

# Bounded rationality and spatio-temporal pedestrian shopping behavior

**Citation for published version (APA):**

Zhu, W. (2008). *Bounded rationality and spatio-temporal pedestrian shopping behavior*. [Phd Thesis 1 (Research TU/e / Graduation TU/e), Built Environment]. Technische Universiteit Eindhoven.  
<https://doi.org/10.6100/IR638883>

**DOI:**

[10.6100/IR638883](https://doi.org/10.6100/IR638883)

**Document status and date:**

Published: 01/01/2008

**Document Version:**

Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

**Please check the document version of this publication:**

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
- The final author version and the galley proof are versions of the publication after peer review.
- The final published version features the final layout of the paper including the volume, issue and page numbers.

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# **Bounded Rationality and Spatio-Temporal Pedestrian Shopping 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 donderdag 23 oktober 2008 om 16.00 uur

door

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geboren te Shanghai, China

Dit proefschrift is goedgekeurd door de promotor:

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Technische Universiteit Eindhoven,  
Faculteit Bouwkunde, Urban Planning Group

Cover design: Tekenstudio, Faculteit Bouwkunde  
Printed by the Eindhoven University of Technology Press Facilities

BOUWSTENEN 128

ISBN 978-90-6814-612-7  
NUR-code 955: Bouwkunde

## PREFACE

This PhD thesis records a four-year research path that I started in November 2004. I really enjoyed this pleasant adventure for the unknown in research and in myself. The journey started in the summer of 2003, when the contents of my master thesis was generally decided. This master thesis was about applying rational choice models to explain pedestrian behavior in shopping streets. I thought this tradition in pedestrian modeling research should be improved or at least augmented with behaviorally more realistic models. Then, I contacted Prof. Harry Timmermans, whom I only knew from reading his and his co-workers' papers on pedestrian behavior, and expressed my interest to join his research group. After reading an email from Harry on a day in late 2003, I experienced for several minutes of confusion, because Harry asked me to write a research proposal for a PhD position. This was a surprise as it is not done in the PhD admission system in China. In the next few weeks, I struggled with this challenging task but learned what a research proposal should include. The development of the research topic was of course not a smooth process, because at the beginning, my motivation to improve existing models was not supported by any theoretical basis until one day, after a week of pondering the question, I noticed the word "bounded rationality" in the topic of a DDSS conference. This topic seemed to me a natural fit to my research motivation and the research proposal was gradually developed around it. Fortunately, the proposal was accepted. The happy moment of receiving Harry's email about the acceptance is still so vivid to me.

During the four years, I experienced real research life. Eindhoven is a quiet city, which is ideal for research and my character. Eindhoven University of Technology provides excellent research conditions: abundant literature access, generous conference subsidies, and sufficient financial support for projects, which allowed me, for the first time, to use all the working hours for my own interests. I believe I would not have tasted the charm of research, had I worked in a restricted research environment. I deeply learned the coexistence of promise and risk, rise and fall, shortcut and detour along the research road. I ecstatically experienced for one more year the power of computer programming by aiming to develop a decision modeling tool based on modularizing mental activities and gene expression programming. It turned out to be impractical due to computational inefficiency. However, the endeavor was not completely wasted, I believe, as the modeling experiences accumulated to a new modeling approach for studying heterogeneous decision heuristics at the end of the second year. What followed this breakthrough, was a long period of developing the coarse ideas into rigorous mathematical representations, collecting data, repeatedly estimating alternative models day and night, presenting results in seminars, conferences, and journals, and finally distilling the essence into this book. There are three most valuable things that I have learned during this rich research life: first, programming techniques, which greatly expand my ability to develop specific models which are not limited to existing methods in order to test my own ideas; second, representing ideas in mathematical language, which adds

rigor and quality to research; third, writing in English, which gives me much confidence in working in an international academic environment.

It is my great honor to have worked under the supervision of Prof. Harry Timmermans. First of all, I show my deep respect to him as a highly responsible supervisor who always gives priority to research activities and supervises students with regular, frequent, and prepared communications. His comments and visions from a wide spectrum of different fields of expertise no doubt inspired and guided the orientation of my project throughout. At the same time, I never felt any restriction from him as he always ‘indulged’ me to try new ideas. One example is that he once allowed me to use his computer and office for months to experiment a computing network. I greatly benefited from his quick but quality paper reviews. My improvement in using mathematical language, making rigorous research statements, writing in English, and finally compiling this thesis, would not have been achieved without his patient, persistent, critical, and detailed reflections. Thank you very much, Harry!

A lot of thanks and gratefulness must be given to Prof. De Wang, the co-promoter of this thesis and the ex-supervisor of my master project. He has been caring about my research progress and career since the beginning of my PhD application. During the four years, all my publications in Chinese and Japanese journals and conferences involve his endeavor. In 2007, he generously gave full support to my field survey in Shanghai, from which I collected data that are crucial to the thesis.

I must thank many other people who made possible my fruitful, smooth, and joyful PhD life. Associate Professor Aloys Borgers, as an experienced top expert in pedestrian research, always asked me incisive questions which made me struggle to defend, and provided valuable comments. Our group secretary, Mandy van de Sande – van Kasteren, gave me efficient support and useful survival information in The Netherlands. Peter van der Waerden, our cheerful computer administrator, helped me a lot in organizing a computing network by providing all the laptops and non-occupied desktop PCs in our group. I thank Leo van Veghel who made sure that conference reimbursements timely reached my account. Theo Arentze, Astrid Kemperman, Caspar Chorus, Qi Han, Marloes Verhoeven, and other PhD candidates all provided to-the-point suggestions and various help. I specially thank my friend Zhongwei Sun, with whom I enjoyed the daily after-work chatting on the way back home, which is truly relaxing and sometimes stimulating. He and his wife’s hospitality and wonderful cooking are my warmest memory of Eindhoven.

Finally, I thank my parents far away in Shanghai for their endless support and care all along, while I feel sorry for rarely being at their side during the past four years and the next few years. This thesis is dedicated to them as a small make-up.

Wei Zhu

# CONTENTS

Preface i  
List of Tables v  
List of Figures vi  
List of Symbols viii

## **1 Introduction 1**

1.1 Background 1  
1.2 The Perspective of Bounded Rationality 3  
1.3 Research Goals 4  
1.4 Thesis Structure 5

## **2 Models of Pedestrian Behavior and Bounded Rationality 9**

2.1 Models of Pedestrian Behavior 11  
2.1.1 Aggregate models 11  
2.1.2 Individual-based models 13  
2.2 Models of Bounded Rationality 27  
2.2.1 Decision heuristics 27  
2.2.2 Choice of strategies 36  
2.3 Summary 38

## **3 Conceptual Framework 41**

3.1 Decisions to Model 42  
3.2 Multinomial Logit Model 43  
3.3 Heuristic Models 44  
3.3.1 Conjunctive model 45  
3.3.2 Disjunctive model 45  
3.3.3 Lexicographic model 46  
3.4 The Heterogeneous Heuristic Model 49  
3.4.1 A two-level two-stage framework 50  
3.4.2 Preference structure 52  
3.4.3 Decision heuristics 55  
3.4.4 Choice of heuristic 58  
3.4.5 Extension to comparative choice decisions 62  
3.5 Summary 65

## **4 Data 67**

4.1 Wang Fujing Street 67  
4.1.1 Survey design 67  
4.1.2 Background 68  
4.1.3 Data collection 69  
4.1.4 Time estimation 70  
4.1.5 Basic sample characteristics 72

4.2	East Nanjing Road	75
4.2.1	Survey design	75
4.2.2	Background	76
4.2.3	Data collection	77
4.2.4	Time estimation	77
4.2.5	Basic sample characteristics	78
4.3	Summary	82
<b>5</b>	<b>Model Estimation</b>	<b>83</b>
5.1	Heuristic Models and the WFS Case	83
5.1.1	Go-home decision	83
5.1.2	Direction choice decision	92
5.1.3	Rest decision	97
5.1.4	Store patronage decision	101
5.2	HHM and the ENR Case	109
5.2.1	Go-home decision	110
5.2.2	Direction choice decision	113
5.2.3	Rest decision	116
5.2.4	Store patronage decision	118
5.3	Summary	121
<b>6</b>	<b>Model Validation</b>	<b>123</b>
6.1	The Simulation Platform	123
6.1.1	System construction	123
6.1.2	Simulation procedures	125
6.1.3	Comparison statistics	129
6.2	Tests	129
6.2.1	Test 1 – WFS 2004	129
6.2.2	Test 2 – ENR 2007	134
6.2.3	Test 3 – ENR 2003	139
6.3	Summary	143
<b>7</b>	<b>Conclusion and Discussion</b>	<b>147</b>
7.1	Findings	147
7.2	Discussion	152
7.3	Future Directions	156
	References	161
	Subject Index	175
	Author Index	179
	Summary	183
	Curriculum Vitae	185

## LIST OF TABLES

Table 4.1	Basic characteristics of the sample (WFS)	72
Table 4.2	Basic characteristics of the sample (ENR)	79
Table 5.1	Critical parameters for having no effect (go-home)	88
Table 5.2	Estimation results of the go-home models (WFS)	90
Table 5.3	Critical parameters for having no effect (direction choice)	95
Table 5.4	Estimation results of the direction choice models (WFS)	96
Table 5.5	Estimation results of the rest models (WFS)	100
Table 5.6	Critical parameters for having no effect (store patronage)	106
Table 5.7	Estimation results of the store patronage models (WFS)	107
Table 5.8	Estimation results of the go-home models (ENR)	112
Table 5.9	Estimation results of the direction choice models (ENR)	115
Table 5.10	Estimation results of the rest models (ENR)	117
Table 5.11	Estimation results of the store patronage models (ENR)	120
Table 5.12	Results of model comparison	122
Table 6.1	Components of the simulation platform	124
Table 6.2	Estimation results of activity duration (WFS)	130
Table 6.3	Estimation results of activity duration (ENR 07)	135



## LIST OF FIGURES

- Figure 3.1 The decisions to be modeled 42
- Figure 3.2 The two-level two-stage decision framework 51
- Figure 3.3 An example of a preference tree of a two factor decision 54
- Figure 3.4 Two conjunctive heuristics 55
- Figure 3.5 Two disjunctive heuristics 56
- Figure 3.6 Lexicographic heuristic from evaluating  $x^B$  first 57
- Figure 3.7 Procedure of forming a heuristic rule for comparison 63
- Figure 3.8 The stopping conditions for comparative choice 64
- Figure 4.1 Illustration of the questions about activities 68
- Figure 4.2 The survey area of WFS 69
- Figure 4.3 The grid space 70
- Figure 4.4 Relationship between spatial and temporal information 71
- Figure 4.5 Distribution of arrival hour (WFS) 73
- Figure 4.6 Cumulative distribution of total duration (WFS) 73
- Figure 4.7 Cumulative distribution of the number of store visits (WFS) 73
- Figure 4.8 Cumulative distribution of activity duration (WFS) 74
- Figure 4.9 Distribution of entries (WFS) 74
- Figure 4.10 Distribution of activities (WFS) 74
- Figure 4.11 The survey area of ENR 76
- Figure 4.12 Procedure for estimating time information (ENR) 78
- Figure 4.13 Distribution of arrival hour (ENR) 80
- Figure 4.14 Cumulative distribution of total duration (ENR) 80
- Figure 4.15 Cumulative distribution of the number of store visits (ENR) 80
- Figure 4.16 Cumulative distribution of activity duration (ENR) 81
- Figure 4.17 Distribution pedestrians in entries (ENR) 81
- Figure 4.18 Distribution of activities in stores (ENR) 81
- Figure 5.1 Reasons for going home 84
- Figure 5.2 Two examples of parameter ineffectiveness of the threshold distribution in the conjunctive go-home model 86
- Figure 5.3 Illustration of an objective function with two threshold variables 89
- Figure 5.4 CDFs of the time thresholds in the conjunctive go-home model 92
- Figure 5.5 CDFs of the time thresholds in the lexicographic rest model 101
- Figure 5.6 Two modeling frameworks for store patronage decision 102
- Figure 5.7 CDF of the floorspace threshold in the store patronage model 109
- Figure 5.8 Distribution of preference structures (go-home) 113
- Figure 5.9 Distribution of preference structures (direction choice) 116
- Figure 5.10 Distribution of preference structures (rest) 118
- Figure 5.11 Distribution of preference structures (store patronage) 121
- Figure 6.1 Illustration of the grid space 124
- Figure 6.2 Screenshot of the interface 126
- Figure 6.3 Flowchart of the multi-agent simulation 127
- Figure 6.4 Segments of WFS 129

Figure 6.5	Distributions of agents by activities over time (WFS)	131
Figure 6.6	Distributions of agents in segments over time (WFS)	132
Figure 6.7	Number of visits and duration in stores (WFS)	133
Figure 6.8	Segments of ENR 07	134
Figure 6.9	Distributions of agents by activities over time (ENR 07)	136
Figure 6.10	Distributions of agents in segments over time (ENR 07)	137
Figure 6.11	Number of visits and duration in stores (ENR 07)	139
Figure 6.12	Segments of ENR 03	140
Figure 6.13	Distributions of agents by activities over time using the ENR 07 models (ENR 03)	140
Figure 6.14	Distributions of agents by activities over time (ENR 03)	141
Figure 6.15	Distributions of agents in segments over time (ENR 03)	142
Figure 6.16	Number of visits and duration in stores (ENR 03)	143

## LIST OF SYMBOLS

$x_j$	factor $j$
$X$	factor set
$\beta_j$	parameter for factor $j$
$u_i$	utility of alternative $i$
$v_i$	observable utility of alternative $i$
$p_i$	choice probability of alternative $i$
$p_{ikj}^{B/W/T}$	probability of alternative $i$ being better / worse / equal to alternative $k$ on factor $j$
$p_{ij}^{S/U/N}$	probability of alternative $i$ being satisfactory / unsatisfactory / neutral on factor $j$
$\delta_{jn}$	threshold $n$ for factor $j$
$\Delta_j$	threshold set for factor $j$
$s_{jn}$	state $n$ of factor $j$
$w_{jn}$	value for state $n$ of factor $j$
$\lambda$	overall threshold for binary judgment
$V_j$	value set for factor $j$
$\bar{v}_k$	factorial combination of value judgments in factor value sets
$\bar{V}$	overall value set where $\bar{v}_k$ are ascending ordered
$\bar{V}_0$	set of rejected $\bar{v}_k$
$\bar{V}_1$	set of accepted $\bar{v}_k$
$\Phi_k$	preference structure $k$ under overall value $\bar{v}_k$
$p_k$	probability of $\Phi_k$ being applied by decision maker
$p_{i k}$	probability of alternative $i$ being satisfactory under $\Phi_k$
$u_k$	value of applying $\Phi_k$
$p_{kh}$	probability of heuristic $h$ implied in $\Phi_k$ being applied
$u_{kh}$	value of applying heuristic $h$ implied in $\Phi_k$
$p_{jn}$	probability belief of factor $j$ being in state $n$
$e_{kh}$	mental effort of applying heuristic $h$ implied in $\Phi_k$
$r_k$	risk perception of applying $\Phi_k$
$o_k$	expected outcome of applying $\Phi_k$
$\beta^{e/r/o}$	parameter for mental effort / risk perception / expected outcome
$v_i^R$	rank of the value of alternative $i$

$v_{il}^R$	rank difference between alternative $i$ and $l$
$\lambda^R$	discriminant threshold for comparative choice
$p_{il}^R$	probability of alternative $i$ being better than alternative $l$ in terms of rank difference
$p_i$	probability of alternative $i$ being chosen over alternative $l$
$\tilde{v}_i$	minimum expected overall value of alternative $i$
$\hat{v}_i$	maximum expected overall value of alternative $i$
$\tilde{v}_i^R$	rank of $\tilde{v}_i$
$\hat{v}_i^R$	rank of $\hat{v}_i$
$t^{R/A/C}$	relative / absolute / action time
$p^H$	probability of going home
$\Gamma$	standard gamma distribution
$G$	cumulative density function of $\Gamma$
$\alpha^X$	constant part of the distribution for the threshold of factor $X$
$\beta^X$	shape parameter of $\Gamma$ for the threshold of factor $X$
$\theta^X$	scale parameter $\Gamma$ of for the threshold of factor $X$
$d^Y$	dummy indicating whether direction $Y$ is the previous walking direction
$q^Y$	total floorspace in direction $Y$
$l^Y$	length of pedestrianized street in direction $Y$
$p_{1/0}^Y$	probability of direction $Y$ being satisfactory / unsatisfactory
$p_{1/0}^{Yx}$	probability of factor $x$ of direction $Y$ being satisfactory / unsatisfactory
$p_{B/W/T}^{Yx}$	probability of direction $Y$ being better / worse / equal to the other alternative on factor $x$
$p^Y$	probability of direction $Y$ being chosen
$c_i$	number of activities that the pedestrian has conducted in store $i$
$q_i$	floorspace of store $i$
$s_{ij}$	store type $j$ of store $i$
$z_{ik}$	interest category $k$ of store $i$
$m_i$	dominance of store $i$
$p_i^{S/U}$	probability of store $i$ being satisfactory / unsatisfactory
$p_I$	probability of store $I$ being chosen
$w_n^X$	value for state $n$ of factor $X$
$\mathbf{W}^X$	vector of state values for factor $X$
$\delta_n^X$	threshold for state $n$ of factor $X$
$\Delta^X$	vector of thresholds for factor $X$
$\Psi(\psi)$	element-wise identity function



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*Chapter*

# 1 INTRODUCTION

## 1.1 Background

During the last decade, pedestrian behavior research has received increasingly more attention. The origins of this research stream can be traced back to at least the 1970s, but there are some distinct differences between the early years and current trends. Early research on pedestrian behavior was mainly stimulated by the imminent need for rehabilitating old city centers in western countries and focused on aggregate patterns in pedestrian behavior and mechanisms that may be suggestive of policy measures to attract people to the targeted regional or city centers. The renewed interest in pedestrian behavior research is characterized by a much more diversified and detailed analyses of individual behavior, decisions, perceptions, cognition, and psychological processes.

Although the rehabilitation problem is still a minor theme in contemporary western cities, the role of urban planning has shifted. While traditionally, urban planning authorities were primarily responsible for the public space of city centers, including a responsibility for creating and maintaining well-balanced retail structures, the gradually lesser role of urban planning in many western countries and the emergence of public-private partnerships has implied a shift away from government to an increased role of developers and retail companies. Although the role of planning has changed, the traditional need to predict how many pedestrians visit particular stores, their expenditures in these stores as a function of supply and characteristics of the pedestrian network has remained. It serves to assess the likely impact of land use, retail and transportation plans and in the new age to assess the feasibility of new retail developments. Thus, although the specific performance criteria may have changed, modeling pedestrian behavior has remained equally relevant.

In addition, new demands and problems have risen and been crying for new solutions. One of these new issues is the pursuit for ecology-friendly environments, encompassing the policy goal of reducing car usage and encouraging walking. A variety of policies has been suggested, ranging from global policies such as traffic regulations, incentives for green industries, subsidies for public transport, and mixed land-use planning (e.g., Cervero and Radisch, 1996), to local policies such as road safety, building facades, and creating pedestrian friendly environment style (e.g., Cao, *et al.*, 2006).

Another factor influencing the renewed interest in pedestrian behavior research was the tragic 9-11 event, which pushed research on pedestrian behavior in emergency situations. Studying evacuees' reactions to danger, response to information, interaction with other people, and behavior under panic is felt crucial as it may determine life and death in case of emergency. Many evacuation models have been developed (e.g., Waldau, *et al.*, 2007).

In addition to these content-driven causes, pedestrian research has received a new impulse as the result of the advancement of computer technology. The ever-increasing computation power and object-oriented programming have allowed

researchers to pack a society into a PC (or at least have stimulated attempts to that effect) by simulating individual behavior using agent-based techniques. This coincides with the interest in complexity theory that emerged across many different disciplines and stimulated investigating emergent aggregate behavior. It also results in the fact that increasingly more scholars and practitioners from fields other than urban planning, such as computer science, cognitive psychology, artificial intelligence, and physics, are now contributing knowledge and techniques, originally developed in these fields, to pedestrian research as it developed in urban planning.

Pedestrian behavior has always been an important topic for retail development. The location of shopping centers and stores, service quality and good diversity, and accessibility are crucial determinants for attracting consumers and increasing retail turnover. Pedestrian behavior research in the context of urban planning can be largely divided into three levels: the macro, meso, and micro level (e.g., Haklay, *et al.*, 2001). Macro-level research mainly focuses on shopping patterns of consumers at the regional or urban scale, such as people's shopping trip to one or more urban or regional centers. Because most consumers travel by vehicles and do not walk, this macro-level research is usually not captured in term of pedestrian behavior.

At the meso level, a shopping center or shopping street is usually viewed as a closed area where the consumers that have been generated at the macro level are redistributed across streets and stores. Patterns and rules related to such distributions are the concern of meso-level pedestrian research. For urban planners and retailers, the number of pedestrians in certain spaces or stores at some point in time is directly linked to their estimates of facility service levels and the development of plans and strategies. To support the design and planning decisions involved, research has analyzed the aggregate activity patterns and pedestrian flows and has examined individual behavior and decisions.

Micro-level pedestrian research concerns the local characteristics of pedestrian movement such as wayfinding, obstacle avoiding and crowd forming, which may support effective designs and arrangements of information signs, street furniture, safety measures, and things alike. Models of that kind thus simulate the micro-behavior of pedestrians, and the results provide overt useful guidelines for design decisions such as width of passages and impact of obstacles. This kind of research is not necessarily confined to public spaces, but is also highly relevant to semi-public spaces such as train stations (e.g., Daamen, *et al.*, 2005a; Hoogendoorn, *et al.*, 2007).

Meso-level pedestrian behavior in shopping environments constitutes the subject matter of this thesis. It involves complex inter-dependent decisions, such as which direction should I go, which route should I take, which store should I visit, for how long should I stay in the store, should I take a rest, and when should I leave? Together, these decisions result in a pattern of pedestrian behavior. The basic motivation for this thesis is to better understand how these patterns of pedestrian behavior and decision can be modeled to support urban and retail planning. That is, the model should allow, in principle, predicting the impact of planning activities, such as developing a new magnet store and constructing a new transport terminal, on the pattern of pedestrian behavior.

## 1.2 The Perspective of Bounded Rationality

The modeling of individual decisions, not only in the field of pedestrian behavior, but also in transportation, consumer marketing, and several other disciplines, has dominantly relied on rational choice models. The best-known example is the Nobel price winning class of discrete choice models based on random utility theory (e.g., McFadden, 1974), interestingly introduced however first in urban planning and transportation research. Behaviorally, random utility models assume that (1) individuals evaluate each alternative in their choice set and attach an overall utility to each alternative; (2) the overall utility is a combination of the utilities derived from each factor or attribute of the choice alternatives that influences the decision, usually according to some compensatory combination rule; (3) individuals compare these overall utilities between alternatives and choose the alternative with the highest overall utility. Although random utility theory has proven its value in an impressive number of academic and applied research projects, the underlying assumptions of fully rational behavior may not be particularly valid in all application contexts. This seems especially true for complex decision problems that involve many choice alternatives, and combination of multiple sub-decisions. Pedestrian behavior is an example of such complex decisions. Under these circumstances, the concept of bounded rationality seems more appealing.

Herbert A. Simon (1916 – 2001), who is considered the father of bounded rationality (BR), questioned the rational choice theory already 50 years ago (e.g., Simon, 1955; 1956; 1959). He argued that rational choice theory weaves a man (woman) who never exists, who is omniscient about the environment and has the unlimited ability to conduct large amount of computation in a single decision. The following statement reflects his motivation:

“The term bounded rationality, is used to designate rational choice that takes into account the cognitive limitations of the decision maker - limitations of both knowledge and computational capacity.” (Simon, 1987, p. 266-268)

Simon advocated the development of decision theories starting by observing the way people actually perform in decision making, rather than extending the theoretical constructs of some assumed theorems. In other words, the focus of bounded rationality research should be on tracing decision processes. As an alternative to the principle of utility-maximization, Simon proposed the notion of “satisficing”, indicating that people just accept a satisfactory alternative, which is not necessarily the optimal one.

Inspired by Simon, theories based on the principle of bounded rationality have been formulated in different disciplines and take on quite different forms. As Aumann (1997) said, there is no and there probably never will be a unified theory of bounded rationality. Criticisms are often thrown back by economists saying that there is no backbone in psychology research, but just sporadic attempts to find cracks in economic theories. Moreover, the interest of applied disciplines such as urban planning and civil engineering has been primarily on developing operational models



as opposed to further elaborating underlying theories of choice behavior and decision processes. At the same time, however, the position of random utility theory has also changed in the sense that some economists have argued that random utility theory does not necessarily mean that people behave in that manner but rather that observed behavior should be interpreted *as if* they do.

Reflecting on this counter-argument, the first part simply articulates the different methodological paths taken by the two camps, while the second part indeed does tell the truth. Abundant research in psychology and many fields of application has revealed behavioral deviations from rational principles, such as intransitivity (Tversky, 1969), preference reversal (e.g., Grether and Plott, 1979), context dependency (Tversky and Simonson, 1993), and framing (e.g., Tversky and Kahneman, 1981). These findings appear to provide empirical evidence for Simon's conjecture on limited knowledge, computation ability of individuals and the satisficing principle. As Payne *et al.* (1993) argued "When faced with more complex choice problems involving many alternatives, people often adopt simplifying (heuristic) strategies that are much more selective in the use of information. Further, the strategies adopted tend to be non-compensatory, in that excellent values on some attributes cannot compensate for poor values on other attributes." (Payne, *et al.*, 1993, p. 2)

Although there is still quite some vagueness in the notion of bounded rationality, such as what is simple and what is complex, the research results showing that rational choice principles are rarely observed in reality are highly convincing. However, although these arguments have been made already some decades ago as indicated by the references above, the challenge is to go beyond this evidence and develop a model, based on the concept of bounded rationality, which represents the process of decision making instead of merely proving a mathematical function that seems to reproduce decision outcomes. If this could be done successfully, rational choice models would face a competing modeling framework. Models of that kind that can start to compete with random utility models have however not been suggested yet in the literature in urban planning and related disciplines.

Back to pedestrian behavior research, the criticisms against fully rational behavior appear to apply to this application domain as well. It is intuitively unrealistic, to assume that a pedestrian knows every store, calculates the utility of each factor, combines these in a weighted additive manner into an overall utility, and selects the best store within a usually very limited decision time, since shopping is often treated as a leisure activity and few people are that serious or put in that much effort in their decisions, even if we would assume that they mentally can process that much information. It seems intuitively more appropriate to model pedestrian behavior using principles of bounded rationality, treating each pedestrian as a human being having limited knowledge and computation capacity. Surprisingly, heuristic models have never been developed and empirically tested in pedestrian research.

### **1.3 Research Goals**

The main goal of this thesis, therefore, is to develop and test a model of pedestrian behavior, based on principles of bounded rationality, using real-world behavioral data.

The starting point for this work is on developing a modeling framework employing basic principles, key specifications and preliminary validation tests. We deliberately start with key principles and operational models that do not include too many variables to test the performance of such models. If results are positive, it is worthwhile to advance the models, incorporating more personal, spatial and contextual variables. By such means, we intend to contribute to the existing literature a basic tested framework for studying pedestrian behavior, based on principles of bounded rationality.

However, we intend to go beyond the heuristic rules that have been examined in the context of choice of transport mode (e.g., Foerster, 1979) and choice of shopping center (e.g., Timmermans, 1983) by elaborating these approaches to incorporate the issue of decision heterogeneity that very recently has found increasing attention across different choice modeling approaches. There is good reason to believe that pedestrians' decision strategies are much more heterogeneous than those of researchers. Hence, a second goal of this thesis is to develop a modeling approach that allows heterogeneity among pedestrians in terms of the decision heuristics they use. The formulation and development of an operational model based on principles of bounded rationality, that would in addition allow for decision heterogeneity was considered a major challenge in its own right, realizing that few, if any, models of heterogeneous decision strategies have been formulated for the easier class of discrete choice models. Therefore, the development of such a modeling approach may have more profound implications for pedestrian research specifically and for decision research in general.

In addition to these methodological contributions, this thesis aims at enriching studies of pedestrian behavior. As indicated, most pedestrian research has been dedicated to analyzing and explaining spatial patterns of pedestrians using either aggregative or individual-based methods. Static analyses were prevalent in the sense that all the activities occurring at some place during the whole period of interest, be it a day, a morning, or an hour, were taken as the dependent variables. It is well-known that the aggregate number of pedestrian activities varies in real time. Furthermore, not only aggregate behavior but also individual behavior is sensitive to temporal factors. Capturing and explaining time-dependent behavior and decisions will make more sense for practitioners to optimize resource allocation and policy measures. Thus, the third goal of this thesis is to systematically examine time-dependent aspects of pedestrian behavior.

To summarize, the goal of this thesis is not to develop the final model of pedestrian behavior based on principles of bounded rationality, with all complexity and explanatory required with specific urban and retail planning applications in mind, but rather to explore the fundamentals of such models and provide evidence of their potential power in pedestrian research.

## **1.4 Thesis Structure**

To that end, the thesis is structured as follows. Chapter 2 reviews the state-of-the-art in modeling pedestrian behavior and bounded rationality. As for the pedestrian models, the focus is especially on individual-based models and techniques as they are

consistent with the methodological path of this thesis. We limit the review of bounded rationality models to the realm of decision heuristics as we think they are the only operationalizable models of this discipline today. Based on this literature review, the end of this chapter derives the potential improvements that should be made in meso-level pedestrian modeling.

Chapter 3 develops the theoretical and methodological foundations of the thesis. It starts by proposing a modeling framework which involves four pedestrian decisions during a shopping trip, namely the go-home, direction choice, rest, and store patronage decision. This is followed by introducing and developing the rationales underlying three types of decision models that will be specified for each proposed decision problem. The first model type is the discrete choice model (more specifically the classic multinomial logit model), which serves as a benchmark. The second model type concerns decision heuristics. We selected three typical heuristics for decision modeling, namely the conjunctive, disjunctive, and lexicographic rule. The rules are extended to deal with threshold heterogeneity. We propose a new model type, which we called the heterogeneous heuristic model, as the third model type. The model incorporates cognitive thresholds and implies heterogeneous decision strategies. The choice of strategy is simultaneously captured by assuming that choice behavior is affected mainly by mental effort, perception of risk, and expected outcome, and that the outcome of that choice can be approximated by a multinomial logit distribution. It should be explicitly noted that we made no references to random utility theory in this step, but simply use the multinomial logit model as a convenient statistical model, mapping mental effort, perception of risk and expected outcome into choice probabilities.

Chapter 4 introduces two datasets about pedestrian behavior in shopping streets, which were used for empirically testing the models. One dataset was collected in Wang Fujing Street, Beijing in 2004 and the other was collected in East Nanjing Road, Shanghai in 2007. Both places are regionally famous shopping streets in China. The design of the surveys, administration, data processing, the basic characteristics of the samples and pedestrian spatio-temporal behavior are discussed.

Chapter 5 specifies and estimates all four decision models based on the three types of models introduced in Chapter 3. The heuristic models are estimated using the data collected in Wang Fujing Street, while the heterogeneous heuristic models are estimated using the data collected in East Nanjing Road. In both cases, the heuristic models are compared with their multinomial logit counterparts, which served as benchmarks, in terms of goodness-of-fit statistics and behavioral implications.

Chapter 6 validates the joint predictive ability of the proposed models, using multi-agent simulation. Note that although this chapter could also be used as a stand-alone multi-agent model of pedestrian behavior, we make no such claims as the multi-agent simulation was only developed to test the overall performance of the models. Having said that, it could easily be developed into a multi-agent system (or can be viewed as one) that can compete with such models by incorporating some constraints and perhaps some inter-agent interactions. A simulation platform based on NetLogo was developed which is used for conducting three tests. The first test examines the overall performance of the heuristic models on the Wang Fujing Street data. The

second test performs a similar analysis of the heterogeneous heuristic models on the East Nanjing Road data. The third test involves an assessment of the temporal transferability of the set of heterogeneous heuristic models by applying these models to another dataset, collected in East Nanjing Road in 2003. All these tests involve a comparison of aggregated, simulated agent activities against observed aggregate spatio-temporal distributions of pedestrian activities. Differences are indicative of possible improvements and elaborations of the model system.

Finally, Chapter 7 discusses the findings of the research project and concludes this thesis with research implications, limitations, and future directions.



*Chapter***2 MODELS OF PEDESTRIAN BEHAVIOR AND BOUNDED RATIONALITY**

Modeling pedestrian behavior has appeared on the international research agenda at least since the early 1970s. Two major incentives may have stimulated the interest in this topic. First, as rehabilitation problems of old city centers in many western countries were becoming imminent, research had provided evidence of the tight relationships between pedestrian movement and the commercial viability of inner city shopping streets. It was realized that the impact of new retail developments is closely related to the locational patterns of magnet stores and the distribution of the transport termini (e.g., Johnston and Kissling, 1971; Pacione, 1980; Walmsley and Lewis, 1989; Lorch and Smith, 1993).

Second, the increasing maturity of the models in transportation research and urban planning inspired city planners and researchers to adopt similar logic in models of pedestrian behavior. Thus, early pedestrian models were largely based on spatial interaction theory, and adopted an approach very similar to the models developed for other phenomena in transportation and urban planning. Consequently, in addition to a considerable amount of descriptive research into the determinants and nature of pedestrian behavior, models of pedestrian behavior were developed, which predicted destination and route choice as a function of locational patterns of stores, characteristics of the pedestrian network and the distribution of bus stops, train station, etc. These models were used to assess and/or predict the impact of retail and transportation plans on the commercial viability of shopping streets and shifts in turnover within inner-city shopping environments.

In the late 1970s, the emergence of random utility theory and the development of discrete choice models (DCM) revolutionized the transportation field, and after some time these models started to appear in pedestrian research as well. As DCMs are disaggregate, individual-based models, researchers may use these finer tools to dive under the aggregate level and anatomize the behaviors of each pedestrian and the complex mechanisms between behavior and the environment. Although ultimately, still a single model, assumed to apply to a homogeneous set of individuals is derived, the fact that discrete choice models could be derived from an individual-level theory of choice behavior, led researchers to believe that the theoretical underpinnings of discrete choice models are much improved compared to the spatial interaction models, which were founded in social physics, assuming that concepts developed for physical phenomena are equally relevant and effective to predict social phenomena. Gravity/spatial interaction models were therefore gradually replaced by DCMs in pedestrian research, and remained dominant until the 1990s.

The following decade witnessed a greater diversification process in pedestrian research methodologies. Modeling approaches, originally developed in quite different disciplines, were introduced to simulate and predict pedestrian choice behavior and movement patterns. Cellular automata models, originally devised for studying larger scale spatial phenomena such as the fractal nature in urban morphology and urban

land use change, for example became a popular approach in pedestrian research to induce local movement rules and simulate micro movement. Similarly, fluid dynamics and social force models, copied from concepts in physics, were applied to model individual and group movement patterns. Principles of cognitive science and psychology also received attention as pedestrian behavior could be better understood if the underlying decision processes could be modeled. Space syntax and visibility graph analysis (VGA), developed in architecture as a general theory of urban space and linked behavior, which assume that pedestrian movement patterns are largely determined by the morphology of the environment, were applied in many studies.

Innovations in the last decade were directly triggered by the tremendous advancements in computing technology. The introduction of multi-agent simulation is an example. Each pedestrian is conceptualized as an agent, with particular characteristics, rules of behavior, perception of the environment, etc. The complexity of these multi-agent systems is rapidly increasing as more concepts are attached to the agents. Object-oriented programming, artificial intelligence and the ever-increasing computation power paved the way to developed models which include increasingly more heterogeneity and have the simulated objects look increasingly more like real human beings. In the first section that follows, we will review pedestrian research that is based on these modeling approaches.

Seminal work on bounded rationality is commonly contributed by H. A. Simon during the 1950s (e.g., Simon, 1955; 1956; 1959). However, substantial progress in examining bounded rationality was not made until 20 years later, in the 1970s. The discussion on the nature of bounded rationality is probably a major cause of such slow progress, as it is to a very large extent established on the notions of limited cognitive capacity and psychological activities, which, although intuitively more realistic, are too intangible to be observed, let alone be modeled formally. As a result, most research on bounded rationality has remained largely descriptive and cannot be used for prediction. This is probably one of the major reasons why the theory of bounded rationality is significantly less popular in practice across disciplines, including urban planning and transportation, than theories based on principles of rational choice behavior. Although in the 1970s formalism to represent simplifying decision strategies received some attention mostly in marketing and consumer research, and to a lesser extent also in planning related fields, this early formal work did not receive a major follow-up in the 1980s and 1990s, mainly due to the strong competition of DCMs. Although to the best of our knowledge full-fledged models based on principles of bounded rationality have never been developed for the choice problems discussed, developments in choice modeling since the late 1990s have somewhat opened up an interest in alternative modeling approaches and theories. The impressive generalizations of the basic multinomial logit model for more complex decision problems have more or less come to a stand still. Moreover, alternative theories have found some recognition, as evidenced by the fact that while McFadden won the Nobel Prize for random utility theory, Kahneman won the same prize for his antagonistic Prospect Theory. The new century witnessed the exploration of different theoretical concepts and modeling approaches, such as rule-based models, context-dependent scripts, regret theory, and relative utility theory to name a few. In that

context, it seems that the time is right to explore again the usefulness of heuristic models, based on principles of bounded rationality as an alternative to rational choice models. The second subsection will dedicate a brief review of research on decision heuristics.

## 2.1 Models of Pedestrian Behavior

### 2.1.1 Aggregate models

Originally developed in transportation research, aggregate models are used to capture aggregate outcomes of individual behavior, such as the distributions of traffic flows between residences and work places. The most widely used aggregate models are the gravity or spatial interaction models. In fact, in many fields of application, these models still dominate planning practice. Wilson (1971) reviewed this approach and suggested a generalized framework, which he called the family of spatial interaction models. The most basic rationale underlying gravity models is the assumption that the number of trips between a zone of origin and a destination zone is a function of the attraction of the destination zone and the distance between the two zones. Formally,  $T_{ij} = O_i A_j^\alpha D_{ij}^\beta$ , where  $T_{ij}$  is the flow generated,  $O_i$  is the total number of commuters in origin zone  $i$ ,  $A_j$  is the attraction of destination zone  $j$  such as the number of work places, and  $D_{ij}$  is the distance or travel time between the origin and destination. The parameter for attraction,  $\alpha$ , is usually estimated to be positive, whereas the parameter for distance decay,  $\beta$ , is usually estimated to be negative. Note that the original motivation for this formulation does not have any foundation in whatever theories of human behavior, but rather used laws of physics as an analogue.

Extensions of the basic gravity model include production-constrained and attraction-constrained models which guarantee that the predicted total numbers of trips, leaving the origin or arriving at the destination zones is equal to the observed total in respectively origins and destinations. Doubly-constrained models ensure that both constraints are satisfied. Because in pedestrian and shopping research in general, the goal is primarily to predict the choice of store (destination), typically production-constrained models have been developed and applied. The theoretical foundations of these models have remained the same. It should be noted, however, that Wilson also suggested using the concept of entropy to derive the most probably aggregate configuration of flows. Again, however, this concept is an aggregate concept, copied from physics, with no immediate interpretations at the individual level.<sup>1</sup>

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<sup>1</sup> The literature in these years also contains several attempts of formulating theories of individual behavior that are consistent with spatial interaction models. A discussion of these theories is beyond the scope of this chapter, especially because none of these did specifically address pedestrian behavior. Interested readers are referred to the review article by Timmermans and Golledge (1990). We argue, however, that demonstrating that the specification of an aggregate model is mathematically consistent with a theory of individual behavior is different from developing a formalism and mathematical specification of a theory of individual behavior and decision making.



Most gravity-based shopping models were developed for the regional level, predicting the choice of shopping center. Examples include Gibson and Pullen (1972); Ghosh (1984), Guy (1987), and Berry, *et al.* (1988). Usually shopping center size and travel distance or time were used as explanatory variables, but later additional variables were included. Cadwallader (1975, 1981) suggested and found that individuals have different cognitions of the size and distance variables. Using perceptions of size and distance, what he called the cognitive gravity model, was tested. Results were positive.

As these applications study macro-level behavior of shoppers, they are not really about pedestrian behavior. However, it cannot be denied that gravity model represents a milestone in research on consumer spatial behavior and heralded finer-scale pedestrian research. Scott (1974) developed a theoretical framework for describing and analyzing pedestrian flows in a street system, which is represented as nodes and links. The model maximizes the entropy of pedestrian flows within the network, and was shown to be a special case of the gravity model. Crask (1979), also inspired by the gravity model, specified a probabilistic model of individual store choice using Monte Carlo simulation. Hagishima, *et al.* (1987) applied a doubly-constrained gravity model to study pedestrian flows in a shopping district in Fukuoka, Japan. They divided the district into street segments and took the number of pedestrians in each segment as the dependent variable. In addition to the commonly used retail floorspace and distance variables, other variables such as traffic condition, pavement, and street safety were also included in the model as explanatory variables.

In addition to exploring different operationalizations of the basic production-constrained models, new specifications were also formulated for predicting shopping behavior at the regional level. For example, Fotheringham (1983a, 1983b, 1986) and Fotheringham and O'Kelly (1989) proposed the competing destination model which emphasizes the possible misspecification of  $\beta$ , the distance decay parameter. They contented that the parameter could be flawed if the relationship between the destination center and other shopping centers are not considered.  $\beta$  will be underestimated if so called "competition" effect exists between adjacent centers and will be overestimated if "agglomeration" effect exists. To correct this, they added an extra term modeling such effects. Although the number of applications of the competing destination model is far less than the number of applications of conventional gravity models, it does make good sense to take into account the context around a shopping destination, which reveals a tip of the complexity in consumer behavior.

In some sense, it is only a small step from the competing destination model to models of multi-stop, multi-purpose behavior, also called trip-chaining in transportation research. It goes without saying that especially these models are potential relevant for pedestrian research as pedestrian behavior typically involves visits to multiple shopping centers or stores during a single trip. Conventional choice theory has been criticized in that no explicit consideration of multi-stop multi-purpose behavior is given (e.g., Hanson, 1980). Choice theory is usually based on axioms of single-choice single-purpose trips, independence, separability and stable utility functions. Choices are assumed to be independent, while the utility associated with a

choice alternative is not affected by the utility of any other choice alternatives, which is also the major reason that the competing destination model was proposed. No wonder, as trip-chaining behavior is dynamic, the spatial and temporal characteristics are much more complicated compared to single choice behavior (e.g., Hanson and Hanson, 1981; Kitamura, 1983; O' Kelly and Miller, 1984; Golob, 1986) and require more sophisticated models. Modeling multi-stop, multi-purpose shopping behavior therefore continued to be an active research topic and actually still is (e.g., Dellaert, *et al.*, 1998; Arentze, *et al.*, 2005; Brooks *et al.*, 2004, 2008).

