ORL: off-route (distant) landmark.*
<table>
<thead>
<tr>
<th>Landmark ID</th>
<th>Distance (m.)</th>
<th>Direction (towards destination)</th>
<th>Blockage (1=open view; 0=closed view)</th>
<th>Landmark type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landmark1</td>
<td>2</td>
<td>West</td>
<td>1</td>
<td>DPL*</td>
</tr>
<tr>
<td>Landmark2</td>
<td>16</td>
<td>East</td>
<td>1</td>
<td>ERL*</td>
</tr>
<tr>
<td>Landmark3</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark4</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark5</td>
<td>4</td>
<td>East</td>
<td>0.4</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark6</td>
<td>6</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark7</td>
<td>2</td>
<td>NW</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark8</td>
<td>4</td>
<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark9</td>
<td>230</td>
<td>South</td>
<td>0.8</td>
<td>ORL*</td>
</tr>
<tr>
<td>Landmark10</td>
<td>4</td>
<td>West</td>
<td>0.9</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark11</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark12</td>
<td>5</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark13</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark14</td>
<td>2</td>
<td>NE</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark15</td>
<td>6</td>
<td>West</td>
<td>0.6</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark16</td>
<td>6</td>
<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark17</td>
<td>8</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark18</td>
<td>15</td>
<td>NE</td>
<td>1</td>
<td>DPL</td>
</tr>
<tr>
<td>Landmark19</td>
<td>2</td>
<td>East</td>
<td>0.2</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark20</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
<tr>
<td>Landmark21</td>
<td>60</td>
<td>NW</td>
<td>0.5</td>
<td>ORL</td>
</tr>
<tr>
<td>Landmark22</td>
<td>4</td>
<td>West</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark23</td>
<td>2</td>
<td>East</td>
<td>1</td>
<td>ERL</td>
</tr>
<tr>
<td>Landmark24</td>
<td>2</td>
<td>North</td>
<td>1</td>
<td>street façade</td>
</tr>
</tbody>
</table>

*DPL: decision-point landmark; ERL: en-route landmark; ORL: off-route (distant) landmark.

**Blockage**

Many things can be perceived as obstacles. Various objects may block other objects, such as trees or other buildings. These obstacles may affect an observer’s spatial perception and thus, the sensitivity of an observation. As part of the on-site measurements, for each landmark, how much of a landmark is blocked by other objects is observed (Tables 5.1 and 5.2). In these tables,
“1” means no blockage between the landmark and the observer, and a value close to zero represents existence of one or more obstacles between the landmark and the observer. Additionally, if the landmark is undetectable from the location of the observer, then $B$ equals zero.

5.3.5. Attention

Attention is a selective behavior. Lang (1987) states that individuals attend to what they know and what they are motivated to recognize, and recognition depends on their previous experiences. As previously stated, sensitivity of an observation depends on visibility and attention. Previous section gave details on data for parameters about visibility, and here data for parameters related to attention will be explained.

**Saliency**

Salient objects have prominent features in the environment that are unique or contrast with their neighborhood. Salient objects are very useful for wayfinding, as they can be used as landmarks. Table 5.3 presents the averages across 20 participants, and is derived from the survey. These values are used as proxies of initial beliefs in the estimation.

**Decision point**

Four types of landmarks (DPL, ERL, ORL and street façade) are used in both experiments, and the classification of landmarks is originated from the studies explained in Chapter 3. As indicated in Chapter 4, $E_j$ is a binary variable in the sensitivity function (Equation 3), which indicates whether or not it is a decision point on link $j$. Landmark types shown in Tables 5.1 and 5.2 give this information.
Table 5.3 Saliency of a landmark on Route-A and Route-B

<table>
<thead>
<tr>
<th>Landmark ID</th>
<th>Route-A</th>
<th>Route-B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Saliency (initial)</td>
<td>Saliency (initial)</td>
</tr>
<tr>
<td>Landmark1</td>
<td>3.1</td>
<td>2.6</td>
</tr>
<tr>
<td>Landmark2</td>
<td>4</td>
<td>4.5</td>
</tr>
<tr>
<td>Landmark3</td>
<td>2.35</td>
<td>2.05</td>
</tr>
<tr>
<td>Landmark4</td>
<td>3.1</td>
<td>1.95</td>
</tr>
<tr>
<td>Landmark5</td>
<td>3.7</td>
<td>3.05</td>
</tr>
<tr>
<td>Landmark6</td>
<td>1.55</td>
<td>2.65</td>
</tr>
<tr>
<td>Landmark7</td>
<td>1.55</td>
<td>2.8</td>
</tr>
<tr>
<td>Landmark8</td>
<td>2.3</td>
<td>2.7</td>
</tr>
<tr>
<td>Landmark9</td>
<td>2.2</td>
<td>4.6</td>
</tr>
<tr>
<td>Landmark10</td>
<td>2.35</td>
<td>4.2</td>
</tr>
<tr>
<td>Landmark11</td>
<td>4.45</td>
<td>2.85</td>
</tr>
<tr>
<td>Landmark12</td>
<td>3.1</td>
<td>2.7</td>
</tr>
<tr>
<td>Landmark13</td>
<td>2.9</td>
<td>1.65</td>
</tr>
<tr>
<td>Landmark14</td>
<td>1.85</td>
<td>2.35</td>
</tr>
<tr>
<td>Landmark15</td>
<td>2.2</td>
<td>3.3</td>
</tr>
<tr>
<td>Landmark16</td>
<td>2.95</td>
<td>2.6</td>
</tr>
<tr>
<td>Landmark17</td>
<td>3.85</td>
<td>2.95</td>
</tr>
<tr>
<td>Landmark18</td>
<td>4.25</td>
<td>2</td>
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<tr>
<td>Landmark19</td>
<td>3.65</td>
<td>3.4</td>
</tr>
<tr>
<td>Landmark20</td>
<td>3.75</td>
<td>1.9</td>
</tr>
<tr>
<td>Landmark21</td>
<td>4.55</td>
<td>2.6</td>
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<tr>
<td>Landmark22</td>
<td>4.6</td>
<td>4.05</td>
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<tr>
<td>Landmark23</td>
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<td>2.8</td>
</tr>
<tr>
<td>Landmark24</td>
<td>1.95</td>
<td>1.65</td>
</tr>
</tbody>
</table>