The contention that the concept of multi-stop, multi-purpose behavior is relevant for understanding pedestrian behavior is evidenced in the work of Borgers and Timmermans (1986a), who developed a framework for modeling and predicting pedestrian flows in shopping streets using time-varying Markov chains. Their work can be seen as an extension of the work by O'Kelly (1981) who also used time-varying Markov chains to model multi-stop, multi-purpose trips. Borgers and Timmermans (1986a) represented the shopping streets as links of a network. A production-constrained gravity model was applied to model the transition probability that a certain type of purpose will be realized in a certain link, given the total retail floorspace of that type of service and the distance between the origin and destination. These probabilities however varied over time which is represented by each stop. The model was estimated using shopping diary data collected in the city center of Maastricht, The Netherlands. In order to capture the time-varying transition probabilities, they estimated three models using three sub-samples which include the first stop, the second stop and more than two stops respectively. This model serves as a destination choice model. In addition, they built another two models representing route choice behavior and impulsive stops using other types of models. They validated the framework by simulation, given the known distributions of pedestrians at entry links, and compared the aggregate number of pedestrians in links with empirical observations. The model performed quite well.

In another publication (Borgers and Timmermans, 1986b), they used Monte Carlo simulation and incorporated two more decisions, namely the number of stops and the sequence of planned stops/purposes, before the destination choice and route choice. The simulation was implemented by drawing random numbers from observed and estimated distributions for each decision, taking the outcome of the previous decision as the input for the next one. This model also performed well. Kurose and Hagishima (1995) took another perspective, rather than concentrating on the dynamics. They estimated the transition probabilities of pedestrians between street links based on a gravity model using retail floorspace and inter-link distance as explanatory variables, and used the first eigenvector of the transition matrix as an index of the accessibility of street network. The accessibility eigenvectors of several cities were compared.

### **2.1.2 Individual-based models**

Although aggregate models are useful for formalizing aggregate spatial movement patterns of commuters, they are not very appropriate to explain the behavior of individuals whose joint decisions result in the aggregate patterns (e.g., Timmermans and Veldhuisen, 1981; Cadwallader, 1981). Through aggregation, individual

differences are lost and there is no straightforward way to incorporate individual socio-demographics into the gravity models. This could be less of a problem for transportation research than for pedestrian research as vehicle trips are more homogeneous in terms of journey purposes and the movement space is usually limited to strictly directed road networks, whereas pedestrians in shopping environments may have various purposes and they are almost free to walk anywhere in any possible direction at whatever comfortable speed. Using individual-based models to solve these problems and study aggregate patterns in a bottom-up perspective has been the mainstream methodology in pedestrian research today and in most fields of application for that matter.

### 2.1.2.1 Discrete choice

Based on random utility theory, discrete choice models have been widely applied in transportation, consumer and pedestrian research since the late 1970s. Over the last 30 years, DCMs have been developed into a family of models (e.g., McFadden, 1974; Ben-Akiva and Lerman, 1985; Train, 2003). The most basic assumption of DCM is that people are rational in the sense that they choose an alternative from among several discrete candidates by evaluating the utility of each alternative and selecting the alternative with the highest utility. Although the discrete choice models can be derived from multiple theories<sup>2</sup>, a commonly made assumption is that utility is stochastic. The mathematical form of utility can be formulated as:  $U_{ij} = V_{ij} + \varepsilon_{ij}$ , where  $U_{ij}$  is the utility of alternative  $j$  evaluated by individual  $i$ ,  $V_{ij}$  is the observable utility part from the perspective of the researcher and  $\varepsilon_{ij}$  is the random utility part that is non-observable by the researcher.  $V_{ij}$  is often specified as a linear summation of weighted attribute values:  $V_{ij} = \sum_k \beta_k x_{ijk}$ , where  $\beta_k$  are weight parameters to be estimated and  $x_{ijk}$  are the explanatory attributes (variables) of alternative  $j$  perceived by individual  $i$ . However, in most applications of DCM, except when attribute values are reported by individuals, attribute values of an alternative do not differ across individuals. Therefore, researchers just use the same  $x_{jk}$  for all the individuals. The alternative  $n$  with the highest utility is chosen, satisfying  $U_{in} > U_{im}, \forall m \neq n$ . Assuming different

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<sup>2</sup> Different theories imply different implicit or explicit assumptions about the error term. Strict utility theory assumes that individuals have deterministic preferences but choose probabilistically. Random utility theory in contrast assumes that individuals have stochastic preferences. To reflect this theory, the multinomial logit model should be estimated at the individual level. If it is estimated at the aggregate level, the error terms usually are also assumed to reflect heterogeneity in consumer preferences. As an econometric tool, finally, error terms also deserve the purpose of indicating that not all influential variables are known to the analyst. Although there are not very strong reasons to assume any particular form for each of these sources, let alone their combined effect, a single error term is usually used, which combines all of these effects, but this is rarely made explicit. In the context of this chapter, we summarize the most commonly made interpretation of the model.

forms for the random utility part, the probability of choosing an alternative can be derived, and results in different models. The multinomial logit model (MNL) can be derived under the assumption of independently and identically Gumbel distributed error terms. Less rigorous assumptions lead to multinomial probit models, nested logit model, generalized extreme value and many other models, but MNL is the most widely used model in pedestrian choice modeling.

Similar to the application of gravity models, the application of DCMs in consumer research started with macro-level shopping center choice behavior. For example, Recker and Kostyniuk (1978) used a MNL to explain the urban grocery shopping trip. They considered three factors as explanatory variables: individual's perception of the destination, individual's accessibility to the destination and the relative number of opportunities to exercise any particular choice. They found that accessibility was the most influential factor. Using a decompositional survey method, Timmermans and Borgers (1985) studied the stated choice of shopping center based on an MNL. They found that the model is robust in general, while the violation of the independence of irrelevant alternative assumption (IIA) was observed. Timmermans, *et al.* (1992) compared the MNL models under revealed choice situation and stated choice situation with regard to shopping center choice. They used the estimated models to predict the choice outcomes when introducing a new clothing store in a shopping center and compared the predictions with the actual choice behavior after the store opened the business. Very similar results were observed between the two models, suggesting the application validity of decompositional method.

With the increasing need for deeper understanding of consumer preferences as a result of diversified marketing segmentation, more environmental and personal factors were included in the utility functions in later research to test their effects along with the conventional attraction and distance factors. For example, Borgers and Timmermans (1987a, b, 1988) and Fotheringham (1988) incorporated spatial structure. This model specification was also meant to avoid the unrealistic IIA of the MNL, which states that the odds of choosing a particular alternatives is independent of the existence and attributes of any other alternatives in the choice set. Hence, the multinomial logit model does not account for any similarity and substitution among choice alternatives. Note that Borgers and Timmermans' (1987a, b) model is the utility-based equivalent of the competing destination model, discussed in the previous section. As an alternative, Timmermans, *et al.* (1991) formulated a mother logit model to test for any cross-effects to account for differences in choice set composition (e.g., competition, agglomeration, etc.). However, although these models are theoretically more appealing, they found only limited improvement in goodness-of-fit over the MNL model. This is because the similarity of alternatives is only relevant for a subset of alternatives while goodness-of-fit is calculated across all observations and all choice alternatives.

Other evidence of a larger list of explanatory variables can be found in Fotheringham and Trew (1993), who modeled the influence of income and race; Oppewal and Timmermans (1997) who used detailed environmental factors such as store variety, window layout, price, quality and shopping atmosphere in their choice

experiment, and Van der Waerden, *et al.* (1998) who focused on the service level and location of the parking facility of a shopping center.

All these models focused on a single shopping trip. For studying trip-chaining in a discrete choice context, an important contribution was made by Kitamura (1984), who introduced the concept of prospective utility. It states that the utility of a destination is not only a function of its inherent attributes and the distance to that destination, but also of the utility of continuing the trip from that destination. Based on this notion, Arentze, *et al.* (1993) developed a model of multi-purpose shopping trip behavior. It assumed a list of items that need to be purchased with a different frequency. The choice of shopping center to purchase a particular item is predicted as an MNL. The probability of buying any other good during the same trip is then the choice between either buying this item during the same trip or buying it during another trip. A recursive equation is derived from this premise, which allows one to predict the frequency of purchasing different goods and the distribution of visits across shopping centers. Dellaert, *et al.* (1998) generalized this approach to account for both multi-purpose and multi-stop aspects of the trip chain. Arentze and Timmermans (2001) showed how store performance indicators can be derived from such models. Popkowski Leszczyc and Timmermans (2001) conducted a conjoint experiment in which they defined four single- or multi-stop shopping trip strategies for respondents to choose. Using an MNL model to explain the choice outcome, they found that single-stop shopping trip was the least-preferred strategy. Limanond, *et al.* (2005), based on the Stockholm Model System, assumed that a household's shopping travel is decided through five consecutive decisions on, household tour frequency, participating party, shopping tour type (varies in stop and purpose number), travel mode, and destination choice. Each former decision determines the content of the latter decision. They used a nested logit model to describe such a decision structure and estimated the model on actual household travel data.

More recently, the influence of multi-purpose trips was further studied. Arentze, *et al.* (2005) used a multi-purpose trip model under a nested logit structure to assess retail agglomeration effects. It was found that not only the agglomeration of the stores which provide the goods for the shopping purposes, but also the agglomeration of the stores which do not provide the intended goods contributes to the utility of a trip destination. Ye, *et al.* (2007) investigated the relationship between trip-chaining decision and mode choice. They tested three models different in causal structures. The first structure implies the trip-chaining decision proceeding mode choice; the second structure is the reverse with mode choice decided first; the third structure implies simultaneous decisions. The test found a weak statistical advantage of the first structure, suggesting a trip-chaining-first decision structure. Thus, this review suggests that increasingly more complexity was added to models for predicting shopping trips. The latest development in this regards is to model shopping trips as part of daily activity-travel scheduling behavior, using context-dependent utility functions (e.g., Arentze and Timmermans, 2005). Shopping trips are not only explained to the commonly used spatial and socio-demographic variables, but also in terms of the larger activity schedule, and the various constraints that act on the schedule.

At the meso street level, pedestrian behavior can be modeled as a sequence of specific choices, such as the choice of an itinerary, the choice of destination, the choice of direction, and the choice where to stop next (Bierlaire, *et al.*, 2003). Borgers and Timmermans (1986a, 1986b) presented a relatively complete model, following such a framework. An MNL model was used by the authors to explain route choice behavior and distance was used as explanatory variable. Because the choice set of alternative routes was not directly observed, they inferred the choice set given the destination link based on some reasonable assumptions such as limited length and degree of detour. Saito and Ishibashi (1992) used a Markov chain to predict the aggregate distribution of pedestrian flows between blocks with retail facilities in a shopping district. Unlike Borgers and Timmermans who used gravity models to estimate the time-varying purpose-destination distribution, they derived general time-invariant transition probabilities of pedestrian flows between blocks by estimating the choice probabilities of choosing a destination block at the current location (a block) from all the blocks within the district, using an MNL model with total retail floorspace and distance between the origin and destination block as explanatory variables. They proved that multiplying the given initial distribution of pedestrians at entry blocks infinitely with the general transition probabilities can converge accurately to the distribution of the observed aggregate static inter-block pedestrian flows. One thing that needs to be noted is that the transition probabilities must have one vector, representing the probabilities that pedestrians end the shopping trip after visiting each block, or else, the infinite multiplication will lead to an infinite number of pedestrian visits in blocks as the number of pedestrians will just be redistributed repeatedly. Saito and Ishibashi (1992) added an extra choice alternative, going-home, and used a single parameter to represent the utility of ending the trip. This has a similar effect as Borgers and Timmermans (1986b) drawing the number of stops in the simulation.

Zhu, *et al.* (2006b) used a similar approach but adopted a nested logit model to separate the shopping alternatives from the going-home alternative, based on the reasoning that a pedestrian's decision process could be hierarchical, choosing between shopping and going-home first, and if shopping is chosen, choosing the place to shop next. Note that the use of different modeling approaches in these studies follows the overall change in modeling with new models entering the field over time. Significant correlations between shopping alternatives were estimated, suggesting that the decision is hierarchical. Along with another model which explains the store choice behavior of pedestrians in the entry stage (Zhu, *et al.*, 2005), Zhu (2004) and Zhu, *et al.* (2008) simulated the pedestrian flows between the blocks and movement trajectories based on Markov chain. The comparisons with the observations showed good matches. A similar framework was adopted by Wang, *et al.* (2006) to study visitor flows in the planning Expo 2010 site in Shanghai. They collected pedestrians' visit dairies through experiment.

However, blocks may not realistically be the spatial unit perceived by pedestrians; individual stores are more realistic. Zhu, *et al.* (2006a) modeled the choice of stores by assuming that every store in the shopping street is a choice alternative, which results in a choice set with over hundred stores. Except for including conventional factors such as store floorspace, type and distance in the utility

function of a multinomial logit model, they especially focused on the temporal effect of pedestrian behavior. By estimating the parameters for the interaction variables between the elapsed time of each pedestrian's shopping trip and other environmental variables, they demonstrated significant systematic changes in the utility function, which suggests that the hypothesis of time-varying behavior is right. To test more sophisticated influences of attributes, Borgers and Timmermans (2004, 2005) incorporated walking history attributes in a street (link) choice model based on MNL to introduce some degree of dependency between the separate decisions; Borgers, *et al.* (2005) modeled the behavioral differences between hedonic and utilitarian consumers; Dijkstra, *et al.* (2007) incorporated personal attitudinal attributes such as shopping urgency and familiarity of store in a logistic model (mathematically a special case of MNL) for predicting the occurrence of buying activity in a store.

Although not based on DCM, the work by Hoogendoorn (2003a, b, 2004), Hoogendoorn and Bovy (2004, 2005) about meso-level pedestrian chaining decisions are consistent with the principle of utility-maximization at large. They assumed that pedestrians maximize the expected utility of activity under uncertainty and developed a theory and model which describe a series of decisions at what they called the tactical level. The model includes activity scheduling, activity area choice, and route choice. They also assumed that pedestrians determine all the features simultaneously for the expected period of activities at the start of the behavior series. More detailed elements were included such as travel time, obstacle, speed limit, and level of service. The key idea of this approach is to simulate a disutility function which is to be minimized by the individual based on the outcomes of the decisions. Space and time were represented as continuous factors in theory, but in the simulations, for illustration, discrete representations were taken. Dynamic programming was applied to solve the problem of optimal route-choice.

Another unique line of research line about meso-level chaining behavior is about visit sequence given a series of stores to visit, which is a reminiscent of the Traveling Salesman problem. It is another perspective to study the extent and content of global planning underlying trip-chaining behavior instead of solely linking independent locally optimized decisions. Van der Hagen, *et al.* (1991) and Kurose, *et al.* (2001) classified the sequencing of pedestrians' store visits in retail environments into several distance-minimization heuristics from the completely globally optimized strategies to the completely locally optimized strategies, with other intermediate strategies in between. The results showed that pedestrians' strategies are much more diversified than what is commonly imagined as sequentially minimizing the distances of successive pairs of movements. This confirms the findings by Gärling, *et al.* (1986), Gärling and Gärling (1988), and Gärling (1989). Kitazawa and Batty (2004) used a genetic algorithm to simulate the shortest path of pedestrians in shopping malls given the stores, implying the global optimization strategy, and compared the simulated route with the observed route. They concluded that some of the mismatches could be caused by pedestrian using local strategies, proving further evidence to the concepts suggested in van der Hagen, *et al.* (1991).

The application of DCM in micro-scale pedestrian movement is relatively rare. A unique example is Antonini, *et al.* (2006). They modeled the acceleration of

walking pedestrians as choices among segmented cones in the radial space before the pedestrian. Each cone was given a utility composed of the directional deviation to the target, the availability of obstacles, the density of activities from other pedestrians, the speed relative to maximum personal speed, etc. They applied a cross-nested logit and a mixed nested logit model because the cones have strong spatial correlations. The models were estimated using real pedestrian movement data, collected through video-cameras.

In recent work, Borgers, *et al.* (2004, 2006) extended the link-node type spatial representation from the meso destination choice level to the micro level. They systematically identified nodes along a street, and assigned to each node a set of links, connecting the node with its neighboring nodes. They assumed that the movement of a pedestrian is the result of sequentially choosing at each node the link with the highest utility, which consists of the type of link (entry, exit, transfer, center), the length of the link, the attraction that the link leads to, the heading of the link relative to the current heading, the side of the street relative to the heading of the link (right- or left-hand side), etc. An MNL was estimated using real pedestrian movement data and was used for validating the approach by simulating the number of movements in the links and comparing these with observations. Results were positive. Note that by focusing on a smaller number of links rather than on complete paths in the network, the problem of correlated alternatives can be expected to be dramatically reduced, implying that a simple MNL model as opposed to a complex discrete choice model accounting for such correlation structures can be used. Moreover, the choice set problem which is especially relevant and problematic for route choice (e.g., van der Waerden, *et al.*, 2004) is avoided.

### 2.1.2.2 Physical analogy

At the micro movement level, if we disregard possible influence of intention, perception and decision, the aggregate movement pattern of a pedestrian crowd has similar physical properties as particle systems like gas and water flows, provided the number of pedestrians is large enough. Handerson (1971, 1974) found that the pedestrian speed-velocity distribution resembles gaseous behavior and agreed with Maxwell-Boltzmann theory. However, this type of approach has not been commonly applied in pedestrian research because its validity relies on several restricted conditions. One condition is that pedestrians, like particles, must be homogeneous (e.g., same size, same kinetic energy). This assumption may, however, be questioned in many real-world situations. Moreover, the environment for measuring pedestrian flows has to be regular, such as a rectangle corridor, just like a test tube, which is only applicable to limited real-world physical environments. The fluid-dynamics equations are too difficult to solve and not flexible enough for incorporating the influence of environmental elements like obstacles which cause the pedestrian to avoid them and change speed (e.g., Helbing, *et al.*, 2001).

Another physics-analogous pedestrian model which has been applied widely in modeling local pedestrian movement is the social force model (e.g., Helbing and Molnar, 1995; Helbing, *et al.*, 2001). Based on Newtonian mechanics, the model states that the movement of a pedestrian can be modeled as the result of the competing



forces exerted on him/her. Viewing movement as constant speed change, the basic social force model is represented by the equation of acceleration:  $d\mathbf{v} / dt = \mathbf{f}(t) + \xi(t)$ , where  $\mathbf{v}$  is a vector representing walking speed and  $t$  representing time. The left term then indicates acceleration.  $\mathbf{f}(t)$  is a vector representing the aggregate influence from the forces at time  $t$  and  $\xi(t)$  represents a random factor. This open-ended function, like the utility function in DCM, has enough flexibility for the researcher to include potential forces that may exert impact on acceleration. The forces may be external from the environment, such as the repulsive force due to boundary and obstacle, the repulsive interactions with other pedestrians, and the attraction force from a store or an interesting event. The source of the forces may also be internal, such as the preference of the pedestrian to walk with a certain speed, the social convention of walking manner (e.g., left- or right-side), and the habit of simply following other pedestrians (Xia, *et al.*, 2007). Aggregating the forces in some way, usually following the mechanical law, determines the speed and heading of the pedestrian at the next moment. Helbing, *et al.* (2001) also found that by simulating pedestrians with the force model defined at the local individual level, so called self-organizing (or emergent) collective behavior can be realistically replicated such as queuing and trail formation (e.g., Helbing, *et al.*, 1997; Bovy and Hoogendoorn, 2006).

The social force model is probably one of the more interesting theoretical frameworks, based on principles of physics, ever proposed for modeling pedestrian micro scale movement and has inspired many extensions and applications (e.g., Helbing, *et al.*, 2000; Gloor, *et al.*, 2004; Yu, *et al.*, 2005; Parisi and Dorso, 2005; Seyfried, *et al.*, 2006). However, the major problem is that the models are very difficult to estimate as the observation of the acceleration and the forces requires considerable effort and special treatment, especially in complicated real-world situations. Therefore, most researchers only built simulation models and tested them based on arbitrary parameters in order to have a qualitative justification of model behavior. Work on model calibration is very rare (e.g., Hoogendoorn, *et al.*, 2007). Technical problems also exist when simulations are conducted. Because the model is based on continuous space, it is often less convenient to implement environmental change in the continuous representation and it requires more computation power to let the simulated pedestrian interact with the environment, compared to other modeling approaches, such as cellular automata.

### 2.1.2.3 Cellular automata

Instead of continuous space, cellular automata (CA) use discrete space for representation. Although not necessary, a grid space consisting of square cells is the mainstream representation format in practice due to operational considerations. Each cell has a finite set of possible states. The state of the cells evolves synchronously in discrete time steps as a function of its current state and a set of rules, which relates the cell to other cells in the system. The purpose of the model is to simulate dynamic processes. CA is very suitable for representing any scales of real or virtual space and dynamics that can be approached by discretization. Batty (2005) reviewed the multi-level applications of CA. However, with the increasing power of computers as well interests in emergent behavior, individual-based CA has become a popular language

for modeling pedestrian movement. The popularity is linked to the relative ease and computation efficiency in operationalizing CA models compared to other approaches (e.g., Blue, *et al.*, 1997; Blue and Adler, 2001). The common basic treatment in movement simulation is that a pedestrian is assigned to a cell and movement is realized by making the pedestrian constantly occupy adjacent neighbor cells (8 neighbor cells by Moore's rule, or 4 neighbor cells by von Neumann's rule) in discrete time. The occupation is controlled by drawing a stochastic cell according to the transition probabilities in the neighbor cells. The transition probabilities can be generated based on any model that suits the discrete representation and spatial conditions can be straightforwardly linked.

For example, Muramatsu, *et al.* (1999) used a lattice gas model to study the jamming effect. Kirchner, *et al.* (2003) modeled the mechanism of pedestrian solving conflicts when they are going to occupy the same cell. Narimatsu, *et al.* (2004) studied a similar topic, but used some adaptive procedure to adjust the parameter responsible for collision avoidance. Bandini, *et al.* (2006b) simulated passenger behavior in a train, such as waiting, getting on board, choosing a seat, and getting off board, as the reaction to perceived signals around such as seat availability. The idea of floor field was introduced by Burstedde, *et al.* (2001), Schadschneider (2001) and Schadschneider, *et al.* (2002), which turned out to be a very useful technique in CA-based modeling. It was devised to overcome the limitation in social force based modeling on representing long-range interactions, by imposing a second virtual grid layer (force field) upon the original layer. The force field may contain information about the influence from forces far away, e.g., a magnet store at two blocks away, and may change its status autonomously or be changed by pedestrians, analogous to an ant leaving chemotaxis to other ants. Complex inter-pedestrian and pedestrian-environment interactions can be simulated more efficiently. However, the difficulty to estimate these models against real behavioral data is also a problem for CA-based pedestrian models (Batty, 2001b, 2005). Therefore, simulation models are ubiquitous.

#### 2.1.2.4 Cognition and psychology

Observation-based descriptive research has already suggested that pedestrian's cognitive, psychological and decision processes are too complex to be captured by any single mechanism. Abundant research has accumulated various cognitive, and psychological aspects of human behavior in spatial environments over the past 40 years (e.g., Lynch, 1960; Golledge and Timmermans, 1990; Herzog, 1992; Zacharias, 2001a, 2001b). Such complexity is most of the time a compound of simple but heterogeneous rules tailored to different problems or contexts. Peponis, *et al.* (1990), following 15 participants when they were exploring a hospital building, and derived a set of rules governing wayfinding behavior: (a) avoid back-tracking; (b) if all else is equal, continue on the same line; (c) divert from the line where a new view allows you to see more space and activity or a longer view and lets you see further ahead; and (d) confirm the unexplored parts of the building before the already explored parts. A key aspect of this work lies in the understanding that cognition depends in part on local information, in part on memory of those areas of a building already explored, and in part on the ability to project or develop hypotheses about those parts of a building that

have yet to be explored so that exploration could maximize new information. Chang (1998) also found that maintaining a straight line appeared to be preferred to maintaining a correctly oriented trajectory toward the final destination, with deviations along shorter lines taking place later in the trip to bring one to the destination. Hochmair (2005) explained such behavior as the result of least-angle heuristic (LA). He contented that one of the strengths of LA is that it requires little cognitive effort for the decision making process. Therefore, it can be used for situations in which decisions have to be made quickly, and where no detailed information is available at hand. LA can be used as a temporary strategy but will fail as a long-term strategy. Similarly, Gärling, *et al.* (1986) and Gärling (1989) found that the application of the distance-minimization strategy depends on the pedestrian's knowledge about and the cognition of space: a global minimization strategy is more probably applied when the knowledge and cognition are good, whereas a local minimization strategy is probably applied when knowledge and cognition are poor.

However, the quantification of the cognition of spatial structure, instead of using qualitative methods such as a cognitive map (e.g., Golledge, 1999), is a major problem when linking pedestrian behavior to cognition in any modeling approach. An extreme and therefore, highly questionable assumption by Hillier (e.g., Hillier and Hanson, 1984) who argued that there is a strong relationship between the morphology of the environment and pedestrian use patterns, and his theory has received a strong following in architecture and urban design. This relationship has been tested in many studies, based on the space syntax method. In fact, space syntax is not really a modeling technique. Its most widely discussed concept, the axial map, represents spaces (usually cities, neighborhoods, or other) as a matrix of the "longest and fewest" lines. The analysis involves translating the line matrix into a graph, and using various versions of the "topological" (i.e., nonmetric) measure of patterns of line connectivity, called "integration" (Hillier, 1999). The integration measure has some tangential link with cognitive spatial structure. For example, a higher integration usually means that a space has more connection to the network, which may correspond to people's cognition as an important place to social life. However, it is never defined from an individual perspective nor applied in individual-based analysis. Basically the integration is a graph-theoretic measure of accessibility. Integration measures of axis have been correlated with pedestrian counts using log-log or even higher order log transformations, and not surprisingly strong correlations have been found (e.g., Penn, 2003). Hillier, *et al.* (1993) even boldly concluded that if planners wish to design well-used urban space, then it is not the local properties of a space that are important but its configurational relations to the larger urban system. Such statements, however, caused one of the major criticisms that have been raised against the method (e.g., Ratti, 2004), as the street network is rarely designed separately from land use planning. Important buildings are usually placed at accessible locations; therefore the integration measure already implies the land use pattern to some extent. In other words, space syntax does not really explain activity behavior but rather expresses a tautological relation in practice between accessibility, land use and user intensity. It is no surprise and highly revealing that correlations were significantly lower if the location of major attractors did not coincide with highly integrated axes (e.g. Read, 1999). The approach is also

taunted with abundant methodological problems, including boundary conditions, the calculation of correlations, the subjectivity in defining the axial map, biases in the axial map due to the size of area under investigation etc. (e.g., Teklenburg *et al.*, 1993; Batty, et al., 1999; Batty, 2001a; Ratti, 2004). It may be used however as an easy to apply, simple design tool to diagnose morphological structure (e.g., Teklenburg, *et al.*, 1994, 1997).

Space syntax is strongly related with visibility graph analysis (VGA), which is, however, easier to understand and technically more sound. Visibility graphs simulate people's vision based on the notion that pedestrian movement and flows rely heavily on lines of sight and visibility when navigating through an area. The visibility graph is computed by overlaying a two-dimensional grid (at some arbitrary resolution) over a layout in plan view, and calculating which points within the grid are able to see which other points. The set of visible locations for each point are stored, and thus the visibility graph can be used to calculate the approximate viewable area, or isovist (e.g., Benedikt, 1979), from each point on the grid. Measures can be derived to characterize the property of space based on the isovists of each discrete point in the space, such as average distance, area, perimeter, compactness ratio and cluster ratio (e.g., Batty, 2001a) and correlated with people's behavior. For example, Turner, *et al.* (2001) conducted correlation analysis between the aggregate space occupancy in London Tate Gallery and the mean shortest path length of isovists, and found an inverse exponential relationship between the two. At the individual level, Franz and Wiener (2005) collected respondents' feelings about virtual spaces and correlated them with the properties of the isovists of the places that the respondents were at. They found high correlations and concluded that isovist-based spatial measures may be a very good predictor of people's spatial behavior.

Based on the experiences with space syntax, Turner and Penn (2002) argued that pedestrian's local movement may be largely explained by the configuration of space alone. They used exosomatic visual architecture, which is a dense-grid visibility graph, to represent a space. They simulated pedestrian movement in a gallery using a very simple mechanism under which the pedestrian randomly selects a point as the destination within the isovist of the current position, based on the principle of so called "natural" movement. The simulation showed that the best resemblance ( $R^2=0.76$ ) between the aggregate simulated pedestrian spatial distribution and the observation was achieved when the visual field of pedestrian was set to  $170^\circ$  and the mean step size was 3, which controls the frequency of the decision to change direction. However, whether such mechanism can explain pedestrian movement in other environments may be doubted as the spatial characteristics in a gallery are relatively homogeneous and visitors usually do not have a priori preference on exhibits, while many daily walking environments are much more diversified and pedestrians are more likely to have established preferences. In addition, it is not realistic to assume that pedestrian behavior in well-known environments is based on the visibility of stores. Many decisions and movement patterns will be based on memory recall or even routine. At least arousal levels will vary considerably while moving through the environment. Furthermore, in environments such as busy shopping streets visibility lines will typically be blurred or blocked due to other pedestrians. Therefore, the inflexibility of

VGA to incorporate specific environmental elements is a major problem to elaborate this approach into a more full-fledged modeling approach to pedestrian behavior. The approach as space syntax simply makes too strong implicit or explicit assumptions about the influence (perhaps even dominance) of morphology on pedestrian behavior. At best, visibility may be one of the factors influencing local movement patterns.

### **2.1.2.5 Multi-agent systems**

O'Sullivan and Haklay (2000) argued that multi-agent systems (MAS) are not models which are conventionally understood as rules and mechanisms that explain phenomena, but problem solving systems which can incorporate models. It is one of the properties that may apply to some multi-agent systems. An agent can be thought of as an autonomous, goal-directed software entity, which has properties and may act, based on the principles of object-oriented programming. Therefore, any entity fitting this criterion can be treated as an agent, no matter what real-world entity it represents. It can be a pedestrian; it can be a unit of the environment which changes and can be changed. In complex simulations, agents can be programmed to interact with each other (e.g., pedestrian-environment, inter-pedestrian). When the computation ability is powerful enough to allow simulating many agents simultaneously, so-called emergent, or self-organizing behavior may appear. Thus, MAS are sometimes also categorized as an emergent algorithm, which represent any computation that achieves formally or stochastically predictable global effects by communicating with only a bounded number of immediate neighbors and without the use of central control or global visibility.

These properties of MAS have greatly prompted research and development of pedestrian MAS since the late 1990s, and many of these studies were motivated to analyze emergent behavior and provide evidence of complexity theory. However, multi-agent systems have also been interpreted in a less stringent matter to refer to micro-simulation in which agents, representing decision makers, hold beliefs, have preferences, apply decision heuristics etc. In other words, the simulation goes beyond the classical Monte Carlo simulations in which the simulation was primarily based on draws from observed and sometimes generalized statistical distributions.

Dijkstra and Timmermans (1999a, b; 2002) and Dijkstra, *et al.* (2000a, b; 2001; 2002), developed the AMANDA system, which focuses more on pedestrian behavior in shopping environments. Originally, a CA model was used to simulate pedestrian movement, but later this representation was replaced with trajectories (Dijkstra, *et al.* 2006a, b). Although that part has not been explicitly developed, it is assumed that the model starts with a synthetic population of pedestrian agents, who enter the area of interest (inner city area or shopping mall) at various entrance points. Agents have an activity agenda that includes the stores they plan to visit according to a sequentially distance-minimizing heuristic or some other heuristic. The focus of development has been on what happens during these successive visits in the sense that the model allows for impulse stops. When moving over the network, agents are assumed to use perceptual fields. Perceptual fields, which guide which stores an agent will perceive, vary according to the agent's awareness threshold and the signaling intensity of the store (Dijkstra, *et al.*, 2005). When stores are signaled and become

included in an agent's perceptual field, the agent decides whether or not to act and visit the store. This is called the activation of the agent, which depends among others on agent's personal characteristics, motivation, familiarity with a store, suitability to conduct a visit, and the agent's consideration set. A consideration set is a set of stores that an agent considers in performing a particular activity. If an agent is not familiar with a store, the activation of the agent towards this store will be lower. Similarly, activation will be equal to zero if the store is not suited to conduct any of the activities that are still scheduled to be completed. If an agent becomes activated, it gradually moves to the store. The model then simulates the duration of window-shopping, if any, the probability and duration of an actual visit to the store, and the probability of successfully completing the activity at the store, by drawing for probability distributions, empirically estimated from data of pedestrian behavior. The probability of a successful completion is a function of availability and predictability of the product, the urgency of completing the activity, the familiarity of the store to the agent, the duration of the visit, and the attractiveness of the store (Dijkstra, *et al.*, 2007).

Kerridge, *et al.* (2001) developed PEDFLOW, a MAS focusing on the detailed level of a section of a sidewalk, or in an open or enclosed space with obstructions. They used a grid-based spatial representation and each pedestrian occupies a cell. The movement rules were set in the form of decision tables which a pedestrian may look into under particular circumstances. The focus of the system is on the interaction of the pedestrian between entities, which can be another pedestrian, a possible goal point, a stationary object, the edge of a building, or the curb between road and pavement. The authors contended that in order to make the system representative of reality, not only objective pedestrian behavior like walking pace (e.g., Walmsley, 1989), speed (e.g., Willis, *et al.*, 2004; Daamen and Hoogendoorn, 2007a, b), crowd and flow (e.g., Daamen and Hoogendoorn, 2003, 2007c; Daamen, *et al.*, 2005b, Hoogendoorn and Daamen, 2006), speed-flow relationship (e.g., Lam, *et al.*, 1995; Lam and Cheung, 1997, 2000; Lam, *et al.*, 2002, 2003; Goh and Lam, 2004; Lee, *et al.*, 2006), and travel time (e.g., Lam and Cheung, 1996, 1999), but also subjective aspects such as perceptions, past experiences, and attitudes should be included, for example, by using the results of perceptual and attitudinal research (e.g., Hine, 1996).

STREETS, another pedestrian MAS proposed by Haklay, *et al.* (2001), is a more comprehensive system. It was designed as a test bed for models of macro (urban), meso (district) and micro movement level behaviors. At the macro level, they used socioeconomic and other data about the urban area to populate the urban center with a statistically reasonable population of pedestrians, for example, based on gravity models or discrete choice models for retail center choice behavior. At the meso level, pedestrians take into account the spatial configuration of the street network and the distribution and land uses, fused by an integrated GIS, and determine the sequence of routes to be taken, given a predetermined plan. At the micro level, pedestrians are enabled to have vision and may choose target places within the visual field towards which they move in a grid-based spatial representation.

Ali and Moulin (2005, 2006) also developed a MAS specific for shopping-environments, called MAGS. It possesses the common features of most MAS with pedestrian agents being able to perceive, memorize, decide, navigate, avoid, and

interact with other pedestrians. The relatively special feature of MAGS is that a higher degree of segmentation such as gender, age group, marital status, and sector of employment of the pedestrian are used. Moreover, pedestrians have different levels of hunger, level of thirst, level of fear or stress, need to go to the restroom, and emotional states. Pedestrians may adjust the priority of tasks based on Maslow's hierarchy of needs. For example, the need for eating or resting will suppress the need for shopping temporarily. The spatial representation is also raster (grid)-based. Different types of information are stored in multi-layer raster maps. There is AgentsMap which contains the location of agents and objects in the environment, ObstacleMap which contains the location of obstacles, ArianeMap which contains the paths that can be followed by mobile agents, HeightMap which represents the elevation of the environment, and other maps. The states of maps can also change, which enables complex dynamics.

Silverman, *et al* (2006a, b) developed a comprehensive behavioral simulation package, called PMFserv, which aims to replicate human behavior highly realistically. Based on existing theories and models, the system was constructed as a complex of five inter-related major modules: (1) biology module which simulates physiological phenomena and stress; (2) personality and culture module which simulates individual's value and emotion; (3) perception and psychology module which simulates how individuals perceive and represent the environment; (4) social module which simulates inter-personal relations such as trust; (5) decision making module which enables agent to make decisions based on subjective expected utility theory. The system provides a test-bed for separate and joint behaviors of the models. For example, the change of an agent's level of stress or time pressure is specified to prompt changes in perception and decision strategy. Pelechano, *et al* (2005) incorporated PMFserv into their MAS, called MACES, for evacuation simulation in order to increase behavioral realism. Basically, MACES simulates agent's higher level wayfinding behavior which is based on a mental map and shortest path algorithm, and lower level movement which is simulated based on the social force model. These behavioral simulations are enhanced by adding communication mechanism between agents which allows agents to learn mental maps from each other for better wayfinding.

From the examples above and many other MAS, CA seems to be a popular framework for representing space and implementing mechanisms, compared to other frameworks such as continuous space representation in which coordinates of floating-point accuracy are used for positioning agents in space (e.g., Hoogendoorn and Bovy, 2001). Although information may be lost by discretizing space and agents are limited to move into a small number of neighboring cells, these limitations can be alleviated by using a smaller size of cells. Actually, since all MAS are run on digital computers and computation is intrinsically discrete, it is only a matter of the degree of discontinuity that the user can feel to be real or unreal (e.g., Klügl, *et al.*, 2005). CA-based MAS are easy to understand and operate, but consume a lot of memory once the scenario becomes large. Models based on continuous space, which are more economical in terms of memory usage, however, use significantly more CPU cycles. It is up to the developer to decide which framework to use or even both. For example, Gloor, *et al.* (2004) developed a hybrid MAS which is basically a continuous system.

But they limited agent's walking directions like under the CA principle in order to save computation. The flexibility is that walking speed can be more accurately modeled, which is limited and problematic under the Moore's rule of CA in the sense that in discrete movement the length of diagonal movement is always longer than that of a vertical or horizontal movement.

Homogeneity is another unrealistic feature of CA-based MAS. Bandini and Simone (2004) contended that this can be overcome by introducing heterogeneous space in terms of property and structure, non-uniform neighborhoods, more distant actions, non-universal transition, and openness to outside influence. Therefore, they developed Mmass, the acronym for Multi-layered Multi-Agent Situated System (e.g., Bandini, *et al.*, 2002, 2006a, 2006b), which is a general-purpose MAS and can be implemented for various types of spatial simulations. The major feature of Mmass is the ability to model heterogeneous spatial relationships by defining different topological structures between sites. The arrangement of the basic spatial unit may not necessarily be in a universal regular grid, but can be defined discretely in continuous space to represent specific environments of interest. Multiple spaces can be defined to represent the heterogeneity in the nature of space. Agents can be situated into different spaces and act based on the different rules of each space. The interaction between agents is implemented by using fields, which contains the properties that can be generated from agents and themselves may evolve according to some mechanisms.

With the help of MAS, planners are able evaluate and adjust their plans much more effectively and efficiently. Lee, *et al.* (2001) used PEDROUTE, a pedestrian simulation model, to simulate the pedestrian movements within the station by incorporating the O-D flow matrix and the travel time functions of the nine classified pedestrian facilities. The simulation results matched well to the observations in terms of pedestrian flow and travel time. Batty, *et al.* (2003) applied a MAS in simulating pedestrian flows in Notting Hill Carnival, for the purpose of controlling the unsafe situations caused by small-scale events, by recursively adjusting the safety measures against those events and simulating pedestrian movement. Johansson and Helbing (2007) used a genetic algorithm to search for an optimal passage design in terms of the efficiency of pedestrian flows through the passage, resulting from evacuation.

The development of MAS is not only limited to the academic world, but also widespread into the commercial and noncommercial world. Legion (see <http://www.legion.com/>) is one of the successful commercial simulation systems, which has been tested against abundant empirical data (e.g., Berrou, *et al.*, 2007). The internet facilitates the MAS fans to share their knowledge and techniques in building MAS in the virtual noncommercial world, often in the form of open-source MAS that can be improved by anyone, such as NetLogo (see <http://ccl.northwestern.edu/netlogo>).

## 2.2 Models of Bounded Rationality

### 2.2.1 Decision heuristics

We use the term “decision strategy” to refer to any rule for decision making, including rational choice rules and decision heuristics. A decision heuristic is commonly defined as an informal method to help solve a problem, which often leads to a solution that is



usually reasonably close to the “best” possible answer (best under the rational rule), or sometimes called “rule of thumb”. Such a definition may not be complete as it only includes the comparison on the decision outcome, while the decision process is not emphasized, which is often thought to be much simpler than that implied by the rational decision rules. Interestingly, rational decision rules gather so tightly around the tenet of utility-maximization that there are not many variations from the classical principle which states that people trade-off (expected) attribute utilities to arrive at an overall utility and choose the alternative with the highest overall utility, while decision heuristics are so diverse that even researchers sometimes feel confused to select a heuristic according to which they can select a heuristic for modeling the decision problem. The major reason is that rational decision rules are largely outcome-oriented and theoretical consistency is emphasized more than procedural realism in their development, while decision heuristics are process-oriented and empirical observation is an importance source for devising them. Therefore, it is not surprising that heuristics have different levels of complexity and accuracy, depending on factors such as the total amount of information processed, the selectivity in information processing, the pattern of processing, and whether the strategy is compensatory or non-compensatory (Bettman, *et al.*, 1998). Only those heuristics that are more frequently discussed in the literature will be reviewed below.

### **2.2.1.1 Compensatory and semi-compensatory rules**

#### *Weighted adding rule (WADD)*

WADD assumes that the individual can assess the importance of each attribute and assign a subjective value to each possible attribute level. Then, the individual considers one alternative at a time, examines each of the attributes for that option, multiplies each attribute’s subjective value times its importance weight, and sums these products across all attributes to obtain an overall value for each option. Then, the alternative with the highest value would be chosen. As can be seen, its rationale is very similar to that of a DCM with a linear utility function except that there is no role for a stochastic utility part. The weighted additive structure can also be found in multiple other normative and descriptive theories. For comparison reasons, WADD is often thought as a typical rational decision rule which is most accurate for a decision and is used as the benchmark for comparing performances of alternative decision strategies (e.g., Zakay and Wooler, 1984; Payne, *et al.*, 1998; Chu and Spires, 2000). As the rule assumes that all alternatives and attributes are considered and the information processing may involve multiple multiplications and summations, it is believed this strategy demands most working memory and computational ability.

#### *Equal weight rule (EW)*

EW is sometimes also called Dawes’ rule (Dawes, 1979), which is a variation of WADD with the difference that attribute weights are ignored and only attribute values are aggregated into the overall value. The choice rule is still to select the alternative with the highest overall value. Since weights are ignored, EW is thought to be easier to implement than WADD. However, ignoring relative attribute importance may only

account for some real-world decision problems as people most time attach importance to attributes.

#### *Frequency of good and/or bad features rule (FGB)*

Instead of aggregating attribute values, FGB (Alba and Marmorstein, 1987) states that individuals may evaluate and choose alternatives by counting the number of good and/or bad features characterizing the alternatives. This requires the individual to develop thresholds for specifying good and bad features. For example, an attribute is considered good if the value exceeds the threshold and considered bad otherwise. The alternative with the largest (least) number of good (bad) attributes is chosen. Weber, *et al.* (1995) provided evidence consistent with such a strategy, noting that encoding such outcomes is often simple. Like WADD and EW, FGB also assumes complete evaluation of alternatives and attributes. Therefore, in general, it still requires quite much effort and does not imply attribute importance.

#### *The majority of confirming dimensions rule (MCD)*

Proposed by Russo and Doshier (1983), MCD assumes that alternatives are processed in pairs, comparing the values of the two alternatives on each attribute. The alternative with a majority of winning (better) attribute values is retained. The retained alternative is then compared to the next alternative from the choice set, and this process of pairwise comparison continues until all the alternatives have been evaluated and one option remains. Such information search pattern is said to be attribute-based rather than alternative-based, as in WADD, EW, and FGB, under which all the attributes of one alternative have to be inspected before evaluating another alternative. Attribute-based search is believed to be more efficient than alternative-based search as it may save the effort from shifting cognitive paradigms between different types of attributes (e.g., Tversky, 1972). This has also been proven empirically by Russo and Doshier (1983), who inferred respondents' information processing patterns through eye-fixing equipment, doubly verified by protocol analysis. The result showed that dimensional strategies (attribute-based) are much more frequently used than holistic strategies (alternative-based). MCD also implies complete information search.

### **2.2.1.2 Non-compensatory rules**

#### *Satisficing rule (SAT)*

Simon (1955) proposed the SAT rule, which assumes that the individual evaluates the alternatives in the choice set in some sequence and evaluates each alternative in an alternative-based manner. Once he/she finds that the alternative is satisfactory against some standard, the decision ends with this alternative being accepted; otherwise, the evaluation continues. Therefore, SAT may imply that not all alternatives are evaluated. Judging the satisfaction of an alternative is usually based on two rules: the conjunctive rule (CONJ) and disjunctive rule (DISJ), both using attribute thresholds. CONJ states that a choice alternative will only be satisfactory if it meets a set of attribute thresholds, implying that the least satisfactory attribute value of a choice alternative is critical to its acceptance. The alternative can be considered unsatisfactory once an unsatisfactory

attribute is found. In contrast, DISJ assumes that an alternative will be satisfactory if it has at least one attribute greater than the corresponding threshold. By using either rule, it is possible to judge an alternative only based on part of the attributes. Therefore, decisions using SAT tend to be quick, although the outcome may not be consistent in the rational sense as the sequence of evaluating alternatives may cause premature stopping of the search process before reaching the optimal alternative.

### *Lexicographic rule (LEX)*

This rule requires a complete ranking of the attributes in terms of relative importance. The individual determines the most important attribute and then compares the values of all alternatives on that attribute. The alternative that presents the best value on the most important attribute is selected. If two alternatives are equal in the sense that they present equal values on that attribute, the second most important attribute is considered and the procedure continues until one option is chosen. By definition, LEX is attribute-based and may only require an incomplete attribute search, risking inconsistency as the choice outcome depends on the sequence of attribute search. Determining the sequence is a major challenge of similar modeling approaches. In a variant called Take The Best (TTB, Gigerenzer and Goldstein, 1999), attribute search sequence is based on the descending ordered attribute validity, which is calculated as the proportion of right judgments using each attribute alone for comparing the two alternatives, based on a training dataset. The derived attribute search sequence is then used to infer the judgments based on a testing dataset. The major problems of such validity are: on one hand, there is no sufficient evidence showing that individuals do so for determining attribute search sequence. On the other hand, it makes people doubt whether the good model estimation result is correlated with such a somehow tautological treatment, something like using the dependent variable to explain itself. The authors defined another rule called Take The Last in which the search of attribute starts from the one at which the previous problem stopped, based on the belief that the attribute which recently stopped the search tends to be more likely than others to stop the search. In another rule called Minimalist, the search sequence is just random, simulating the situation that the individual only has the minimum (no) information about the search strategy.

### *Elimination-by-aspect rule (EBA)*

Proposed by Tversky (1972), EBA combines elements of both the lexicographic and satisficing strategies. Under this rule, the individual eliminates alternatives that do not possess certain aspects for the most important attribute. This elimination process is repeated for the second most important attribute, with the processing continuing until a single option remains. The consistency of EBA also depends on the attribute search sequence. The attribute search sequence is specified to be probabilistic, proportional to the attribute importance. An extension called elimination-by-cutoff (EBC) was proposed by Manrai and Sinha (1989). It overcomes the limitation of EBA that only discrete attribute aspects are compared by introducing thresholds for continuous attributes so that an alternative can be eliminated if the attribute does not exceed the threshold. They showed the statistical advantage of EBC over the multinomial logit

model using experimental choice data. Actually before them, Recker (1979) already used a similar concept of attribute tolerance. Attribute tolerances were estimated in applications of EBA to transport mode choice and shopping center choice behavior. However, they determined the attribute search sequence by ordering the stated attribute importance provided by the respondents, which means that the model requires extra input. In a case study of residential choice, Young (1984) assumed that individuals have a set of minimally acceptable satisfaction levels which are used to judge the satisfactoriness of corresponding attributes and are expressed as a fractional tolerance of the maximum satisfaction level of each attribute over all choice alternatives. These tolerances were estimated, while attribute importance was provided by respondents, using rating scales. The model showed satisfactory results. However, it suggested different implications compared to the compensatory logit model, because EBA model does not imply the IIA assumption. Therefore, the change of attributes does not always result in the same marginal choice probability for all the alternatives. One operational limitation of EBA is that the model specification becomes exponentially cumbersome when the number of alternatives increases. Hence, most theoretical statements of EBA as well applications are limited to using no more than three alternatives.

Goldstein and Gigerenzer (1999, 2002) suggested the Recognition Heuristic (RH). It belongs to the set of so called ignorance-based strategies, but can also be categorized as a special case of EBA. RH only applies to the situation when some alternatives can be recognized by the individual while others cannot. The first (only) attribute for consideration is whether an alternative is recognizable and unrecognized alternatives are eliminated. The rationale is based on the reasoning that the inference task may benefit from the ecological correlation between the recognition (exposure) of the alternative and its property that is to be inferred. When both alternatives are recognizable or neither is recognizable, other information must be used for judgment. This fast-and-frugal, less-is-more heuristic shows its interesting inferential ability in an experiment in which both American and Germany students were asked to infer which of two cities (San Diego or San Antonio), is larger. 62% of the American students answered right, while this percentage was 100% for the Germany students because the former knew both cities, whereas all of latter had heard of San Diego, but only half of them knew San Antonio. A similar effect was observed by Borges, *et al.* (1999) in experiments of selecting portfolios, which showed that laypeople selected better stocks than experts only based on the recognition of companies.

### 2.2.1.3 Combined and hybrid rules

#### *Combined rules (COM)*

Individuals may also use a combination of decision strategies instead of relying on only one rule. A typical combined strategy has an initial phase in which some alternatives are eliminated and a second phase where the remaining options are analyzed in more detail. Payne (1976) found that there was a shift from compensatory strategies to non-compensatory strategies that involved elimination of alternatives on the basis of a subset of information. Moreover, having eliminated some alternatives in

this way, thereby having reduced task complexity, some decision makers returned to a compensatory strategy to decide among the remaining alternatives. Such decision pattern is also often discussed in the choice set formation problem under the discrete choice modeling framework. Borgers, *et al.* (1986c) adopted a two-stage model. The first stage was specified as a conjunctive process using attribute thresholds. They assumed the thresholds to be normally distributed and derived the probabilities of each alternative being included in the choice set as the joint probability of each attribute exceeding the threshold. The second stage was represented by a multinomial logit choice model conditional upon the choice set determined in the first stage. Applied in the residential choice experiment, the model was estimated using a recursive estimation procedure with the attribute thresholds being estimated and the probabilities of possible choice sets being derived first, followed by estimating the parameters in the MNL model, until the goodness-of-fit statistic cannot be improved. Although behaviorally more realistic and complex, the model only showed slight improvement compared with a single MNL model without choice set specification.

Under a similar framework, Ben Akiva and Boccara (1995) incorporated the effects of stochastic constraints or elimination criteria and the influence of attitudes and perception as latent indicators on the choice set generation process. Cantillo and Ortuzar (2005) also applied the two-stage model with the extension that socio-demographics were added to the distribution of attribute thresholds in the first choice set formation stage in order to capture heterogeneity. Because this model generated much better results than the one-stage MNL model, they concluded that if there is evidence of the existence of thresholds in the population the use of a fully compensatory model, such as MNL or even Mixed Logit, can lead to serious errors in estimation and predictions. However, a critical problem of this combined approach is that researchers usually cannot observe the choice set, and hence typically assume that all possible choice set combinations have some probability of being considered. This implies that the number of choice sets exponentially increases with the number of choice alternatives, which is not only unrealistic but also requires impractical computation cost. Therefore, applications of the approach are limited to cases with a small number of alternatives.

### *Hybrid rules (HYB)*

Unlike COM, which combine pure forms of decision rules, representing either unbounded or bounded rationality, hybrid models usually are developed from the framework of rational decision models and incorporate principles of bounded rationality to improve the representation of the decision process. The threshold effect has been widely observed and mostly discussed. Many consumer decisions that involve accepting or rejecting a good or brand may be attributed to this effect. Kau and Hill (1972) proposed a multivariate probit model for such decisions in which an individual is assumed to calculate the overall utility of a good first based on a compensatory linear attribute utility function, followed by comparing this overall utility against a threshold value. If the threshold is exceeded, the good is accepted. By assuming the threshold is standard normally distributed to represent heterogeneity of individual decision standards, the probability of acceptance was derived. A maximum

likelihood estimation procedure was used to estimate the model in the context of a corn treatment decision. The same approach was applied by Bettman (1974) to model consumer's satisfaction of brand attributes. He also suggested using dual thresholds to classify judgments into unsatisfactory, undecided, and satisfactory attitudes. Gilbride and Allenby (2004) also included this model in their comparative study as a compensatory screening rule for the decision stage of choice set formation.

Discrete choice models are another important starting point for threshold-based extensions. An early attempt was made by Krishnan (1977), who introduced a model that incorporates thresholds of indifference into the binary logit model. The model states that an alternative will be preferred only if its utility is greater than that of the other alternative plus some threshold value. The model was applied in the context of mode choice behavior. More recently, based on the observation by Gupta and Cooper (1992) that consumers do not buy a good unless the promotion discount is above a threshold level, Han, *et al.* (2001) proposed a hybrid model in which a good will only be bought when the difference between the observed price and the reference price is above some threshold. The inclusion of reference price borrowed the notion of Prospect Theory (Kahneman and Tversky, 1979) which states that people weigh loss more than gain relative to the reference point.<sup>3</sup> The authors assumed the thresholds to be random distributions and used factors such as price volatility, discounting, and deal-proneness as explanatory variables. The probability of an attribute exceeding the threshold was further specified as a logistic function. The expected price difference was calculated as the multiplication between the observed price difference and the probability, which was inserted as a term in the utility function of an MNL model.

Theoretically, including expected price difference in the utility function is not rigorous for representing threshold heterogeneity. Cantillo, *et al.* (2006), therefore, proposed a model with a similar underlying rationale but with an improved specification. They similarly assumed that a change in an attribute has to be larger than a threshold value in order to be perceived and thresholds are probabilistically distributed. The difference is that it is not the attribute change that is expected under the distribution but the probability of choice. As a result, the estimated choice probability is the expectation of the choice probabilities under certain thresholds weighted by the density of the threshold distribution, which however does not have a close form solution and was computed by simulation.

Swait (2001a) incorporated attribute thresholds into the utility function of an MNL model in a different way. He postulated that the threshold effect may not necessarily be drastic, in the sense that an attribute utility becomes 0 when the threshold is not satisfied (or satisfied, depending on the problem definition). Instead, consumers may attach different degrees of penalty to the attribute utility if the threshold conditions are violated. Such penalties were represented by an extra parameter imposed on the original utility function and multiple thresholds and corresponding penalty parameters were allowed for an attribute. This resulted in a piecewise utility function with each threshold as the turning point for the marginal

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<sup>3</sup> The concept of reference point is not confined to prospect theory. Alternative theories and specifications, such as ideal point concepts and relative utility theory, also use references. A detailed and comparative discussion of these theories goes beyond the scope of this thesis.

utility. The author showed that with this flexible specification, CONJ can be approximated when the penalty parameter approaches negative infinity, and DISJ can be approximated when the penalty parameter approaches positive infinity. The model was applied to a car choice experiment. A major shortcoming of the study, also mentioned by the author, is that threshold values were reported by the respondents. The reliability of self-reported thresholds are doubtful as evidenced by for example Weitz and Wright (1979), who found that although respondents report whether they used thresholds for attributes or not, their reports of the quantitative threshold values are very poor.<sup>4</sup> In general, HYB provide more mathematical convenience than behavioral realism, as the major information processing structure still assumes complete information search and compensation.

#### **2.2.1.4 Comparing the rules**

With such diversified models of decision strategies in the toolbox of researchers, how can they know which models are appropriate for modeling individual decisions? This is probably the most difficult question in decision research with no concrete answer yet and perhaps never to come. Nevertheless, a common heuristic practice is based on the belief that the model which has the best goodness-of-fit in representing or predicting observed decision outcomes, using statistical criteria such as squared error and likelihood, should be the one closest to the true decision process. Although, this is a very partial view of validity, most research has followed this methodological principle and compared models of rational behavior against alternative models. Results generally suggested that heuristic models were more appropriate. For example, within the still escalating torrent of using discrete choice models in transportation field, Foerster (1979) is among the earliest endeavors of introducing heuristic models into the field. He compared the MNL model with WADD, LEX, Maximin, CONJ+WADD, and CONJ+LEX in an application of transport mode choice, and found that almost all heuristic models performed better than the MNL model, especially the two COM models. Therefore, he tentatively suggested exploring decision processes in transportation with more diversified models other than rational choice models.

Similarly, Phipps and Meyer (1985) compared the predictive ability of a normative stopping model, based on maximizing expected utility when making sequential decisions, and a heuristic stopping model, to explain the behavior of subjects in an apartment search game. The results tended to favor the heuristic model: stopping appears best characterized by a set of individual-specific utility-difference thresholds. Martignon and Schmitt (1999) compared TTB with a multiple regression model and a Bayesian network model using cross-validation and found that TTB was robust, at least for small sample size. A more systematic comparison was conducted by Czerlinski, *et al.* (1999), who compared TTB, Minimalist, EW and WADD on 20

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<sup>4</sup> There is a larger literature and discussion on the identification of thresholds and bifurcation points, for example in the literature on willingness to pay. Rather than asking respondents to report thresholds and bifurcation directly, double anchors have been used. Wang, *et al.* (2004) developed a stepwise elicitation method. Thus, although thresholds can be measured in a more sophisticated manner, still asking respondents to self-report and articulate thresholds remains problematic.

decision problems. It turned out that TTB and Minimalist only took one third of the information on average. When fitting the existing data, Minimalist and TTB scored 69% and 75%, while EW and WADD scored 73% and 77%. For predicting new data, TTB scored 71%, Minimalist scored 65%, EW scored 69%, and WADD scored 68%. The robustness of TTB was again verified. Gilbride and Allenby (2004) compared five models as screening rules applied in a choice experiment: heterogeneous probit model, compensatory screening rule, CONJ, DISJ, and a structural heterogeneous rule composed of CONJ and DISJ. The best result was attained for CONJ. Even under the heterogeneous rule, CONJ represented 99% of the respondents' decision strategies. Finally, the hybrid models proposed by Swait (2001a) and Cantillo, *et al.* (2006) were also tested to be better than the MNL models in terms of commonly used goodness-of-fit statistics.

Of course, there is also counter-evidence, although relatively little. Timmermans (1983) tested whether some of the non-compensatory rules can reproduce overt shopping choice behavior. He found that their predictive ability was significantly less than that of compensatory decision rules.

Overall, this review of the literature suggests that the use of decision strategy may depend on the decision problems and the situational and contextual circumstances embedding the decision problem. In many cases, however, the literature suggests that non-compensatory heuristics outperform the dominant multinomial logit model. The major problem of research on decision heuristics is the seemingly arbitrariness in proposing and applying heuristics. As the true decision processes cannot be observed, and are difficult to be elicited directly, admitting that this is an important area of ongoing research, researchers can at best infer the processes from the behavior of the decision makers. Such an inference process may entangle experience, knowledge, and intuition of the researcher.

Having said that, it should be realized that a best fit only shows that the assumed model and its underlying theory is consistent with observations and more successful than other models/theories. It should also be realized that different models may be almost equally successful in reproducing observations. In such situations, which heuristic to apply or to select as the "true" process is a highly arbitrary judgment.

A related problem is that the motivation to select one champion strategy as the "true" strategy for all decision cases is unjustified in the first place. Compared to the evidence of the coexistence of heterogeneous strategies for a decision, the modeling of such coexistence is scarce. Gilbride and Allenby (2004) provided an example, which however, is not flexible enough to incorporate in single model more strategies other than the conjunctive and disjunctive rule.

Another problem is about modeling the sequence of information search when the related models are applied such as SAT, LEX, and EBA. The search sequence may virtually be more important than the judgment rules as it largely determines the efficiency and consistency of a decision. Most current researches still treating this process as a separate part and derive the sequence from respondent's report, rather than integrating it in the whole modeling framework. Fixing this insufficiency will make a stronger normative heuristic model.



### **2.2.2 Choice of strategies**

Another factor complicating the modeling of individual decision making with a single decision strategy is that an individual does not always stick to a single strategy, which is also rarely true for the group of individuals under investigation. This is because personal preference, the aim of the decision, the context and framing of the problem, time constraints, incentives, and other factors may all influence the use of decision strategy. Beach and Mitchell (1978) and Payne (1982) called this a contingent process. A mainstream theory about this process assumes that people choose a strategy among the repertoire of alternative strategies in their mind for solving the problem at hand, or in simple words, this involves a decision of a decision. This means in principle that if we understand the mechanisms underlying this lower level decision making, the problem at the upper level (the observed behavior or decision) can be deduced. The funny thing is that this lower problem level is at least as complicated as the upper level as the problem series is epistemologically endless – we may dive into the problem as deep as we want to explain the decision of the decision of the decision of ... Nevertheless, solving the first order problem, if we can, is already sensible enough for practical problems (e.g., Conlisk, 1996).

The problem is usually formalized by starting to assume that there is a choice set of decision strategies for each individual, not matter the set is static or dynamic (e.g., constructive, as suggested by Bettman, *et al.*, 1998). An accuracy-effort (cost-benefit) framework is dominantly used to predict the choice of strategy. This framework states that an individual will minimize the cognitive effort required for executing a strategy and maximize the accuracy of the decision outcome under the strategy, implying that a rational utility-maximizing mechanism is assumed. The definition and measurement of accuracy is relatively straightforward, and usually takes the decision outcome under the rational choice rules (e.g., WADD) as the benchmark of the most accurate strategy. The accuracy of other strategies is represented as some relative measure to the benchmark accuracy. In contrast, the measurement of effort is much more difficult as it can only be perceived by the decision maker (and only if he/she is conscious about it) and any indirect measurement by the researcher may be distorted.

Wright (1975) conducted an experiment in which respondents were asked to apply some of 15 decision rules, including WADD, EW, LEX, CONJ, DISJ, etc., and report their feeling about each strategy, regarding ease of use, usage frequency, confusion, storage difficulty, etc.. The complexity of the experiment was controlled by adjusting the number of alternatives presented to the respondent. Interestingly, not all results supported the hypotheses. For example, compensatory rules were not reported as particularly strenuous to execute, although perceived strain increased as alternatives increased. They were not seen as very likely optimizers by the respondents, but were reported being used at least as frequently as CONJ or LEX for six alternatives or less. CONJ was perceived at least as difficult to execute as a compensatory strategy under these conditions. It shortcuts the procedure only when it happens to detect quickly a “veto” property. Also somewhat unexpected was the perception of CONJ as a more likely optimizer than the other strategies, since CONJ was the only one not entailing alternative vs. alternative comparisons. LEX was generally viewed as quite simple to

execute for up to six alternatives. For 10 alternatives, it had no advantage as a simplifier. Results did not support the prediction that using thresholds is necessarily simpler for an individual than using compensatory strategies. Using thresholds would not seem to be a preferred simplifying tactic if as many as four constraints must be kept in mind. Individuals might employ thresholds on only one or two key dimensions when simplifying becomes important.

Wright's work suggests an important characteristic of strategy choice: context-dependency. No single strategy is optimal in all environments. This was also demonstrated by Payne, *et al.* (1988) using simulation. After comparing the accuracy and effort of 10 strategies, they found that in some environments, heuristics can approximate the accuracy of WADD, with substantial savings in effort. But a combination of EBA+WADD performed well across all task conditions. They suggested that if a decision maker wants to achieve both a reasonably high level of accuracy and low effort, he or she would have to use a repertoire of strategies, with selection contingent upon situational demands. The authors used a different approach to estimate effort, called Elementary Information Process (EIP), such as reading an item of information, comparing two items of information, adding items of information, or eliminating items of information, and so on. The effort of each strategy is constructed by organizing the EIPs according to the information flow.

Chu and Spires (2000) demonstrated the calculations of several typical strategies. They tested the shifts of strategy use when a decision is aided by computer. Four rules were compared, WADD, EW, LEX, and EBA. As the rule that was used by the respondent is not observable, to provide a rough measure of the likelihood that a rule would be the chosen strategy, the proportion of the iso-preference-line slopes that would favor the rule over WADD, represented by the angle difference between the line linking the point in the accuracy-EIP chart representing the rule and that of the WADD, and the vertical line, was calculated. The smaller the angle, means the more preferred the strategy over WADD. The effects of the decision aid were tested to be significant as expected. If cognitive limitations are removed by the aid, decision makers may increase their effort to achieve better solutions. The aid may also change the cost-benefit relationships for various strategies such that a more effortful strategy is preferred. Some flaws of the EIP method are apparent. First, they were only hypothetical and never estimated. Second, the magnitudes, due to operational ease, of each elementary process are often assumed to be the same, which is also unjustified. These flaws may affect the calculation of the effort and the conclusions.

Shugan (1980) focused on calculating the effort under different sequences of comparing attributes between two alternatives. He incorporated the criterion that the decision maker tolerates a mistaken decision as a probabilistic stopping rule for information search. In order to make the calculation, the approach assumes a sampling procedure of the individual on items to be chosen so that attribute variances can be derived. Whether such a sampling process is applied in reality by decision makers is questionable. Similarly, Swait and Adamowicz (2001) assumed a pre-evaluation stage to empirically derive the prior choice probabilities needed to calculate a complexity measure of a choice task, using an entropy type index. Then, a latent class structure was specified to derive the expected choice probabilities of alternatives under different

choice strategies whose probability of being applied is a logistic function of the complexity measure. The model was estimated to be better than an MNL model against experimental choice data.

Besides effort and accuracy, other influential factors were also discussed. Ben Zur and Breznitz (1981) found through experimentation that under high time pressure, individuals tend to use less risky strategies than under low time pressure. Bockenholt, *et al.* (1991) tested the influence of information pattern. An analysis of the number of processed attributes revealed that individuals employed selective information processing rather than processing all features of a choice pair. They selected more attributes with small differences and less with large attribute differences. They terminated their information search earlier when an alternative was dominant than when none of the alternatives were dominant. Finally, the effects of cost and reward on strategy choice were experimentally tested by Gilliland, *et al.* (1993) and the more cost – less information search, more reward – more information search phenomena were clear.

### **2.3 Summary**

Pedestrian modeling is a multilevel, multidisciplinary research field in which different methodologies have been applied. The state-of-the-art in this field of research demonstrates various lines of rapid development. In the context of this thesis, some of these approaches seem more valuable than others as a starting point for studying meso-level pedestrian behavior. Some aspects need further improvement and exploration.

First, meso-level pedestrian studies have been dominated by rational choice models. Although these models can capture some essence of individual decision making and provide a convenient and flexible framework, it is well known that normative choice theory will not fully cover real-life human choice behavior (e.g., Hoogendoorn, 2003a). The general criticisms against the unrealistic assumptions of rational decision models also apply to current practice of pedestrian modeling. Assuming omniscience of pedestrians' knowledge about the environment and ignoring pedestrians' cognitive limitations and decision processes may lead to wrong policy recommendations and policy measures. It has shown that models of bounded rationality have been widely studied in psychology and consumer research and they are in many cases at least as competitive as rational choice model in predicting decision outcomes with the extra advantage of explicitly representing decision process. In fact, much of this research is already quite old, but it never led to a strong consistent modeling tradition. Especially, developments and applications of BR models in urban planning and transportation are scarce, and most surprisingly, to the best of our knowledge, no such models have ever been empirically tested to meso-level pedestrian behavior. Perhaps one of the most important reasons is that the study of consumer research has traditionally focused on experimental hypothesis testing and has kept away from and still does not show many signs of model building. Attempts of model building are more common in econometrics and applied disciplines, but these are dominantly inspired by rational choice theories. In other words, these fields have largely developed in their own right as two separate research communities and very

few people or groups would have been able to bridge the gaps between these communities and traditions. Developments in modeling in general however do provide new opportunities. Therefore, in the context of exploring an alternative modeling approach, BR models are definitely worth trying.

Second, taste variation has been partially represented in random utility models by estimating parameter distributions. However, the decision strategy implied in these models is homogeneous across the sample. As has been shown by BR research, this is rarely true. People's use of a decision strategy is contingent upon both internal and external decision situations. Therefore, modeling and identifying pedestrians' different decision strategies will be very helpful for segmenting the pedestrians based on their distinct ways of information processing and for developing tailored policy measures for each targeted group. In this regard, modeling strategy choice will be a good starting point. However, although the general relationships between the choice outcome and influential factors such as accuracy, effort, and others have been qualitatively verified, operational models which can be applied universally in various situations, like the MNL, are not available yet. Problems such as the definition, calculation, and operationalization of the factors have to be solved before strategy choice models can really take off.

Third, the framework of studying pedestrian behavior as a trip chain is useful for modeling behavioral dynamics. Approaches of different degree of realism and complexity may be incorporated in such a framework. Markov chain models are capable of capturing the general dynamics quite well, except for their major limitation of state independence. This problem has been partially solved by incorporating independent variables which represent the behavior of other states, such as visit history, while still keeping the generally independent model structure. Models concerning expectations of long-term activities over local decisions, such as multi-purpose multi-stop models and route planning models, are theoretically more complete, but of course more complex and require more information for modeling. Although studying expectation and scheduling behavior is itself a very interesting and meaningful topic, we will ignore it in this thesis as our major aim is to test the general validity of BR models in modeling pedestrian behavior rather than a full-fledged model. Therefore, we believe that capturing the general dynamics will suffice for basic planning practice and we will adopt the methodology which assumes local and independent decisions. On the other hand, we feel that it could be more relevant for planning practice to enrich pedestrian behavior study by considering more basic behavioral elements in the first place, such as the influence of time. This is based on the fact that temporal effects on decisions and behavior have been insufficiently studied, while the spatio-temporal dynamics is critical for planning, retailing, and public space administration. Although the time-varying Markov chain is theoretically reasonable, it was only modeled in separate stops. Considering real time will be more realistic and useful for practice.

Fourth, multi-agent systems are a very useful tool for simulating pedestrian behavior and testing theories and models. With the help of MAS, one emerging trend in pedestrian modeling is that the models are increasingly more built for pedagogic use while less and less calibrated against data (e.g., Batty, 2001b). What the

researchers commonly do is setting the parameters based on past experience or just arbitrarily, and simulating individual behaviors, investigating the aggregate patterns and comparing these with observations. Based on the discrepancy, they adjust the parameters to reduce such discrepancy and repeat the process until satisfactory results are obtained. Although this can also be viewed as a calibration procedure, the accuracy of the estimates is discounted because such a recursive procedure can only be limitedly conducted by human intervention, especially when the simulation takes a long time. This trend is partially caused by the complex interdependency between behaviors, which if it would be formulated as a statistical model system and calibrated, must employ complex variance-covariance structures which could very likely have no analytical solutions and more computational expensive algorithms, such as simulation-based estimation, have to be used. Another reason is that as very detailed behaviors are studied, the corresponding conditions influencing the behaviors and decisions are difficult to measure, such as the service level of a place at the moment of the decision and the perception of the environment. Nevertheless, at least for the purpose of understanding pedestrian behavior, model calibration should be carried out whenever possible, which will be the basic methodology of this thesis. MAS will serve as a test bed for the estimated models.

Therefore, the methodological path of this thesis is a four-step procedure: setting up conceptual frameworks and developing models, collecting data, estimating models against data, and validating models through multi-agent simulation. The next chapter will articulate the development of the conceptual framework.

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*Chapter***3 CONCEPTUAL FRAMEWORK**

The major conclusion of the literature review is that models of bounded rationality (BR) have not yet been empirically tested in pedestrian behavior research. The success of BR models in other fields suggests that pedestrian behavior research may benefit from further examining the process of individual decision making instead of merely applying conventional outcome-based modeling approaches. This potential improvement is also consistent with today's decision environment with an ever increasing ocean of information, and the advancement of technology and media, exponentially increasing the choice complexity faced by decision makers. For a decision maker, knowing what to choose and how to choose is important; for a researcher, knowing how a decision maker knows what to choose and how to choose is important; for retailers, planners, policy-makers, knowing the mechanism of decision making is important too in order to provide effective information and plans.

Returning to pedestrian behavior and other planning-related fields, the what to choose problem and the related choice set problem, have been discussed for quite some time (e.g., Ben-Akiva and Boccara, 1995; Haab and Hicks, 1997; Swait, 2001b), while the problem of how to choose (information selection, cognition, manipulation, etc.) has received much less research attention. Conventional rational choice models emphasize the concept of utility to represent individual's preferences for alternatives. By assuming that utility is a combination (often linear) of weighted part-worth utilities, defined for attribute values, the models cannot reflect the process of information processing. The compensatory specification suggests that individuals make decisions as if the information comes altogether into the mind of the individual. However, in complex decision environments like shopping streets, this kind of model specification is far from realistic. Individuals will usually not take complicated decisions between various possible alternative behaviors, but apply an optimized behavioral strategy, which has been learned over time by trial and error (Helbing, *et al.*, 2001). BR models, in particular, heuristic models emphasize the non-compensatory nature of decision processes and the attribute-by-attribute information processing, which is often easier than alternative-based evaluation as implied by compensatory-utility choice models (e.g., Tversky, 1972). This seems a more naturally way of studying decision processes, although also not without limitations.

The purpose of this chapter is to develop the conceptual framework for analyzing and modeling pedestrian behavior using principles of bounded rationality. The first section will discuss the major decisions during a pedestrian's shopping trip that are modeled. The following three sections will introduce different approaches for modeling these decisions, while the second section will give a brief introduction to the classic multinomial logit model. Section 3 will then discuss the specifications of three types of well-known heuristic models: the conjunctive, disjunctive and lexicographic model. Section 4 will address the limitations of the conventional heuristic modeling approach and propose an extended approach (called the Heterogeneous Heuristic

Model), which captures heterogeneity in decision strategies and the selection of these strategies. The final section will provide a summary of this chapter.

### 3.1 Decisions to Model

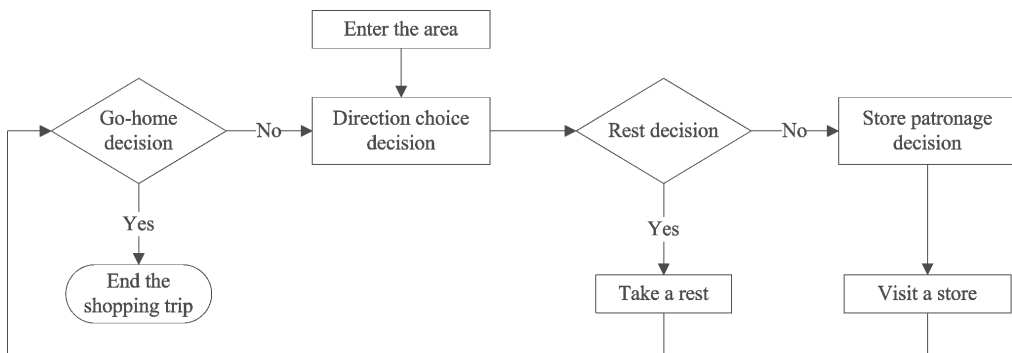
Models are developed to serve the purpose of research or practice. For example, shopping center choice models have been developed to predict the distribution of demand across shopping centers, given overall demand; route choice models have been formulated for predicting the distribution of pedestrians in different streets of the shopping area, given the total number of pedestrians; local movement models have been suggested for predicting the microscopic behavior of individuals to optimize the setting of the walking environment. The purpose of the model system advanced in this thesis is to predict (1) the spatial distribution of pedestrian activities; (2) the temporal distribution of pedestrian activities; and (3) the distribution of pedestrian activities in space and time simultaneously, given the total number of pedestrians in the shopping area. Four decisions will be modeled: go-home, direction choice, rest and store patronage. Figure 3.1 shows the assumed relationships between these decisions.

#### *Go-home decision*

The go-home decision refers to a pedestrian deciding whether or not to end the shopping trip and leave the shopping area. In principle, when leaving the shopping area, pedestrians do not necessarily need to go home, but as we are not modeling the trip chain, it does not matter. Thus, we use the term go-home as a general term for the decision to end the shopping trip. This decision has most impact on the distributions of pedestrian activities, because if the pedestrian decides to go home, no more activities will be generated. Time constraints, fatigue, personal schedule and other factors may influence this decision.

#### *Direction choice decision*

After the pedestrian decides not to go home (keep shopping) or when he/she just enters the shopping area, he/she will choose a walking direction, if there are alternative directions. This is probably the second most important decision because it determines the activity space of the pedestrian. Pedestrians can only visit the stores



**Figure 3.1 The decisions to be modeled**

that belong to a pedestrian's activity space and not the stores outside this space. This decision is similar to the one studied by Borgers and Timmermans (1986b). They defined the shopping streets as links and nodes and assumed that pedestrians choose alternative links when they are at a certain node. Factors influencing this choice may be the retail attractiveness of the link, amenities of the walking environment, landmarks, and orientation habits.

#### *Rest decision*

Pedestrians may take a rest when they feel tired. Modeling the decision to take a rest is not negligible because rest behavior takes time and space too. Given a fixed personal time budget, the more time the pedestrian uses for rest the less time can be allocated to other activities (shopping, dining, and walking). Rest behavior may also be influenced by the physical environment. At some specific locations, such as near large shopping facilities, pedestrians may have a common feeling of tiredness after spending sufficiently long time on conducting activities. Consequently, at these locations, the aggregate demand for rest may be high.

#### *Store patronage decision*

If the pedestrian decides not to rest, store visits will continue and the problem then is which store to visit next. This store patronage decision directly influences the distribution of pedestrian in-store activities, which is the most relevant decision for retailers. Pedestrians may evaluate stores in terms of type, variety, quality, price level, and location.

Although more detailed pedestrian behavior can be studied with more sophisticated models, these four decisions may be sufficient for modeling the general activity distributions in space and time, such as how many pedestrians are in a certain part of the street during certain time period, how many pedestrians are resting in a certain place, how many pedestrians are shopping in stores, and how many pedestrians are walking in the street.

### **3.2 Multinomial Logit Model**

Discrete choice models have been the work horse for modeling individual choice behavior. Among these, the multinomial logit model (MNL) is the most fundamental one, which has been most frequently applied in various fields, mainly because it is easy to apply. It assumes that, when an individual chooses an alternative from multiple alternatives  $i = 1, \dots, I$ , he/she evaluates the utility of each alternative,  $u_i$ , and selects the one with the highest utility. By assuming that the utility is composed of an observable part  $v_i$  which is often specified as a linear combination of factor values  $X = \{x_j, j = 1, \dots, J\}$  weighted by parameters  $\beta_j$ , and a stochastic unobserved part  $\varepsilon_i$  which is further assumed to be an independently and identically Gumbel distribution across decision cases, of the form,



$$\begin{aligned} u_i &= v_i + \varepsilon_i \\ v_i &= \sum_j \beta_j x_{ij} \end{aligned} \quad (3.1)$$

The probability of an alternative being chosen,  $p_i$ , is derived as

$$p_i = \frac{\exp(v_i)}{\sum_{i'=1}^I \exp(v_{i'})} \quad (3.2)$$

Applying the model to the pedestrian decisions, the go-home decision can be modeled as a choice between the alternative “keep shopping” and the alternative “go home”; the direction choice decision can be more straightforwardly modeled as a choice among alternative directions; the rest decision can also be modeled as a choice between “take a rest” and “keep shopping”; the store patronage decision can be modeled as choosing the store with the highest utility composed of attractiveness and spatial factors. More detailed model specifications will be given in the next chapter.

### 3.3 Heuristic Models

Satisficing is a fundamental decision mechanism in the theory of bounded rationality. It assumes that alternatives are evaluated on an attribute-based, non-compensatory manner with certain stopping conditions controlling the decision process. If some conditions are met (or say, when people feel satisfied or unsatisfied with the results), the search for more alternatives or more factors may stop. In contrast, rational choice models imply that all alternatives are evaluated and all factors are taken into account.

Let  $X = \{x_j, j = 1, \dots, J\}$  be the set of factors to be taken into account during the decision process, and let the satisficing function  $S_j(x_j, c_j)$  represent the judgment process which gives a positive response when some condition  $c_j$  for factor  $x_j$  is satisfied, and gives a negative response otherwise. In many empirical cases, including those to be studied in this thesis, factors are coded into real values and therefore conditions can be represented by real valued thresholds,  $\delta_j$ . In turn, the satisficing function can be implemented as a comparison relationship  $S_j = x_j \geq \delta_j$  (for the less than relationship, just simply change the signs of the arguments). Such relationships are the fundamental building blocks of various heuristic models.

Aside from being used as the mechanism for evaluating alternatives, satisficing is also used for determining the inclusion of alternatives in order to limit the consideration set, especially when the number of available alternatives is large. A common assumption is that the decision maker will stop looking for more alternatives when the first satisfactory alternative is found, or when the first X-number of alternatives have been evaluated.

The following discussions will only concern the heuristic models for alternative evaluation, as there is not much opportunity, if at all, to apply the mechanism of alternative inclusion in our empirical study. First, the go-home and rest

decision involve the dichotomous rejection/acceptation problem, for which the inclusion mechanism is irrelevant. Second, the empirical cases have at most three alternatives. Assuming full inclusion of alternative will therefore not be too unrealistic. Third, stopping at the first satisfactory store will be assumed in the store patronage models. In the next section, we will discuss three typical models: the conjunctive, disjunctive and lexicographic model.

### 3.3.1 *Conjunctive model*

The conjunctive rule is a typical heuristic decision rule which states that all thresholds of related factors have to be met in order to arrive at a positive overall judgment. Thus, the choice probability or decision outcome can be expressed as,

$$p_i = \begin{cases} 1 & \text{if } x_{i1} \geq \delta_1 \wedge \dots \wedge x_{ij} \geq \delta_j \\ 0 & \text{otherwise} \end{cases} \quad (3.3)$$

The individual applying this rule evaluates the factors in some sequence. Once a factor does not meet the threshold value, the information search will immediately stop and the alternative will no longer be considered. The search process continues if the threshold is met until all factors have been evaluated.

However, at the aggregate level, a single threshold value for each factor is unrealistic because people likely have different habits, purposes, schedules, taste variations or behavioral heterogeneities. These factors must cause threshold values to differ among decision makers. Incorporating such heterogeneity into the model specification makes the model more general and may improve its performance. Assuming that the thresholds belong to some probability distribution with density function  $f_j$  and cumulative density function  $F_j$ , and that the thresholds are independent of each other, the relevant equations become,

$$\begin{aligned} S_{ij} &= \delta_j \leq x_{ij} = F_j(x_{ij}) = p_{ij} \\ p_i &= \prod_j p_{ij} \end{aligned} \quad (3.4)$$

The probability of an alternative being satisfactory is the joint product of the cumulative densities of the thresholds at respective factor values.

Heuristic models also emphasize the sequence of information search because the result of a decision may differ under different sequences. However, it does not apply to this conjunctive model since the model formulations will be the same under difference sequences. The limitation is that individual patterns of information search cannot be identified from the model.

### 3.3.2 *Disjunctive model*

The disjunctive rule adopts another organization of the building block relationships, which says that an alternative is satisfactory if at least a single factor meets the threshold value. Expressed formally,

$$p_i = \begin{cases} 1 & \text{if } x_{i1} \geq \delta_1 \vee \dots \vee x_{iJ} \geq \delta_J \\ 0 & \text{otherwise} \end{cases} \quad (3.5)$$

Under this rule, the individual also evaluates factors in some sequence. The information search process stops and the alternative is accepted when a single factor turns out to be satisfactory; the process continues when the threshold value is not met. The alternative is rejected when all factors have been evaluated and none is satisfactory. Given the same assumption of probabilistically distributed threshold values, the probabilistic version of Equation 3.5 is,

$$\begin{aligned} p_i &= p_{i1} + p_{i2}' - p_{i1}p_{i2}' \\ p_{i2}' &= p_{i2} + p_{i3}' - p_{i2}p_{i3}' \\ &\dots \\ p_{ij}' &= p_{ij} + p_{ij+1}' - p_{ij}p_{ij+1}' \\ &\dots \\ p_{iJ-1}' &= p_{iJ-1} + p_{iJ} - p_{iJ-1}p_{iJ} \end{aligned} \quad (3.6)$$

Here, the probability that an alternative is satisfactory is a nested structure of probabilistic “or” relationships. In the equation,  $p_i$  is still the final probability that the alternative is judged satisfactory. Starting from the last line,  $p_{iJ-1}'$  is the joint probability that either factor  $J-1$  or  $J$  is satisfactory, which then is further joined with the probability of factor  $J-2$  being satisfactory,  $p_{iJ-2}'$ , to derive the probability of any of the factors  $J-2$ ,  $J-1$ , and  $J$  being satisfactory. This procedure continues until all the factors have been evaluated and joined into  $p_i$ . However, similar to the conjunctive model, the model specifications are the same under different factor search sequences. Therefore, the subscripts in the equation do not refer to any specific factor.