5.4. Estimation method

The current and the following sections will report respectively the estimation method and results. In this section, two models are estimated. The first model is the Bayesian model of perception update, which is the same as Equation (1), and is used to estimate the parameters of the sensitivity function. Furthermore, a straightforward simple Binary logit model is estimated for comparison purposes. The proposed Bayesian model of perception updating to be estimated can be written as:
where $X = 1$ indicates the object is present, $Y$ indicates the outcome of the observation ($Y = 1$ the object has been observed, and $Y = 0$ the object has not been observed), and $\rho$ is the probability of an observation (belief). As explained in Section 5.2, the model to be estimated is about perception updating after an observation and the current data-set includes measurements about recognition of an object. The conditional probabilities on the right-hand side of the equation define the probability of observing an object given that it is present. Thus, the probabilities are a function of observation sensitivity of the individual (Equation 3). The following logit model is used for predicting the probabilities:

$$ P(Y = 1 | X = 1) = \frac{\exp(\theta)}{1 + \exp(\theta)} $$

(16)

$$ P(Y = 0 | X = 1) = \frac{1}{1 + \exp(\theta)} $$

(17)

The initial probability of an observation is modeled as a function of reported saliency, as follows:

$$ P(X = 1) = \frac{\exp(Z)}{1 + \exp(Z)} $$

(18)

where $Z$ is defined as:

$$ Z = a + b \ln(S) $$

(19)

where $a$ and $b$ are parameters to be estimated and $S$ is the reported saliency on a 5-point scale ($S = 1..5$). Thus, it is expected that $b < 0$, meaning the larger the saliency, the smaller the initial probability of observing the object. The log transformation is a proposal based on trying several functional forms: the log form resulted in the largest fit and was therefore adopted.
As an operationalization of Equation (3), sensitivity of an observation (\( \theta \)) is modeled as a function of attributes of the object:

\[
\theta = \delta + \sum_i \omega_i X_i
\]

(20)

where \( X_i \) are attributes (e.g., distance, decision point, saliency, direction, blockage), \( \delta \) (delta) and \( \omega_i \) (omega) are parameters (see also Equation 3). In Equation (3), function \( f(A, V) \) was not specified; here it is namely \( f(A, V) = f(A) + f(V) \) and Equation (20) is used to estimate the parameters of sensitivity function.

In addition to the first model, a straight-forward simple Binary logit model is used as a benchmark (for comparison purposes):

\[
P(X = 1 | Y = 1) = \frac{\exp(\theta)}{1 + \exp(\theta)}
\]

(21)

where \( \theta \) is defined as before. Note that this model reduces to the Bayesian model where the initial probability always equal one – i.e., where individuals ignore the base line probability of an observation.

5.5. Results

The models are estimated on a total of \( N = 1440 \) observations (60 participants x 24 landmarks). The NLM (Non-Linear Minimization) model in R (statistical computing environment) is used to find the parameters that maximize a log likelihood function. The dependent variable is given by two response variables in the data set: 1) Yes/no recognition of the object \( I \) and 2) The degree of certainty of the recognition on a 5-point scale \( C \):

\[
q = 0.5 + (0.09C) \quad \text{if} \quad I = 1
\]

(22)

\[
q = 0.5 - (0.09C) \quad \text{if} \quad I = 0
\]

(23)

where \( q \) is the calculated reported probability of remembering corresponding to the posterior belief \( P(X | Y) \), \( C \) is the degree of certainty and \( I \) is yes/no
recognition. This is a simple linear model where \( q \) runs from 0.05 \((C = 5 \text{ and } I = 0)\), to 0.5 \((C = 1 \text{ and } I = 0, \text{ or } C = 1 \text{ and } I = 1)\) to 0.95 \((C = 5 \text{ and } I = 1)\).

The continuous measure, \( q \), uses more information than the binary measure, \( I \). However, the binary measure may be more robust for the same reason. Therefore, both measures are tested in estimations.

Table 5.4 Estimation results: binary recognition assumption \((I)\)

<table>
<thead>
<tr>
<th>Metric</th>
<th>Binary logit value</th>
<th>t-value</th>
<th>Bayesian value</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant (delta)</td>
<td>-4.17</td>
<td>-7.25</td>
<td>-4.15</td>
<td>-0.02</td>
</tr>
<tr>
<td>Distance</td>
<td>0.26</td>
<td>3.02</td>
<td>0.18</td>
<td>1.97</td>
</tr>
<tr>
<td>Decision point</td>
<td>0.99</td>
<td>5.83</td>
<td>1.20</td>
<td>6.93</td>
</tr>
<tr>
<td>Saliency</td>
<td>0.27</td>
<td>3.48</td>
<td>2.83</td>
<td>6.15</td>
</tr>
<tr>
<td>Direction</td>
<td>1.05</td>
<td>2.78</td>
<td>1.34</td>
<td>3.34</td>
</tr>
<tr>
<td>Blockage (1: open view)</td>
<td>2.48</td>
<td>8.93</td>
<td>2.19</td>
<td>7.66</td>
</tr>
<tr>
<td>(a)</td>
<td></td>
<td></td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>(b)</td>
<td></td>
<td></td>
<td>-7.23</td>
<td>-5.66</td>
</tr>
<tr>
<td>LL0</td>
<td>-979.5</td>
<td></td>
<td>-1274.2</td>
<td></td>
</tr>
<tr>
<td>Lfinal</td>
<td>-877.9</td>
<td></td>
<td>-861.3</td>
<td></td>
</tr>
<tr>
<td>rho-squared</td>
<td>0.12</td>
<td></td>
<td>0.48</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.4 shows the estimation results for the binary recognition assumption \((I)\). In Table 5.4, the parameter estimates for the Bayesian model indicate that all attributes have a positive effect on recognition: distance (unexpected), decision point (expected), saliency (expected), direction (expected) and blockage (expected). Distance is a continuous attribute and estimation results unexpectedly indicate that if the distance between the landmark and the observer increases, the recognition increases as well. This may be caused by the specific distribution of very well-known distant (off-route) landmarks in the experiment environment (e.g., blob-shaped building, a high-rise building with a big company sign on the roof, etc.). According to the results, a landmark located on a decision point is recognized more. As expected, objects located on decision points tend to be remembered more easily than others. Also it is easier to recall a landmark, if it has salient features. Direction is a binary variable (forward-facing field-of-vision of the observer = 1). The outcome with regard to direction is as expected: if the landmark is ahead of the observer, it is
recognized more. Blockage is a continuous attribute, which has a value between 1 and 0 (1 represents an open view and 0 corresponds to a blocked view). Estimates show that the less the blockage between the landmark and the observer, the more the recognition. As indicated in the previous section, \( b \) (Equation 19) was expected to be smaller than zero, and the results support this expectation. Saliency has a negative effect on the initial probability (expected). The comparison of the models suggests that including the initial probability increases the fit of the model substantially (rho squares increase from 0.12 to 0.48).

Table 5.5 Estimation results: continuous recognition assumption (\( q \))

<table>
<thead>
<tr>
<th></th>
<th>Binary logit</th>
<th></th>
<th>Bayesian</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>value</td>
<td>t-value</td>
<td>value</td>
<td>t-value</td>
</tr>
<tr>
<td>Constant (delta)</td>
<td>-5.33</td>
<td>-6.32</td>
<td>-5.18</td>
<td>-0.25</td>
</tr>
<tr>
<td>Distance</td>
<td>0.38</td>
<td>2.80</td>
<td>0.24</td>
<td>1.62</td>
</tr>
<tr>
<td>Decision point</td>
<td>2.28</td>
<td>3.72</td>
<td>2.60</td>
<td>4.07</td>
</tr>
<tr>
<td>Saliency</td>
<td>0.32</td>
<td>2.55</td>
<td>4.63</td>
<td>5.14</td>
</tr>
<tr>
<td>Direction</td>
<td>1.59</td>
<td>2.86</td>
<td>2.08</td>
<td>3.14</td>
</tr>
<tr>
<td>Blockage (1: open view)</td>
<td>3.14</td>
<td>7.70</td>
<td>2.79</td>
<td>5.65</td>
</tr>
<tr>
<td>( a )</td>
<td>-0.10</td>
<td></td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>( b )</td>
<td>-12.24</td>
<td></td>
<td>-4.81</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.5 shows the estimation results for continuous recognition assumption (Equations 22 and 23). As seen in Table 5.5, similar results are achieved; however, distance is no longer significant (<1.96). The rest of the attributes have a positive effect on recognition. The \( b \) is also smaller than zero, as expected. Here again, rho squares increase from 0.14 to 0.45, which means that the fit of the model increased considerably, with the inclusion of the initial probability.

5.6. Conclusions

In this chapter, two studies are briefly reported. This is followed by a description of the estimation method and then the results. In order to estimate
the model, the data of the landmark recollection task from the experiment and an additional survey connected to the experiment were used in the model estimation.

Two estimates are conducted according to binary recognition assumption (Table 5.4) and continuous recognition assumption (Table 5.5). Also, a simple binary logit model is estimated (for comparison purposes). Results with regard to the first assumption (Table 5.4) indicate that distance, decision point, saliency, direction and blockage have a positive effect on recognition. Similar results are achieved for the continuous recognition assumption; all attributes except distance is significant (Table 5.5). These findings show that the model fits the data satisfactorily and results are reasonable. The comparison (Bayesian model versus binary logit model) shows that the model improves when prior probabilities are taken into account, which provides evidence for the Bayesian model. To conclude, the Bayesian model is valid enough to integrate with the multi-agent model in the future.
6.1. Summary and conclusions

Shortcomings of the existing activity-based models of travel demand have led to the need of developing dynamic activity-travel models. Considering that existing models do not pay enough attention to spatial cognition and that research on modeling cognitive learning of urban networks is still limited, this situation presents an opportunity for exploring the dynamics of spatial relations of an environment with its habitants and developing applications of such models. For these reasons, the modeling approach introduced in this dissertation is believed to be a vital contribution to these models.

The aim of the research project, therefore, is to develop and test a modeling approach for cognitive learning of urban networks in daily activity-travel behavior. Arentze and Timmermans (2005) developed a model based on Bayesian belief networks for representing mental maps and cognitive learning into micro-simulation models of activity-travel behavior. However, their study was not integrated into a comprehensive framework, and some parts were left
for future studies. Following their study, a modeling approach to simulate perception updating based on individual observations in the built environment is proposed in this dissertation. Their approach is revised to be able to integrate into a large-scale multi-agent framework and sensitivity of an observation is further detailed in this dissertation with the inclusion of an important aspect, landmarks. One of the important aspects of this research project is to explore the impacts of landmarks on spatial cognition. An illustration of the part of the model concerned with attribute learning and limited forgetting, and also the estimation of the parameters of the sensitivity function are explained in this dissertation.

Following the introductory chapter, Chapter 2 reviewed the state-of-the-art progress in activity-travel behavior research. The purpose of this chapter was to explain the existing activity-travel models, to highlight their shortcomings, and why it was important to include cognitive learning in these models.

Chapter 3 described human spatial behavior. This chapter briefly reviewed the existing literature on human spatial behavior and the development of spatial cognition. The theories on spatial knowledge and the empirical studies related to these theories explained in this chapter shaped the framework of this research project.

Chapter 4 reported basic notions and the motivation behind the cognitive learning model. This chapter described a model of how spatial information is processed in human beings and presented the design of a modeling approach for cognitive learning of urban networks in daily activity-travel behavior. In this chapter, the key mechanisms of the model were described, and the results of the numerical simulations designed to test the validity of the part of the model concerned attribute learning (with limited memory retention) were presented. The current model used an implemented activity-travel schedule, and it was assumed that route choice was handled by another model. As explained in Chapter 4, an agent traveled with his private vehicle, consulted a navigation system and used the shortest path between origin and destination points. After having implemented the schedule, the agent updated the probabilities based on the perception results of the observations. The results showed that frequently observed activity locations retain in the memory longer than less observed activity locations. Similarly, frequently observed links and the
landmarks on these links had higher perception values and as a result, kept in the memory for a longer period of time. Findings indicated that familiarity with the city leads to a stabilization (on an optimum level) in the learning curve. In brief, the face validity of the modeling approach was enabled by the results of these numerical simulations. Results indicated that processes and outcomes are reasonable within the framework of theoretical basis.

The purpose of Chapter 5 was to empirically estimate the parameters of the sensitivity function of the model described in Chapter 4. In this chapter, an experiment was briefly explained. However, in order to estimate the parameters, additional data had to be collected using a survey that was designed specifically for this purpose. This chapter reported the design of these two studies, estimation method and then showed main findings.

To summarize, the research reported in this dissertation led to a better understanding of the dynamics of spatial relations of an environment with its habitants. Additionally, it led to gain insight in individuals' behavioral mechanisms of daily activity-travel patterns and in their learning processes. Numerical simulations and the model that was estimated in this dissertation showed that the proposed model was valid enough to combine it with the multi-agent model.

6.2. Discussion and directions for future research

In addition to those described above, current section will discuss the contributions of the modeling approach, what still can be improved in the model and how this improvement can be achieved.

The approach proposed in this dissertation offers a way to incorporate behavioral mechanisms in an enhanced model for simulating learning of urban networks in daily activity-travel behavior. Current illustration of the model is focused on the part on attribute learning and limited forgetting; however there is still room for improvement.

It is believed that the research described in this dissertation is an important contribution, not only for developing dynamic activity-based transportation models, but also to enable further development in the field of spatial cognition. However, the research objectives are partially met. A conceptual model of
cognitive learning was presented in Chapter 4. The idea is that by performing so-called activity schedules an agent updates its knowledge about the urban network. The only aspect that has been empirically tested is the recognition of landmarks (Chapter 5). Although this is an important step, additional research is required to find out how the recognition of landmarks and links affects an agent's cognitive map (which is used to generate and execute activity schedules).