### 3.3.3 Lexicographic model

#### 3.3.3.1 Specification in case of comparison judgment

The lexicographic rule is usually used to represent decision processes for comparing two alternatives with comparable factors and selecting the better one. It assumes that alternatives are compared on an attribute-by-attribute basis following some information search sequence which is organized according to descending factor importance. Thus, alternatives are first compared in terms of the most important attribute; if they tie the factor next in importance is evaluated and so on until a choice can be made or all factors have been evaluated. In the latter case, the two alternatives are indifferent. The comparisons between factors depend on the levels of each factor. There must be at least two levels to differentiate the alternatives. In this simplest situation, let  $\delta_j$  be the threshold which divides the factor into a higher level when  $x_j \geq \delta_j$  and into a lower level when  $x_j < \delta_j$ . There are three situations after comparing factor levels of two alternatives,

$$\begin{aligned}
 p_{ikj}^B &= \begin{cases} 1 & \text{if } x_{ij} \geq \delta_j \wedge x_{kj} < \delta_j \\ 0 & \text{otherwise} \end{cases} \\
 p_{ikj}^W &= \begin{cases} 1 & \text{if } x_{ij} < \delta_j \wedge x_{kj} \geq \delta_j \\ 0 & \text{otherwise} \end{cases} \\
 p_{ikj}^T &= 1 - p_{ikj}^B - p_{ikj}^W \quad i, k = 1, \dots, I; k \neq i
 \end{aligned} \tag{3.7}$$

where  $p_{ikj}^B$  is the result that factor  $j$  of alternative  $i$  is better than factor  $j$  of alternative  $k$ ,  $p_{ikj}^W$  means worse, and  $p_{ikj}^T$  means the two alternatives tie on this factor. When thresholds are heterogeneous, the probability versions of the first two components in Equation 3.7 are,

$$\begin{aligned}
 p_{ikj}^B &= p_{ij}(1 - p_{kj}) \\
 p_{ikj}^W &= (1 - p_{ij})p_{kj}
 \end{aligned} \tag{3.8}$$

If the factor search sequence (importance) is  $x_1 \rightarrow x_2 \rightarrow \dots \rightarrow x_J$ , the probability of alternative  $i$  being better than alternative  $k$ ,  $p_{ik}$ , is

$$\begin{aligned}
 p_{ik} &= p_{ik1}^B + p_{ik1}^T p_{ik2}' \\
 p_{ik2}' &= p_{ik2}^B + p_{ik2}^T p_{ik3}' \\
 &\dots \\
 p_{ikj}' &= p_{ikj}^B + p_{ikj}^T p_{ikj+1}' \\
 &\dots \\
 p_{ikJ} &= p_{ikJ}^B + p_{ikJ}^T 0.5
 \end{aligned} \tag{3.9}$$

This nested probability structure means that at each factor, the probability of  $i$  being better than  $k$  is composed of the probability that  $i$  is better than  $k$  on this factor, and the joint product of the probability of being a tie and the expected probability of being better on the factors considered later. Note that the last equation means that when all factors have been searched and all turn out to tie, a uniform random selection will be applied. Finally, when there are multiple alternatives, the probability of alternative  $i$  being chosen is,

$$p_i = \prod_k p_{ik} \tag{3.10}$$

Different from the conjunctive and disjunctive model, when the factor search sequence changes, the model specifications of the lexicographic model will change accordingly. Consequently, the choice probabilities may also change. This property allows investigating the effects of information search patterns on decision outcomes and identifying the optimal search sequence through model comparison. The number of potential models equals the number of factor permutations  $J!$ .

### 3.3.3.2 Specification for judging a single choice alternative

If we just keep the logic of the lexicographic rule and disregard the comparison task to which it is usually applied, some modifications make the rule suitable for satisficing tasks. Assume that the individual uses two thresholds for each factor, a lower threshold  $\delta_j^L$ , and a higher threshold  $\delta_j^H$ , which divide the factor into three states. For example, an individual may think that a factor is unsatisfactory when  $x_j < \delta_j^L$ , feels neutral when  $\delta_j^L \leq x_j < \delta_j^H$ , and that the factor is satisfactory when  $x_j \geq \delta_j^H$ . Expressed in probabilities:

$$\begin{aligned} p_{ij}^S &= p_{ij}^L p_{ij}^H = F_j^L(x_{ij}) F_j^H(x_{ij}) \\ p_{ij}^U &= (1 - p_{ij}^L)(1 - p_{ij}^H) \\ p_{ij}^N &= 1 - p_{ij}^S - p_{ij}^U \end{aligned} \quad (3.11)$$

Here,  $p_{ij}^S$  is the probability that the factor is satisfactory, which is the joint probability of the factor exceeding both threshold values<sup>5</sup>;  $p_{ij}^U$  is the probability that the factor is unsatisfactory which is the joint probability of the factor exceeding neither threshold;  $p_{ij}^N$  is the probability of being neutral. The decision process is that, under a certain factor search sequence, the individual accepts the alternative that is satisfactory on the factor considered; rejects the alternative when the factor is unsatisfactory, and continues searching for the factor next in importance when the current factor is neutral. If all factors have been searched and turn out to be neutral, the individual makes a random choice, captured by a uniform distribution. Given the search sequence  $x_1 \rightarrow x_2 \rightarrow \dots \rightarrow x_j$ , the probability of alternative  $i$  being accepted is,

$$\begin{aligned} p_i &= p_{i1}^S + p_{i1}^N p_{i2}^U \\ p_{i2}^U &= p_{i2}^S + p_{i2}^N p_{i3}^U \\ &\dots \\ p_{ij}^U &= p_{ij}^S + p_{ij}^N p_{ij+1}^U \\ &\dots \\ p_{ij}^U &= p_{ij}^S + p_{ij}^N 0.5 \end{aligned} \quad (3.12)$$

All these heuristic models will be more specifically tailored to the decision problems under investigation in the next chapter.

<sup>5</sup> From the perspective of a single decision maker, it may be more realistic to assume that the thresholds are inter-dependent as the higher threshold must be larger than the lower threshold, if the decision maker makes consistent judgments and classification of response into the three categories is done simultaneously. In that case, the joint distributions should be specified and estimated, making the model more complex and more difficult to estimate. We leave that for future research and view the current specification as a limiting case, where decision makers use a simplifying strategy and judge the thresholds independently.

### 3.4 The Heterogeneous Heuristic Model

Although the existing heuristic models are of interest, the state-of-the-art indicates some shortcomings. First, the models are limited in the sense that they focus on the non-compensatory nature of the decision rule. The process that leads to the selection of factors entered in the decision process is usually not modeled. A common practice is that factor selection and search sequence are a priori assumed by the researcher (e.g. Tversky, 1972), obtained from direct reports of respondents (e.g., Recker, 1979; Gensch and Svestka, 1984; Young, 1984), or derived from statistical analyses related to factor importance (e.g., Gigerenzer, *et al.*, 1999).

Second, heuristic models have been developed in a fairly fragmented manner. Except the three typical heuristic rules that have been discussed before, there are many other rules, such as Dawes' rule (Dawes, 1979), frequency of good/bad features rule (Alba and Marmorstein, 1987), and elimination-by-aspect (Tversky, 1972). The number of possible models is even significantly higher when a decision can be characterized by some complex hybrid process that combines the features of several simple heuristics (e.g., Payne, *et al.*, 1988). Such a top-down way of researching heuristics leaves considerable arbitrariness in selecting a heuristic decision rule. The major problem is that a bottom-up mechanism to generate heuristics has not been systematically studied, with a few exceptions. One stream of research does not really aim to reveal the mechanism; rather, the researchers try to use functions that approximate the heuristic rules. For example, Einhorn (1970) used a hyperbolic function to approximate disjunctive rules and a parabolic function to approximate conjunctive rules. He admitted the difficulty in approximating the lexicographic rule. Swait (2001a) showed that incorporating attribute cutoffs and varying utility functions in conventional logit models can approximate disjunctive and conjunctive rule. However, approximation is not exact. It is unclear what heuristics are represented when indicator parameters are somewhere between conjunctive and disjunction rules. Moreover, the information search process cannot be identified and cutoffs were self-reported in his experiment. Another stream of research attempted to model the mechanisms underlying the formation of elements in heuristics rules, including threshold selection and variability, using a cost-benefit framework (e.g., Grether and Wilde, 1984).

Third, researchers typically have selected a particular heuristic model, or at best have compared particular alternative models. In reality, however, it is unlikely that different individuals will use the same choice rule. Even for the same individual, decision strategies may be context-dependent (Bettman, *et al.*, 1998). Thus, the meaning of such comparison is that it indicates which model specification performs best at the aggregate level. An approach that accounts for heuristic heterogeneity would thus enhance models of bounded rationality. The general idea about this question tightly relates to how different individuals select a certain decision strategy as a result of trading off cognitive effort and accuracy of applying the strategy (e.g., Payne, 1982, 1988; Russo and Doshier, 1983), under different circumstances. This notion assumes that decision makers select strategies in a specific situation based on some compromise between the desire to make an accurate decision and the desire to minimize cognitive effort. As defining accuracy is relatively straightforward which is

usually realized by using some relative measures of predictive ability of a heuristic against that of a rational choice model, most discussions concentrated on decision effort. To represent effort, one stream of research uses elementary information processes (EIP) such as reading the values of two alternatives on an attribute, comparing them, and so forth (e.g., Newell and Simon, 1972; Payne, *et al*, 1988; Bettman, *et al*, 1998; Chu and Spires, 2000). EIP may be a close representation of the information processing mechanism and operationally manageable in experiment-based studies when the decision problem is specific, relatively simple and the data size is limited, but it still costs the researcher a lot of EIP to carefully trace the flow of information for a given strategy. It is very difficult to automate the calculation of EIPs of heterogeneous strategies when some generalized approach has to be applied to general decision problems. Shugan (1980) focuses on calculating the effort under different sequences of comparing attributes between two alternatives. The effort accumulates through information search until the decision stops at some stage. It incorporates a probabilistic stopping rule for information search. At the same time, the decision maker tolerates a mistaken decision (low accuracy) due to incomplete information. The approach assumes a sampling procedure which is used by the individual to obtain attribute variances for estimating the degree of inaccuracy. Whether people actually do such sampling is disputable. Similarly, Swait and Adamowicz (2001) assumed a pre-evaluation stage to empirically derive the prior choice probabilities needed to calculate the complexity measure (an entropy type index) of a choice task. They specified a latent class structure to derive the expected choice probabilities of alternatives under different choice strategies, in which the probability of being applied is a logistic function of the complexity measure. Thus, in conclusion, decision strategy heterogeneity and its determinants have been identified for quite some time in the literature, but formal operational models representing the mechanism underlying the choice of strategy are still scarce and immature.

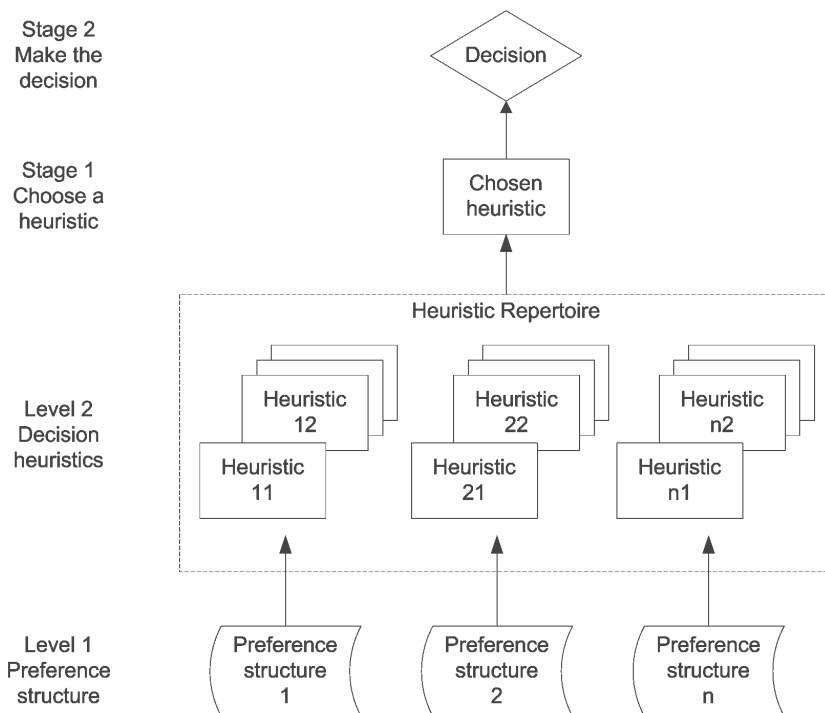
Based on this previous research, the following subsections propose an alternative approach, called the Heterogeneous Heuristic Model (HHM), which overcomes the limitations discussed above. It provides richer behavioral implications, including: (1) factor thresholds are incorporated in the utility function and estimated; (2) heterogeneous decision heuristics can be exactly identified; (3) the application of heuristics is modeled as a latent class structure which can be used further to study the context-dependent nature of strategy selection; (4) mental effort, risk perception and expected outcome of heuristics are defined and their influences on heuristic choice are estimated.

### **3.4.1 A two-level two-stage framework**

Decision heuristics do not come out of the blue. It is logical to contend that there must be reasons behind the execution of a heuristic so that the individual knows to stop information search after finding some evidence rather than another. Heuristics are easy to implement and reasonably accurate because they are based on good reasons which however may take much effort to establish. For example, habit is the heuristic of everyday life, which can be executed even unconsciously. However, to form a habit may take months or years of time. Therefore, we propose a two-level structure for

understanding the formation of decision heuristics. At the lower level, there is preference structure, which is a value system involving the relevant cognized factors and relationships between these factors and defining the preference. The computations related to the preference structure may be relatively complicated, like algebraic rules. The establishment of the preference structure may take times of try and error. On the contrary, the heuristics at the higher level requires simple computations such as logical judgments. A heuristic is a logical inference of the preference structure. It achieves the same preference by referring to the internal relationships of the preference structure. Multiple heuristics may be inferred from the same structure (see later). As an analogy, we may imagine a multiplication table as such a preference structure. To get the result of  $m \times n$ , we do not go through the process of adding  $m$  times  $n$ , but just locate the number at the intersection of the  $m$ th row and  $n$ th column in the table.

It is common that people have different value systems, and for the same person, his/her value inclination also shifts with the situation. That means people's preference structures are heterogeneous, so as to the heuristics. We assume that the individual has a repertoire of heuristics for dealing with different decision problems or the same problem under different situations/contexts. Upon making the decision, he/she first select a heuristic from the repertoire (e.g., to locate  $m$  before  $n$ , or the reverse?), then uses the chosen heuristic to make the decision. Therefore, every decision is a two-stage process. Figure 3.2 illustrates such a two-level two-stage decision framework in general. We will articulate each elements of this framework in the following sections.



**Figure 3.2 The two-level two-stage decision framework**



### 3.4.2 Preference structure

Based on the concept of bounded rationality, any decision or choice process can be understood as a problem-solving process in which an individual processes information to arrive at a decision that achieves a particular goal within some *margin of accuracy*. Based on this principle, assume that individuals will construct a mental representation of the decision problem. Literally, such representation can be depicted as a value system, from which the individual judges what is good, bad, right, or wrong. The establishment of this system may involve a long learning time, may use the structure of other systems for reference, or may be quickly created on the spot when the problem is unfamiliar. This cognitive process is assumed to consist of at least three sequential processes: filtering of information, factor representation into states, and judging the resulting states, individually and combined. Jointly, these processes lead to preference formation.

Let  $X = \{x_j, j = 1, \dots, J\}$  represent the set of attributes or factors influencing the decision of interest. Assume that individuals do not necessarily take all these factors into account, but rather solve a decision problem by mentally (re)constructing the problem and selecting a subset of these factors. This *filtering* process is not invariant, but will depend on the decision problem, and more importantly on the activation level of the individual. This process may either be memory-based or triggered by environmental factors. In the latter case, filtering and translation/representation will take place, mapping environmental factors into mental states of the environment.

Let  $\delta_j$  represent an activation threshold for factor  $x_j$ . These thresholds act as filters. Thus, by applying these thresholds, a subset of activated factors will enter the decision making process. Only if all thresholds are equal to zero (assuming that all factor stimulation can be transformed into positive real numbers and larger values represent stronger stimulation), all factors will be considered. Mathematically, this can be expressed as:

$$s_j = \begin{cases} 0 & \text{if } x_j < \delta_j \\ 1 & \text{if } x_j \geq \delta_j \end{cases} \quad (3.13)$$

where  $s_j$  is the state of the factor in mental representation. Consequently, the set of factors considered,  $X' = \{x_j \mid s_j = 1, \forall j\}$ .

Once the irrelevant factors have been filtered and the relevant factors kept, the principle of bounded rationality suggests that individuals tend not to discriminate between all possible values of factors as this may cost a lot of cognitive effort to differentiate small but insignificant differences to the problem result at large. Rather, they will categorize the continuous factors into discrete classes or states, or re-categorize discrete factors. Assume that in case of continuous factors, this process of factor representation involves the application of a monotonically increasing set of threshold values, which discretize the continuous factors into an ordered set of discrete classes. Let  $\Delta_j = \{\delta_{j1} < \delta_{jn} < \delta_{jN}, n = 1, \dots, N\}$  be a set of successively increasing

activation thresholds for  $x_j$ , corresponding to stricter judgment standards. (Note that  $N$  can be factor-dependent, so it should be  $N_j$ . For representation simplicity, however, the subscript is ignored.) A factor may then meet one or more of these increasingly stricter activation thresholds and hence becomes more informative. The relevant equations then become,

$$s_{jn} = \begin{cases} 0 & \text{if } x_j < \delta_{jn} \\ 1 & \text{if } x_j \geq \delta_{jn} \end{cases} \quad (3.14)$$

$$X' = \{x_j \mid s_{jn} = 1, \forall j, n\}$$

Thus, filtering and factor representation transforms categorical and continuous factors into a set of activated and non-activated internal (mental) factor states.

Individuals will judge these states by (1) attaching values, (2) assigning relative importance weights, (3) integrating these values for individual states in some way to arrive at an overall judgment, and (4) evaluating the overall judgment against some overall threshold value in light of underlying goals. Attaching judgment values to states implies that the state is judged and valued in light of the decision goal. Weights indicate the relative importance of states in the decision problem. Because these values and weights are all unknown parameters in this approach, they are combined into a single value,  $w_{jn}$ , which can be interpreted as a part-worth utility. Let  $u_{jn} = w_{jn}s_{jn}$  denote the value judgment of state  $n$  of factor  $x_j$ . All states that are incorporated in the decision making process need to be combined according to some integration rule to arrive at an overall value judgment for each choice alternative. Various rules can be used. Thus, if an additive integration rule is assumed, the overall value judgment of choice alternative  $i$  equals:

$$v_i = \sum_j \sum_n u_{ijn} \quad (3.15)$$

In the final step, assume that the overall values are also categorized and mapped by checking them against a set of successively increasing overall thresholds  $A = \{\lambda_1 < \lambda_m < \lambda_M, m = 1, \dots, M\}$ , resulting in the overall states,  $p_{im}$ . This can be expressed as:

$$p_{im} = \begin{cases} 0 & \text{if } v_i < \lambda_m \\ 1 & \text{if } v_i \geq \lambda_m \end{cases} \quad (3.16)$$

In case this mapping only involves two preference orders (reject or accept), only one  $\lambda$  is needed and  $p_{i1} = 0$  defines rejecting the alternative, whereas  $p_{i1} = 1$  implies accepting it. For representation simplicity, the following model formulations assume only two preference levels exist.

Define a state value set for each factor, which includes all possible value judgments related to the factor,

$$V_j = \{v_{j1} = 0, v_{j2} = w_{j1}, v_{j3} = w_{j1} + w_{j2}, \dots, v_{jN+1} = \sum_{n=1}^N w_{jn}\} \quad (3.17)$$

Let  $\bar{v}_k$  represent any factorial combination from value judgments in the sets, that is,

$$\bar{v}_k = \sum_j v_{jn} \quad \forall n \in [1, \dots, N_j + 1] \quad (3.18)$$

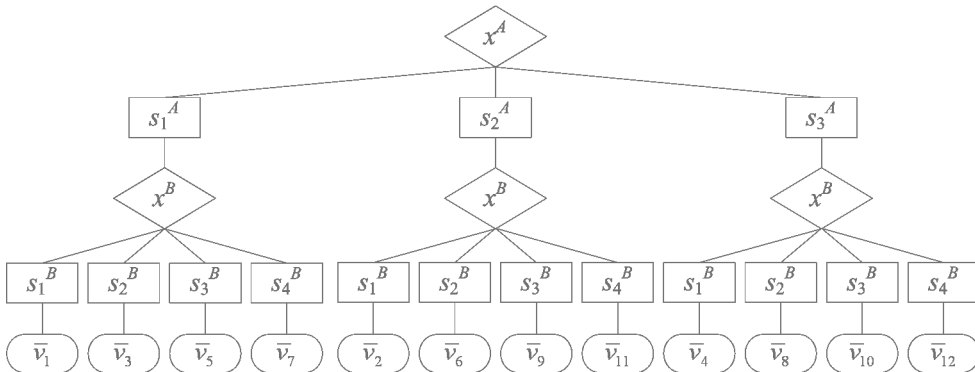
Ordering all the  $\bar{v}_k$  ascending forms an overall value set,

$$\bar{V} = \{\bar{v}_1 < \bar{v}_2 < \dots < \bar{v}_K; k = 1, 2, \dots, K; K = \prod_j (N_j + 1)\} \quad (3.19)$$

Checking these overall value judgments against the overall threshold  $\lambda$  results in a unique pattern of relationships with some value judgments above the threshold, and some below the threshold. Thus, the set of overall value judgments  $\bar{V}$  can be divided into a subset  $\bar{V}_0$  of rejected overall value judgments and a set  $\bar{V}_1$  of accepted ones. This pattern can be viewed as a discrete preference structure,  $\Phi$ , that is used to classify overall value judgments of alternatives into an ordered set of preferences (in this case reject or accept). Mathematically,

$$\Phi = \left\{ \begin{array}{l} \bar{v}_k \in \bar{V}_0 \mid \bar{v}_k < \lambda \\ \bar{v}_k \in \bar{V}_1 \mid \bar{v}_k \geq \lambda \end{array} \right\} \quad (3.20)$$

For example, assume the decision problem has two related factors,  $x^A$  and  $x^B$ .  $x^A$  is represented into three states,  $s_1^A - s_3^A$ , divided by two thresholds,  $\delta_1^A$  and  $\delta_2^A$ .  $x^B$  is represented into four states,  $s_1^B - s_4^B$ , divided by three thresholds,  $\delta_1^B - \delta_3^B$ . Such a representation can be expressed in a tree structure, called preference tree, as shown in Figure 3.3. At the bottom, the ovals represent overall value judgments  $\bar{v}$ , each element of which is a value combination from a state value of  $x^A$  and a state value of  $x^B$ .



**Figure 3.3 An example of a preference tree of a two factor decision**

### 3.4.3 Decision heuristics

Once the preference structure is established, it serves as a template based on which information is represented and organized. It is part of a person's value system. Assume that in every choice context, individuals will define a set of threshold values and apply choice heuristics which are logically consistent with the preference structure. Because for different individuals or in different contexts preference structures may differ in terms of the pattern of the sets of accepted and rejected values, this implies that the cognitive process model automatically generates *heterogeneous choice heuristics*. One extreme is the strictest preference structure in the sense that no single value (judgment) combination survives the overall threshold,

$$\Phi = \{\bar{v}_k \in \bar{V}_0 \mid \bar{v}_k < \lambda\} \quad (3.21)$$

That means that regardless of the states of the factors, the choice alternative under consideration will be rejected. In this case, no choice heuristics are implied (or the unconditional rejection heuristic) since the individual has no need to evaluate any information. To illustrate for the above example, it corresponds to the situation when  $\lambda > \bar{v}_{12}$ .

Relaxing  $\lambda$  a little could lead to a preference structure where only the value combination of factor states with the highest threshold values is accepted,

$$\Phi = \left\{ \begin{array}{l} \bar{v}_k \in \bar{V}_0 \mid \bar{v}_k < \lambda \\ \bar{v}_k \in \bar{V}_1 \mid \bar{v}_k \geq \lambda, \bar{v}_k = \sum_j v_{jN+1} \end{array} \right\} \quad (3.22)$$

This preference structure implies a conjunctive rule according to which an alternative will be accepted only when all factors are acceptable at their highest states. During the decision process, any single unsatisfactory factor will cause the decision process to stop, regardless of the states of the other factors. In the example, this may correspond to the situation when  $\bar{v}_{11} < \lambda \leq \bar{v}_{12}$ . To explain further, two decision trees, one starting searching from  $x^A$  and the other from  $x^B$ , are shown in Figure 3.4. The alternative

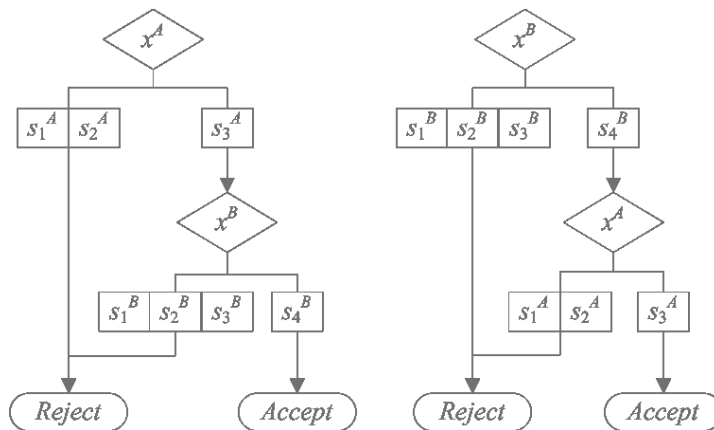


Figure 3.4 Two conjunctive heuristics

will be rejected when either  $x^A$  is not in  $s_3^A$  or  $x^B$  is not in  $s_4^B$ . Not all factor thresholds will be used for a particular decision. As can be seen from the figure, only  $\delta_2^A$  and  $\delta_3^B$  are actually effective. Some factor states lead to the same result and may be treated as a single state.

At the opposite end is the most relaxed preference structure, representing the case that all factor combinations are accepted.

$$\Phi = \{ \bar{v}_k \in \bar{V}_1 \mid \bar{v}_k \geq \lambda \} \tag{3.23}$$

This preference structure implies the unconditional acceptance heuristic since factors being in whatever state will lead to the alternative being accepted. In the example,  $\lambda \leq \bar{v}_1$  represents such a situation.

A little less tolerance for  $\lambda$  may result in a preference structure where all but the value combinations of non-activated factor states are accepted,

$$\Phi = \left\{ \begin{array}{l} \bar{v}_k \in \bar{V}_0 \mid \bar{v}_k < \lambda, \bar{v}_k = \sum_j v_{j1} \\ \bar{v}_k \in \bar{V}_1 \mid \bar{v}_k \geq \lambda \end{array} \right\} \tag{3.24}$$

Disjunctive heuristics can be inferred from this preference structure since any satisfactory factor state (except the non-activated state) will cause the decision process to stop and the choice alternative to be accepted, regardless of the state of the other factors. Figure 3.5 shows two disjunctive heuristics for the example, when  $\bar{v}_1 < \lambda \leq \bar{v}_2$ . The alternative will be accepted either when  $x^A$  is in  $s_2^A / s_3^A$  or  $x^B$  is in  $s_2^B / s_3^B / s_4^B$ . Then only the lowest thresholds for both factors are effective.

Within the spectrum, various other preference structures and heuristics can be identified. For example, the lexicographic heuristic is implied by a preference structure,

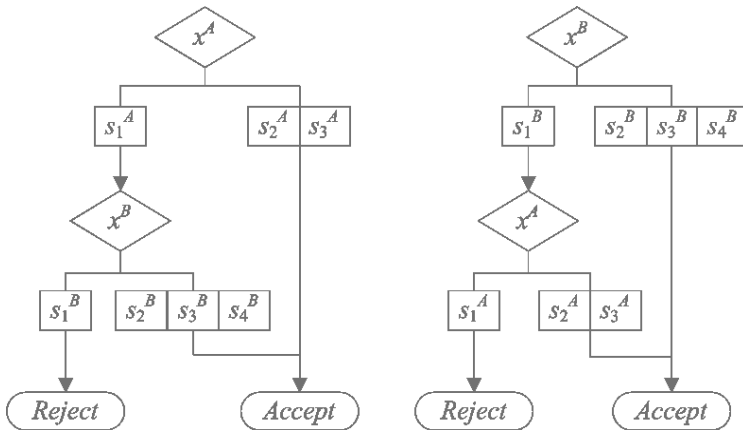


Figure 3.5 Two disjunctive heuristics

$$\Phi = \left\{ \begin{array}{l} \bar{v}_k \in \bar{V}_0 \mid \bar{v}_k < \lambda, \sum_k \sum_{t=1}^n s_{jt|k} = 0 \\ \bar{v}_k \in \bar{V}_1 \mid \bar{v}_k \geq \lambda, \prod_k \prod_{t=n'}^N s_{jt|k} = 1 \end{array} \right\} \quad n < n' \quad (3.25)$$

According to this preference structure, there exists at least one factor  $j$ . When some states of this factor are not activated, the decision process will stop and the alternative will be rejected. When some states are activated, the decision process will stop and the alternative will be accepted. In-between are those states whose status cannot determine whether the alternative is accepted or rejected and further evaluation of other factors is needed. In the example, this preference structure can be found when  $\bar{v}_4 < \lambda \leq \bar{v}_5$ . The two implied heuristics are shown in Figure 3.6.

Different from the above preference structures, however, the lexicographic heuristic only holds when  $x^B$  is evaluated first. That is, the alternative will be accepted if  $x^B$  is in  $s_3^B / s_4^B$ , and will be rejected if  $x^B$  is in  $s_1^B$ . However, the individual needs to further evaluate  $x^A$  if  $x^B$  is in  $s_2^B$ . The lexicographic interpretation does not hold when  $x^A$  is evaluated first because  $x^A$ , regardless of its state, will not generate a definite outcome and  $x^B$  must be evaluated anyway. The effort of decision making then may differ between using the two heuristics although they generate the same result.

By varying the value of the overall threshold, many other decision rules can be identified based on this approach. Some may have been independently proposed; some could be a hybrid of other heuristics. The location of  $\lambda$  determines how a problem will be looked at (a serious problem with very high standard or a minor problem with very low standard) and the involvement of the decision maker (extensive or limited information search), which, of course, vary from person to person, from context to context.

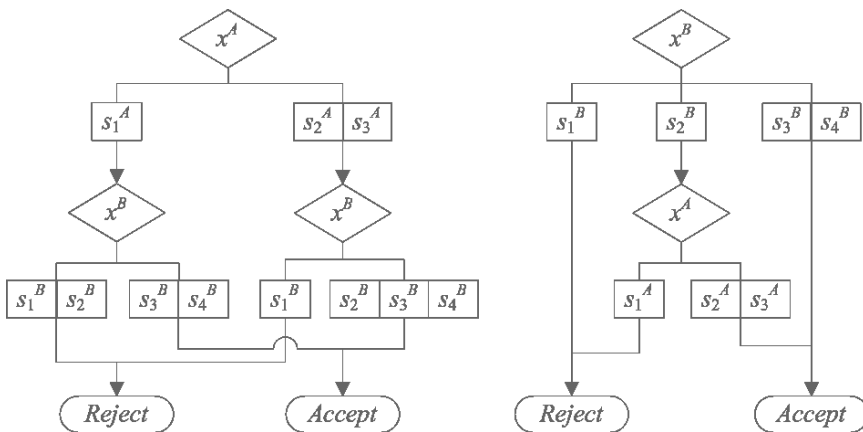


Figure 3.6 Lexicographic heuristic from evaluating  $x^B$  first

### 3.4.4 Choice of heuristic

Assume that different individuals or the individual in different contexts may apply different preference structures and corresponding choice heuristics to solve problems. That is, people have a context-dependent repertoire of preference structures and corresponding heuristics, as suggested by many researchers (e.g., Beach and Mitchell, 1978; Payne, *et al.*, 1988). Although we should always try to specify the context as much as possible, there will always remain some stochastic element from the viewpoint of the analyst. Such randomness can be mathematically included into the overall threshold, so that we get  $\lambda \sim f$ , where  $f$  is a probability density function. Because  $\bar{V}$  is a discrete set, between consecutive pairs of  $\bar{v}_k$ , there is a range of  $\lambda$ , satisfying  $\bar{v}_{k-1} < \lambda \leq \bar{v}_k$ . It represents the range of an invariant preference structure. The probability of this preference structure  $\Phi_k$  being applied,  $p_k$ , equals the probability of  $\lambda$  being in this range, given  $f$  is a continuous distribution:

$$p_k = \int_{\bar{v}_{k-1}}^{\bar{v}_k} f dt \quad (3.26)$$

We may equivalently view this as the probability of applying choice heuristics implied by the preference structure. Thus, any single decision may be a two-stage process, (1) choosing an appropriate preference structure and applying this structure to the choice task, and then (2) forming preferences among alternatives and making the choice. Because the preference structure actually applied by the decision maker is usually unknown, the final probability of an alternative being satisfactory can be modeled as the expected result of choice outcomes aggregated across all possible choice outcomes under these latent preference structures, or mathematically:

$$p_i = \sum_{k=1}^{K+1} p_k p_{i|k} \quad (3.27)$$

where  $p_{i|k}$  is the probability that alternative  $i$  is satisfactory when preference structure  $k$  is applied. It has the same specification as  $p_{im}$  in Equation 3.16. However, because within an invariant range the value of  $\lambda$  does not affect choice outcomes,  $\lambda$  does not need to be identified. Instead, the upper bound of  $\lambda$ ,  $\bar{v}_k$ , is enough as a critical value for the overall threshold. Although the process of selecting a preference structure itself may be susceptible to bounded rationality, here only the outcome of this process is modeled. Assuming the distribution of preference structures can be represented by a multinomial logit distribution, the individual selects the preference structure probabilistically based on its expected value. The probability of a preference structure being applied can then be modeled as

$$p_k = \frac{\exp(u_k)}{\sum_{k'=1}^{K+1} \exp(u_{k'})} \quad (3.28)$$

where  $u_k$  is the value that the individual expects from applying preference structure  $k$ . In fact, Equation 3.28 represents the probability that the heuristics which are implied by the preference structure are selected. Because for certain preference structure applying different heuristics does not affect the choice outcome, Equation 3.28 can also be formulated as the aggregation of the probabilities of the heuristics being chosen,

$$p_k = \sum_{h=1}^{J!} P_{kh} = \frac{\sum_{h=1}^{J!} \exp(u_{kh})}{\sum_{k'=1}^{K+1} \sum_{h'=1}^{J!} \exp(u_{k'h'})} \quad (3.29)$$

where  $u_{kh}$  is the expected value of heuristic  $h$  implied by preference structure  $k$ . We assume that this value is composed of three factors: mental effort, risk perception and expected outcome.

#### 3.4.4.1 Mental effort

It is the obvious that the more factors considered and the more alternatives evaluated to make a decision, the more mental effort has to be invested. In this thesis, the influence of the number of alternatives will not be modeled. It is treated as part of the context of the decision problem. The emphasis is on the factors involved, and moreover, on the factor search sequence. This emphasis is motivated by the fact that the influence of factors on decisions differs. Important factors may be decisive for a decision and if they are evaluated earlier, they may obliterate the need to search other factors, which costs less mental effort. However, different types of information may also cause the processing effort to differ between factors. For example, judging the shape of an object may be more difficult than judging color. A complicating factor is that individuals cannot be sure about the amount of mental effort that will be involved in the decision that follows. They can only subjectively estimate it based on their uncertain (probability) beliefs  $p_{jn}$  that the activated factors occupy certain states that make any further consideration of subsequent factors useless.

To illustrate, let three factors  $x_1$ ,  $x_2$ , and  $x_3$  have,  $A$ ,  $B$ , and  $C$  states respectively ( $a = 1, \dots, A$ ;  $b = 1, \dots, B$ ;  $c = 1, \dots, C$ ). Assume that the heuristic under consideration implies the factor search sequence  $x_1 \rightarrow x_2 \rightarrow x_3$ . Let  $e_1$ ,  $e_2$ , and  $e_3$  denote the amount of the expected mental effort inflicted when searching and evaluating factors  $x_1$ ,  $x_2$ , and  $x_3$  respectively, and let  $p_a$ ,  $p_b$ , and  $p_c$  represent the individual's beliefs that the factors are in the states with value judgments  $v_a$ ,  $v_b$ , and  $v_c$  respectively, such that  $\sum_a p_a = 1, \sum_b p_b = 1, \sum_c p_c = 1$ . The expected amount of mental effort is then defined as:

$$e_h = e_1 + \sum_a (p_a e_2 Y_a + \sum_b p_a p_b e_3 Y_{ab}) \quad (3.30)$$



$$Y_a = \begin{cases} 0 & \text{if } v_{abc} < \lambda \vee v_{abc} \geq \lambda \quad \forall b, \forall c \\ 1 & \text{otherwise} \end{cases} \quad (3.31)$$

$$Y_{ab} = \begin{cases} 0, & \text{if } v_{abc} < \lambda \vee v_{abc} \geq \lambda \quad \forall c \\ 1, & \text{otherwise} \end{cases} \quad (3.32)$$

Equation 3.30 reflects the fact that  $e_1$  is inevitably fully inflicted since  $x_1$  is searched first. For each possible state of  $x_1$ , expected efforts are derived from two terms. First, the effort of searching  $x_2$  is weighted by the probability of  $x_1$  being in a particular state and  $Y_a$ , an identity function defined by Equation 3.31.  $Y_a$  represents a judgment process, according to which an individual checks whether all subsequent value combinations  $v_{abc} | a$ , are inactivated against  $\lambda$ , or all values are activated. If all value combinations are inactivated, the corresponding factor is not searched and no additional mental effort is involved. If all value combinations are activated, it means that the same decision or preference applies to all instances of that factor and hence searching the factor will not have any effect on the preference ordering or decision. In these cases,  $Y_a = 0$ . In contrast, when  $Y_a = 1$ ,  $x_2$  needs to be searched.

According to the same logic, the second term relates to searching  $x_3$  when at a state of  $x_2$ .  $e_3$  is weighted by  $p_a p_b$ , the joint probability of being in the previous two factor states, and  $Y_{ab}$  is another identity function judging whether the simultaneous conditions  $v_{abc} | a, b$  against  $\lambda$  are satisfied or not. According to this definition, due to the fact that efforts of searching factors may differ and different factor values may cause earlier or later termination of the decision process, the expected efforts of different search sequences may differ as well when the expected overall values are homogeneously against the overall threshold.

#### 3.4.4.2 Risk perception

The saying ‘‘Don’t put all eggs in one basket’’ suggests that extreme investment is very risky. Avoiding extreme situations seems to be human nature. For example, humans try to maintain biological diversity so that creatures will be less vulnerable to catastrophic environmental changes; many social phenomena are normally distributed, etc. Assume that this rule also applies to individuals selecting a decision strategy. By selecting a very high or very low  $\lambda$  within the overall value space, the individual will have a very high probability to reject or accept an alternative since most of the information will fall into the overall value set that is lower or higher than  $\lambda$ . The advantage of judging the alternative in a nearly monotonic way is that the decision process will be very simple and will cost little effort. However, the expected opportunity costs will increase if the result would be better when the alternative is looked at in another way. Such opportunity costs are tightly related to the expected regret resulting from a potentially false rejection or false acceptance. This notion is similar to what Bettman, *et al.* (1998) called negative experienced emotion, which is to be minimized in a decision. In contrast, selecting a mild  $\lambda$  will control the expected

regret to a minimum by staying uncertain about the outcome at every stage of information search. It will induce looking for more information in order to get a comprehensive view of the choice alternatives. The drawback of doing so is it requires more effort.

For this reason, more outcome variety after every factor search means lower decision risk. The risk perception is determined by the location of  $\lambda$  and the probability beliefs. To model this property, Shannon's Information Entropy is applied because it has been developed specifically for measuring information uncertainty. Let  $\bar{p}_k$ , corresponding to  $\bar{v}_k$ , be the factorial joint product of the probability beliefs on factor states. The probability of a positive,  $r_{kh}^+$ , respectively negative,  $r_{kh}^-$ , outcome equals:

$$\begin{aligned} r_{kh}^+ &= \sum_k \bar{p}_k Y(\bar{v}_k \geq \lambda) \\ r_{kh}^- &= 1 - r_{kh}^+ \end{aligned} \quad (3.33)$$

where  $Y(\zeta)$  is an identity function being 1 when  $\zeta$  is true and 0 when  $\zeta$  is false. It follows that the risk perception for heuristics implied by the same preference structure is the same because different information search sequences do not change the preference/choice outcome. Therefore, subscript  $h$  may be excluded. Then, the risk perception of a preference structure is,

$$r_k = -r_k^+ \log_2(r_k^+) - r_k^- \log_2(r_k^-) \quad (3.34)$$

The property of the Information Entropy measure is that its value is at its maximum when all outcomes are equally possible and at its minimum when the outcomes are absolutely certain. In this case, the maximum value is 0.5, which represents the lowest risk perception, and the minimum value is 0, which represents the highest risk perception.

#### 3.4.4.3 Expected outcome

Individuals may have expectations about the outcome of a decision which is directly related to the context of the decision problem because people may favor some outcomes more than others. This makes the selection of judgment standards not a neutral process but it likely involves value biases. A decision standard which leads to more probable occurrences of preferred outcomes is more likely to be selected. Assuming that each outcome brings a particular value, the expected outcome can be represented as:

$$o_k = o_k^+ r_k^+ + o_k^- r_k^- \quad (3.35)$$

where  $o_k^+$  is the value of the satisfactory outcome and  $o_k^-$  is the value of the unsatisfactory outcome. Like in the risk perception, the factor search sequence does not have an influence either. Various rules can be applied to represent the joint effects of the three elements. If a linear weighted linear combination rule is assumed, then we have,

$$u_{kh} = \beta^e e_{kh} + \beta^r r_k + \beta^o o_k \quad (3.36)$$

where  $\beta^e$  is the parameter for effort, and is assumed to be negative because  $e_{kh}$  represents a kind of costs,  $\beta^r$  is a parameter for risk perception and is also assumed to be positive because people are assumed to prefer low decision risks, and  $\beta^o$  is a parameter for expected outcome. We do not have any a priori expectations about the sign of  $\beta^o$ . These weights are influenced by a variety of decision problem characteristics, such as the importance, irreversibility, and time limit for a decision. In general, for a relatively important and irreversible decision, a low weight for effort and a high weight for risk perception may be expected; the situation will be the reverse when the decision has to be made quickly.