This dissertation presents the design and initial empirical results of a study conducted within certain restrictions. Learning of activity locations and landmarks (points), and learning of links between these points are investigated in this dissertation. As a result, it is believed that a significant step in learning of urban networks is achieved. However, in order to validate the modeling approach, several features of the model are simplified. The rest of the features are remained to be estimated in the future. As an example, it is assumed that route choices (and transport mode choices) are known beforehand via external information sources. Even though exploration behavior is conceptually included in the model system, it is yet to be empirically tested. By the inclusion of such features, the development of cognitive maps will be fully investigated and thus all research objectives will be completely achieved.

After the face validation, an obvious next step was the empirical validation of the model. In order to do that, the parameters of the sensitivity function were empirically estimated with the real-world measurements. The experiment explained in Chapter 5 was originally designed for a study by Wielens, Cenani, Kemperman, and Borgers (2011), and the data used to estimate the parameters of the sensitivity function of the cognitive learning model was taken from that study. In addition to that data collection, several on-site measurements and an additional survey were conducted recently. However, the goal of their study was to explore the differences in spatial knowledge acquisition while using an electronic navigation device and traditional map. As a result, the tasks as well as the experiment method were specifically designed accordingly. However, current research project is different when compared with their study. Therefore, some improvements can be done to the data collection in the future. The empirical testing of the cognitive learning model requires repetitive tasks. This means that participants should repeat both in-field (route) and cognitive tasks several times, in order to observe their learning processes over time. Thus, it
could be possible to monitor the process during cognitive map development and spatial learning acquisition. One would assume that both the accuracy and the details of the cognitive maps should increase after several trips. Furthermore, as an additional task, the participants can do the route task without help from any kind of information source, which means that they should be able to complete the round-trip without any navigational aid. By this way, it can be seen whether they gained advanced spatial knowledge or not. Moreover, the practical application of the model can be improved with a larger sample size and by diversifying the socio-demographic structure of the sample.

Future research can focus on the extent to which transport modes and route choices influence spatial learning. For example, the number and the type of the landmarks can be different for a car driver and a pedestrian. This may be the result of speed (while driving, there is not enough time to pay attention to landmarks as much as while walking) or may be caused by differences due to the routes (neighborhoods surrounding a bicycle path and a highway may be different). Furthermore, some routes can be more attractive (e.g., scenic route, route with shopping locations, recommended route by a social contact) or less attractive (e.g., unsafe route, traffic congestion, etc.) than other routes. Therefore, another topic needs further attention is to incorporate the effects of individual preferences on route choices into the model.

In the future, environmental dynamics (impacts of seasonal changes or different times of the day on route choices) can be investigated. Examining the same sample for a longer period can give important insight on spatial learning processes. Data collection via GPS trackers is getting more attention in recent studies (Moiseeva, Jessurun, & Timmermans, 2010), as a result of the ease of tracking many people at the same time. Yet, there are still some issues need to be resolved, such as controlling the accuracy of the information gathered via GPS trackers and having difficulties in finding participants (due to heavy workload for both participants and the researcher during data cleaning).

In summary, findings reported in this dissertation suggest that individuals develop spatial knowledge over time by implementing their activity-travel schedules. Findings are as expected; meaning they are in line with existing literature on spatial cognition, therefore the proposed model simulates learning processes properly and the modeling approach is valid enough to
integrate into future multi-agent model. It is believed that better understanding of the development of spatial cognition of urban networks and the inclusion of the suggested modeling approach to the activity-based models of travel demand may provide new insights into the planning practice in the future.


development of metric knowledge and the integration of separately learned places. *Cognitive Psychology, 52*, 93-129.


**AUTHOR INDEX**

<table>
<thead>
<tr>
<th>Author</th>
<th>Pages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acacio, J.</td>
<td>25</td>
</tr>
<tr>
<td>Alberts, D. M.</td>
<td>2, 22</td>
</tr>
<tr>
<td>Allen, G. L.</td>
<td>26</td>
</tr>
<tr>
<td>Anderson, J. R.</td>
<td>43, 44</td>
</tr>
<tr>
<td>Appleyard, D.</td>
<td>18, 21, 22</td>
</tr>
<tr>
<td>Arentze, T. A.</td>
<td>2, 3, 6, 8, 31, 33, 40, 43, 53, 85</td>
</tr>
<tr>
<td>Auld, J.</td>
<td>6, 7</td>
</tr>
<tr>
<td>Axhausen, K. W.</td>
<td>2, 6, 7, 8</td>
</tr>
<tr>
<td>Balmer, M.</td>
<td>6</td>
</tr>
<tr>
<td>Ben-Akiva, M. E.</td>
<td>6</td>
</tr>
<tr>
<td>Bertolo, L.</td>
<td>23, 24</td>
</tr>
<tr>
<td>Bhat, C. R.</td>
<td>6</td>
</tr>
<tr>
<td>Book, A</td>
<td>27</td>
</tr>
<tr>
<td>Borgers, A</td>
<td>13, 14, 65, 66, 87, 88</td>
</tr>
<tr>
<td>Bovy, P. H.</td>
<td>13, 17</td>
</tr>
<tr>
<td>Bowman, J. L.</td>
<td>6</td>
</tr>
<tr>
<td>Cenani, S.</td>
<td>8, 23, 24, 33, 65, 66, 87, 88</td>
</tr>
<tr>
<td>Chapin, F. S.</td>
<td>6</td>
</tr>
<tr>
<td>Clarke, M. I.</td>
<td>6</td>
</tr>
<tr>
<td>Cornell, E. H.</td>
<td>2, 22</td>
</tr>
<tr>
<td>Cornoldi, C.</td>
<td>23, 24</td>
</tr>
<tr>
<td>Couclelis, H.</td>
<td>17</td>
</tr>
<tr>
<td>Davies, C.</td>
<td>14</td>
</tr>
</tbody>
</table>
AUTHOR INDEX

Denis, M. ................. 23, 24, 25, 26
Devlin, A. S. .................. 21
Dijkstra, J. ...................... 35
Dix, M. C. ...................... 6
Downs, R. M. ................. 20

E
Ettema, D. ................... 6
Evans, G. W. ............... 19, 27, 29

F
Fontaine, S. .................. 25
Fujii, S. ....................... 6
Fujiwara, H. ................. 26

G
Gale, N. ....................... 17
Hägerstrand, T. ............ 2, 24, 27
Golledge, R. G. .... 2, 12, 15, 17, 24, 25, 26, 27, 32, 38
Guo, J. Y...................... 6