### 3.4.5 Extension to comparative choice decisions

The previous model specifications are based on situations where an individual needs to decide whether an alternative is satisfactory, judged against some existing standards. This subsection extends this approach to comparative choice decisions, involving two alternatives.

Assume that the formation of preference structure involves alternative-based comparison of alternatives as in the discrete choice models, and people prefer the alternative with the higher utility. Further, assume that people compare the ranks of utilities instead of the utility itself. This means that only the relative relationships between the utilities count in this cognitive system and that their absolute values do not matter. Based on Equation 3.16, the probability that alternative  $i$  is better than alternative  $l$  is,

$$p_{il}^R = \begin{cases} 0 & \text{if } v_{il}^R < \lambda^R \\ 1 & \text{if } v_{il}^R \geq \lambda^R \end{cases} \quad 1 \leq \lambda^R \leq K, l=1, \dots, I, l \neq i \quad (3.37)$$

$$v_{il}^R = v_i^R - v_l^R$$

where  $v_i^R$  is the rank of alternative  $i$  within the set of value combinations  $\bar{V}$ .  $v_{il}^R$  is the rank difference between alternative  $i$  and  $l$ . Here  $\lambda^R$  represents the discriminant threshold against which the rank difference is judged. Thus, the number of rank differences and  $\lambda^R$  are limited to  $K$ , the maximum number of overall value judgments. Equation 3.37 implies that an individual sets a discriminant threshold to judge whether an alternative is sufficiently better than another, which may be a more realistic assumption than assuming an individual discriminates alternatives in terms of infinitively small utility differences. Note that  $p_{il}^R$  is not equivalent to the probability that alternative  $i$  is chosen over alternative  $l$ , which is defined as:

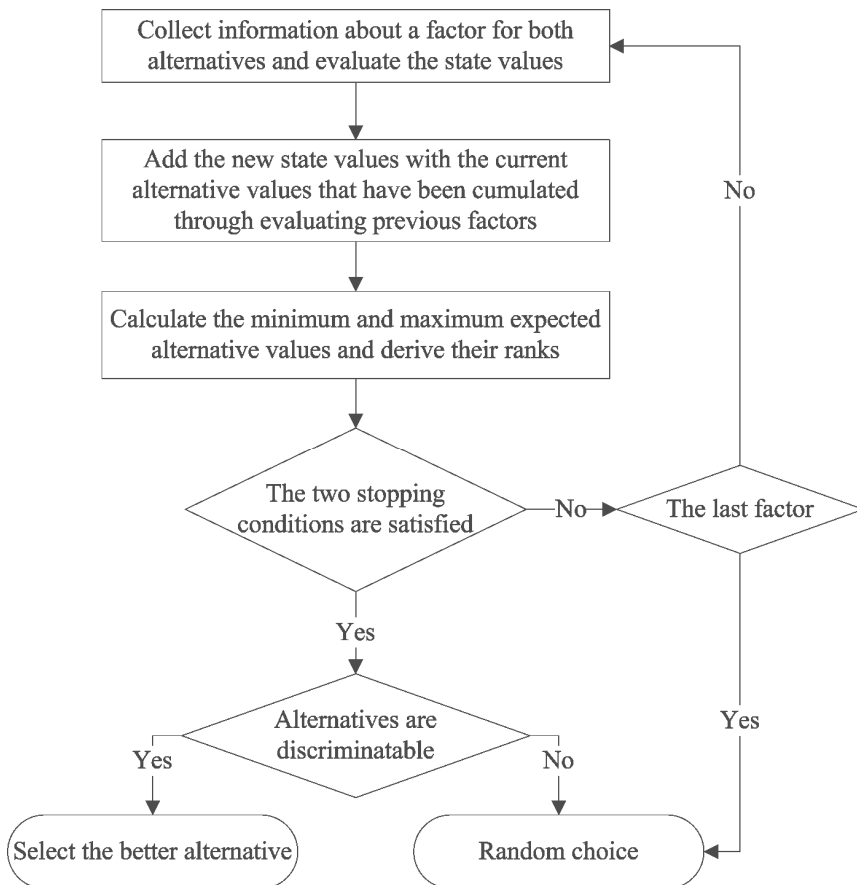
$$p_{il} = \begin{cases} 1 & \text{if } p_{il}^R = 1 \\ 0 & \text{if } p_{li}^R = 1 \\ 0.5 & \text{if } p_{il}^R = 0 \wedge p_{li}^R = 0 \end{cases} \quad (3.38)$$

This means that alternative  $i$  is chosen when it has sufficiently higher rank than alternative  $l$ . It is assumed that a uniform random choice is applied when neither alternative is sufficiently better, given the discriminant threshold.

The heuristic rule for guiding information search may be formed based on the cognitive structure. The procedure is shown in Figure 3.7. Given discriminant threshold  $\lambda^R$  and factor search sequence  $1 \rightarrow \dots \rightarrow J$ , the individual searches the first factor of both alternatives. Assuming that alternative  $i$  is in state  $n$  and alternative  $l$  is in state  $m$ , let  $v_{ijn}$  and  $v_{ijm}$  represent the state values of factor  $j$  for the two alternatives. Define  $v_i$  and  $v_l$ , as the cumulative state values of the factors that have been evaluated for each alternative, given that factor  $j$  is the latest one that has been evaluated,

$$v_i = \sum_{t=1}^j v_{itn} \quad (3.39)$$

Then the individual calculates the minimum and maximum expected overall values,  $\check{v}_i$



**Figure 3.7 Procedure of forming a heuristic rule for comparison**

and  $\widehat{v}_j$ , by adding the current alternative values with the sum of the minimum or maximum state values of the unsearched factors,  $\widetilde{v}_j$  respective  $\widehat{v}_j$ ,

$$\begin{aligned} \widetilde{v}_i &= v_i + \sum_{t=j+1}^J \widetilde{v}_t \\ \widehat{v}_i &= v_i + \sum_{t=j+1}^J \widehat{v}_t \end{aligned} \tag{3.40}$$

Let  $\widetilde{v}_i^R$  and  $\widehat{v}_i^R$  be the ranks of the minimum and maximum expected overall values in  $\overline{V}$ . Next, the individual judges whether the information search process should stop. There are two stopping conditions: (1) when the two alternatives can be definitely discriminated,

$$\arg \min(|\widetilde{v}_i^R - \widehat{v}_i^R|, |\widetilde{v}_l^R - \widehat{v}_l^R|) \geq \lambda^R \tag{3.41}$$

(2) when the two alternatives can definitely not be discriminated:

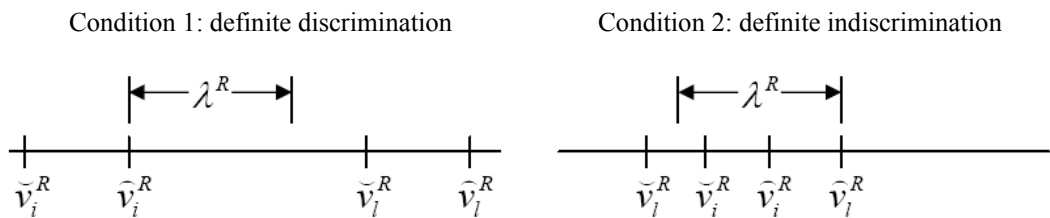
$$\arg \max(|\widetilde{v}_i^R - \widetilde{v}_l^R|, |\widehat{v}_i^R - \widehat{v}_l^R|) < \lambda^R \tag{3.42}$$

Figure 3.8 gives an illustration of some possible situations satisfying the two stopping conditions.

If neither of these conditions is met, the decision cannot be made and another factor has to be searched. This procedure is repeated until the stopping conditions are met or the last factor is searched. In case that the alternatives cannot be discriminated after all the factors are evaluated, random choice is assumed. After practicing this judgment procedure a sufficient number of times, the individual may establish the decision rules (e.g., in the form of if...then...else) for fast decisions.

Again, the variation of  $\lambda^R$  controls the heterogeneity of comparison strategies. The general trend is that when  $\lambda^R$  is large, it is less likely that the alternatives will be discriminated, so that random choice will be more frequent and the decision requires less effort. When  $\lambda^R$  is small, the decision also requires less effort because the alternatives will be easier to discriminate. When  $\lambda^R$  has an intermediate value, more extensive search is required to discriminate the alternatives.

Similarly, the expected choice probability considering latent preference structures turns out to be:



**Figure 3.8 The stopping conditions for comparative choice**

$$\bar{p}_{il} = \sum_{k=1}^K p_k p_{il|k} \quad (3.43)$$

The same specification as in Equation 3.29 can be used to model the selection of comparison heuristics, with some extra modifications on mental effort, risk perception and expected outcome. The stopping rule for factor search under a heuristic depends on whether two alternatives can or cannot be discriminated when subsequent possible value ranks are considered. Based on Equation 3.30-32, expected effort is defined as:

$$e_h = e_1 + \sum_{ia} \sum_{la} (p_{ia} p_{la} e_2 Y_a^R + \sum_{ib} \sum_{lb} p_{ia} p_{la} p_{ib} p_{lb} e_3 Y_{ab}^R) \quad (3.44)$$

$$Y_a^R = \begin{cases} 0 & \text{if } v_{|il|abc}^R < \lambda^R \vee v_{|il|abc}^R \geq \lambda^R \quad \forall b, \forall c \\ 1 & \text{otherwise} \end{cases} \quad (3.45)$$

$$Y_{ab}^R = \begin{cases} 0 & \text{if } v_{|il|abc}^R < \lambda^R \vee v_{|il|abc}^R \geq \lambda^R \quad \forall c \\ 1 & \text{otherwise} \end{cases} \quad (3.46)$$

In Equation 3.44, because searching one factor implies factors of both alternatives are searched, the major difference is that the factor state probabilities of both alternatives have to be included in order to form a joint probability. Identity function  $Y_a^R$  is 0 when after  $x_1$  is searched, all subsequent possible value rank differences,  $v_{|il|abc}^R$  ( $|il|$  means regardless of comparison sequence between alternatives), are all smaller than the discriminant threshold, meaning alternatives cannot be discriminated, or are all equal to or larger than the discriminant threshold, meaning alternatives can be discriminated. The search process can stop here. Otherwise, factor search will continue and the effort for searching the next factor must be paid. The same definition logic applies to  $Y_{ab}^R$ .

For the specification of risk perception, only  $r_{kh}^+$  needs to be modified as,

$$r_{kh}^+ = \sum_{s=1}^K \sum_{t=1}^K \bar{p}_{is} \bar{p}_{it} Y(|v_{st}^R| \geq \lambda^R) \quad (3.47)$$

where  $\bar{p}_{is}$  is the probability of alternative  $i$  having overall value  $\bar{v}_s$ , and  $v_{st}^R$  is the rank difference between the overall value ranks of the two alternatives. The specification of the expected outcome changes accordingly, with  $o^+$  representing the situation that the two alternatives can be discriminated under  $\lambda^R$ , and  $o^-$  representing the situation that they cannot be discriminated.

### 3.5 Summary

This chapter discussed the building blocks of the models that are to be empirically tested in the next few chapters. Four major decision models for predicting and/or simulating pedestrian behavior were outlined. They are expected to significantly influence the general spatio-temporal distributions of pedestrian activities. The specification of the multinomial logit model was also given, which will be applied to all the decision problems and serve as the benchmark for the heuristic models.

Moreover, the rationales underlying three typical heuristic models (conjunctive, disjunctive and lexicographic model) were introduced. By incorporating threshold heterogeneity, these models were specified in a probabilistic manner so that likelihood-based model estimation techniques can be used.

To overcome some limitations in modeling bounded rationality, the Heterogeneous Heuristic Model was proposed, which adopts a two-level two-stage modeling framework. By introducing factor thresholds, the mechanisms of factor filtering, problem representation, and the formation of preference structures were modeled. It was shown that the variation of the overall threshold may lead to heterogeneous decision heuristics. Evidence of utility-maximizing behavior would be obtained if estimated thresholds would be such that all factors are taken into account, the number of states for each factor would be high as this would indicate detailed discrimination. Any deviations from this outcome, in contrast, would support aspects of bounded rationality. This property allows capturing individual- or context-dependent decision strategies in one single model by applying a latent class structure. The choice of heuristic was further looked into, whose outcome was modeled in terms of an MNL distribution which is proportional to the value of each heuristic, defined as a combined evaluation of mental effort, risk perception, and expected outcome. Finally, the approach was extended to model comparative choice decisions.

Without requiring more input information from data than conventional rational choice models, HHM provides much richer behavioral output. Estimates of factor thresholds will show how the environment is cognized and represented by pedestrians. Perhaps the most valuable behavioral output is the set of different decision heuristics that can be probabilistically estimated. These advantages will be shown in the applications discussed in the next chapter by empirically estimating these models on pedestrian behavioral data.

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*Chapter*

## 4 DATA

This chapter introduces the data that were used to estimate the models proposed in the previous chapter. Two datasets on pedestrian shopping behaviors were collected, one in Wang Fujing Street (WFS), Beijing, and the other one in East Nanjing Road (ENR), Shanghai, China. Both streets are located in the downtown shopping areas. The WFS dataset was collected in 2004, before the PhD project started. It was used to estimate the conventional heuristic models. The ENR dataset was collected in 2007. Some modifications were made to the data collection format used for WFS. It was used to estimate the HHMs.

The chapter includes three sections. This first section introduces the data collection in WFS. It includes five subsections. The first subsection introduces the survey design. The second subsection introduces the survey area. The administration of the data collection is introduced in the third subsection. In the fourth subsection, an approach that was specifically developed for estimating spatio-temporal information of pedestrian behavior is discussed. This is followed by a brief overview of the basic characteristics of the samples, such as pedestrians' socio-demographics, and activities in space and time. The second section introduces the data collection in ENR with the same subsections. The last section is a short summary.

### 4.1 Wang Fujing Street

#### 4.1.1 Survey design

In order to model the four decisions (go-home, direction choice, rest, and store patronage), data on pedestrian behavior, resulting from these decisions must be obtained. The data should be able to tell when the pedestrians decided to go home, which direction was chosen, when and where a rest stop was made, and which stores were patronized. Behavioral data should also pertain to a certain time span to model the influence of time on decisions. The demands on the data collection are therefore quite high.

Two types of survey methods are commonly used in pedestrian behavior research: collecting data in experiments or in the real world. The major advantage of experimentation is that the researcher can control the conditions that generate particular behavioral responses. The major disadvantage is that the experiment cannot replicate the complexity of the real world. Although some new technologies such as Virtual Reality have been applied to collect pedestrian data (e.g., Tan, *et al.*, 2006), the representations, however realistic, still do not allow respondents to experience subjective feelings such as fatigue, boredom, and sense of time, which are not ignorable for studying time-dependent pedestrian behavior. Therefore, a real-world survey method was applied to collect data. Instead of using high accuracy tracking methods such as GPS, mobile phone, RFID, or tracking the pedestrian (for comprehensive review on this topic, see Hoogendoorn, *et al.*, 2003; Bandini, *et al.*, 2007, Millonig and Gartner, 2007, Borgers, *et al.*, 2008), a questionnaire was used



Please report in sequence your activities

Arrival time: 14:00							
	Entry	Visit 1	Visit 2	Visit 3	...	Visit 20	Exit
Store/Place (No.)	1	101	101	204			20
Planned visit (0/1)	/	1	1	0			/
Activity (No.)	/	1	2				/
Planned activity (0/1)	/	1	0				/
Expense	/	200	0				/
Departure time: 18:00							

**Figure 4.1 Illustration of the questions about activities**

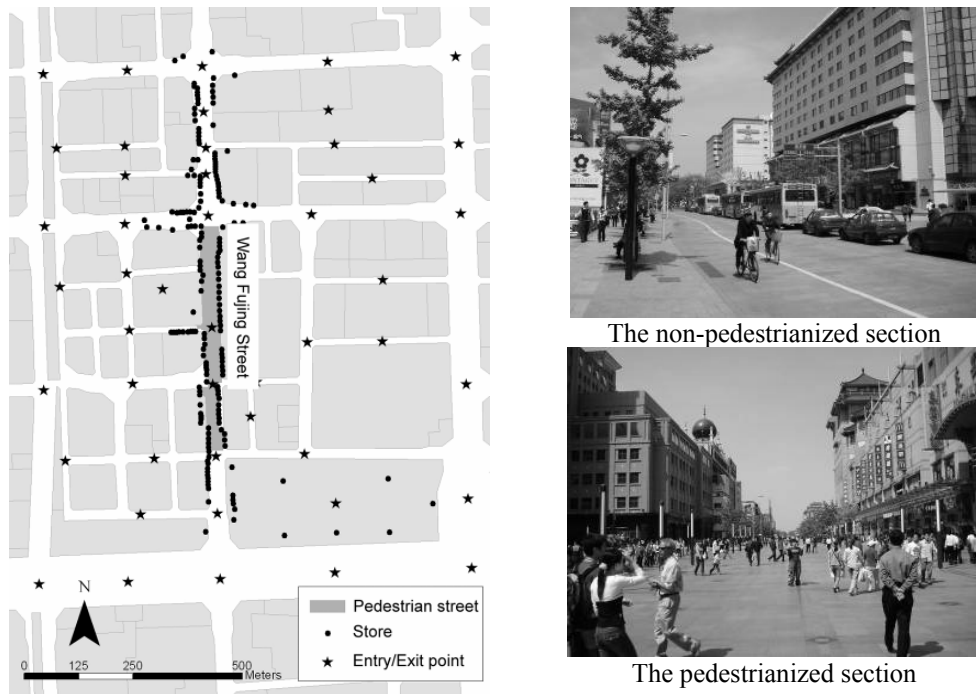
because it is relatively easy to administer, implying that a large number sample (which provides stable behavioral heterogeneity) and rich information can be obtained for limited resources. Although the method could reduce data accuracy, it may be tolerated given the research aim (e.g., Hill, 1984).

The major purpose of the survey was to collect detailed information about pedestrian shopping diaries. These diaries include two types of questions: (1) pedestrian's socio-demographics, such as gender, age, income, purpose, etc.; (2) the activities a pedestrian conducted since the beginning of the shopping trip, including the sequence of visits to stores, types of activities, items bought, plan of visits and activities, expenditures, start time of the trip, (expected) end time of the trip, and entry and (expected) exit point of the survey area. Figure 4.1 illustrates the questions related to activities. The arrival time was recorded first. Then, in sequence, the pedestrian reported the entry point and all following stores or places that were visited, which were recorded using pre-defined code. For each visited store, the interviewer recorded whether the visit was planned or not, the activity in the store (e.g., cloth, fast food, visiting), whether this activity was planned or not, and the expenditure. Note that multiple visits of the same store for different activities were recorded separately. Finally, the pedestrian was asked to estimate the expected time for ending the shopping trip.

The major disadvantage of this method of data collection is that the quality of interview, especially for the second type of questions, is difficult to control because it largely depends on respondent's self report, which may be affected by memory loss, fatigue, intention to cooperate and other factors. As a result, biases are inevitable and hard to identify, at least from the survey itself.

### **4.1.2 Background**

Located in the center of Beijing city, Wang Fujing Street (WFS) is a shopping street with over 700 hundred years of history. It is now a modern multifunctional city center with retail, entertainment, leisure, culture, office, hotel and other functions. The survey area is about 1.3 km<sup>2</sup> around the street and includes the major section of WFS where most retail stores in this area are located (Figure 4.2). The street is about 1,200 m long from south to north, of which about 530 m is the pedestrianized section which was constructed in 1999. Public transportation concentrates at the southern end of the street, including a metro station of the two most important lines and several bus stops.



**Figure 4.2** The survey area of WFS

Some bus stops are also located in the middle section and northern end of the street. The Forbidden City and Tianan Men Square are located 1,000 m to its west. The north of the street locates many cultural facilities such as China Fine Art Museum and Beijing People's Art Theater. The street is one of the busiest shopping areas in Beijing. The latest estimate of the number of pedestrians is 250,000 per day on normal days and 300,000 on holidays (Beijing Dong Cheng District Government, 2005). In this linear shopping space, large department stores are all located south to the northern end of the pedestrianized section, with approximately 320,000 m<sup>2</sup> total retail floorspace. The rest retail floorspace, about 37,000 m<sup>2</sup>, is distributed in the section to the northern end of the pedestrianized section.

#### **4.1.3 Data collection**

Twenty undergraduate students from the Department of Regional and Urban Planning, Peking University, administered the survey on May 17 (Monday) and 22 (Saturday), 2004. At 9 survey spots evenly distributed along the street from 11:00 to 20:00, they asked randomly selected pedestrians who indicated that they had completed their shopping trip, to fill out a questionnaire. The selection of these pedestrians was based on the consideration that their diaries are nearly complete, which provides the largest degree of accuracy for studying the full activity chain. However, this sampling procedure may result in a sample that is not representative of the population in the street, because the surveying time did not spread across store operation hours. As a result, the sample may only represent a sub-population of pedestrians who ended the

trip relatively early. Consequently, some systematic bias related to the number of visits and time use may have been introduced. Those pedestrians who agreed to participate usually spent 15-20 minutes completing the interview. Answers depended on memory recall. Interviewers provided two maps to respondents for improving recall. One map portrayed the survey area and identified entry/exit points; the other map portrayed the WFS with the names and locations of major stores. A total of 760 valid diaries were collected, 275 (36%) during the first day and 485 (64%) during the second day.

#### 4.1.4 Time estimation

Compared to the spatial information collected from the pedestrian diaries, the temporal information is much scarcer: only the start time and the (expected) end time of the trip is available. Although it is not impossible to ask respondents about the clock time they conducted a certain activity at a particular place, respondents may have difficulty to recall the time because people usually do not notice it. The reliability of their answers is therefore probably very low and even worse, the quality of other questions may be harmed when respondents become anxious due to such annoying, difficult-to-report questions. An approach was therefore developed to estimate the missing time information. It consists of the following steps:

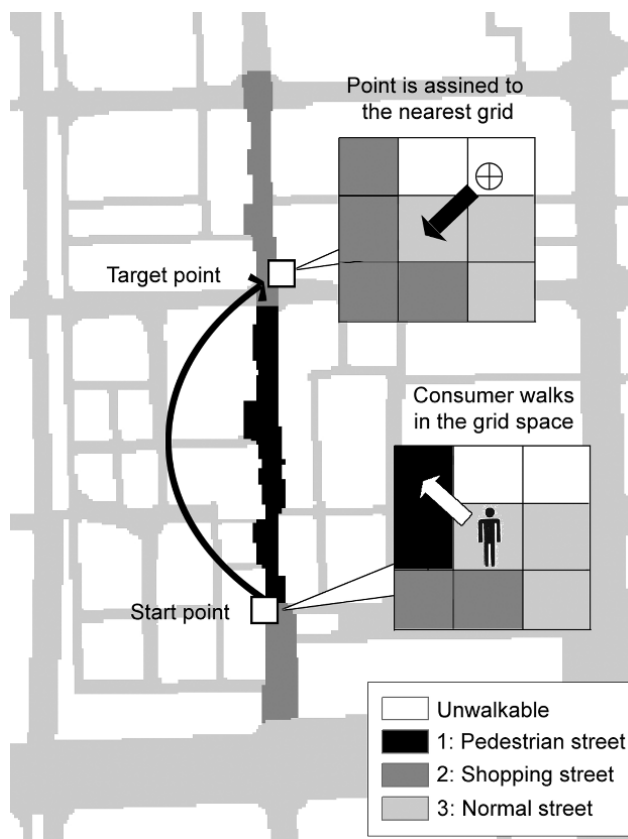
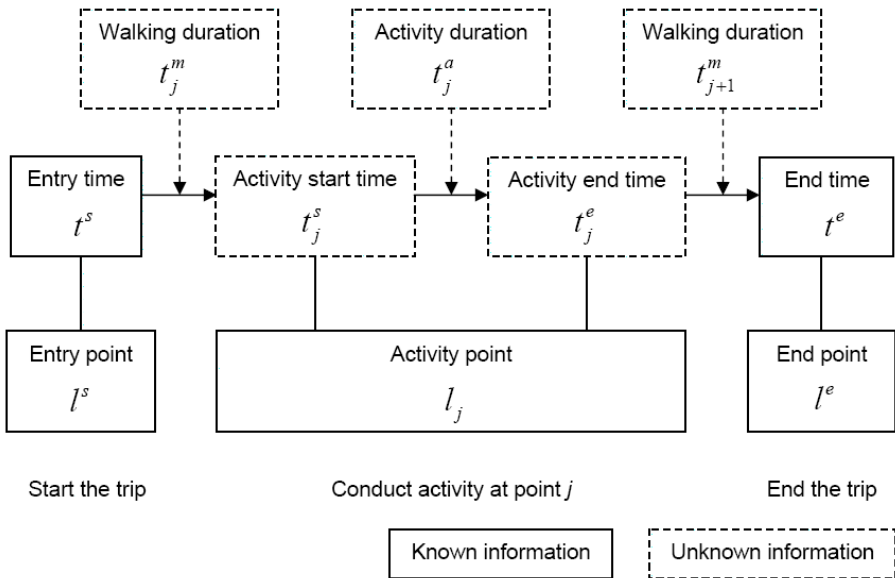


Figure 4.3 The grid space

- (1) Represent the survey area into a grid space composed of  $5 * 5$  m cells (Figure 4.3). The grid size was determined through a balance between accuracy and computation cost. Each cell was assigned an arbitrary walking cost, assuming that the pedestrianized section has the least cost (1 in this case), which implies that pedestrians will prefer walking in this type of cell to others. The non-pedestrianized section of the shopping street has cost 2 and other normal streets have cost 3. These are the walkable cells. All relevant spatial points (entry/exit points and stores) were assigned to their nearest walkable cells.
- (2) Generate a dataset in which each record represents a movement pair with an origin and a destination, based on the consecutive visits in the activity diary.
- (3) Simulate pedestrian “walking” in the space for each movement pair and estimate the distance between origin and destination using a shortest path algorithm, given the assumed preference on walking costs.
- (4) Estimate the walking duration based on the distance, given a walking speed of 1 m/s. Although researches have suggested that pedestrian walking speed in non-shopping environments is about 1.5 m/s (e.g., Willis, *et al.*, 2004), it is reasonable to use this slower average speed because shopping behavior is more leisurely and people search information from the environment more frequently, especially tourists.
- (5) Estimate the duration for each activity, represented by  $j$ , using equation  $t_j^a = (t^e - t^s - \sum_j t_j^m) / N$ , where  $t_j^a$  is activity duration,  $t^e$  is the end time of the shopping trip and  $t^s$  is the start time,  $t_j^m$  is the walking duration for a movement pair,  $N$  is the total number of activities that the pedestrian



**Figure 4.4 Relationship between spatial and temporal information**

conducted during the shopping trip. This means that activity duration is the average of the overall duration in the street, excluding walking duration (Figure 4.4).

#### 4.1.5 Basic sample characteristics

Table 4.1 lists some basic characteristics of the sample. There are slightly more male pedestrians than female pedestrians. Young pedestrians are the major group, followed by middle-aged and old pedestrians. More than half of the pedestrians lived in the city while the rest came from outside. Among the major purposes for visiting WFS, leisure is the most-reported one; tourism also has a large percentage. The number of pedestrians purely shopping is relatively low. This finding can probably be explained by the many historical sites near this area, WFS itself being one of these. Most pedestrians used public transport to reach the survey area, mainly bus and metro. This makes that the overall distributions of activities is strongly affected by the locations of metro and bus stops. Most pedestrians were with a companion.

The distribution of pedestrians' arrival hours is shown in Figure 4.5. It is almost a single modal distribution with the peak hour between 13:00 – 14:00. The mean is 12:55, with a standard deviation of 2.3 hours. Figure 4.6 shows the cumulative distribution of the pedestrians' total duration in the street. The value, as said before, was calculated as the difference between the self-reported end time and arrival time. There are frequent small jumps in the figure, because people are used to round time to the nearest quarter. The mean is 4.4 hours, and the standard deviation is 2.2 hours. The distribution of the number of store visits is shown in Figure 4.7. It shows that about 10% of the pedestrians did not visit any store during the trip. 80% of the pedestrians conducted no more than 4 activities. There are very few pedestrians who conducted more than 8 activities. The mean is 3.1 times, and the standard deviation is 2.3 times. The distribution of the number of stops to rest is as follows: 0 time = 51.7%, 1 time = 39.2%, 2 times = 7.4%, 3 times = 1.2%, and 4 times = 0.5%. 90% of the pedestrians rested no more than once, while half of the pedestrians did report not to have taken any rest at all. The mean is 0.6 stops, and the standard deviation is 0.7 stops. Figure

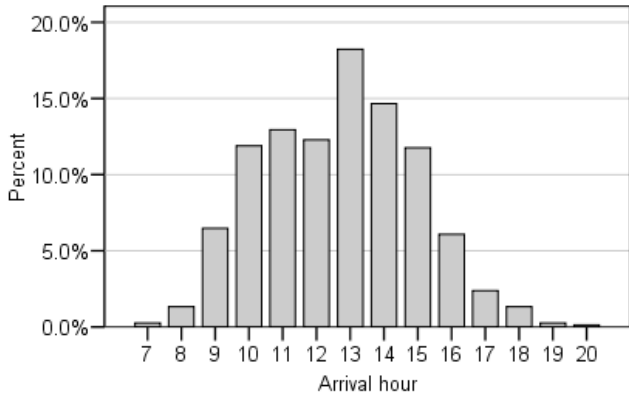
**Table 4.1 Basic characteristics of the sample (WFS)<sup>(1)</sup>**

Gender	Male	Female			
	54	46			
Age <sup>(2)</sup>	Young	Middle	Old		
	53	34	13		
Residence	In town	Out of town			
	55	45			
Purpose	Shopping	Tourism	Leisure	Others	
	26	29	31	14	
Transport	Metro	Bus	Car, Taxi	Walk	Others
	31	36	19	10	4
Group size	1 person	2 persons	≥ 3 persons		
	23	69	8		

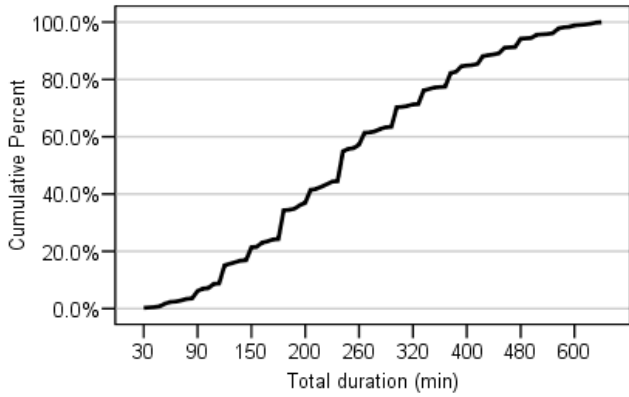
<sup>(1)</sup> Numbers in percentages

<sup>(2)</sup> Young = 16 – 29; middle = 30 – 49; old ≥ 50

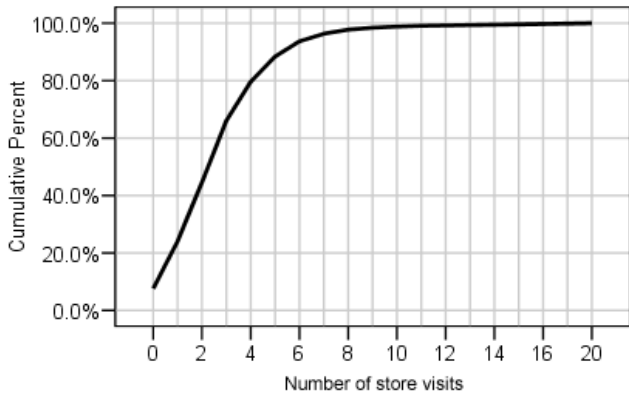
4.8 shows the distribution of activity duration. The mean is 62.7 minutes, and the standard deviation is 49.4 minutes.



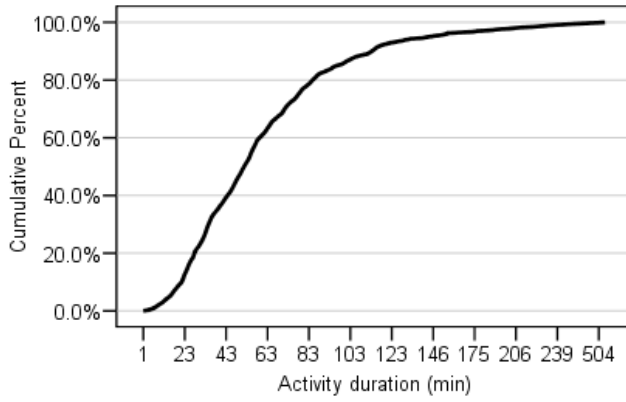
**Figure 4.5 Distribution of arrival hour (WFS)**



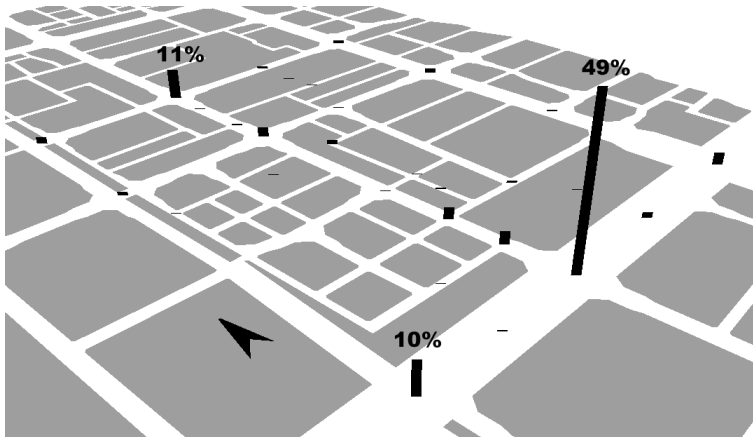
**Figure 4.6 Cumulative distribution of total duration (WFS)**



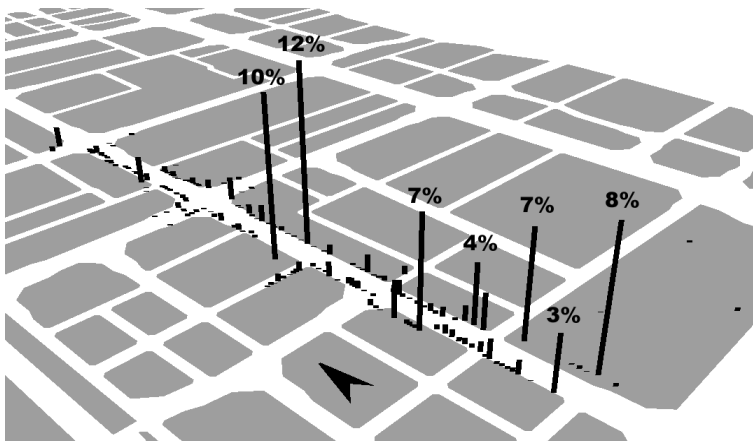
**Figure 4.7 Cumulative distribution of the number of store visits (WFS)**



**Figure 4.8** Cumulative distribution of activity duration (WFS)



**Figure 4.9** Distribution of entries (WFS)



**Figure 4.10** Distribution of activities (WFS)

Figure 4.9 shows that the main entrance where near to 50% of the pedestrians entered the survey area is at the southern end of WFS, where the only metro station in this area and several bus stops are located. 10% of the pedestrians entered from a point somewhere 400 m to the west of the major entrance, because several tourism sites including The Forbidden Palace are located in that direction. It is reasonable to infer that the pedestrians either entered from the west or east side of the main entrance and finally converged to this site because it is a good place to start the shopping trip. Taking this into account, nearly 60% of the pedestrians started at the southern end of WFS, while 11% of the pedestrians entered at the northern end of the street.

Figure 4.10 shows the distribution of activities in individual stores. Large retail facilities like department stores and shopping malls attracted more than 50% of the total number of activities. The first 1/3 section of the street starting from the southern end has most activities, because this is the part where the stores are most densely located and it is closest to the main entrance. The 1/3 section in the middle locates a department store and a shopping mall, both locally famous, which attracted most activities in this section. The last 1/3 section is non-pedestrianized. Substantially fewer activities were conducted here. Although a department store is also located at the northern end, it only attracted 2% of the total activities.

## **4.2 East Nanjing Road**

### **4.2.1 Survey design**

The same survey method as the one used to WFS case was applied in the ENR case, albeit with some modifications. One modification is that multiple activities in the same store were not recorded separately. Instead, the visit to a store was only recorded once and pedestrians were asked to estimate the amount of time they spent in that store. This additional question was based on the consideration that averaging the duration across all types of activities is not realistic since, for example, people usually spend more time in large stores than in small stores; spend more time on shopping than on rest. It was expected that, by doing so, the general differences in activity time use can be obtained, although it might not be accurate because people's estimation might be crude.

The second modification is that no prior conditions were set for inviting respondents. Administrators were instructed to invite respondents completely at random, regardless of respondents' current status. Furthermore, respondents' status was recorded as "Just started", "In-between", or "Almost finished" for analysis purposes. This decision aimed at reducing potential sample bias due to selection strategy. It was expected that, by doing so, the obtained sample and pedestrian behaviors would be closer to the population characteristics. However, one drawback is that the number of records with complete trip chains is reduced. Thus, it is more problematic to represent full behavioral complexity and heterogeneity in some analyses. Based on the reported sequences of store visits, it is not difficult to elicit pedestrians' routes since both streets are almost linear. However, this method cannot guarantee that pedestrians did not move to somewhere outside the space between origins and destinations. Thus, the third modification is recording "turning points"



where pedestrians changed their walking direction. This will provide more accurate data for direction choice modeling.

### 4.2.2 Background

ENR is named “The No. 1 shopping street in China” both for its historic position and its current symbolic meaning for Chinese retailing. In the early 20th century, when the area near ENR was leased to the British, several English retail department stores were established in ENR, followed by hundreds of retailers opening their businesses before the 1920s. Many of these old brand stores still exist today, adding much charm and an international ambiance, with many other modern stores. It is also a famous tourism site so that there is a saying “You don’t really have been in Shanghai if you haven’t been to Nanjing Road”. The latest estimate of the number of pedestrians reported by the Research Center of Shanghai Commercial Economy (2006) is an average of 680,000 per day on normal days. The number is 97% higher during important holidays such as May 1st and October 1st. Part of ENR was pedestrianized in 1999. The street is about 1,600 m long, and 1,000 m of this is pedestrianized (Figure 4.11). People’s Square, a multifunctional place for gathering, leisure, shopping, museums and a public transportation terminal, is located at the western end of the street. The eastern end locates The Bund, an internationally famous tourism site featuring buildings of the early 20th century. Many public transport stops are located near the Bund. There are two metro stations in the area, one near People’s Square, and the other at the eastern end of the pedestrianized section, Mid Henan Road. There are two very important

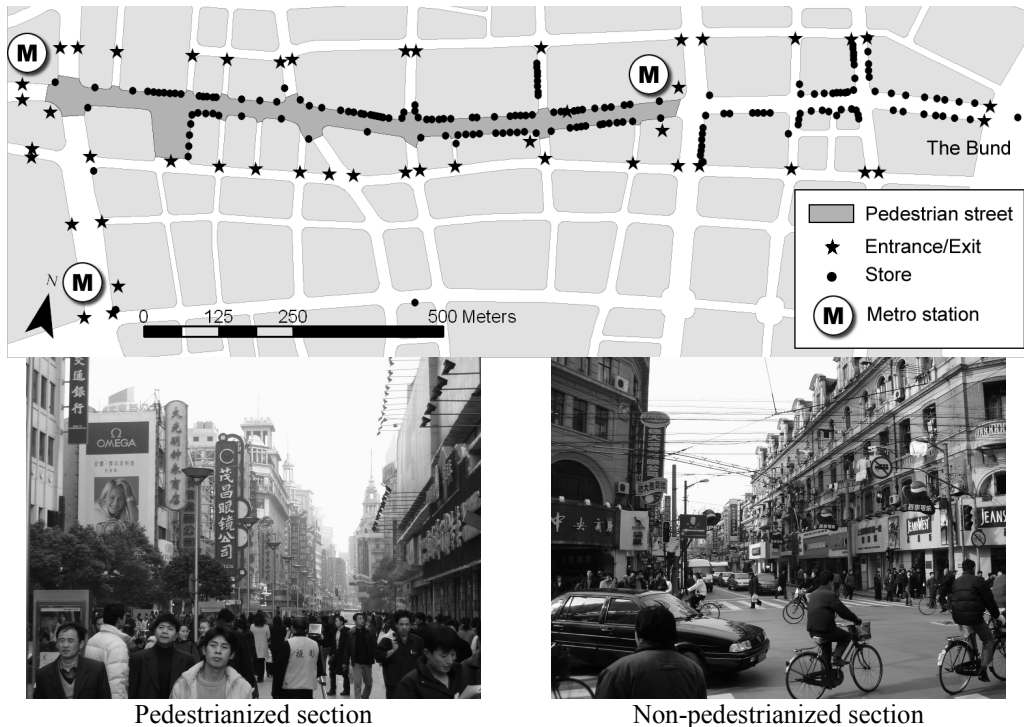


Figure 4.11 The survey area of ENR

metro lines running across these two stations, which carry a huge number of passengers everyday. Most of the shops are located along both sides of the street, shaping a linear shopping space. The west end locates 4 department stores, forming a strong retail magnate. There are also several department stores along the pedestrianized section but not in the non-pedestrianized section, leading to much a significant difference in total retail floorspace between the two sections: 330,000 m<sup>2</sup> versus 25,000 m<sup>2</sup>.

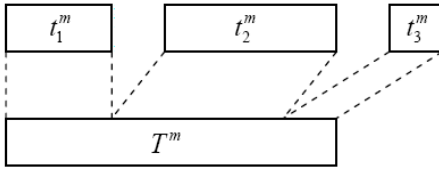
#### 4.2.3 Data collection

Twenty students from the Department of Urban Planning, Tongji University, administrated the survey during two days, May 19 (Saturday) and May 22 (Tuesday), 2007. Each day from 12:00 to 20:00, they randomly invited pedestrians to answer the questions and recorded the respondent's activity diary, up to the moment of the interview. The administration procedures were the same as those in WFS case. However, due to practical reasons, almost all administrators were arranged in the pedestrianized section because there are no resting facilities in the non-pedestrianized section, which makes it very difficult to intercept pedestrians when they are moving. As can be expected, most of the time interviewers asked pedestrians who were resting in the pedestrian section to participate because the questionnaire requires some effort to complete. Such arrangement may cause some biases in the distributions of pedestrian activities in the street, such as that it ignores the pedestrians who did not take any rest during the whole shopping trip. Therefore, the average number of rest activity for each pedestrian may be overestimated. The valid number of records is 811, 393 (48.5%) of which were collected on Saturday, while 418 (51.5%) were collected on Tuesday.