H
Habib, K. M. .................. 6
Hägerstrand, T. ............. 6
Hamed, M. M. ............... 8
Hanley, G. L. ............... 20
Hardy, J. K. .................. 18
Hayes-Roth, B. ............. 19, 20
Hegarty, M. ... 20, 23, 24, 26, 27, 67
Heggie, I. G.................. 6
Heth, C. D. ................... 2, 22
Hirter, S. C. ................. 18, 26
Hofmann-Wellenhof, B. ... 26
Hund, A. M. ................. 25
Hutchinson, B. G......... 6

I
Iachini, T. ................... 27
Imai, O. ..................... 26
Ishikawa, T............... 2, 26

J
Jessurun, J................... 89
Joh, C. H. .................... 6
Jones, P. M.................. 6

K
Kallai, J. ..................... 24
Kemperman, A. D.... 65, 66, 87, 88
Kikuchi, A. ................. 6
Kitamura, R. ............... 6
Klippel, A. ............... 23, 24, 26
Klügl, F. ................. 45
Kuse, A. R.................. 42

L
Lang, J. T.................. 12, 20, 78
Lapin, E. A. ................ 27
Law, A. M. .................. 45
Lawton, C. A. .............. 24, 25
Legat, K. .................... 26
Leiser, D. .................. 16, 17
Lenntorp, B. ............... 6
Leon, C. .................. 25
Levine, M. ................. 20
Logie, R. H.................. 27
Loomis, J. M............... 19
Lovelace, K... 23, 24, 25, 26, 27, 67
Lynch, K....... 13, 18, 22, 23, 24, 42

M
Makar, R. O............... 25
Mannering, F. L........... 8
Marchon, I. ......................... 20
McNamara, T. P. . 16, 18, 24, 26, 41
Meister, K. ......................... 6
Miller, E. J. ......................... 6
Millonig, A. ........... 25, 27, 28
Mohammadian, A. ....... 6, 7
Moiseeva, A. ............. 89
Montello, D. R. .... 2, 14, 20, 23, 24, 25, 26, 27, 67

N
Nagel, K. .................... 6
Newell, A. ................. 38

O
Okabe, A. .................. 26

P
Pazzaglia, F. .......... 23, 24
Pederson, E. .......... 14
Pendyala, R. M. .... 6
Peruch, P. ............. 27
Pezdek, K. ............... 19

R
Richardson, A. E........ 20, 67
Rieser, M. ............... 6
Roorda, M. J. ............ 6
Rosenbloom, P. S..... 38
Rump, B. ............. 16, 18, 24, 26

S
Schechtner, K. ........... 25, 27, 28
Schönfelder, S. ........ 2, 7, 8
Self, C. M. ............. 25
Sholl, M. J. ............ 25
Siegel, A. W. ...... 15, 16, 22, 32, 33
Sivakumar, A. .......... 6
Sluzenski, J. ......... 16, 18, 24, 26
Snellen, D. .......... 13, 14
Sorrows, M. E. ....... 26
Srinivasan, S. ....... 6
Stea, D. ................. 20
Steinitz, C. ........... 20
Stern, E. ............. 13, 16, 17
Stimson, R. J. ....... 2, 12
Subbiah, I. ........... See

T
Thorndyke, P. W. 15, 16, 19, 20, 32, 33
Timmermans, H. J. P... 2, 3, 6, 7, 8, 13, 14, 23, 24, 31, 33, 35, 40, 43, 53, 85, 89
Tobler, W. ............... 17
Tolman, E. C. ........... 20
Tversky, B. ............. 18

V
Valiquette, C. M. .... 41
Vandenberg, S. G. .... 42

W
Waller, D. ................. 41
White, S. H. .......... 15, 16, 22, 32, 33
Wielens, N. J. 20, 21, 65, 66, 87, 88
Wieser, M. ............ 26
Winter, S. .............. 23, 24, 26
Worchel, P. ........... 16, 19