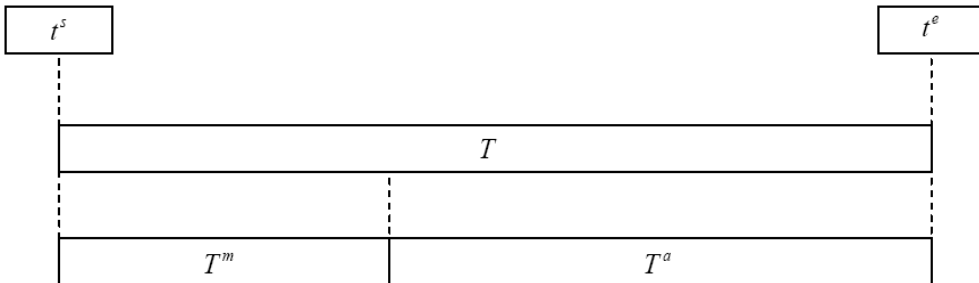
#### 4.2.4 Time estimation

The grid-based approach was also used in this case for estimating unknown time information during a pedestrian's shopping trip. The improvement is that the duration estimates could now be based on reported activity durations. First, distances between the origin and the destination of each movement pair were calculated using the shortest route algorithm. Then, walking durations,  $t_j^m$ , were estimated still using the assumed 1 m/s walking speed. Next, the total duration,  $T$ , was calculated as the difference between the end time,  $t^e$ , and the start time,  $t^s$ . The definition of the end time differs between pedestrians of different status. For pedestrians who reported that they had almost finished their shopping trip, the end time is their expected time to finish the trip. For pedestrians who reported that they just started or were in-between, their expected end time is much more unreliable. For them, the time when the interview started was treated as the latest time for calculating duration. The total activity duration,  $T^a$ , was derived by subtracting the sum of the walking durations,  $T^m = \sum_j t_j^m$ , from the total duration. This total activity duration may not be consistent with the sum of the reported in-store/rest durations,  $t_j^r$ . If the reported durations are assumed to be accurate and the average walking duration of a movement pair is 53

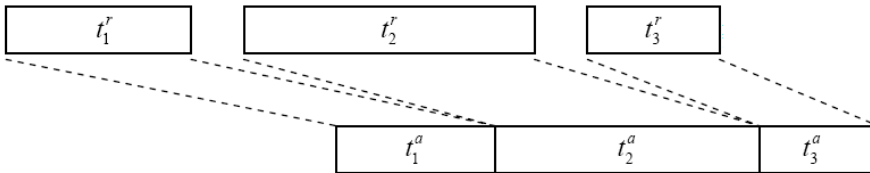
Step 1: Estimate the walking durations based on the shortest movement distances and the assumed walking speed 1 m/s.



Step 2: Calculate the total duration based on the end time and the start time. Calculate the total activity duration.



Step 3: Estimate the activity durations based on the ratios of the reported activity durations.



**Figure 4.12 Procedure for estimating time information (ENR)**

minutes, which is unrealistically long since finishing the whole street may take no more than 30 minutes. That means that respondents in general underestimated activity durations. However, the relative ratios between reported durations may be more reliable. Based on this reasoning, the estimated activity durations,  $t_j^a$ , are the reallocation of the total activity duration according to the ratios between reported durations. That is  $t_j^a = T^a t_j^r / \sum_j t_j^r$ . Figure 4.12 illustrates this procedure.

### 4.2.5 Basic sample characteristics

Table 4.2 shows some socio-demographics of the sample. There were 10% more male pedestrians than female pedestrians, almost the same as in the WFS case. The distribution of age is also very similar, with the young pedestrians being the dominant group, followed by the middle aged and the old pedestrians. 60% of the pedestrians were from within town while the rest were from the outside. The distribution of the

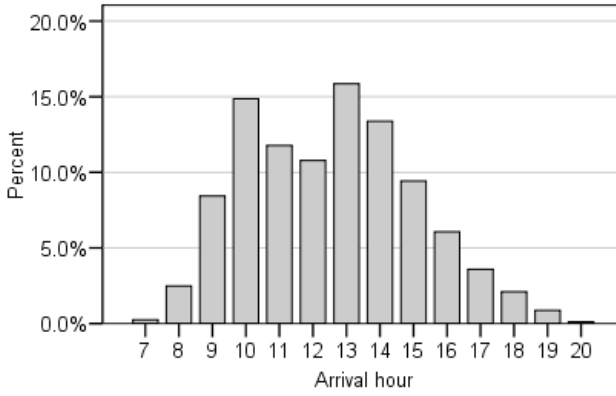
**Table 4.2 Basic characteristics of the sample (ENR)**

Gender	Male	Female			
	55	45			
Age	Young	Middle	Old		
	51	32	17		
Residence	In town	Out of town			
	60	40			
Purpose	Shopping	Tourism	Leisure	Others	
	29	34	22	15	
Transport	Metro	Bus	Car, Taxi	Walk	Others
	37	34	12	9	8
Group size	1 person	2 persons	≥ 3 persons		
	18	47	35		
Status	Just started	In-between	Almost finished		
	14	52	34		

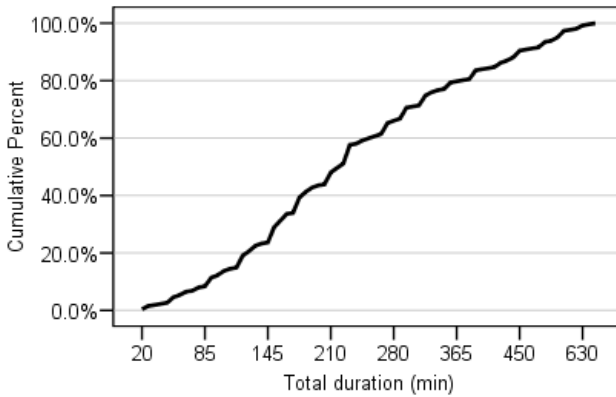
major purposes differs more from the WFS case. The percentages of shopping and tourism increased, especially tourism, reflecting the number of tourists in ENR. Accordingly, the percentages of leisure and other purposes dropped. Public transportation is the major transport mode that the pedestrians used. Probably because of the better accessibility of public transportation, the use of car and taxi is less. Nearly half of the respondents were with a companion, but this percentage is still much less than in the WFS case. In contrast, the percentage of larger groups is higher, because many respondents were member of some tourism group. As for the pedestrians' status when they were being interviewed, half of them had visited some stores and indicated they would continue the shopping trip; 34% of them reported that they were preparing to leave; the remaining 14% just started the trip.

The distribution of pedestrians' arrival hours (Figure 4.13) has two peaks. The first peak is between 10:00 – 11:00; the second peak, same as for the WFS case, is between 13:00 – 14:00. The mean arrival hour is 12:30, and the standard deviation is 2.5 hours. Figure 4.14 shows the distribution of total duration. Because the end time reported by the respondents who just started or were in-between the shopping trip might not be reliable, this distribution only uses the respondents who were near the end of the trip. The mean total duration is 4.2 hours, and the standard deviation is 2.4 hours. This same subsample is also used for generating the distributions of the number of store visits and rest behavior. In Figure 4.15, 80% of the pedestrians visited less than 5 stores. The mean is 2.9 stores, and the standard deviation is 1.9 stores. The distribution of number of stops to rest is: 0 stop = 44.5%; 1 stop = 51.3%; 2 stops = 3.8%; 3 stops = 0.4. 96% of the pedestrians rested no more than once. The mean is 0.6 stops, and the standard deviation is 0.6 stops. The distribution of the activity durations can be differentiated between four activity types, shop, eat, rest, and tour. From Figure 4.16, it seems that the pedestrians spent the least amount of time on rest, with a mean of 38.9 minutes and standard deviation of 44.2 minutes. The duration of shopping is more than resting with a mean of 47.6 minutes and standard deviation of 52.9 minutes. The duration of eating is even longer, with a mean of 58.2 minutes and standard deviation of 55.6 minutes. The duration of tourism activities, in this case visiting The

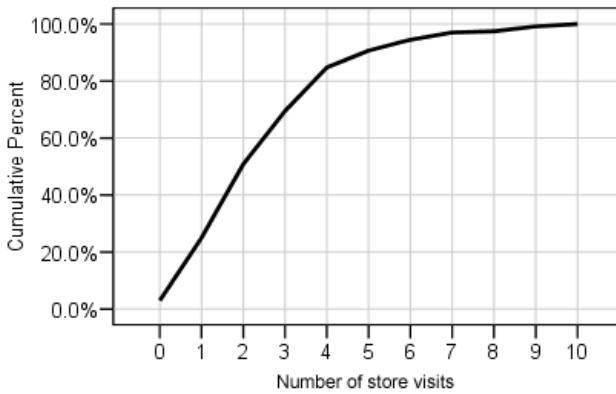
Bund, is the longest, with a mean of 109.9 minutes and standard deviation of 108.2 minutes.



**Figure 4.13 Distribution of arrival hour (ENR)**



**Figure 4.14 Cumulative distribution of total duration (ENR)**



**Figure 4.15 Cumulative distribution of the number of store visits (ENR)**

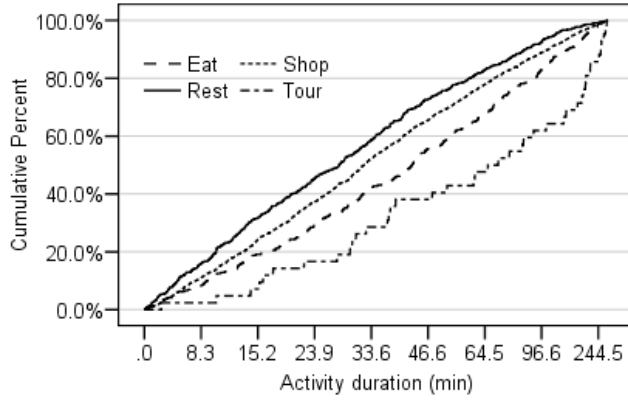


Figure 4.16 Cumulative distribution of activity duration (ENR)



Figure 4.17 Distribution pedestrians in entries (ENR)

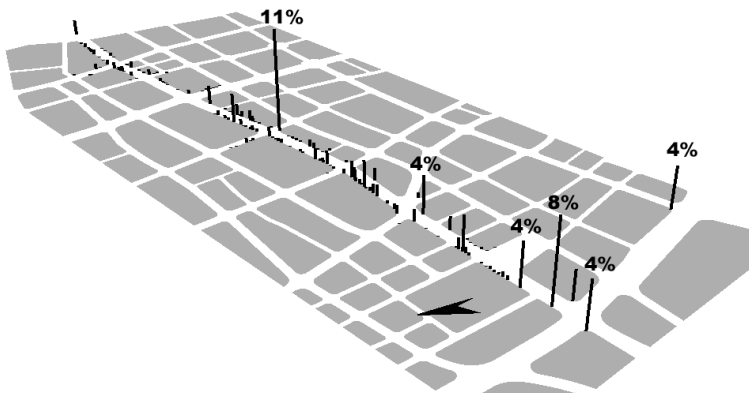


Figure 4.18 Distribution of activities in stores (ENR)

Figure 4.17 suggests that three entry clusters can be identified. The largest cluster is the western end of ENR, where 50% of the pedestrians entered. The location with the highest number of entries (18%) is a metro terminal with 4 lines. The second largest cluster is at the eastern end of the street, near The Bund. Around 20% of the pedestrians entered from here as there are many bus stops. The third cluster is at the eastern end of the pedestrianized street, where about 17% of the pedestrians entered because of a nearby metro station. The distribution of activities in individual stores is shown in Figure 4.18. Similar to the WFS case, large stores attracted significantly more pedestrians than small stores. At the western end, 20% of the activities concentrated in the four department stores. That is why this area is named “The Golden Triangle”. In the middle section, one department store received outstanding attention. In general, the activity intensity in the non-pedestrianized section is significantly lower than that in the pedestrianized section.

### **4.3 Summary**

Two pedestrian behavior datasets and their collection have been discussed in this chapter. These descriptive analyses are kept concise for the purpose of clarifying the necessary information for understanding the data. For more detailed information about the two places and pedestrian behavior, readers are referred to Wang, *et al.* (2003, 2004, 2006) and Zhu, *et al.* (2005, 2007). The major content of the data is a pedestrian shopping diary which will be used for model estimation, the results of which will be described in the next chapter. In both cases, questionnaire-based personal interviews were used so that the complexity of pedestrian behavior and their reaction to the environment can remain real. However, a negative effect of the data collection approaches is that sampling bias seems inevitable either from the focus on pedestrian’s specific status or from the uneven distribution of survey locations. Nevertheless, we argue that the validity of the methods can be inferred to some extent from generally consistent pedestrian behaviors in both cases, including the number of store visits, the number of rest stops, activity duration, and the relationship between the entry distribution and public transport. Moreover, two approaches for estimating the temporal information of pedestrians’ activities were developed.

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*Chapter*

## 5 MODEL ESTIMATION

In Chapter 3, four decisions (go-home, direction choice, rest and store patronage) were proposed as the major decisions that determine the general spatio-temporal behavior of pedestrians. The basic rationales underlying three different mode types (multinomial logit model, heuristic model, and the heterogeneous heuristic model) were also discussed as general-purpose decision models, but these models were not tailored to each proposed decision problem. We argued that models based on the principle of bounded rationality are theoretically more appropriate than conventional rational choice models for representing the decision processes of pedestrians, which can be assumed to be often characterized by simplifying decision heuristics. However, without justification, this argument will be nothing more than just an argument.

The purpose of this chapter therefore is to provide a partial justification (as it is indirect and incomplete) for the appropriateness of models based on the principle of bounded rationality and their advantage over rational choice models. This is the core and main purpose of this thesis. The proposed models are estimated using the real-world data of pedestrian behavior, discussed in Chapter 4. As the emphasis is on testing the appropriateness of alternative modeling approaches, comparing the empirical results of the various models will be the major concern. The first section will apply the heuristic models and the multinomial logit models to the WFS case for all four pedestrian decisions and compare their results. The second section will apply the HHM to the ENR case. MNL models will be applied to this data and results will be compared with those of HHM too. The third section will provide a summary for this chapter.

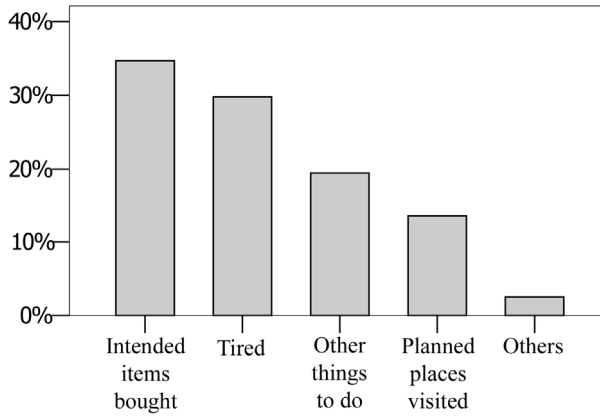
### 5.1 Heuristic Models and the WFS Case

#### 5.1.1 Go-home decision

Because data on when pedestrians decided to go home is not available, it was assumed that the go-home decision is considered consciously or unconsciously by pedestrians every time after they completed a visit to a store or took a rest. Thus, if there are, for example, 10 visits during a shopping trip, the pedestrian is assumed to have decided to continue shopping after each of the first 9 visits, and assumed to have decided to go home after finishing the 10th visit. That is, every visit was treated as a decision case and this led to a total of 2,741 cases.

To understand the factors influencing pedestrians' go-home decisions, respondents were asked for their major reasons for going home. Figure 5.1 shows the distribution of the answers. Except for the "others" option, which only represents a small part, the remaining four options all suggest that there are some limits that do not allow pedestrians to continue shopping. Figure 5.1 indicates that important reasons for going home are that they completed their shopping list and that they felt tired. Although it is possible to ask respondents for such information and build a model based on such data, such an information-eager model could be too specific to be useful





**Figure 5.1 Reasons for going home**

in a new environment when such detailed personal information is missing. In order to develop a more general model, time was therefore selected as a substitute factor. This choice is based on the reasoning that time is generally highly correlated with the specific reasons listed in Figure 5.1. The more time a pedestrian spends on shopping, the more likely he/she has bought the items on the shopping list, has visited the places he/she intended to visit, has become tired, or has felt the urge to conduct other planned activities.

Two kinds of real time were used in the models: relative time ( $t^R$ ) and absolute time ( $t^A$ ), both in minutes. Relative time refers to the time elapsed since the pedestrian started the shopping trip. It correlates with the progress of purchasing the planned items during the shopping trip, visiting schedules and how tired the pedestrian has become. Absolute time refers to the time difference between the current activity time and the 0:00 base. It correlates with available time budgets reflecting when pedestrians must turn to other business. Four models will be specified and estimated for comparison. The first is the conventional multinomial logit model (MNL). The remaining three heuristic models are specified based on the conjunctive, disjunctive and lexicographic model respectively.

### 5.1.1.1 Models

#### *MNL*

Under the discrete choice framework, the go-home decision can be seen as a choice between two options: keep shopping and going home. Their respective observable utilities are specified as,

$$\begin{aligned} v^S &= \beta^R t^R + \beta^A t^A \\ v^H &= \beta^H \end{aligned} \quad (5.1)$$

where  $v^S$  is the observable utility of shopping which is the sum of  $t^R$  and  $t^A$  weighted by their parameters,  $\beta^R$  and  $\beta^A$ , respectively. It is hypothesized that the

utility of shopping should decrease as time increases, implying these two parameters should be negative. The observable utility of going home,  $v^H$ , is represented by  $\beta^H$ , an alternative-specific constant whose sign is not hypothesized. The probability of going home then equals:

$$p^H = \frac{\exp(v^H)}{\exp(v^S) + \exp(v^H)} \quad (5.2)$$

This linear additive utility function is typical for MNL models. However, the pedestrian may not necessarily use both  $t^R$  and  $t^A$  for the decision. Another unrealistic characteristic is that a smaller value in one factor can be (at least partially) compensated by higher values of one or more other factors, so that, for example, even when the absolute time is very late (e.g., the stores are going to close at 22:00), the pedestrian could still decide to shop if he arrives at the shopping street at exactly this time as long as the utility of  $t^R$  is large enough compared to that of  $t^A$ .

### *Conjunctive model*

Applied to the go-home decision, the conjunctive model implies that both time limits have to be reached before the pedestrian end the shopping trip. Let  $\delta^R$  and  $\delta^A$  be the threshold values for  $t^R$  and  $t^A$  respectively. The decision mechanism is simply that if the pedestrian finds that both thresholds are exceeded, he/she will decide to go home and keep shopping if otherwise. Formally,

$$p^H = \begin{cases} 1 & \text{if } t^R \geq \delta^R \wedge t^A \geq \delta^A \\ 0 & \text{otherwise} \end{cases} \quad (5.3)$$

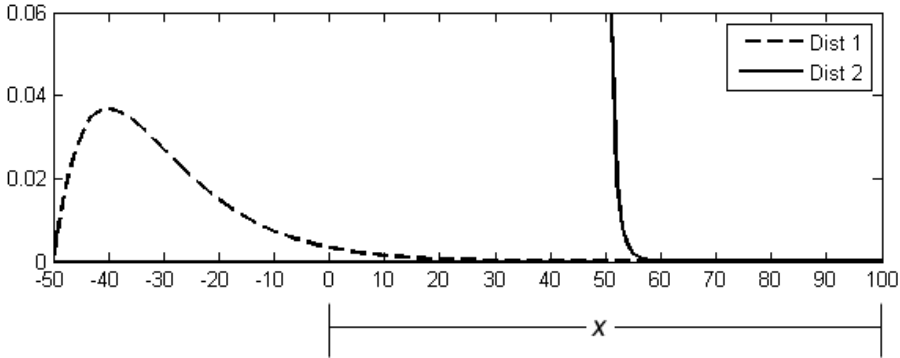
Considering threshold heterogeneity, that is, pedestrians have their own time thresholds. We assumed that the threshold values of  $t^R$  and  $t^A$  follow the distributions,  $\delta^R \sim \alpha^R + \Gamma(\beta^R, \theta^R)$  and  $\delta^A \sim \alpha^A + \Gamma(\beta^A, \theta^A)$ . Here  $\Gamma$  represents the standard gamma distribution,  $\alpha$  is a constant,  $\beta$  is the shape parameter and  $\theta$  is the scale parameter. Note that by introducing  $\alpha$ , the thresholds may also be negative under this gamma-based distribution. The reason for assuming this distribution is that it is relatively flexible. Then, transforming Equation 5.3 into the probabilistic case yields:

$$p^H = \prod_X p_1^X \quad X = R, A \quad (5.4)$$

$$p_1^X = G^X(t^X - \alpha^X, \beta^X, \theta^X)$$

The probability of going home is the joint product of the probabilities that both factors exceed their corresponding thresholds. These probabilities are just simply the cumulative probabilities of factor values under their respective cumulative density functions,  $G$ .

To sum up, there are six parameters related to threshold distributions to be estimated in this model. Different from the conventional utility models, the influence of the parameters depends on the model specification and a parameter value of 0 does



**Figure 5.2 Two examples of parameter ineffectiveness of the threshold distribution in the conjunctive go-home model**

not necessarily means that the corresponding parameter has no effect. For this conjunctive model, it can be seen from the first line in Equation 5.4 that a factor will have a null effect (or is ineffective) if its probability of being satisfactory is 1. It indicates that if the factor is always satisfactory under all circumstances, it is virtually useless for the decision and can be simply ignored. Therefore, if the estimated threshold distribution is such that most of the relevant values in the data are larger than the threshold, all parameters for this distribution have little effect and can be ignored (e.g., Dist 1 in Figure 5.2). Even if this is not the case,  $\alpha^x$  will also be ineffective if it is equal 0, suggesting a standard gamma distribution;  $\beta^x$  will be ineffective if it is very close to 0, meaning that the distribution is highly concentrated around  $\alpha^x$  and the threshold can be treated as “hard” - a single value (e.g., Dist 2 in Figure 5.2);  $\theta^x$  will be ineffective if it equals 1, meaning that no scaling on the variable is needed. Empirically, we statistically test whether the parameter estimates are close enough to these null-effect values.

#### *Disjunctive model*

If the decision rule is disjunctive, the pedestrians decides to go home on the finding that either  $t^R$  or  $t^A$  exceeds the threshold value. Formally,

$$p^H = \begin{cases} 1 & \text{if } t^R \geq \delta^R \vee t^A \geq \delta^A \\ 0 & \text{otherwise} \end{cases} \quad (5.5)$$

In a probabilistic format, given the same specification of threshold distributions as in the conjunctive model,

$$p^H = p_1^R + p_1^A - p_1^R p_1^A \quad (5.6)$$

The specific impact of parameter values is slightly different from the conjunctive model. Here, a factor will be ineffective if its probability of being satisfactory is very close to 0 for all cases in the data, implying that another factor must be searched anyway. Hence, a factor has null effect if the threshold distribution

is estimated to have a large enough  $\alpha^X$ , larger than almost all the variable values. The way of judging the effect of  $\beta^X$  and  $\theta^X$  is the same as in the conjunctive model, if  $\alpha^X$  is smaller than some values of the corresponding variable.

### Lexicographic model

Since the go-home decision implies judging satisfaction, the satisficing specification of the lexicographic model should apply if the pedestrians use the lexicographic rule for their decision. Assume that a pedestrian applies two thresholds for each factor,  $\{\delta_1^R, \delta_2^R; \delta_1^R < \delta_2^R\}$  for  $t^R$ , and  $\{\delta_1^A, \delta_2^A; \delta_1^A < \delta_2^A\}$  for  $t^A$ . Thus, a pedestrian feels satisfied with a factor, say  $t^R$ , when  $t^R \geq \delta_2^R$ , feels unsatisfied when  $t^R < \delta_1^R$ , and feels neutral when  $\delta_1^R \leq t^R < \delta_2^R$ . The decision process is, supposing  $t^R$  is searched first, that when the pedestrian finds  $t^R$  satisfactory, he/she will decide to go home; when  $t^R$  is found to be unsatisfactory, the decision is to keep shopping; when  $t^R$  is neutral, the pedestrian will continue to search  $t^A$ . In the last situation, if  $t^A$  is satisfactory, the decision will be to go home; to keep shopping if  $t^A$  is unsatisfactory; and to make a random decision when  $t^A$  is neutral. This process can be represented formally as follows:

$$p^H = \begin{cases} 1 & \text{if } t^R \geq \delta_2^R \vee (\delta_1^R \leq t^R < \delta_2^R \wedge (t^A \geq \delta_2^A \vee E^H(\delta_1^A \leq t^A < \delta_2^A))) \\ 0 & \text{otherwise} \end{cases} \quad (5.7)$$

where  $E^H(\zeta)$  represents the random decision process under condition  $\zeta$  and the result is going-home. Also assuming that all threshold values conform to gamma-based distributions, that is  $\delta_j^X = \alpha_j^X + \Gamma_j^X(\beta_j^X, \theta_j^X)$  ( $j=1,2; X=R,A$ ), the probability of going-home is,

$$\begin{aligned} p^H &= p_1^R + (1 - p_1^R - p_0^R)(p_1^A + (1 - p_1^A - p_0^A)0.5) \\ p_1^X &= G_1^X(t^X - \alpha_1^X, \beta_1^X, \theta_1^X)G_2^X(t^X - \alpha_2^X, \beta_2^X, \theta_2^X) \\ p_0^X &= (1 - G_1^X(t^X - \alpha_1^X, \beta_1^X, \theta_1^X))(1 - G_2^X(t^X - \alpha_2^X, \beta_2^X, \theta_2^X)) \end{aligned} \quad (5.8)$$

Note that the probability of a factor being satisfactory is the joint probability that both thresholds are exceeded, and the probability of being unsatisfactory is the joint probability that neither threshold is exceeded. The remainder is the probability of being neutral.

Different from the conjunctive and the disjunctive model, the formulation of the lexicographic model changes when the sequence of information search changes. This allows identifying which sequence might be more appropriate for the decision based on model estimation. In total, 12 parameters related to threshold distributions are to be estimated. Judging the effects of parameters becomes more complicated. Looking at the first line in Equation 5.8,  $p_1^X$  and  $p_0^X$  being 0 will have nil impact on the probability of going home. Especially when both these probabilities are 0, it means

**Table 5.1 Critical parameters for having no effect (go-home)**

Conjunctive	Disjunctive	Lexicographic
$\alpha^X \rightarrow -\infty$	$\alpha^X \rightarrow \infty$	$\alpha_1^X, \alpha_2^X \rightarrow -\infty, \infty$
Common: $\beta^X \rightarrow 0, \theta^X = 1$		

the probability of the factor being neutral is 1. In that case, the factor is virtually useless for reaching a decision and the other factor must be searched. For  $p_1^X$  to be equal to 0, at least one term on the right hand side of the second line in Equation 5.8 should be equal to 0, which means that either the lower or the higher threshold should be very large. In contrast, if either the lower or higher threshold is very small  $p_0^X$  will be equal to zero. Consequently, for this to happen  $\alpha_1^X$  and  $\alpha_2^X$  are either very small so that all variable values exceed the thresholds implied by the threshold distribution, or they are so large that no variable value exceeds any threshold value. Table 5.1 summarizes the critical values of the parameters in all the heuristic go-home models for judging whether they have any effect in the decision making process.

### 5.1.1.2 Estimation issues

Given the specifications of choice probabilities, all the parameters of the four models can be estimated using maximum likelihood estimation. The assumption applied to the models is that all probability distributions are independently and identically distributed across cases, so that the objective function is:

$$LL = \sum_{n=1}^{N^C} y_n^H \ln(p_n^H) + y_n^S \ln(p_n^S) \quad (5.9)$$

where LL is the log-likelihood,  $y_n^Y$  ( $Y = S, H$ ) is the observed decision outcome (shopping or going-home) of case  $n$ ,  $p_n^Y$  is their respective probabilities, and  $N^C$  is the number of cases. This assumption may be criticized in that pedestrians are involved in a similar decision multiple times and hence the observations may not be independent. However, the assumption of independence is commonly made in models of complex behavior. It serves as a benchmark and we leave more complex covariance structures for future tests.

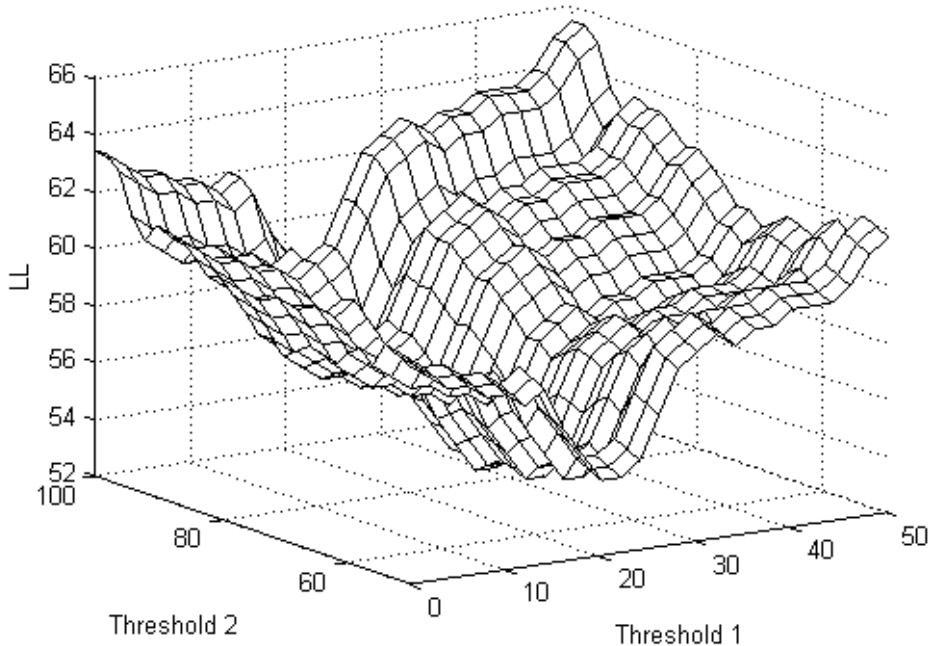
Different estimation algorithms were used to estimate the models. Algorithms for calibrating MNL models have been quite mature. In this case, SAS software was used to estimate the MNL models. However, there are no existing algorithms for calibrating the proposed heuristic models. Moreover, the LL functions of some models, such as the lexicographic models and HHM, are multi-modal and non-smooth (e.g., see Figure 5.3). Consequently, conventional gradient-based algorithms may be trapped in local optimums easily. Therefore, a hybrid algorithm was developed, which is composed of a genetic algorithm for global search, the Taxi-Cab algorithm providing tunneling-like functionality when the genetic algorithm gets stuck, and a gradient-based algorithm for optimizing the final estimation locally. MATLAB was used as the platform for coordinating these algorithms. Global optima are not guaranteed using

these algorithms, although different starting points were tried and much computation time was invested.

To select the optimal model in the sense of being closest to the true model, model selection methods were applied. Various model selection methods and selection criteria have been proposed in the literature (e.g., Bozdogan, 2000; Browne, 2000; Busemeyer and Wang, 2000; Cutting, 2000; Forster, 2000; Myung, 2000; Zucchini, 2000). Among the criteria suggested, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Consistent AIC (CAIC) are the most frequently applied mainly because they are easy to calculate. They are defined as the trade-off between model goodness-of-fit and model complexity:

$$\begin{aligned} AIC &= -2LL + 2N^P \\ BIC &= -2LL + N^P \ln(N^C) \\ CAIC &= -2LL + N^P (\ln(N^C) + 1) \end{aligned} \quad (5.10)$$

where  $N^P$  is the number of free parameters in the model. All three criteria use log-likelihood as a goodness-of-fit measure. Only the complexity components are different. AIC only uses the number of parameters; BIC adds the number of cases into complexity, implying that a larger sample size will result in a larger BIC; CAIC just adds one more  $N^P$  compared to BIC. Under each criterion, the model with the smallest index is chosen as the best model. Using different criteria for model selection may lead to different optimal models.



**Figure 5.3** Illustration of an objective function with two threshold variables

Dayton and Lin (1997) compared the accuracy of the three criteria through experiments and found pros and cons of each. They did find evidence however of a general tendency to prefer BIC and CAIC over AIC. In this thesis, we therefore decided to use CAIC to select models because it is more complete as it takes into account data complexity (sample size) and is the strictest which in turn, leads to the selection of the most parsimonious model specification that may have good robustness.

**Table 5.2 Estimation results of the go-home models (WFS)**

MNL normal variables		MNL logged variables		Conjunctive	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\beta^R$	-0.007 *	$\beta^R$	-1.471 *	$\alpha^R$	0
$\beta^A$	-0.008 *	$\beta^A$	-8.510 *	$\beta^R$	2.575 *
$\beta^H$	-10.501 *	$\beta^H$	-67.117 *	$\theta^R$	57.648 *
				$\alpha^A$	671.078 *
				$\beta^A$	4.335 *
				$\theta^A$	75.640 *
$N^C$	2,741	$N^C$	2,741	$N^C$	2,741
$N^P$ +	3	$N^P$	3	$N^P$	5
$LL$	-1,121	$LL$	-1,085	$LL$	-1,075
$CAIC$	2,269	$CAIC$	2,197	$CAIC$	2,195
Disjunctive		Lexicographic $t^R \rightarrow t^A$		Lexicographic $t^A \rightarrow t^R$	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\alpha^R$	98.919 *	$\alpha_1^R$	0	$\alpha_1^R$	0
$\beta^R$	1.365 *	$\alpha_2^R$	$\infty$	$\alpha_2^R$	0
$\theta^R$	309.229 *	$\beta_1^R$	2.656 *	$\beta_1^R$	1.025 *
$\alpha^A$	768.613 *	$\beta_2^R$	-	$\beta_2^R$	4.605 *
$\beta^A$	2.621 *	$\theta_1^R$	55.523 *	$\theta_1^R$	400.251 *
$\theta^A$	178.723 *	$\theta_2^R$	-	$\theta_2^R$	28.228 *
		$\alpha_1^A$	0	$\alpha_1^A$	0
		$\alpha_2^A$	0	$\alpha_2^A$	$\infty$
		$\beta_1^A$	5.340 *	$\beta_1^A$	92.724 *
		$\beta_2^A$	32.922 *	$\beta_2^A$	-
		$\theta_1^A$	170.454 *	$\theta_1^A$	10.152 *
		$\theta_2^A$	33.664 *	$\theta_2^A$	-
$N^C$	2,741	$N^C$	2,741	$N^C$	2,741
$N^P$	6	$N^P$	6	$N^P$	6
$LL$	-1,141	$LL$	-1,072	$LL$	-1,073
$CAIC$	2,336	$CAIC$	2,198	$CAIC$	2,200

\* Parameters are effective / significant

+ Only effective parameters are counted

### 5.1.1.3 Results

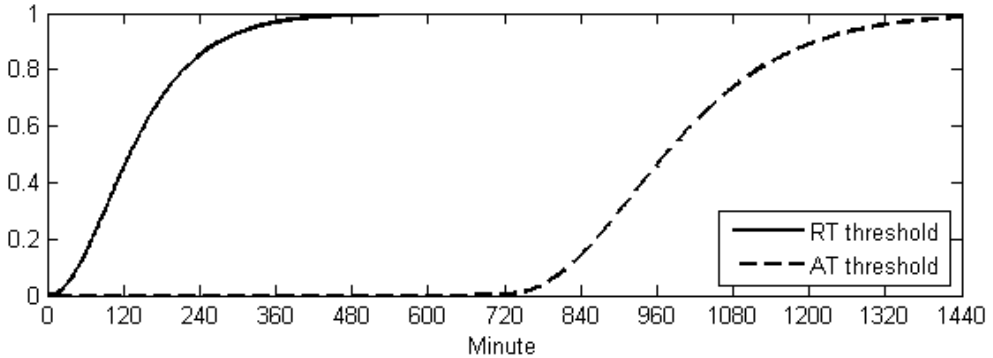
Table 5.2 shows the estimation results of all proposed models. Note that not all parameter estimates are shown because those that have a negative influence on CAIC have been excluded and may be considered to have insignificant effects. One more version of the MNL model was added, which uses the natural logs of the time variables to represent their marginally decreasing effects on utility. The MNL model with normal variables performed quite well with LL = -1,121, which corresponds to a 0.41 McFadden's Likelihood Ratio (MLR). Parameters for the time variables are all significant and negative as hypothesized, suggesting that the utility of shopping decreases with time and correspondingly the impetus for going home increases. When the variables are logged, the MNL model fitted the data much better, suggesting that this nonlinear utility specification is more appropriate.

The conjunctive model has a better LL, with an insignificant constant parameter for  $t^R$ . In contrast, the LL of the disjunctive model is the worst of all models. The two lexicographic models have the highest LLs, with the one under the factor search sequence from  $t^R$  being slightly better. However, in both models, there are more insignificant parameters, which suggests that the model specifications are saturate relative to the data and some factor thresholds are redundant. In the model of searching  $t^R$  first,  $\alpha_2^R$  is positive infinite, suggesting that the higher threshold is so large that there is actually no satisfactory judgment against this standard. In this sense, the model does not have a pure lexicographic form, but rather regresses closer to the conjunctive form. When the search sequence is reversed,  $\alpha_2^A$  appears to be positive infinite, suggesting a similar decision pattern.

Table 5.2 demonstrates that the conjunctive model has the smallest CAIC. Thus, it should be considered as the optimal model to represent pedestrian go-home decision process. This result suggests that the go-home decision process is quite simple. All the factors are not necessarily considered and the decision process may stop before complete information search. Thus, the conjunctive rule is fast, effort-saving, but also fugal in this case. It also reflects the fact that pedestrians set strict standards for the go-home decision so that they may have enough opportunity to fulfill their purposes or spend their time.

Figure 5.4 shows the two cumulative densities of the estimated time threshold distributions according to the conjunctive model. For  $t^R$ , there is approximately a 15% probability that the threshold is less than 1 hour, 30% for between 1 - 2 hours, 40% for between 2 - 4 hours and 15% for over 4 hours. The mean is 148 minutes, or about 2.5 hours. For  $t^A$ , the probability that the thresholds are located before 14:00 is 14%, 32% between 14:00 - 16:00, 28% between 16:00 - 18:00, and 26% later than 18:00. The mean is 999 minutes, which is near to 16:30 hour. These estimates are behaviorally reasonable. Note that the CAIC of the MNL model with logged variables is very close to that of the conjunctive model, which means the model is at least statistically competitive for predicting decision outcomes. However, behaviorally, it is less realistic since both factors are implied to be considered and calculating utilities every time the situation changes is mentally more costly than threshold-based true/false judgments. The lexicographic models seem less appropriate because they





**Figure 5.4 CDFs of the time thresholds in the conjunctive go-home model**

gain in goodness-of-fit at larger number of parameters. The disjunctive model, although also simple in mechanism, represents the least probable decision strategy being used by pedestrians for their go-home decisions.

### 5.1.2 Direction choice decision

If the pedestrian decides to continue shopping, the next decision assumed in the framework is to select a walking direction. It is assumed, similar as in the go-home decision, that the pedestrian makes direction choice decisions each time after visiting a store or resting at some place. Pedestrian may also simply change direction, but as this was not observed in the WFS data, the model could only be based on this subset of observations. Although respondents did not explicitly report their chosen directions, it is not difficult to infer the choice outcome from the destination of their next movement relative to their current location. The situation in WFS is relatively simple because the street is almost linear, and only two directions, north and south, relative to the current location of the pedestrian need to be identified as choice alternatives. The current location is the store or place where the pedestrian just conducted some activities.

For each direction, three factors were considered relevant for the pedestrian's decision. The first factor is whether the direction is the same as the one that the pedestrian just came from, represented by a dummy variable  $d^Y$  ( $Y = N$  (North),  $S$  (South)). Because there is a natural tendency that pedestrians follow the previous direction and try to minimize the number of back-turns, a positive influence is expected from this factor. The second factor is the total retail floorspace in the direction,  $q^Y$ . Although a pedestrian does not actually know the total amount of floorspace, the variable substitutes the pedestrian's estimate about the attractiveness of retail activities based on his/her perception of the environment. The third factor,  $l^Y$ , is the length of the part of the street that is pedestrianized in the direction, representing the amenity of walking. Because there is a considerable number of observations in the data showing that pedestrians turned back at the end of the pedestrianized section and did not go further into the non-pedestrianized sections, it is reasonable to hypothesize that the longer the pedestrianized part the more attractive the direction.

### 5.1.2.1 Models

#### MNL

Assume that the pedestrian chooses the direction that has the highest utility. Under the MNL framework, the probability of choosing a particular direction then equals:

$$p^Y = \frac{\exp(v^Y)}{\sum_{Y'} \exp(v^{Y'})} \quad Y, Y' = N, S \quad (5.11)$$

$$v^Y = \beta^d d^Y + \beta^q q^Y + \beta^l l^Y$$

where  $p^Y$  is the choice probability,  $v^Y$  is the observable utility and the  $\beta$  s are parameters for the respective variables.

#### Conjunctive model

If satisficing is the rule underlying direction choice decision rather than utility maximization, the decision process is assumed to consist of two stages. The first stage is the screening stage in which the pedestrian judges whether a direction is satisfactory. If the rule for judging satisfaction is conjunctive, this process can be represented as,

$$p_1^Y = \prod_x p_1^{Yx} \quad x = d, q, l$$

$$p_1^{Yd} = \alpha^d (1 - d^Y) + \beta^d d^Y \quad (5.12)$$

$$p_1^{Yq} = G^q(q^Y - \alpha^q, \beta^q, \theta^q)$$

$$p_1^{Yl} = G^l(l^Y - \alpha^l, \beta^l, \theta^l)$$

where  $p_1^Y$  is the probability that the direction is satisfactory,  $p_1^{Yx}$  is the probability that an individual factor is satisfactory. That implies all the factors have to be satisfactory in order to have a satisfactory direction at large. For the factor of previous direction,  $d$ , there are only two possible values. Being 1 means the direction is the same as the previous direction, and being 0 means it is not the same. Because the pedestrian may be satisfied with either situation,  $\beta^d$  is the parameter representing the probability of being satisfied when the direction is the same as the previous direction, and  $\alpha^d$  represents the probability of being satisfied if the direction is opposite to the previous direction. Gamma-based distributions, as in the go-home decision, were assumed to be the distributions for factor thresholds,  $\delta^q$  and  $\delta^l$ , of  $q^Y$  (floorspace) and  $l^Y$  (length of pedestrianized street) whose probabilities of being satisfactory are the cumulative densities of their values under the threshold distributions.