Y
Yamamoto, T. ....... 6
<table>
<thead>
<tr>
<th>Subject</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>destination</td>
<td>7, 18, 26, 34, 47, 62, 75, 76, 77, 86</td>
</tr>
<tr>
<td>direction</td>
<td>14, 16, 26, 41, 42, 43, 69, 72, 73, 75, 81, 82, 84</td>
</tr>
<tr>
<td>distance</td>
<td>16, 22, 39, 41, 42, 46, 56, 60, 73, 75, 81, 82, 83, 84</td>
</tr>
<tr>
<td>distant landmark</td>
<td>23, 25</td>
</tr>
<tr>
<td>dynamics</td>
<td>3, 5, 8, 35, 87</td>
</tr>
<tr>
<td>en-route</td>
<td>23, 24, 72, 76, 77</td>
</tr>
<tr>
<td>environment</td>
<td>2, 8, 12, 13, 16, 17, 21, 25, 26, 27, 28, 78</td>
</tr>
<tr>
<td>exploration</td>
<td>34, 35, 42, 61</td>
</tr>
<tr>
<td>familiarity</td>
<td>13, 21, 28, 87</td>
</tr>
<tr>
<td>forgetting</td>
<td>40, 43, 44, 45, 53, 56, 59, 60, 62, 86, 87</td>
</tr>
<tr>
<td>ICT</td>
<td>1, 8, 33</td>
</tr>
<tr>
<td>illustration</td>
<td>45, 46, 47, 51, 53, 56</td>
</tr>
<tr>
<td>initial probability</td>
<td>40, 53, 59</td>
</tr>
<tr>
<td>landmark</td>
<td>22, 23, 26, 34, 42, 47, 51, 53, 62</td>
</tr>
<tr>
<td>link</td>
<td>34, 40, 41, 42, 43, 44, 51, 53, 62</td>
</tr>
<tr>
<td>memory decay</td>
<td>43, 62</td>
</tr>
<tr>
<td>memory retention</td>
<td>43, 86</td>
</tr>
<tr>
<td>mobility</td>
<td>6</td>
</tr>
<tr>
<td>multi-agent</td>
<td>3, 6, 36, 63, 84, 86, 87, 90</td>
</tr>
<tr>
<td>N</td>
<td>navigation</td>
</tr>
<tr>
<td>neighborhood</td>
<td>23, 43, 78</td>
</tr>
<tr>
<td>network</td>
<td>1, 2, 8, 13, 14, 17, 35, 37, 38, 39, 51, 53, 88</td>
</tr>
<tr>
<td>newcomer</td>
<td>46, 52, 57</td>
</tr>
<tr>
<td>node</td>
<td>23, 51</td>
</tr>
<tr>
<td>O</td>
<td>object learning</td>
</tr>
<tr>
<td>observation</td>
<td>2, 34, 40, 41, 44, 45, 61, 62</td>
</tr>
<tr>
<td>obstacle</td>
<td>18, 39, 41, 77, 78</td>
</tr>
<tr>
<td>off-route</td>
<td>23, 24, 72, 76, 77, 82</td>
</tr>
<tr>
<td>orientation</td>
<td>13, 23, 24, 28, 38, 43</td>
</tr>
<tr>
<td>P</td>
<td>perception</td>
</tr>
<tr>
<td>perception updating</td>
<td>9, 32, 33, 56, 63, 66, 79, 80, 86</td>
</tr>
<tr>
<td>point</td>
<td>16, 17, 20, 22, 23, 25, 34, 43, 44, 51</td>
</tr>
<tr>
<td>probability</td>
<td>1, 40, 41, 43, 52, 53, 57, 59, 61, 80, 81, 82, 83, 84</td>
</tr>
<tr>
<td>R</td>
<td>representation</td>
</tr>
<tr>
<td>route choice</td>
<td>7, 13, 34, 47, 86</td>
</tr>
<tr>
<td>S</td>
<td>saliency</td>
</tr>
<tr>
<td>salient</td>
<td>42, 67, 73, 74, 83</td>
</tr>
<tr>
<td>scenario</td>
<td>2, 51, 63</td>
</tr>
<tr>
<td>Subject</td>
<td>Pages</td>
</tr>
<tr>
<td>------------------</td>
<td>-------</td>
</tr>
<tr>
<td>sensitivity</td>
<td>40, 41, 42, 44, 46, 56, 62</td>
</tr>
<tr>
<td>shopping</td>
<td>1, 15, 32, 42, 46, 49, 59, 89</td>
</tr>
<tr>
<td>short-cut</td>
<td>16</td>
</tr>
<tr>
<td>simulation</td>
<td>3, 6, 45, 85</td>
</tr>
<tr>
<td>spatial behavior</td>
<td>4, 11, 16, 18, 19, 21, 26, 28, 29, 31, 86</td>
</tr>
<tr>
<td>spatial cognition</td>
<td>3</td>
</tr>
<tr>
<td>spatial knowledge</td>
<td>2, 15, 16, 17</td>
</tr>
<tr>
<td>spatial learning</td>
<td>16, 19, 21</td>
</tr>
<tr>
<td>spatial memory</td>
<td>11, 18, 19, 26, 28, 42</td>
</tr>
<tr>
<td>transportation</td>
<td>6, 7, 9, 47, 50, 87</td>
</tr>
<tr>
<td>trip</td>
<td>6, 13, 16, 27, 34, 42, 47, 89</td>
</tr>
<tr>
<td>U</td>
<td>7</td>
</tr>
<tr>
<td>uncertainty</td>
<td>11, 13, 14, 15</td>
</tr>
<tr>
<td>urban form</td>
<td>11, 13, 14, 15</td>
</tr>
<tr>
<td>urban network</td>
<td>1, 2, 3, 8, 9, 29, 31, 62, 85, 86, 87, 88, 90</td>
</tr>
<tr>
<td>urban planning</td>
<td>5, 6, 29, 31</td>
</tr>
<tr>
<td>V</td>
<td>45, 46</td>
</tr>
<tr>
<td>validation</td>
<td>22, 41, 60, 69, 74, 78</td>
</tr>
<tr>
<td>W</td>
<td>13, 23, 24, 25, 28, 35, 42, 78</td>
</tr>
</tbody>
</table>
Limitations in the current comprehensive activity-based models of travel demand, have led to the need of developing dynamic activity-based models. Unlike current models, dynamic models will simulate how changes in personal and household characteristics, exogenous or endogenous changes in urban and transportation environments may trigger adaptation in activity-travel behaviors. For modeling short-term dynamics, it is important to realize that individuals make decisions on the basis of their beliefs of their environment. These beliefs are not necessarily compatible with the real-world. Moreover, they change over time as people learn and forget. In the context of activity-based modeling, both cognitive learning of locations and of networks are important. Both topics have received little attention from a modeling perspective. An assessment of studies in this area indicates that current activity-travel models do not contain development of dynamic cognitive maps and their relationships with different aspects of activity-travel patterns. Research on modeling cognitive learning of activity-travel patterns is still limited to date. Therefore, exposing the dynamics of spatial relations of an
environment with its habitants and developing applications of these models remain challenging tasks and thus, the model described in this dissertation is a vital contribution to such models.

The model proposed here is one of the layers of a large-scale multi-agent model that is capable of handling short-term, mid-term and long-term dynamics. Daily scheduling decisions are dependent on the state of the agent and, at the same time, implementing a schedule can change an agent’s state. After having implemented the schedule, an agent updates its knowledge about transport networks, transport modes and route networks, and develops habits for implementing these activities (e.g., habitual routes). At the beginning of each day, an agent generates a schedule and during the day, it executes the schedule in space and time. When there is an unexpected event, the agent makes adaptations to its schedule (within-day re-planning). At any decision moment during the implementation process, memory receives perception results of the observations made so far and beliefs are updated. Also, at the end of the day, beliefs are updated according to the observations made during traveling and conducting activities at locations, simulating learning especially through exploration and/or encountering unexpected events during the day.

The model described in this dissertation predicts spatial learning processes of individuals using their activity-travel patterns, and simulates their perception updating procedures for different activity locations and landmarks. Results of the numerical simulations designed to test the face validity of the part of the model concerned with attribute learning and limited forgetting are presented in this dissertation. Results revealed that, as expected, frequently observed activity locations retain in the memory longer than less observed activity locations. Similarly, frequently observed links and landmarks are preserved in the memory for a longer period of time.

The NLM (Non-Linear Minimization) model is used to find the parameters that maximize a log likelihood function. The model estimation includes two estimates, and they are conducted according to binary recognition assumption and continuous recognition assumption. Also, a simple binary logit model is estimated (for comparison purposes). Estimation results show that the Bayesian model fits the data satisfactorily and results are reasonable. The
comparison of the Bayesian model with binary logit model shows that model improves when prior probabilities are taken into account.

In conclusion, the proposed model is valid enough to integrate with the multi-agent model. Research reported in this dissertation led to a better understanding of learning processes of individuals, and particularly, incorporating behavioral mechanisms in a model of cognitive learning through activity-travel behaviors.
Sehnaz Cenani Durmazoglu was born on April 22nd, 1979 in Gaziantep, Turkey. She studied Architectural Restoration at Mimar Sinan Fine Arts University in Istanbul, and graduated with honors in 2000. She also holds a Bachelor of Science degree in Architecture. After graduating with honors in 2004 at the Department of Architecture, Istanbul Technical University in Istanbul, she started her Master of Science study at the Architectural Design Computing Program, Istanbul Technical University in Istanbul, Turkey. In 2007, for six months, within the ERASMUS exchange program, she studied at the Department of Building Technology, Delft University of Technology. The topic of her thesis was agent-based representation of user movements in shopping malls. She graduated with honors in 2007.

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Her research interests are cognitive processes in individuals’ daily activity-travel behaviors, spatial cognition, travel behavior, design and decision support system development, generative design, and shape grammars.
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Kees Noort

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A.J. Bosch

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A. Nauta
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Strukturierung und Verwerking van Tijdgegevens voor de Uitvoering van Bouwwerken
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Stedebouw en de Vorming van een Speciale Wetenschap
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Informatica en Ondersteuning van Ruimtelijke Besluitvorming
G.G. van der Meulen

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Staal in de Woningbouw, Korrosie-Bescherming van de Begane Grondvloer
Edwin J.F. Delsing

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Een Thermisch Model voor de Berekening van Staalplaatbetonvloeren onder Brandomstandigheden
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De Wijkgedachte in Nederland: Gemeenschapsstreven in een Stedebouwkundige Context
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Diaphragm Effect of Trapezoidally Profiled Steel Sheets: Experimental Research into the Influence of Force Application
Andre W.A.M.J. van den Bogaard

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Versterken met Spuit-Ferrocement: Het Mechanische Gedrag van met Spuit-Ferrocement Versterkte Gewapend Betonbalken
K.B. Lubir
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De Tractaten van
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G. van Zeyl

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Wonen onder een Plat Dak:
Drie Opstellen over Enkele
Vooronderstellingen van de
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K. Doevendans

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Supporting Decision Making Processes:
A Graphical and Interactive Analysis of
Multivariate Data
W. Adams

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Self-Help Building Productivity:
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by Low-Income Groups Applied to Kenya
1990-2000
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De Verdeling van Woningen:
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Vincent Smit

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Flexibiliteit en Kosten in het Ontwerpproces:
Een Besluitvormingondersteunend Model
M. Prins

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Spontane Nederzettingen Begeleid:
Voorwaarden en Criteria in Sri Lanka
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Fundamentals of the Design of
Bamboo Structures
Oscar Arce-Villalobos

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Concepten van de Bouwkunde
M.F.Th. Bax (red.)
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Meaning of the Site
Xiaodong Li

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Het Woonmilieu op Begrip Gebracht:
Een Speurtocht naar de Betekenis van het
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Urban Environment in Developing Countries
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Strategische Plannen voor de Stad:
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Stedebouwkunde en Stadsbestuur
Piet Beekman

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De Architectuur van Djenné:
Een Onderzoek naar de Historische Stad
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Conjoint Experiments and Retail Planning
Harmen Oppewal

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Strukturformen Indonesischer Bautechnik:
Entwicklung Methodischer Grundlagen
für eine 'Konstruktive Pattern Language'
in Indonesien
Heinz Frick arch. SIA

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Styles of Architectural Designing:
Empirical Research on Working Styles
and Personality Dispositions
Anton P.M. van Bakel

nr 35
Conjoint Choice Models for Urban
Tourism Planning and Marketing
Benedict Dellaert

nr 36
Stedelijke Planvorming als Co-Produktie
Helga Fassbinder (red.)
nr 60
Merlin: A Decision Support System for Outdoor Leisure Planning
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Urban Form and Activity-Travel Patterns
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Design Research in the Netherlands 2000
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Computer Aided Dimensional Control in Building Construction
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Das Globalrecyclingfähige Haus
Hans Löfflad

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Cool Schools for Hot Suburbs
René J. Dierkx

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A Bamboo Building Design Decision Support Tool
Fitri Mardjono

nr 69
Driving Rain on Building Envelopes
Fabien van Mook

nr 70
Heating Monumental Churches
Henk Schellen

nr 71
Van Woningverhuurder naar Aanbieder van Woongenot
Patrick Dogge

nr 72
Moisture Transfer Properties of Coated Gypsum
Emile Goossens

nr 73
Plybamboo Wall-Panels for Housing
Guillermo E. González-Beltrán

nr 74
The Future Site-Proceedings
Ger Maas
Frans van Gassel

nr 75
Radon transport in Autoclaved Aerated Concrete
Michel van der Pal

nr 76
The Reliability and Validity of Interactive Virtual Reality Computer Experiments
Amy Tan

nr 77
Measuring Housing Preferences Using Virtual Reality and Belief Networks
Maciej A. Orzechowski

nr 78
Computational Representations of Words and Associations in Architectural Design
Nicole Segers

nr 79
Measuring and Predicting Adaptation in Multidimensional Activity-Travel Patterns
Chang-Hyeon Joh

nr 80
Strategic Briefing
Fayez Al Hassan

nr 81
Well Being in Hospitals
Simona Di Cicco

nr 82
Solares Bauen: Implementierungs- und Umsetzungs-Aspekte in der Hochschulausbildung in Österreich
Gerhard Schuster
nr 83
Supporting Strategic Design of Workplace Environments with Case-Based Reasoning
Shauna Mallory-Hill

nr 84
ACCEL: A Tool for Supporting Concept Generation in the Early Design Phase
Maxim Ivashkov

nr 85
Brick-Mortar Interaction in Masonry under Compression
Ad Vermeltfoort

nr 86
Zelfredzaam Wonen
Guus van Vliet

nr 87
Een Ensemble met Grootstedelijke Allure
Jos Bosman
Hans Schippers

nr 88
On the Computation of Well-Structured Graphic Representations in Architectural Design
Henri Achten

nr 89
De Evolutie van een West-Afrikaanse Vernaculaire Architectuur
Wolf Schijns

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ROMBO Tactiek
Christoph Maria Ravesloot

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External Coupling between Building Energy Simulation and Computational Fluid Dynamics
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Design Research in the Netherlands 2005
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Ein Modell zur Baulichen Transformation
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Human Lighting Demands: Healthy Lighting in an Office Environment
Myriam Aries