If only one direction survives the screening, then the decision process stops with this direction chosen. If both directions are satisfactory or unsatisfactory, then the decision enters the second stage. To simplify the specification, assume that a random choice is applied in the second stage. Aggregating the two stages, the overall probability that a direction is chosen,  $p^Y$ , is

$$\begin{aligned}
 p^Y &= p_1^Y p_0^{\bar{Y}} + (p_1^Y p_1^{\bar{Y}} + p_0^Y p_0^{\bar{Y}})0.5 \\
 p_0^Y &= 1 - p_1^Y
 \end{aligned}
 \tag{5.13}$$

If  $\alpha^d$  and  $\beta^d$  are equal to 1, the corresponding variables will have no effect on the probability of the direction being satisfactory. The other parameters of the threshold distributions have the same effect as those discussed for the go-home conjunctive model.

#### *Disjunctive model*

If it is assumed that the satisficing stage follows a disjunctive rule, the first expression in Equation 5.12 needs to be replaced by

$$p_1^Y = \sum_x p_1^{Yx} - p_1^{Yd} p_1^{Yq} - p_1^{Yd} p_1^{Yl} - p_1^{Yq} p_1^{Yl} + \prod_x p_1^{Yx}
 \tag{5.14}$$

which is a function of “or” relationship between the three factors. If  $\alpha^d$  and  $\beta^d$  are 0,  $p_1^Y$  is not affected.

#### *Lexicographic model*

In the MNL, conjunctive, and disjunctive model, the way of evaluation is said to be alternative-based because either utility or satisfaction related to an alternative has to be evaluated before looking into another alternative. In contrast, the lexicographic rule is said to be attribute-based because attributes of alternatives are compared sequentially and the utility or satisfaction of an alternative is not necessarily evaluated. The comparison depends on the number of levels of factors and implies that at least two levels for each factor are needed in order to differentiate the alternatives. Assume that each factor has two levels: a higher level and a lower level. Once the pedestrian finds one direction better than the other direction, this direction will be chosen. The probabilities of factor comparison are equal to:

$$\begin{aligned}
 p_B^{Yx} &= p_1^{Yx} p_0^{\bar{Yx}} \\
 p_W^{Yx} &= p_0^{Yx} p_1^{\bar{Yx}} \\
 p_T^{Yx} &= 1 - p_B^{Yx} - p_W^{Yx}
 \end{aligned}
 \tag{5.15}$$

Here,  $p_1^{Yx}$  represents the probability that factor  $x$  of direction  $Y$  is at the higher level, and  $p_0^{Yx}$  refers to the probability of being at the lower level;  $p_B^{Yx}$  is the probability that the factor of this direction is better than that of the other direction, while  $p_W^{Yx}$  means it is worse. Parameter  $p_T^{Yx}$  represents the probability of a tie, i.e., the two directions cannot be discriminated based on this factor. In the last situation, another factor is used to compare the two directions. If they still cannot be discriminated after the last factor is compared, a random choice is assumed. The probability of a direction being chosen given this assumed decision process, assuming the sequence of factor comparison is  $d \rightarrow q \rightarrow l$ , can thus be expressed as:

**Table 5.3 Critical parameters for having no effect (direction choice)**

Conjunctive	Disjunctive	Lexicographic
$\alpha^d, \beta^d = 1$	$\alpha^d, \beta^d = 0$	$\alpha^d, \beta^d = 0, 1$
$\alpha^x \rightarrow -\infty \quad x = q, l$	$\alpha^x \rightarrow \infty$	$\alpha^x \rightarrow -\infty, \infty$
Common: $\beta^x \rightarrow 0, \theta^x = 1$		

$$\begin{aligned}
 p^y &= p_B^{yd} + p_T^{yd} p' \\
 p' &= p_B^{yq} + p_T^{yq} p'' \\
 p'' &= p_B^{yl} + p_T^{yl} 0.5
 \end{aligned}
 \tag{5.16}$$

There are 6 (3!) possible factor comparison sequences implied by this lexicographic model. From Equation 5.16, it can be seen that if  $p_B^{yx}$  and  $p_T^{yx}$  are 0, they will not affect the probability of the alternative being chosen. That means the alternative is not better or worse than the other. If these two conditions are met simultaneously, the two alternatives will be indiscriminant based on this factor, which is equivalent to disregarding the factor. Such indiscrimination will appear when  $\alpha^d$  or  $\beta^d$  is 0 or 1,  $\alpha^q$  or  $\alpha^l$  approaches  $-\infty$  or  $\infty$ . Table 5.3 summaries the critical values for judging whether a factor has an effect for the direction choice models.

**5.1.2.2 Results**

Table 5.4 shows the estimation results of the 10 models. The goodness-of-fit of the MNL model with normal variables is good with a MLR of 0.32. The parameters for previous direction and length of the pedestrianized street are significant and their signs are consistent with the formulated hypotheses. The parameter for floorspace is insignificant, probably because of its high correlation with length of the pedestrianized street as most retail activities concentrate in the pedestrianized section. Introducing nonlinearity into the MNL model leads to a slightly worse LL, although all three parameters are significant.

All the heuristic models are statistically better than the MNL models. In case of the conjunctive model, the two parameters for previous direction have a reasonable relationship, with  $\beta^d > \alpha^d$ , which means that a higher satisfaction is more probable when the direction is the same as the previous walking direction. This relationship also holds for the other heuristic models. As for floorspace, the gamma distribution part turned out to have no effect and only the constant is significant. This means that  $\delta^q$  was estimated as a single value and the result of the judgments is binary (0/1). The constant part of the distribution of  $\delta^l$  is negative, which means that the threshold can be negative and the direction without the pedestrianized street could also be satisfactory. The disjunctive model is the worst heuristic model and is very close to the MNL model with normal variables as it excludes the influence of floorspace by setting its threshold to  $\infty$ . This means that considering floorspace in the early stage of

the decision process does not lead to an outcome so that other factors need to be searched.

In general, the lexicographic models perform better than the other models, suggesting that attribute-based comparison of choice alternatives is more appropriate for the direction choice decision. The influence of factor search sequence is notable. The sequences starting from  $d$  have an inferior CAIC compared to other sequences. Although judging and following the previous direction is much easier, the condition of shopping environments seems to be more important. This is understandable since most pedestrians visit the street for fulfilling their needs. In particular, floorspace appears to be more important than pedestrianized street, which is reflected in that the optimal search sequence is  $q \rightarrow d \rightarrow l$  and its counter sequence  $l \rightarrow d \rightarrow q$  is much worse. It looks like a wise decision strategy, well balanced between accuracy and speed.

**Table 5.4 Estimation results of the direction choice models (WFS)**

MNL normal variables		MNL logged variables		Conjunctive	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\beta^d$	1.058 *	$\beta^d$	1.089 *	$\alpha^d$	0.508 *
$\beta^q$	0	$\beta^q$	0.214 *	$\beta^d$	1.000
$\beta^l$	0.003 *	$\beta^l$	0.195 *	$\alpha^q$	46,516.155 *
				$\beta^q$	-
				$\theta^q$	-
				$\alpha^l$	-952.698 *
				$\beta^l$	110.709 *
				$\theta^l$	9.044 *
$N^C$	2,098	$N^C$	2,098	$N^C$	2,098
$N^P$	2	$N^P$	3	$N^P$	5
$LL$	-989	$LL$	-991	$LL$	-966
$CAIC$	1,996	$CAIC$	2,008	$CAIC$	1,975
Disjunctive		Lexicographic $d \rightarrow q \rightarrow l$		Lexicographic $d \rightarrow l \rightarrow q$	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\alpha^d$	0	$\alpha^d$	0.638 *	$\alpha^d$	0.638 *
$\beta^d$	0.518 *	$\beta^d$	1.000	$\beta^d$	1.000
$\alpha^q$	$\infty$	$\alpha^q$	46,727.287 *	$\alpha^q$	46,889.179 *
$\beta^q$	-	$\beta^q$	-	$\beta^q$	-
$\theta^q$	-	$\theta^q$	-	$\theta^q$	-
$\alpha^l$	0	$\alpha^l$	333.952 *	$\alpha^l$	320.443 *
$\beta^l$	23.868 *	$\beta^l$	0.278 *	$\beta^l$	0.382 *
$\theta^l$	19.813 *	$\theta^l$	587.799 *	$\theta^l$	400.694 *
$N^C$	2,098	$N^C$	2,098	$N^C$	2,098
$N^P$	3	$N^P$	5	$N^P$	5
$LL$	-987	$LL$	-963	$LL$	-962
$CAIC$	2,000	$CAIC$	1,968	$CAIC$	1,968

**Table 5.4 Estimation results of the direction choice models (WFS) (continued)**

Lexicographic $q \rightarrow d \rightarrow l$		Lexicographic $q \rightarrow l \rightarrow d$		Lexicographic $l \rightarrow d \rightarrow q$	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\alpha^d$	0.381 *	$\alpha^d$	0	$\alpha^d$	0
$\beta^d$	0.767 *	$\beta^d$	0.732 *	$\beta^d$	0.698 *
$\alpha^q$	17,999.620 *	$\alpha^q$	17,998.930 *	$\alpha^q$	17,953.650 *
$\beta^q$	-	$\beta^q$	-	$\beta^q$	-
$\theta^q$	-	$\theta^q$	-	$\theta^q$	-
$\alpha^l$	348.636 *	$\alpha^l$	0	$\alpha^l$	0
$\beta^l$	-	$\beta^l$	0.863 *	$\beta^l$	0.958 *
$\theta^l$	-	$\theta^l$	961.738 *	$\theta^l$	787.450 *
$N^C$	2,098	$N^C$	2,098	$N^C$	2,098
$N^P$	4	$N^P$	4	$N^P$	4
$LL$	-946	$LL$	-953	$LL$	-970
$CAIC$	1,926	$CAIC$	1,941	$CAIC$	1,974
Lexicographic $l \rightarrow q \rightarrow d$					
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\alpha^d$	0	$\alpha^q$	17,997.180 *	$\alpha^l$	0
$\beta^d$	0.732 *	$\beta^q$	-	$\beta^l$	0.863 *
		$\theta^q$	-	$\theta^l$	961.737 *
$N^C$	2,098				
$N^P$	4				
$LL$	-953				
$CAIC$	1,941				

Comparing floorspace first, although it could involve more mental effort, has the highest probability to guarantee that pedestrian needs will be better realized in the chosen direction. Moreover, when the directions are not differentiated under floorspace, comparing with the previous direction is quick and easy. In the optimal model, both threshold values are hard. Directions with a total floorspace larger than 18,000 m<sup>2</sup> and a length of pedestrianized street longer than 350 m will be considered satisfactory for these factors respectively.

### 5.1.3 Rest decision

It is assumed in the framework that after the walking direction has been decided, pedestrians make decisions about whether or not to take a rest. The data only recorded the behavior of pedestrians taking a rest. That implies for cases in which the behavior is not resting, the true decision outcome could be to rest but the intention was not realized due to other limits such as unavailability of seats. In fact, although throughout WFS there are rest facilities within reasonable walking distances, the survey did not collect information about the service level of those facilities. Therefore, the assumption made for modeling the rest decision is that rest facilities were always

available when the decision was made; the reason that the pedestrian did not take a rest was purely because he/she did not want to.

Among those factors influencing the rest decision, tiredness is naturally one. Because it was not directly observed, a time variable call action time,  $t^C$ , was derived. It was defined as the difference between the current time when the rest decision was being made and the time when the last rest or meal related activity was completed, assuming that the pedestrian regained strength when conducting these activities. It is reasonable to assume that a pedestrian becomes more tired as action time increases. The decision may also be affected by a pedestrian's intention to shop. We may expect that for the same degree of tiredness, the pedestrian may have a stronger intention to shop and a higher tolerance for resting in the earlier stages of the shopping trip, while being more inclined to take a rest later during the trip and when the shopping intention is weaker. Relative time,  $t^R$ , was used to approximate the intention of shopping, and thus impacting the rest decision. The last factor included is absolute time,  $t^A$ , to represent some scheduled time for rest.

### 5.1.3.1 Models

Similar to the go-home decision, the rest decision can be modeled as a binary acceptance/rejection decision, and the same set of models will be applied and compared.

#### *MNL*

Under the framework of discrete choice, the two choice options in the rest decision can be defined as taking a rest or shopping. Pedestrians were assumed to choose the option with the highest utility, which can be formulated as:

$$\begin{aligned}
 p^E &= \frac{\exp(v^E)}{\exp(v^E) + \exp(v^S)} \\
 v^E &= \sum_X \beta^X t^X \quad X = C, R, A \\
 v^S &= \beta^S
 \end{aligned} \tag{5.17}$$

where  $v^E$  is the observable utility for taking a rest,  $v^S$  represents the observable utility of shopping/non-rest,  $\beta^S$  is an alternative-specific parameter for the shopping alternative, and  $\beta^X$  are parameters for corresponding factors which are hypothesized to be positive as the need for rest should increase with the time factors.

#### *Conjunctive model*

If pedestrians use the conjunctive rule to decide to rest or shop, the outcome will be positive only when all time factors exceed their thresholds. Similar as the go-home model, we assume that factor thresholds conform to the gamma-based distributions  $\delta^X = \alpha^X + \Gamma(\beta^X, \theta^X)$ . The decision process can be represented probabilistically as:

$$\begin{aligned}
 p^E &= \prod_X p_1^X \\
 p_1^X &= G^X(t^X - \alpha^X, \beta^X, \theta^X)
 \end{aligned}
 \tag{5.18}$$

Here,  $p_1^X$  is the probability that a factor is considered satisfactory (the threshold is exceeded), which is the product of the cumulative density functions of the threshold distributions.

#### *Disjunctive model*

In contrast, under the assumption that a disjunctive rule is used by pedestrians for their rest decision, any factor being satisfactory will make the pedestrian decide to rest and the factor being unsatisfactory will prompt for searching for another factor. The probability of taking a rest is then equal to:

$$p^E = \sum_X p_1^X - p_1^C p_1^R - p_1^C p_1^A - p_1^R p_1^A + \prod_X p_1^X
 \tag{5.19}$$

#### *Lexicographic model*

Assuming that pedestrians use a lower and a higher threshold for each factor under the lexicographic rule for the rest decision, they will decide to rest when the searched factor is satisfactory (factor exceeding the higher threshold) and they will decide to shop if the searched factor is unsatisfactory (factor being less than the lower threshold). Another factor has to be searched if the factor value is between the two thresholds. Since there are three factors involved in the rest decision, there are 6 (3!) possible model specifications under the lexicographic rule. For example, under the factor search sequence  $t^C \rightarrow t^R \rightarrow t^A$ , the probability of taking a rest is,

$$\begin{aligned}
 p^E &= p_1^C + (1 - p_1^C - p_0^C) p' \\
 p' &= p_1^R + (1 - p_1^R - p_0^R) p'' \\
 p'' &= p_1^A + (1 - p_1^A - p_0^A) 0.5 \\
 p_1^X &= G_1^X(t^X - \alpha_1^X, \beta_1^X, \theta_1^X) G_2^X(t^X - \alpha_2^X, \beta_2^X, \theta_2^X) \\
 p_0^X &= (1 - G_1^X(t^X - \alpha_1^X, \beta_1^X, \theta_1^X))(1 - G_2^X(t^X - \alpha_2^X, \beta_2^X, \theta_2^X))
 \end{aligned}
 \tag{5.20}$$

Again, gamma-based distributions were assumed for the factor thresholds. The probability of a factor being satisfactory,  $p_1^X$ , is the joint probability that both thresholds are exceeded. The joint probability of neither threshold being exceeded is just the probability of the factor considered unsatisfactory,  $p_0^X$ .

### **5.1.3.2 Results**

Some preliminary analyses showed that action time statistically has very little impact on the decision to rest, probably because of high correlations with the other two time factors. In the data, rest behavior occurred mostly near the end of the shopping trip and most respondents (91%) reported taking no more than 1 rest during the whole trip

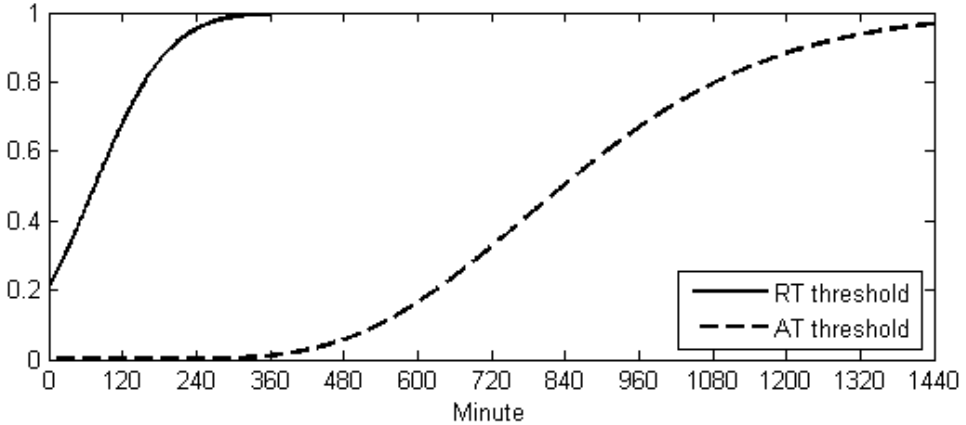


(the sample mean of the number of rests is 0.62, the standard deviation is 0.72). Thus, the values of  $t^C$  overlap with those of  $t^R$  and  $t^A$  considerably. For this reason,  $t^C$  was excluded from the models and will not be shown in the results. Consequently, only two models were left relevant for the lexicographic model, one starting with searching  $t^R$  and the other starting with searching  $t^A$ .

Table 5.5 shows the estimation results of the 6 models. The MNL model with normal variables fits the data well with a MLR of 0.42. Both parameters for time are significant and positive, which means that the need for rest strengthens as the

**Table 5.5 Estimation results of the rest models (WFS)**

MNL normal variables		MNL logged variables.		Conjunctive	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\beta^R$	0.003 *	$\beta^R$	2.929 *	$\alpha^R$	-2,100.360 *
$\beta^A$	0.004 *	$\beta^A$	0.312 *	$\beta^R$	529.570 *
$\beta^S$	5.170 *	$\beta^S$	22.812 *	$\theta^R$	4.114 *
				$\alpha^A$	-997.209 *
				$\beta^A$	18.178 *
				$\theta^A$	121.811 *
$N^C$	2,741	$N^C$	2,741	$N^C$	2,741
$N^P$	3	$N^P$	3	$N^P$	6
$LL$	-1,108	$LL$	-1,105	$LL$	-1,089
$CAIC$	2,243	$CAIC$	2,237	$CAIC$	2,232
Disjunctive		Lexicographic $t^R \rightarrow t^A$		Lexicographic $t^A \rightarrow t^R$	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\alpha^R$	82.000 *	$\alpha_1^R$	-656.494 *	$\alpha_1^R$	-1,068.340 *
$\beta^R$	0.328 *	$\alpha_2^R$	$\infty$	$\alpha_2^R$	$\infty$
$\theta^R$	20,958.620 *	$\beta_1^R$	59.362 *	$\beta_1^R$	146.467 *
$\alpha^A$	-1,891.760 *	$\beta_2^R$	-	$\beta_2^R$	-
$\beta^A$	40.828 *	$\theta_1^R$	12.389 *	$\theta_1^R$	7.822 *
$\theta^A$	85.777 *	$\theta_2^R$	-	$\theta_2^R$	-
		$\alpha_1^A$	0	$\alpha_1^A$	0
		$\alpha_2^A$	$\infty$	$\alpha_2^A$	$\infty$
		$\beta_1^A$	9.880 *	$\beta_1^A$	9.876 *
		$\beta_2^A$	-	$\beta_2^A$	-
		$\theta_1^A$	87.466 *	$\theta_1^A$	87.630 *
		$\theta_2^A$	-	$\theta_2^A$	-
$N^C$	2,741	$N^C$	2,741	$N^C$	2,741
$N^P$	6	$N^P$	5	$N^P$	5
$LL$	-1,093	$LL$	-1,091	$LL$	-1,091
$CAIC$	2,240	$CAIC$	2,226	$CAIC$	2,226



**Figure 5.5 CDFs of the time thresholds in the lexicographic rest model**

shopping duration increases. The MNL model with logged variables improves the goodness-of-fit only slightly. All heuristic models outperform the MNL models in terms of LL. The negative  $\alpha^R$  in the conjunctive model means that  $\delta^R$  could be less than zero. It reflects the fact that there were some pedestrians taking a rest in the very beginning of their shopping trips probably because they were already tired from traveling or conducting other activities before arriving in the street. The decision patterns implied by the two lexicographic models are almost identical. For both  $t^R$  and  $t^A$ , there is a infinitive threshold, which means that only the lower thresholds are actually effective and the decision process is very similar to the conjunctive rule except that a random decision is assumed when both factors exceed the lower thresholds.

The two lexicographic models have the best, almost identical, CAIC of all models. However, as said before, the decision processes implied by these models are not really lexicographic, but a hybrid of a conjunctive rule with a random choice. Based on the model starting from searching  $t^A$ , which is slightly better, Figure 5.5 shows the two cumulative distributions of the time thresholds. There is a 21% probability that the threshold for  $t^R$  is less than 0; a 23% probability that it is between 0 – 1 hours; 24% that it is between 1 – 2 hours; 18% that it is between 2 – 3 hours, and 14% that it is more than 3 hours. The mean is approximately 77 minutes. As for the threshold of  $t^A$ , there is a 33% probability that it is before 12:00, a 34% probability that it is between 12:00 – 16:00; a 21% probability that it is between 16:00 – 20:00, and an 8% probability that it is between 20:00 – 24:00. The mean of pedestrians' scheduled resting time is approximately 14:30 hour.

#### **5.1.4 Store patronage decision**

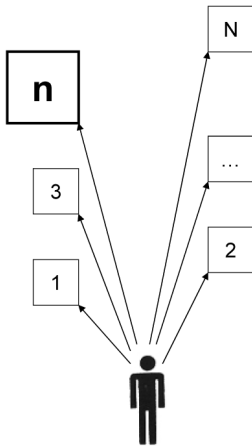
If the pedestrian's decision outcome about resting is negative, he/she will look for a store to visit, as assumed in the framework. The modeling of this decision is largely inherited from shopping choice models developed for larger geographical areas such as store and shopping center choice (e.g., Gautschi, 1981; Opperwal and Timmermans,

1997), in which consumers are assumed to choose a shopping center among alternative centers whose utilities are usually specified to consist of attractiveness factors like center size and friction factors like spatial or temporal distance.

Following the same framework, the pedestrian store patronage decision has been modeled as a choice among alternative stores, similarly based on the utility composed of store attractiveness factors such as floorspace and friction factors like distance between a pedestrian’s current location and the store (e.g., Saito and Ishibashi, 1992). The left picture in Figure 5.6 displays this framework, named the Simultaneous Choice Framework (SCF). Defining an individual’s choice set is an important procedure in the framework. However, the researcher usually does not know this choice set and therefore assuming that all the stores in the shopping area form the choice set is common practice. This assumption is obviously unrealistic in the sense that a pedestrian with limited mental capacity and decision time considers the information of each store and compares their utilities in a single decision, even though the distance factor can sometimes be interpreted as information decay, which relaxes the common choice set assumption somewhat. As it is also well-known that the parameter estimates depend on the definition of the choice set (e.g. William and Ortuzar, 1982; Pellegrini, *et al.*, 1997), different interpretations may be derived if researchers define different choice sets based their own research assumptions.

Instead, the framework displayed in the right picture of Figure 5.6 is more realistic and will be applied to the models developed in this thesis. We named it the Sequential Satisficing Framework (SSF). It assumes that a pedestrian judges stores one by one whether it is satisfactory. Stores are judged in sequence based on their

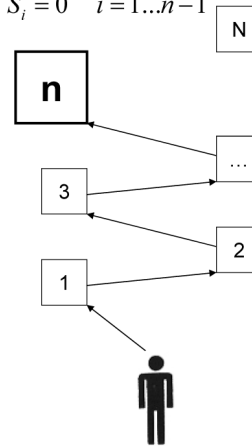
$$U_n = f(a_n, d_n) = \max(U_1, \dots, U_N)$$



The Simultaneous Choice Framework: Pedestrian calculates the utility of each store based on attractiveness and distance, and patronizes the store with the highest utility.

$$S_n = f(a_n) = 1$$

$$S_i = 0 \quad i = 1 \dots n-1$$



The Sequential Satisficing Framework: Pedestrian sequentially judges if a store is satisfactory based on attractiveness, and patronizes the first store that is found satisfactory.

**Figure 5.6 Two modeling frameworks for store patronage decision**

distance to the pedestrian, with the nearest store being judged first. It simulates the fact that store patronage decision is most of the time a process of searching for an ideal store which may satisfy pedestrians' needs. We may often observe that when a pedestrian walks through a street, he/she constantly looks around in the vicinity environment to find a satisfactory store. A Chinese saying in retail business, "Don't miss it when you pass by it", also implies that such "walk and see" strategy does capture the essential characteristic of pedestrian store patronage behavior. The search process stops until a satisfactory store is found and the pedestrian visits this store. By such means, not all stores in the shopping area are necessarily evaluated. Although distance is not explicitly incorporated in the satisficing function, it does have its functionality since the opportunity of more distant stores being visited is possibly intercepted by nearer stores. Another theoretical difference between the two frameworks is that SCF assumes that the choice of store depends on its relative utility against other stores, while SSF assumes that the satisfaction of a store may only depend on some priori criterion and does not necessarily take into account the influence of other stores.

However, although SSF improved some extent of realness of modeling store patronage behavior, it at the same time goes to the opposite of evaluating all the stores in the street, by assuming only one store is evaluated in each decision, while actually it is possible that some small number of alternative stores are evaluated. The pedestrian may even suppress the visit to the satisfactory store and try to find a better store in the next few searches. Such kind of behavior may be viewed as that the pedestrian is adapting his/her standard to the shopping environment. Either the size of the choice set or the adaptation behavior is itself a question of bounded rationality. As a first attempt to test the validity of the proposed models, we will keep the decision model simple.

#### 5.1.4.1 Models

##### *MNL*

Under SSF, not all stores in the walking direction are necessarily evaluated by the pedestrian; only the stores from the pedestrian's current location up to the chosen store are. Let  $i=1, \dots, I$  represent these stores in order of ascending distance to the pedestrian's current location,  $d_i$ . The last store  $I$  is chosen because it is satisfactory to the pedestrian and stores evaluated earlier are unsatisfactory. Expressed in probabilistic terms:

$$p_I = p_I^S \prod_{i=1}^{I-1} p_i^U \quad d_1 < \dots < d_{I-1} < d_I \quad (5.21)$$

$$p_i^S + p_i^U = 1$$

where  $p_i^S$  is the probability of the store being considered satisfactory and  $p_i^U$  the probability of being considered unsatisfactory.

Modeling the satisficing judgment as a binary choice and representing it in MNL framework gives:

$$\begin{aligned}
p_i^S &= \frac{\exp(v_i^S)}{\exp(v_i^S) + \exp(v_i^U)} \\
v_i^S &= \beta^c c_i + \beta^q q_i + \sum_{j=1}^{15} \beta_j^s s_{ij} \\
v_i^U &= \beta^U
\end{aligned} \tag{5.22}$$

The observable store utility,  $v_i^S$ , is composed of: (1)  $c_i$ , the number of activities that the pedestrian has conducted in the store. Noting that different activities in a store were recorded separately, it is hypothesized that the probability to conduct activities in the store will decrease if the store has been visited during the trip, implying its parameter  $\beta^c$  should be negative; (2)  $q_i$ , the retail floorspace of the store representing store attractiveness, whose parameter  $\beta^q$  is hypothesized to be positive; (3)  $s_{ij}$ , a dummy variable representing the type of the store. Sixteen store types were identified and each store was labeled a retail type, including, department store ( $j = 1$ , Dept), clothes ( $j = 2$ , Clth), shoe ( $j = 3$ , Shoe), fast food ( $j = 4$ , Fdfa), formal meal ( $j = 5$ , Fdfo), food retail ( $j = 6$ , Fdre), equipment ( $j = 7$ , Equi), pharmaceutical ( $j = 8$ , Phar), sport ( $j = 9$ , Spor), jewelry ( $j = 10$ , Jewe), optical ( $j = 11$ , Opti), book & media ( $j = 12$ , Book), fine arts ( $j = 13$ , Arts), children ( $j = 14$ , Chil), tourism ( $j = 15$ , Tour), and other types ( $j = 16$ , Oths).  $\beta_j^s$  is the parameter for each corresponding type. Because only the relative utility between alternatives matters in MNL models, one type variable can be excluded and the remaining 15 type parameters need to be estimated. The category “other types” was set as the base and the other type parameters mean the relative attractiveness compared to the “other” store types. Finally,  $v_i^U$  is the utility of not visiting the store (it is not satisfactory), represented by parameter  $\beta^U$ .

### *Conjunctive model*

If the decision rule is conjunctive, all three factors,  $c$ ,  $q$ , and  $s$ , must be satisfactory in order to make an overall satisfactory judgment. Assume that pedestrians use thresholds for this purpose on  $c$  and  $q$ ,  $\delta^x \sim \alpha^x + \Gamma^x(\beta^x, \theta^x)$  ( $x = c, q$ ), which are gamma-based distributions. The probability of a store being satisfactory is:

$$\begin{aligned}
p_i^S &= \prod_x p_{i1}^x \quad x = c, q, s \\
p_{i1}^c &= 1 - G^c(c_i - \alpha^c, \beta^c, \theta^c) \\
p_{i1}^q &= G^q(q_i - \alpha^q, \beta^q, \theta^q) \\
p_{i1}^s &= \sum_{j=1}^{16} \beta_j^s s_{ij}
\end{aligned} \tag{5.23}$$

where  $p_{i1}^c$  is the probability of the number of store visits being less than threshold  $\delta^c$ ,  $p_{i1}^q$  is the probability of the store floorspace being larger than threshold  $\delta^q$ , and  $p_{i1}^s$  is

the probability of certain store type being satisfactory. Note that all store types have to be included and their parameters,  $\beta_j^s$  between 0 - 1, will be estimated. If  $\alpha^c$  is very large,  $\alpha^q$  is very small, and  $\beta_j^s$  is equal to 1, the probability of store satisfaction will not be affected.

### *Disjunctive model*

If pedestrians use the disjunctive rule for judging store satisfaction, then any of the three factors being satisfactory will make the pedestrian patronize the store. Under the same assumption of threshold distributions, simply replacing the first line in Equation 5.23 with the probabilistic “or” relationship between factor satisfactoriness will yield:

$$p_i^s = \sum_x p_{i1}^x - p_{i1}^c p_{i1}^q - p_{i1}^c p_{i1}^s - p_{i1}^q p_{i1}^s + \prod_x p_{i1}^x \quad (5.24)$$

Contrary to the conjunctive model, the factors will have no effect and can be ignored if  $\alpha^c$  is very small,  $\alpha^q$  is very large, and  $\beta_j^s$  is 0.

### *Lexicographic model*

Similar to the previous lexicographic models for the go-home and rest decisions, assume that each factor has three judgment levels, unsatisfactory, neutral and satisfactory. The pedestrian will patronize the store when a factor is found satisfactory; will skip the store when a factor is unsatisfactory; will continue the search for another factor when the considered factor is neutral. A random decision is made when all three factors are found neutral. Two thresholds are applied to  $c$  and  $q$ , with  $\delta_k^x \sim \alpha_k^x + \Gamma_k^x(\beta_k^x, \theta_k^x)$  ( $x = c, q; k = 1, 2$ ). Again, 6 potential factor search sequences are implied. If the sequence is  $c \rightarrow q \rightarrow s$ , the probability that the store is satisfactory equals:

$$\begin{aligned} p_i^s &= p_{i1}^c + (1 - p_{i1}^c - p_{i0}^c) p' \\ p' &= p_{i1}^q + (1 - p_{i1}^q - p_{i0}^q) p'' \\ p'' &= p_{i1}^s + (1 - p_{i1}^s - p_{i0}^s) 0.5 \\ p_{i1}^c &= (1 - G_1^c(c_i - \alpha_1^c, \beta_1^c, \theta_1^c))(1 - G_2^c(c_i - \alpha_2^c, \beta_2^c, \theta_2^c)) \\ p_{i0}^c &= G_1^c(c_i - \alpha_1^c, \beta_1^c, \theta_1^c) G_2^c(c_i - \alpha_2^c, \beta_2^c, \theta_2^c) \\ p_{i1}^q &= G_1^q(q_i - \alpha_1^q, \beta_1^q, \theta_1^q) G_2^q(q_i - \alpha_2^q, \beta_2^q, \theta_2^q) \\ p_{i0}^q &= (1 - G_1^q(q_i - \alpha_1^q, \beta_1^q, \theta_1^q))(1 - G_2^q(q_i - \alpha_2^q, \beta_2^q, \theta_2^q)) \\ p_{i1}^s &= \sum_{j=1}^{16} \beta_j^s s_{ij} \\ p_{i0}^s &= \sum_{j=1}^{16} \alpha_j^s s_{ij} \quad \alpha_j^s + \beta_j^s \leq 1; \alpha_j^s, \beta_j^s \geq 0 \end{aligned} \quad (5.25)$$

**Table 5.6 Critical parameters for having no effect (store patronage)**

Conjunctive	Disjunctive	Lexicographic
$\alpha^c \rightarrow \infty$	$\alpha^c \rightarrow -\infty$	$\alpha^c \rightarrow -\infty, \infty$
$\alpha^q \rightarrow -\infty$	$\alpha^q \rightarrow \infty$	$\alpha^q \rightarrow -\infty, \infty$
$\beta_j^s = 1$	$\beta_j^s = 0$	$\alpha_j^s, \beta_j^s = 0$
Common: $\beta^x \rightarrow 0, \theta^x = 1 \quad x = c, q$		

The probability that the store type is not satisfactory ( $p_{i0}^s$ ) and the probability that it is ( $p_{i1}^s$ ), are represented by two sets of 0 – 1 parameters,  $\alpha_j^s$  and  $\beta_j^s$ , respectively. Then  $\theta_j^s = 1 - \alpha_j^s - \beta_j^s$  is defined as the probability that the pedestrian regards store type as neutral.  $\alpha_j^s$  and  $\beta_j^s$  being 0 simultaneously (the probability of neutral being 1) will make the type factor redundant. Table 5.6 gives an overview of parameters for judging whether a factor has any effect on the store patronage decision.

#### 5.1.4.2 Results

Table 5.7 shows the results of five models. Because presenting all the results of the lexicographic models takes a lot of space, we will report the results of the best lexicographic model only. The MNL model with normal variables performs well with an MLR of 0.83. When the variable for floorspace is logged, the LL is much better, suggesting that the increase in utility from store size decreases marginally. The negative parameter for the number of visits is consistent with the hypothesis that pedestrians tend to switch stores. Among the parameters for store type, the one for tourism is the highest. Since there is only one tourism site in WFS, this parameter is alternative-specific. The second most attractive store type is department store, followed by sports store, book store, and art store. The parameter for dummy variable,  $\beta^U$ , is quite high compared to the other parameters, implying a high average probability of rejecting (i.e., not visiting) a store, because there are much more rejection decisions in the data compared to the acceptance decisions.

The LL of the conjunctive model is even better. Only the shape parameter in the distribution of the threshold for the number of visits is significant. This distribution implies that the probability of this factor being satisfactory is 1, when the pedestrian has not patronized this store. It drops drastically to 0.08 when the store has been patronized once, and to 0.02 when the store has been patronized twice. This suggests that pedestrians' intention to switch stores is quite strong. The constant in the distribution of the threshold for floorspace is negative, implying the thresholds can be negative and very small stores can also be satisfactory. The parameters for store types directly reflect the probabilities of being satisfactory. The pattern of the five most satisfactory types is the same as the pattern estimated by the MNL model with logged variables. The disjunctive model has the worst LL of all models, suggesting that this rule is not strict enough for judging whether a store is satisfactory in general.

The best model both in terms of LL and CAIC is the lexicographic model with factor search sequence  $s \rightarrow c \rightarrow q$ . This means that store type is the factor being searched first when evaluating a store, which is consistent with common sense that people patronize a store which can satisfy their needs. However, the parameters show that most judgments based on store type do not follow the lexicographic pattern, otherwise all three state judgments, unsatisfactory, neutral, and satisfactory should have significantly non-zero probability for rejecting the store, continuing the search or accepting the store, represented by  $\alpha_j^s$ ,  $\theta_j^s$ , and  $\beta_j^s$  respectively. As can be seen, only

**Table 5.7 Estimation results of the store patronage models (WFS)**

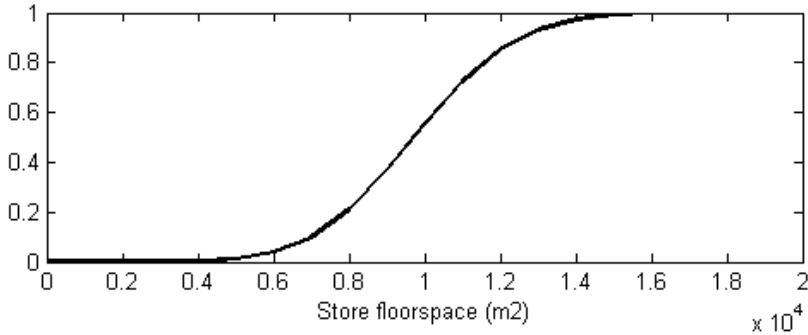
MNL normal variables		MNL logged variables		Conjunctive	
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\beta^c$	-3.100 *	$\beta^c$	-3.017 *	$\alpha^c$	0
$\beta^q$	1.290e-5 *	$\beta^q$	0.415 *	$\beta^c$	0.296 *
$\beta_{Dept}^s$	2.843 *	$\beta_{Dept}^s$	1.801 *	$\theta^c$	1.000
$\beta_{Clth}^s$	0.527 *	$\beta_{Clth}^s$	0.742 *	$\alpha^q$	-57,712.774 *
$\beta_{Shoe}^s$	0.589 *	$\beta_{Shoe}^s$	1.245 *	$\beta^q$	92.275 *
$\beta_{Fdfa}^s$	0.785 *	$\beta_{Fdfa}^s$	0.876 *	$\theta^q$	709.857 *
$\beta_{Fdfjo}^s$	0	$\beta_{Fdfjo}^s$	-0.699 *	$\beta_{Dept}^s$	0.443 *
$\beta_{Fdre}^s$	0	$\beta_{Fdre}^s$	0	$\beta_{Clth}^s$	0.134 *
$\beta_{Equi}^s$	0	$\beta_{Equi}^s$	0	$\beta_{Shoe}^s$	0.149 *
$\beta_{Phar}^s$	0	$\beta_{Phar}^s$	0	$\beta_{Fdfa}^s$	0.166 *
$\beta_{Spor}^s$	2.123 *	$\beta_{Spor}^s$	1.651 *	$\beta_{Fdfjo}^s$	0.044 *
$\beta_{Jewe}^s$	0	$\beta_{Jewe}^s$	0.745 *	$\beta_{Fdre}^s$	0.086 *
$\beta_{Opti}^s$	0	$\beta_{Opti}^s$	0	$\beta_{Equi}^s$	0.050 *
$\beta_{Book}^s$	2.361 *	$\beta_{Book}^s$	1.417 *	$\beta_{Phar}^s$	0.098 *
$\beta_{Arts}^s$	1.737 *	$\beta_{Arts}^s$	1.270 *	$\beta_{Spor}^s$	0.330 *
$\beta_{Chil}^s$	0	$\beta_{Chil}^s$	0	$\beta_{Jewe}^s$	0.089 *
$\beta_{Tour}^s$	3.555 *	$\beta_{Tour}^s$	3.021 *	$\beta_{Opti}^s$	0.074 *
$\beta^U$	4.547 *	$\beta^U$	6.867 *	$\beta_{Book}^s$	0.321 *
				$\beta_{Arts}^s$	0.245 *
				$\beta_{Chil}^s$	0.042 *
				$\beta_{Tour}^s$	1.000
				$\beta_{Oths}^s$	0.070 *
$N^C$	63,328	$N^C$	63,328	$N^C$	63,328
$N^P$	11	$N^P$	13	$N^P$	19
LL	-7,471	LL	-7,291	LL	-7,201
CAIC	15,075	CAIC	14,739	CAIC	14,632



department stores and sport stores conform to this requirement. The judgment patterns represented by the parameters of the remaining store types may be conjunctive (when  $\alpha_j^s > 0$ ,  $\theta_j^s > 0$ , and  $\beta_j^s = 0$ ), disjunctive (when  $\alpha_j^s = 0$ ,  $\theta_j^s > 0$ , and  $\beta_j^s > 0$ ), solely type-dependent (when  $\alpha_j^s > 0$ ,  $\theta_j^s = 0$ , and  $\beta_j^s > 0$ ), or something else. Apparently, the higher the values of  $\beta_j^s$  and  $\theta_j^s$ , the less probable a store will be finally rejected. In this sense, the tourism site still has the highest probability of being accepted, followed by department stores.