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A Spatial Decision Support System for the Provision and Monitoring of Urban Greenspace
Claudia Pelizaro

nr 96
Leren Creëren
Adri Proveniers

nr 97
Simlandscape
Rob de Waard

nr 98
Design Team Communication
Ad den Otter

nr 99
Humaan-Ecologisch Georiënteerde Woningbouw
Juri Czabanowski

nr 100
Hambase
Martin de Wit

nr 101
Sound Transmission through Pipe Systems and into Building Structures
Susanne Bron-van der Jagt

nr 102
Het Bouwkundig Contrapunt
Jan Francis Boelen

nr 103
A Framework for a Multi-Agent Planning Support System
Dick Saarloos

nr 104
Bracing Steel Frames with Calcium Silicate Element Walls
Bright Mweene Ng‘andu

nr 105
Naar een Nieuwe Houtskeletbouw
F.N.G. De Medts
nr 108
Geborgenheid
T.E.L. van Pinxteren

nr 109
Modelling Strategic Behaviour in
Anticipation of Congestion
Qi Han

nr 110
Reflecties op het Woondomein
Fred Sanders

nr 111
On Assessment of Wind Comfort
by Sand Erosion
Gábor Dezsö

nr 112
Bench Heating in Monumental Churches
Dionne Limpens-Neilen

nr 113
RE. Architecture
Ana Pereira Roders

nr 114
Toward Applicable Green Architecture
Usama El Fiky

nr 115
Knowledge Representation under
Inherent Uncertainty in a Multi-Agent
System for Land Use Planning
Liying Ma

nr 116
Integrated Heat Air and Moisture
Modeling and Simulation
Jos van Schijndel

nr 117
Concrete Behaviour in Multiaxial
Compression
J.P.W. Bongers

nr 118
The Image of the Urban Landscape
Ana Moya Pellitero

nr 119
The Self-Organizing City in Vietnam
Stephanie Geertman

nr 120
A Multi-Agent Planning Support
System for Assessing Externalities
of Urban Form Scenarios
Rachel Katoshevski-Cavari

nr 121
Den Schulbau Neu Denken,
Fühlen und Wollen
Urs Christian Maurer-Dietrich

nr 122
Peter Eisenman Theories and
Practices
Bernhard Kormoss

nr 123
User Simulation of Space Utilisation
Vincent Tabak

nr 125
In Search of a Complex System Model
Oswald Devisch

nr 126
Lighting at Work:
Environmental Study of Direct Effects
of Lighting Level and Spectrum on
Psycho-Physiological Variables
Grazyna Górnicka

nr 127
Flanking Sound Transmission through
Lightweight Framed Double Leaf Walls
Stefan Schoenwald

nr 128
Bounded Rationality and Spatio-Temporal
Pedestrian Shopping Behavior
Wei Zhu

nr 129
Travel Information:
Impact on Activity Travel Pattern
Zhongwei Sun

nr 130
Co-Simulation for Performance
Prediction of Innovative Integrated
Mechanical Energy Systems in Buildings
Marija Trčka

nr 131
Allemaal Winnen
M.J. Bakker
nr 132
Architectural Cue Model in Evacuation Simulation for Underground Space Design
Chengyu Sun

nr 133
Uncertainty and Sensitivity Analysis in Building Performance Simulation for Decision Support and Design Optimization
Christina Hopfe

nr 134
Facilitating Distributed Collaboration in the AEC/FM Sector Using Semantic Web Technologies
Jacob Beetz

nr 135
Circumferentially Adhesive Bonded Glass Panes for Bracing Steel Frame in façades
Edwin Huveners

nr 136
Influence of Temperature on Concrete Beams Strengthened in Flexure with CFRP
Ernst-Lucas Klamer

nr 137
Sturen op Klantwaarde
Jos Smeets

nr 139
Lateral Behavior of Steel Frames with Discretely Connected Precast Concrete Infill Panels
Paul Teewen

nr 140
Integral Design Method in the Context of Sustainable Building Design
Perica Savanović

nr 141
Household Activity-Travel Behavior: Implementation of Within-Household Interactions
Renni Anggraini

nr 142
Design Research in the Netherlands 2010
Henri Achten

nr 143
Modelling Life Trajectories and Transport Mode Choice Using Bayesian Belief Networks
Marloes Verhoeven

nr 144
Assessing Construction Project Performance in Ghana
William Gyadu-Asiedu

nr 145
Empowering Seniors through Domotic Homes
Masi Mohammadi

nr 146
An Integral Design Concept for Ecological Self-Compacting Concrete
Martin Hunger

nr 147
Governing Multi-Actor Decision Processes in Dutch Industrial Area Redevelopment
Erik Blokhuis

nr 148
A Multifunctional Design Approach for Sustainable Concrete
Götz Hüsken

nr 149
Quality Monitoring in Infrastructural Design-Build Projects
Ruben Favié

nr 150
Assessment Matrix for Conservation of Valuable Timber Structures
Michael Abels

nr 151
Co-simulation of Building Energy Simulation and Computational Fluid Dynamics for Whole-Building Heat, Air and Moisture Engineering
Mohammad Mirdadeghi

nr 152
External Coupling of Building Energy Simulation and Building Element Heat, Air and Moisture Simulation
Daniel Cóstola
nr 175
Modeling Recreation Choices over the Family Lifecycle
Anna Beatriz Grigolon

nr 176
Experimental and Numerical Analysis of Mixing Ventilation at Laminar, Transitional and Turbulent Slot Reynolds Numbers
Twan van Hooff

nr 177
Collaborative Design Support: Workshops to Stimulate Interaction and Knowledge Exchange Between Practitioners
Emile M.C.J. Quanjel

nr 178
Future-Proof Platforms for Aging-in-Place
Michiel Brink

nr 179
Motivate: A Context-Aware Mobile Application for Physical Activity Promotion
Yuzhong Lin

nr 180
Experience the City: Analysis of Space-Time Behaviour and Spatial Learning
Anastasia Moiseeva

nr 181
Unbonded Post-Tensioned Shear Walls of Calcium Silicate Element Masonry
Lex van der Meer

nr 182
Construction and Demolition Waste Recycling into Innovative Building Materials for Sustainable Construction in Tanzania
Mwita M. Sabai

nr 183
Durability of Concrete with Emphasis on Chloride Migration
Przemysław Spiesz

nr 184
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Modeling Cognitive Learning of Urban Networks in Daily Activity-Travel Behavior

How people perceive and process the information they receive, and how they store it in their memories are essential factors of cognitive learning. In general, people learn through observation, ICT and imitating other people. Regardless of how people learn, their cognitive skills affect spatial learning. Cognitive skills such as attention, memory, visual and auditory processing, and reasoning carry vital importance to learning. Since people may have different cognitive skills and different interpretations to similar spatial experiences, individuals develop their own mental representation of an urban environment. This is why it is difficult, however very important to include cognitive learning in activity-travel models.

This dissertation presents a modeling approach to simulate spatial perception updating process through activity-travel patterns. An illustration of the model, numerical simulations designed to test the part of the model concerned with attribute learning and forgetting, and validation of the model with real-world data are presented in this dissertation. The findings allow drawing conclusions that the development of spatial cognition is strongly related to interactions within the built environment. Better understanding of the development of spatial cognition of urban networks and the inclusion of the proposed modeling approach to the activity-based models of travel demand may provide new insights into urban and transport planning.

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