**Table 5.7 Estimation results of the store patronage models (WFS) (continued)**

Disjunctive		Lexicographic $s \rightarrow c \rightarrow q$			
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\alpha^c$	-0.471 *	$\alpha_1^c$	-0.146 *	$\alpha_1^q$	-43,185.510 *
$\beta^c$	0.787 *	$\alpha_2^c$	1.000 *	$\alpha_2^q$	$\infty$
$\theta^c$	0.116 *	$\beta_1^c$	7.489 *	$\beta_1^q$	606.187 *
$\alpha^q$	-108,618.887 *	$\beta_2^c$	0.010	$\beta_2^q$	-
$\beta^q$	182.620 *	$\theta_1^c$	0.010 *	$\theta_1^q$	87.302 *
$\theta^q$	1,350.234 *	$\theta_2^c$	1.000	$\theta_2^q$	-
$\beta_{Dept}^s$	0.170 *	$\alpha_{Dept}^s$	0.149 *	$\beta_{Dept}^s$	0.062 *
$\beta_{Clth}^s$	0.007 *	$\alpha_{Clth}^s$	0	$\beta_{Clth}^s$	0
$\beta_{Shoe}^s$	0.009 *	$\alpha_{Shoe}^s$	0	$\beta_{Shoe}^s$	0
$\beta_{Fdfa}^s$	0.013 *	$\alpha_{Fdfa}^s$	0.977 *	$\beta_{Fdfa}^s$	0.023
$\beta_{Fdfc}^s$	0	$\alpha_{Fdfc}^s$	0.802 *	$\beta_{Fdfc}^s$	0
$\beta_{Fdre}^s$	0	$\alpha_{Fdre}^s$	0	$\beta_{Fdre}^s$	0
$\beta_{Equi}^s$	0	$\alpha_{Equi}^s$	0.609 *	$\beta_{Equi}^s$	0
$\beta_{Phar}^s$	0	$\alpha_{Phar}^s$	0	$\beta_{Phar}^s$	0
$\beta_{Spor}^s$	0.074 *	$\alpha_{Spor}^s$	0.455 *	$\beta_{Spor}^s$	0.032 *
$\beta_{Jewe}^s$	0	$\alpha_{Jewe}^s$	0.989 *	$\beta_{Jewe}^s$	0.011
$\beta_{Opti}^s$	0	$\alpha_{Opti}^s$	0	$\beta_{Opti}^s$	0
$\beta_{Book}^s$	0.097 *	$\alpha_{Book}^s$	0	$\beta_{Book}^s$	0
$\beta_{Arts}^s$	0.048 *	$\alpha_{Arts}^s$	0	$\beta_{Arts}^s$	0
$\beta_{Chil}^s$	0.019 *	$\alpha_{Chil}^s$	0.971 *	$\beta_{Chil}^s$	0.029
$\beta_{Tour}^s$	0.259 *	$\alpha_{Tour}^s$	0	$\beta_{Tour}^s$	0.254 *
$\beta_{Oths}^s$	0	$\alpha_{Oths}^s$	0.442 *	$\beta_{Oths}^s$	0
$N^C$	63,328	$N^C$	63,328		
$N^P$	15	$N^P$	18		
$LL$	-7,601	$LL$	-7,126		
$CAIC$	15,382	$CAIC$	14,469		



**Figure 5.7 CDF of the floorspace threshold in the store patronage model**

The number of activities that have already been conducted in the store is the second factor searched if the judgment based on store type does not generate a choice. The assumed two threshold distributions are both significant. Nevertheless, they imply a very simple judgment pattern. The distribution for the lower threshold,  $\delta_1^c$ , implies that the probability of being satisfactory when the store has not been patronized is only 1.5%, and is 0 when the store has been patronized at least once. The distribution for the higher threshold,  $\delta_2^c$ , is completely hard, and hence equal to 1. Consequently, the probability of the factor being less than the higher threshold when the pedestrian has not patronized the store during the trip is 1, and is 0 when the store has been patronized. Jointly, if the store has been patronized, it will be rejected. Otherwise, the probability of being accepted is only 1.5%; the probability of being rejected is 0; the remaining 98.5% is left for searching the third factor, floorspace. Only the lower threshold for floorspace is significant. The higher threshold is positive infinite against which each store is unsatisfactory. Thus, the judgment pattern on this factor is conjunctive.

Figure 5.7 shows the probability of the thresholds being less than 6,000 m<sup>2</sup> is only 3.9%. Small stores are very likely rejected. The probability is 51.6% for the thresholds between 6,000 – 10,000 m<sup>2</sup>, 42% for thresholds between 10,000 – 14,000 m<sup>2</sup>, and 2.6% for thresholds larger than 14,000 m<sup>2</sup>. The second best model which is not shown is another lexicographic model with factor search sequence  $c \rightarrow s \rightarrow q$ . For both models, retail floorspace seem to be the least import factor for pedestrians when judging if a store is satisfactory.

## 5.2 HHM and the ENR Case

By comparing different models according to some criterion as in the WFS case, a best fitting model can always be identified. This is conventional practice of modeling bounded rationality. Sometimes such optimal models are considered the one closest to the true decision process. This may be true. However, it is not enough for negating other less true models as alternatives. As can be seen in the previous section, the goodness-of-fit statistics of different models may be very close. In such situations, interpreting all the decision outcomes as the result of a single decision model may just give a partial view of reality. One major advantage of the HHM is that the coexistence

of heterogeneous decision strategies can be estimated probabilistically, so that our understanding of pedestrian decision processes can potentially be more comprehensive.

## 5.2.1 Go-home decision

### 5.2.1.1 Models

#### *MNL*

The same two time factors, relative time ( $t^R$ ) and absolute time ( $t^A$ ), were used to explain the go-home decision as was done in the WFS case. Therefore, the specification of the MNL model is the same as Equation 5.1 and Equation 5.2.

#### *HHM*

Under the framework of HHM, the pedestrian decides to go home, if

$$\sum_X \mathbf{W}^X \Psi(t^X \geq \Delta^X) \geq \lambda \quad X = R, A \quad (5.26)$$

Here  $\mathbf{W}^X = [w_1^X, \dots, w_n^X, \dots, w_N^X]$  is an  $N$ -element (more accurately,  $N$  is specific to each  $X$ ) row vector of factor state values,  $\Delta^X = [\delta_1^X, \dots, \delta_n^X, \dots, \delta_N^X]^T$  is a column vector of factor threshold values, and  $\Psi(\psi)$  is an element-wise identity function being 1 for the true relationships  $\psi$ , being 0 for the false relationships. That means that if the overall value of going-home, represented by the left term in the equation aggregated from the state values of the two time factors, is larger than the overall threshold,  $\lambda$ , then the pedestrian will go home. Otherwise, he/she will keep shopping. As has been explained in Chapter 3,  $\lambda$  is assumed to be a multinomial logit distribution from which heterogeneous decision strategies originate.

To estimate this distribution as depicted by Equation 3.29, the value of each decision heuristic was calculated. The estimations of  $\mathbf{W}^X$  and  $\Delta^X$  provide the cognitive structure, from which the stopping conditions for each heuristic can be inferred. To complete the calculation of mental effort, the effort for searching each factor can be estimated as separate effort parameters. However, empirical results showed that estimating factor-specific effort parameters does not bring significant improvement to the model compared to only one effort parameter for all factors. This is largely because  $\mathbf{W}^X$  is already flexible enough to adjust the relationships for factor importance. Furthermore, it is easy to see that this effort parameter cannot be separated from the weight parameter  $\beta^e$  in Equation 3.36. Thus,  $\beta^e$  was set to be negative to represent some kind of cost.

The last element required for calculating mental effort is the probability beliefs of factors being in certain states. Although people may have different distributions which can be estimated for each factor state, empirical results showed that they add more complexity than goodness-of-fit to the model compared with uniform probability beliefs. The uniform probability means that the belief that a factor being in a particular state is equally probable. With the probability beliefs, the risk

perception of each heuristic can be calculated. Interestingly, single factor search effort and uniform state beliefs were found to be valid for all decision models that will follow. This could be the result of following reasons. First, as the main statistical functionality of probability belief is adjusting the importance relationship between factors, the value parameters have captured enough variance in the data and made the need for varying probability beliefs unnecessary. Second, pedestrians' beliefs are so heterogeneous that no particular factor state is at the aggregate level believed to be more probable than another. Third, pedestrians could be ignorant about the situation, or not willing to put more effort in recognizing the situation as more complex than a uniform distribution. This is related to the fourth reason, that if a cognitive structure is used by a pedestrian as some kind of universal decision machine that can be transferred to solving other similar problems, then a uniform belief may on average fit other situations better than a belief specifically estimated against a particular situation.

Given the estimated distribution of preference structures, the expected probability of a pedestrian deciding to go home is estimated using the latent class structure described in Equation 3.27. In total, the parameters that were simultaneously estimated include, factor state weights,  $\mathbf{W}^x$ , and factor thresholds,  $\Delta^x$ . The number of their elements were not set a priori, but estimated through model selection. The parameter for mental effort,  $\beta^e$ , as discussed before, is assumed to be negative; the parameter for risk perception,  $\beta^r$ , is assumed to be positive because pedestrians, *ceteris paribus*, are assumed to prefer diverse decision outcomes to betting on very few highly probable outcomes; the sign of the parameter for expected outcome,  $\beta^o$ , is not assumed, but determined empirically.

### 5.2.1.2 Results

A subsample of the respondents who reported to be near the end of the shopping trip was used to estimate the models. This is because their reported end time should be most reliable. The other reason is that their decision cases are relatively complete and the bias, if any, from the concentration of decision cases around earlier shopping stages can be avoided. Of course, the disadvantage is the smaller sample size, with 808 decision cases, which may not be representative of the heterogeneity in the behavior of the population.

Table 5.8 shows the results of the two MNL models and the HHM. The MRL of the MNL model with normal variables is 0.26, which means it performs well. The signs of the parameters are consistent with our hypotheses. When the time variables are logged, the goodness-of-fit is better, as in the WFS case, suggesting a marginally decreasing increment of the utilities with time. The optimal HHM turns out to have two thresholds for  $t^R$  and three thresholds for  $t^A$ . The pedestrians seem to have represented  $t^R$  into three states [ $< 70$  min,  $70 - 240$  min,  $\geq 240$  min) and represented  $t^A$  into four states [ $< 14:30$ ,  $14:30 - 16:00$ ,  $16:00 - 20:00$ ,  $\geq 20:00$ ). These segments are quite reasonable and conform with people's habit of using typical clock hours as decision references. The positive weights mean that as time goes by, the value of going home increases, but not in a linear fashion. The negative  $\beta^o$  suggests that

decision strategies with strict judgment standards are preferred by the pedestrians. As a result, it is less likely that pedestrians decide to go home earlier during the trip so that they may have more opportunities to enjoy shopping.

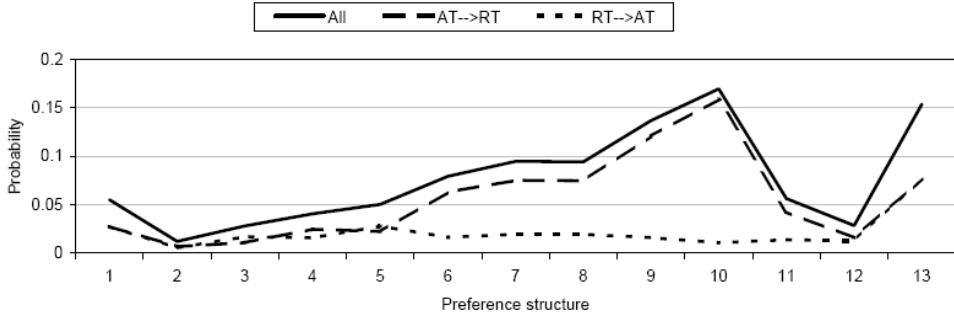
Three states for relative time and four states for absolute time mean that the number of preference structures implied by this cognitive structure is  $13 = 3 * 4 + 1$ . Every preference structure implies 2 heuristics, one from searching  $t^R$  and the other from searching  $t^A$ . The probabilities of these 26 heuristics were estimated; the results are shown in Figure 5.8. In the figure, the larger the index for a preference structure, the higher the overall threshold or the judgment standard. The general trend is that the probability increases as the standard becomes stricter, due to the negative  $\beta^o$ , implying that simpler rules are preferred. The probabilities drop at  $\Phi_{11}$  and  $\Phi_{12}$  (preference structure) because they imply risky heuristics with high probabilities of rejection. However, although  $\Phi_{13}$  implies one of the most risky strategies -

**Table 5.8 Estimation results of the go-home models (ENR)**

MNL normal variables		MNL logged variables	
Parameter	Estimate	Parameter	Estimate
$\beta^R$	-0.005 *	$\beta^R$	-0.869 *
$\beta^A$	-0.004 *	$\beta^A$	-4.402 *
$\beta^H$	-6.006 *	$\beta^H$	-35.424 *
$N^C$	808	$N^C$	808
$N^P$	3	$N^P$	3
$LL$	-415	$LL$	-410
$CAIC$	854	$CAIC$	843
HHM			
Parameter	Estimate	Parameter	Estimate
$\delta_1^R$ <sup>(1)</sup>	70 min	$\delta_1^A$	14:30
$\delta_2^R$	240 min	$\delta_2^A$	16:00
$(w_1^R)$ <sup>(2)</sup>	1.000 *	$\delta_3^A$	20:00
$w_2^R$	0.766 *	$w_1^A$	0.822 *
$\beta^e$	-2.690 *	$w_2^A$	0.710 *
$\beta^r$	4.526 *	$w_3^A$	2.566 *
$\beta^o$	-1.026 *		
$N^C$	808		
$N^P$	8		
$LL$	-396		
$CAIC$	853		

<sup>(1)</sup> Thresholds are not counted as free parameters as only their corresponding weights potentially have an effect

<sup>(2)</sup> Parameters in ( ) were set for the estimation. One value parameter is set to 1 because only the relative relationships between the values matter.



**Figure 5.8 Distribution of preference structures (go-home)**

unconditional rejection, its probability is still high because it costs almost no effort.

Looking at the distributions of the two factor search sequences, they differ very little before  $\Phi_6$ . That means that when the judgment standard is low (i.e. under which pedestrians are more prone to go home), the factor search sequence does not matter too much. We may imagine that in similar situations some people may say “Anything will be OK.” While after this point, when the judgment standard becomes stricter, the importance of search sequence increases and  $t^A$  becomes the first factor to search most of the time. This is probably because judgments based on external reference, such as checking the watch or agenda, usually gives people the feeling of certainty, compared to the fuzzy feeling of fatigue, boredom, level of fulfillment, or saves effort from estimating how much time has passed. Excluding the “no action” heuristics implied by  $\Phi_1$  and  $\Phi_{13}$ , the probability of  $t^A$  to be searched first is 62% in total, while  $t^R$  has a probability of 18%.

The best model in terms of CAIC is the MNL model with logged variables. The LL of HHM is the highest, but the complexity of the model is much higher.

## 5.2.2 Direction choice decision

### 5.2.2.1 Models

#### *MNL*

The full sample was used for calibrating the direction choice models because the influence of time was tested to have no significant effect on the decision. Therefore, the bias from incomplete trip diaries and missing decision cases is negligible. The physical environment is a little more complicated in ENR than in WFS. There may be up to four directions for each decision (e.g., East, South, West, North), depending on specific locations. The specification of the MNL model here is generally the same as in the WFS case, except the definition of the utility function. The factor about walking direction,  $d^Y$  ( $Y = E$  (East),  $S$  (South),  $W$  (West),  $N$  (North)), is now a dummy variable representing whether the alternative direction is the direction where the pedestrian just came from (1 – Yes, 0 – No). Its parameter,  $\beta^d$ , is hypothesized to be negative to

represent pedestrian's unwillingness to turn back. The factor of total retail floorspace and the length of the pedestrianized section are still kept. Tailored to the situation of ENR, an additional factor is the location of The Bund. Because The Bund is a special landmark in this area and just located at the eastern end of ENR, it is common among pedestrians to use it for orientation, especially for tourists. It is represented by a dummy variable,  $b^Y$ , being 1 when The Bund is located in the direction and being 0 when it is not. Then the utility function is,

$$v^Y = \sum_x \beta^x x^Y \quad x = d, q, l, b; Y = E, S, W, N \quad (5.27)$$

### HHM

The framework of comparison choice under HHM applies to the direction choice decision. The value function of each direction is defined as,

$$v^Y = \mathbf{W}^x \Psi(x^Y \geq \Delta^x) + w^d d^Y + w^b b^Y \quad x = q, l \quad (5.28)$$

where  $\mathbf{W}^x$  and  $\Delta^x$  are vectors of state values and factor thresholds, similarly defined as in the go-home model;  $w^d$  and  $w^b$  are scalar state values for the two dummy variables. It is assumed that the pedestrian pairwise compares the values of alternative directions under a certain discriminant threshold,  $\lambda^R$ , and the direction with the highest value rank is selected. If no choice can be made on this basis, random choice is assumed. The choice probability of each direction is the expected outcome under the latent multinomial logit distribution of  $\lambda^R$ , which is also estimated by calculating the mental effort, risk perception, expected outcome, and value of each heuristic.

#### 5.2.2.2 Results

Table 5.9 shows the estimation results. The MNL model with normal variables has a good goodness-of-fit with MLR equal to 0.41. The parameters for floorspace and length of pedestrianized section are positive, suggesting the attractiveness of retail activity and walking condition. The positive parameter for the location of The Bund articulates its role as a point of orientation. The negative parameter for previous direction is consistent with the hypothesis that pedestrians are less willing to make back-turns. Introducing non-linearity into  $q$  and  $l$  results in a lower LL, probably because logged variables make the alternatives less discriminable based on utility. A similar result is also observed in the WFS case.

HHM has a significant improvement over the MNL models both in terms of LL and CAIC. It shows that only one threshold, 2,005 m<sup>2</sup>, is used for representing retail floorspace. Directions with the more retail floorspace than this number are satisfactory on this factor. The length of the pedestrianized section is represented into three states [ $< 110$  m,  $110 - 341$  m,  $\geq 341$  m). Maybe 100 m should be considered as the least length for a pedestrianized street to be constructed. The signs of  $w^b$  and  $w^d$  are both consistent with those of the MNL models. The positive  $\beta^o$  suggests that smaller overall thresholds were preferred so that alternatives can be differentiated

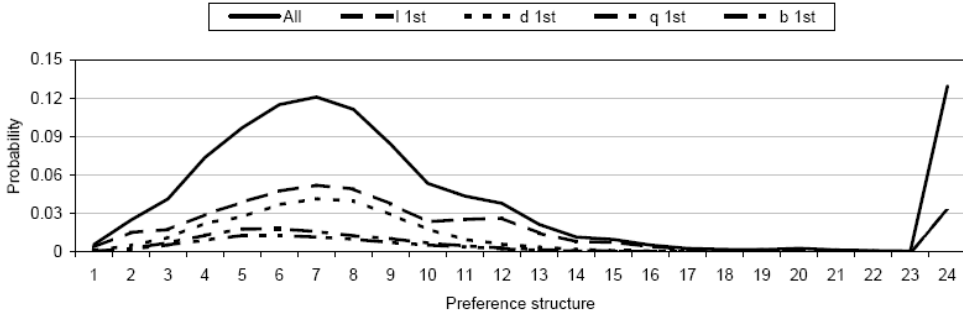
more easily. Nevertheless, Figure 5.9 shows that risk perception is the dominant force controlling the choice of heuristic. It indicates that the distribution concentrates around  $\Phi_r$ . From this point, when preference structure becomes smaller, the probability drops, suggesting that pedestrians tend to avoid using extremely low discriminant thresholds which would make an alternative preferable to another even with trivial factor advantages, although the decision process tends to be quick. When the preference structure becomes larger, the probability also drops due to the fact that fewer alternatives can be differentiated under such high standards and random choices has to be made, which gives the pedestrians the feeling of loosing control. The exception is that the probability of PS 24 is high, even though pedestrians make random choices all the time without considering any information, because this strategy is almost effortless. In general, pedestrians are risk averse and prefer information search in this particular decision problem. Their way of decision making approaches rational mechanisms.

The full factorial combination implies 24 factor search sequences, 6 for each factor. The figure also shows the probabilities of factors being searched first aggregated from all the 6 sequences starting from each factor. Under all preference structures, the length of pedestrianized section is always the most probable factor to be searched first. The second most probable first-to-search factor is the previous direction.

**Table 5.9 Estimation results of the direction choice models (ENR)**

MNL normal variables		MNL logged variables	
Parameter	Estimate	Parameter	Estimate
$\beta^q$	3.466e-6 *	$\beta^q$	0.432 *
$\beta^l$	1.287e-3 *	$\beta^l$	0.137 *
$\beta^b$	0.638 *	$\beta^b$	0.509 *
$\beta^d$	-0.983 *	$\beta^d$	-1.020 *
$N^C$	2,268	$N^C$	2,268
$N^P$	4	$N^P$	4
$LL$	-1,048	$LL$	-1,056
$CAIC$	2,131	$CAIC$	2,147
HHM			
Parameter	Estimate	Parameter	Estimate
$\delta^q$	2,005 m <sup>2</sup>	$w^b$	0.787 *
( $w^q$ )	1.000 *	$w^d$	-6.936 *
$\delta_1^l$	110 m	$\beta^e$	-3.437 *
$\delta_2^l$	341 m	$\beta^r$	7.652 *
$w_1^l$	7.452 *	$\beta^o$	4.116 *
$w_2^l$	6.111 *		
$N^C$	2,268		
$N^P$	8		
$LL$	-1,002		
$CAIC$	2,074		





**Figure 5.9 Distribution of preference structures (direction choice)**

This relationship explains the fact that there were many pedestrians who stopped following their current walking direction into the non-pedestrianized section and turned back at the end of the pedestrianized section. The probabilities of searching floorspace and The Bund first are relatively low. Excluding  $\Phi_{24}$ , the aggregate probabilities of factors being searched first are,  $l - 41\%$ ,  $d - 26\%$ ,  $q - 12\%$ , and  $b - 9\%$ .

### 5.2.3 Rest decision

#### 5.2.3.1 Models

##### *MNL*

Again the subsample of the near-the-end respondents was used for modeling the rest decision because the influence of time is considered. The same three factors as in the WFS case, action time ( $t^C$ ), relative time ( $t^R$ ), and absolute time ( $t^A$ ), were used as explanatory variables. Therefore, the specification of the MNL model is also the same as Equation 5.17.

##### *HHM*

Similar to Equation 5.29, the pedestrian will decide to take a rest if:

$$\sum_X \mathbf{W}^X \Psi(t^X \geq \Delta^X) \geq \lambda \quad X = C, R, A \quad (5.29)$$

That is, if the overall value aggregated from the factor values in the left side of the equation is larger than the assumed multinomial logit distribution  $\lambda$ , the pedestrian will take a rest. Otherwise, he/she will look for a store for patronage.

#### 5.2.3.2 Results

In the results of the three models shown in Table 5.10, action time appears to have no effect again. The MLR of the MNL model with normal variables is 0.38. The parameters for the time variables are both positive as hypothesized. The LL improves when the variables are logged, suggesting that pedestrians' utility derived from time is

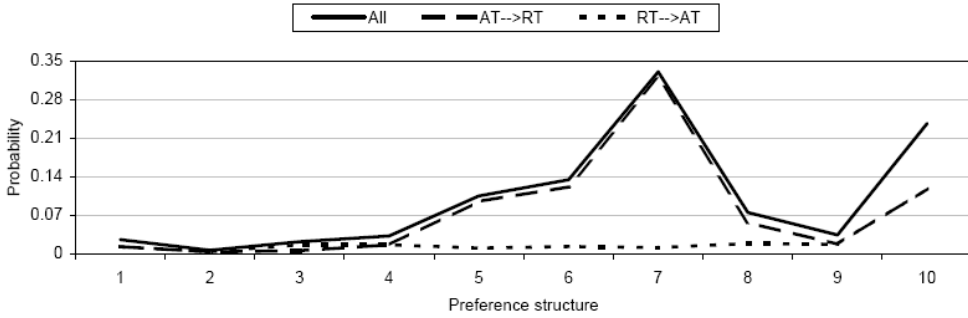
more appropriately represented as nonlinear function. Once more, the MNL model with logged variables outperforms the more complex HHM in terms of CAIC, even though the LL of the HHM is better.

Under the HHM model,  $t^R$  is represented into three states, [ $< 3$  min,  $3 - 179$  min,  $\geq 179$  min). The first state reflects that some pedestrians rested just after they arrived, probably because they had already felt tired from traveling or other activities. The second threshold is the 3rd hour from the start of the trip.  $t^A$  is also represented into three states, [ $< 11:44$ ,  $11:44 - 19:50$ ,  $\geq 19:50$ ). The first rest reference is near noon and the other threshold is around 20:00, probably after dinner. Their values are all positive, meaning that the need for rest becomes higher as time elapses.

In Figure 5.10, the pattern of the distributions resembles that of the go-home decision. Strict heuristics are preferred in general, except  $\Phi_8$  and  $\Phi_9$  whose risk perception are high. The probability of applying the strategy of unconditional rejection implied in  $\Phi_{10}$  is also high. This explains the fact that only 17% of the activities were rest and 45% of the respondents did not report any rest behavior. Under those relaxed preference structures, before  $\Phi_3$ , the two factors have almost no difference in

**Table 5.10 Estimation results of the rest models (ENR)**

MNL normal variables		MNL logged variables.	
Parameter	Estimate	Parameter	Estimate
$\beta^R$	0.004 *	$\beta^R$	0.353 *
$\beta^A$	0.002 *	$\beta^A$	1.868 *
$\beta^H$	4.131 *	$\beta^H$	15.636 *
$N^C$	822	$N^C$	822
$N^P$	3	$N^P$	3
LL	-351	LL	-342
CAIC	724	CAIC	707
HHM			
Parameter	Estimate	Parameter	Estimate
$\delta_1^R$	3 min	$\delta_1^A$	11:44
$\delta_2^R$	179 min	$\delta_2^A$	19:50
$(w_1^R)$	1.000 *	$w_1^A$	0.884 *
$w_2^R$	0.347 *	$w_2^A$	5.742 *
$\beta^e$	-3.377 *		
$\beta^r$	5.568 *		
$\beta^o$	-2.229 *		
$N^C$	822		
$N^P$	7		
LL	-329		
CAIC	713		



**Figure 5.10 Distribution of preference structures (rest)**

probability of being searched first. But after this point,  $t^A$  is dominantly searched first, suggesting that absolute time is still preferred as the reference for making the rest decision over relative time, as in the go-home decision. In total,  $t^A$  has a much higher probability to be searched first with 63% against 10% for  $t^R$ .

## 5.2.4 Store patronage decision

### 5.2.4.1 Models

#### *MNL*

Because the temporal effect was still tested to be insignificant in the pedestrians' utility function or the usage preference structure, the full sample was used for calibrating the store patronage decision. Four factors were considered to influence the decision. The three factors, number of visits in the store  $c_i$ , store floorspace  $q_i$ , and store type  $s_{ij}$ , were inherited from the WFS case. The extra factor is called store dominance,  $m_i$ , defined as the ratio of the store floorspace to the total floorspace of the stores within 100 m radius of the store, to represent the uniqueness or competitiveness of a store relative to its retail environment. The value is between 0 – 1. Moreover, two more store types were added. The new coding is: art ( $j = 1$ , Arts), book & media ( $j = 2$ , Book), children ( $j = 3$ , Chil), clothes ( $j = 4$ , Clth), department ( $j = 5$ , Dept), equipment ( $j = 6$ , Equi), drink and food ( $j = 7$ , Fddr), fast food ( $j = 8$ , Fdfa), formal meal ( $j = 9$ , Fdfo), food retailing ( $j = 10$ , Fdre), jewelry ( $j = 11$ , Jewe), optical ( $j = 12$ , Opti), pharmaceutical ( $j = 13$ , Phar), shoe ( $j = 14$ , Shoe), sports ( $j = 15$ , Spor), tobacco ( $j = 16$ , Toba), tourism ( $j = 17$ , Tour), and others ( $j = 18$ , Oths). The utility function of each store is,

$$v_i^S = \sum_x \beta^x x_i + \sum_{j=1}^{17} \beta_j^S s_{ij} \quad x = c, q, m \quad (5.30)$$

Here the parameter for the others type was set to 0 and the other parameters for store types represent the relative attractiveness to the others type.

### HHM

For the continuous and ordinal variables,  $c$ ,  $q$ , and  $m$ , thresholds were used for representing factors. For discrete variable,  $s$ , each store type is represented as an interest category. This set of categories reflects that the pedestrian may recognize different types of stores into limited degrees of interests, with  $Z = \{z_1, \dots, z_k, \dots, z_K; K \leq J\}$ . Then each category is assigned a value,  $w_k^z$ . The pedestrian will patronize the store, if he/she finds that,

$$\sum_x \mathbf{W}^x \Psi(x_i \geq \Delta^x) + \sum_{k=1}^K w_k^z z_{ik} \geq \lambda \quad x = c, q, m \quad (5.31)$$

The number of the interest categories,  $K$ , is determined by model selection, as was done for determining the numbers of thresholds for the other variables.

#### 5.2.4.2 Results

The estimation results in Table 5.11 show that the number of visits in the store does not have any impact on all the three models. This difference from the WFS case is because multiple visits in one store were not recorded in the ENR survey. In the estimation, it was assumed that the store is not considered by the pedestrian just after it has been patronized. However, it is still possible to consider the patronized store later if it is in the intended walking direction. Nevertheless, the decision cases including the patronized stores are much less.

The MNL model with normal variables performs well with MLR equal to 0.78, because most of the rejection decisions can be modeled easily. The model improves considerably when the floorspace variable is logged, suggesting a decreasing trend in utility increment relative to increasing store size. Store dominance has no significant effect. Tourism site, in this case only The Bund, is the most attractive type as its parameter is the highest. The second most attractive store type is department store, followed by food store and book store. The stores for formal meals seem to be the least attractive to the pedestrians.

The HHM has the best LL as well as CAIC. Floorspace is represented into four states, [ $< 50 \text{ m}^2$ ,  $50 - 420 \text{ m}^2$ ,  $420 - 24,000 \text{ m}^2$ ,  $\geq 24,000 \text{ m}^2$ ). The surprising thing is that, in the third state stores with the floorspace over 50 times difference, could be treated similarly attractive on size. The influence of store dominance is effective. Its threshold value is near 1, suggesting that a dominant store to other stores can enhance the attractiveness of the store, probably because pedestrians can fully concentrate their attention on the store. However, since only one store suffices this condition, there is the possibility that this variable represents alternative-specific tastes. As for store type, four interest categories were estimated, from the most interesting (4) to the least interesting (1). The most interesting category only includes tourism sites, in this case only The Bund, which can also be treated as an alternative-specific effect. The second most interesting category includes department store and food store, mainly those selling local special food.

Figure 5.11 indicates that in most decisions the pedestrians could have rejected the stores being evaluated without considering any information. This is

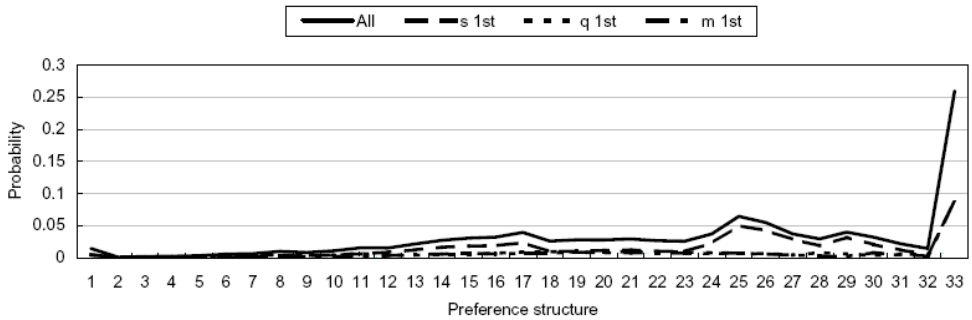
understandable since there are so many stores which are assumed to be potentially evaluated by the pedestrian before the satisfactory store is found. The negative  $\beta^o$  suggests pedestrians using high decision standards in general. A similar decreasing trend as in the go-home and rest decision is found after  $\Phi_{25}$  as the result of high decision risk. Store type seems to be the most important factor for store evaluation since it almost always has the highest probabilities to be searched first in the preference structures implying information search behavior. This is consistent with the result of the lexicographic model in the WFS case. The probabilities of floorspace and store dominance being searched first are very similar. In total, the aggregated probabilities of first-to-search factors are,  $s - 41\%$ ,  $q - 17\%$ , and  $m - 14\%$ .

**Table 5.11 Estimation results of the store patronage models (ENR)**

MNL normal variables		MNL logged variables	
Parameter	Estimate	Parameter	Estimate
$\beta^q$	2.480e-5 *	$\beta^q$	0.193 *
$\beta^m$	0	$\beta^m$	0
$\beta_{Arts}^s$	0	$\beta_{Arts}^s$	0
$\beta_{Book}^s$	1.151 *	$\beta_{Book}^s$	0.817 *
$\beta_{Chil}^s$	1.268 *	$\beta_{Chil}^s$	0
$\beta_{Clth}^s$	0.575 *	$\beta_{Clth}^s$	0.410 *
$\beta_{Dept}^s$	2.217 *	$\beta_{Dept}^s$	1.823 *
$\beta_{Equi}^s$	0	$\beta_{Equi}^s$	0
$\beta_{Faddr}^s$	0	$\beta_{Faddr}^s$	0
$\beta_{Fdja}^s$	0.660 *	$\beta_{Fdja}^s$	0.546 *
$\beta_{Fdfo}^s$	0	$\beta_{Fdfo}^s$	-1.154 *
$\beta_{Fdre}^s$	0.954 *	$\beta_{Fdre}^s$	0.895 *
$\beta_{Jewe}^s$	0	$\beta_{Jewe}^s$	0
$\beta_{Opti}^s$	-0.788 *	$\beta_{Opti}^s$	-0.670 *
$\beta_{Phar}^s$	0	$\beta_{Phar}^s$	0
$\beta_{Shoe}^s$	0	$\beta_{Shoe}^s$	0
$\beta_{Spor}^s$	0	$\beta_{Spor}^s$	0
$\beta_{Toba}^s$	0	$\beta_{Toba}^s$	0
$\beta_{Tour}^s$	3.328 *	$\beta_{Tour}^s$	2.935 *
$\beta^U$	3.977 *	$\beta^U$	4.892 *
$N^C$	47,111	$N^C$	47,111
$N^P$	10	$N^P$	10
LL	-7,138	LL	-7,095
CAIC	14,394	CAIC	14,308

**Table 5.11 Estimation results of the store patronage models (ENR) (continued)**

HHM					
Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
$\delta_1^q$	50 m <sup>2</sup>	$z_{Clth}$	2	$z_{Spor}$	2
$\delta_2^q$	420 m <sup>2</sup>	$z_{Dept}$	3	$z_{Toba}$	1
$\delta_3^q$	24,000 m <sup>2</sup>	$z_{Equi}$	2	$z_{Tour}$	4
$w_1^q$	4.293 *	$z_{Fddr}$	2	( $z_{Oths}$ )	1
$w_2^q$	4.775 *	$z_{Fdfa}$	2	( $w_1^z$ )	0
$w_3^q$	1.405 *	$z_{Fdfo}$	1	( $w_2^z$ )	1.000 *
$\delta^m$	0.999	$z_{Fdre}$	3	$w_3^z$	3.895 *
$w^m$	9.370 *	$z_{Jewe}$	1	$w_4^z$	9.770 *
$z_{Arts}$	1	$z_{Opti}$	1	$\beta^e$	-2.893 *
$z_{Book}$	2	$z_{Phar}$	1	$\beta^r$	6.450 *
$z_{Chil}$	2	$z_{Shoe}$	1	$\beta^o$	-2.894 *
$N^C$	47,111				
$N^P$	10				
$LL$	-7,012				
$CAIC$	14,141				



**Figure 5.11 Distribution of preference structures (store patronage)**

### 5.3 Summary

This chapter applied the heuristic models and HHM to the two pedestrian behavior datasets collected in WFS and ENR respectively. They were also compared with the MNL models. The results are summarized in Table 5.12. In the WFS case, the heuristic models perform ubiquitously better than the MNL models both in terms of LL and CAIC, on the four decision problems. This suggests that pedestrians use simplifying decision strategies rather than the principle of rational choice, at least as represented by the MNL model, for making the decisions examined in this thesis. One

**Table 5.12 Results of model comparison**

Decision	WFS		ENR	
	Best LL	Best CAIC	Best LL	Best CAIC
Go-home	LEX $t^R \rightarrow t^A$	CONJ	HHM	MNL logged
Direction choice	LEX $q \rightarrow d \rightarrow l$	LEX $q \rightarrow d \rightarrow l$	HHM	HHM
Rest	CONJ	LEX $t^A \rightarrow t^R$	HHM	MNL logged
Store patronage	LEX $c \rightarrow s \rightarrow q$	LEX $s \rightarrow c \rightarrow q$	HHM	HHM

commonality is that the disjunctive rule is never the optimal strategy and often has significantly worse goodness-of-fit statistics than the other models, suggesting that pedestrians' judgment standards are not low in general. A further look into the optimal lexicographic models reveals that some of them do not have a pure lexicographic form. The one for the rest decision actually is a combination of a conjunctive rule with random choice. The one for the store patronage model is a more complicated mixture of conjunctive, disjunctive, lexicographic, and other unnamed rules. Table 5.2 also shows that there are always models, including the MNL model, which are nearly as competitive as the best performing model. These results provide strong evidence of the coexistence of different decision strategies for a single decision.

The application of HHM to the ENR data showed a way to overcome this limitation by estimating heterogeneous decision heuristic probabilistically. The distributions of the preference structures of the three satisficing decisions (go-home, rest, and store patronage) share similar patterns. Strict and simple decision heuristics are generally preferred by the pedestrians. However, strict but too risky heuristics, such as pure conjunctive rules, are rarely applied. The exception is the unconditional rejection heuristic, just because it costs little mental effort. In contrast, in the direction choice decision, pedestrians appear to be very risk-averse as the distribution of the preference structure concentrates around low-risk heuristics which imply extensive information search. Although the HHMs are the best models in terms of LL, only two of them outperformed MNL in terms of CAIC. The two MNL models with logged variables are better in the go-home and rest decision mainly because their simple model specifications are enough for the simple data, while HHM requires more parameters to model both outcome and process. This fact already shows that using such model selection criterion might be too crude to give a fair comparison, let alone the fact that there has not been any convincing solution for comparing non-nested models (e.g., Timmermans, *et al.*, 1992). The HHMs estimated much simpler cognitive structures which are composed of limited numbers of factor states divided by factor thresholds, compared with the continuous utility functions in the MNL models which imply projecting every unit change of the variable values. The final merit of HHM is the capability to show factor importance for a decision from factor search sequence. It gives a more direct indication than comparing weight parameters in conventional utility-based models.

Having derived these model estimations, we may conclude the empirical validity of BR models for modeling pedestrian behavior. Whether they can be useful for practical prediction of spatio-temporal behavior will be further tested in the next chapter.

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*Chapter*

## 6 MODEL VALIDATION

It has been shown in the previous chapters that models of bounded rationality do have theoretical as well empirical advantages in modeling pedestrian shopping behavior. Then, the next question is that whether they are practically useful, too. In urban planning and retail development, policy makers usually care more about aggregate level behavior such as the number of pedestrians in certain public spaces or individual stores within a certain period of time. However, each of the four decision models is estimated separately to the specific decision problem and independence between these decisions is assumed. This is insufficient to judge the practical usefulness of these models. Therefore, the purpose of this chapter is to validate the ability of the estimated models of bounded rationality, as an integrated system, to reproduce aggregate spatio-temporal pedestrian shopping behaviors. This is realized using multi-agent simulation.

The chapter includes three sections. The first section will introduce the development of the multi-agent simulation platform, the procedures used in the simulation, and the generation of the aggregate behavior from the simulation, which will be compared with observed behavior. It is followed by three tests in the second section of this chapter. The first test concerns the WFS 2004 case to validate the heuristic models. The HHM models will be validated in the second test using the ENR 2007 data. The third test is conducted on another dataset, collected in ENR in 2003, using the models estimated on the basis of the 2007 data, in order to validate model transferability. The third section is a summary.

### 6.1 The Simulation Platform

#### 6.1.1 System construction

Although many multi-agent pedestrian simulation systems have been developed over the years, they are based on mechanisms for simulating pedestrian behavior, different from those developed in this thesis. For this reason, a specific simulation platform tailored to the models of bounded rationality suggested in this study was developed using NetLogo (see <http://ccl.northwestern.edu/netlogo>), an open-source multi-agent programmable modeling environment. This platform is not designed for specific problems, but allows defining almost any problem of interest through programming. It also provides a graphical representation, called World, which is especially useful for visualizing spatial activities. World is a grid-based graph composed of cells, each cell, called patch, with definable size, where an agent, called turtle, stands and moves. The simulation of agent movement is controlled by the commands which adjust the heading and the number of movement steps, with each step occupying a cell. NetLogo is designed to be object-oriented, implying that agents and cells may contain properties implemented as variables, and behaviors which are programmed procedures. It simulates the real world situation by representing changes in the status of multiple agents “simultaneously” (of course, processed sequentially in computation) as if they occur in parallel. Interactions between agents can also be modeled.

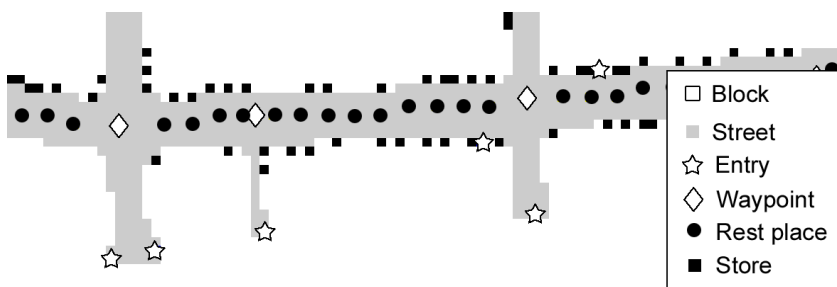


**Table 6.1 Components of the simulation platform**

Component	Function / Behavior	Element / Property
Global variable	Provides information that can be used by all the agents and cells in the system	Model parameters, time, counter, etc.
Agent	Represents pedestrian, makes decisions, moves in grid space	Need, location, orientation, duration, activity history, etc.
Grid space	Represents physical environment, contains physical information, records individual activities	Type, area, store type, utility, direction, activity counter, etc.
Interface	Controls and visualizes simulation	Control button & slide, grid space, result output

This specific pedestrian simulation platform consists of the following four components (Table 6.1). (1) *Global variable*, used to store global information that is accessible throughout the simulation process. Model parameters are stored as global variables that can be accessed by each agent and cell. (2) *Agent* represents a pedestrian who makes decisions and moves in space. Each agent is assigned a need which includes five main intentions, going home, choosing direction, taking rest, patronizing store, and staying at the same place. Different needs are assigned at different stages to indicate to the agent which decision should be made next. Agents of course contain their own location and orientation information in order to move in the grid space. An agent's activity history is also recorded for related decisions. (3) *Grid space* represents the physical environment. Each cell in the grid space represents a 5 \* 5 m area in the real environment. The size is determined considering the required accuracy relative to simulation speed. Five meters is representative for the width of narrow streets and the facades of small stores. This implies that detailed movement pattern of agents within the cell cannot be simulated. Nevertheless, the micro-scale movement simulation is not the focus of this study. Although many agents may simultaneously step into the same cell and make the space unrealistically dense, or walk in the streets which are supposed for vehicles, such problems may be tolerated as long as its impact on the aggregate behaviors of interest is limited.

Each cell has a type which includes 6 categories (Figure 6.1): (i) block, where agents cannot stand or move into, (ii) street, where agents can stand or move into, (iii) entry, where agents enter the shopping area and start the trip, (iv) waypoint, which may serve as general orientation guidance for agents and is usually set at street

**Figure 6.1 Illustration of the grid space**

intersections or locations where the street shape changes sharply, (v) rest place, where agents may take rests, and (vi) store, where agents shop and each store of whatever size is represented by a cell. Except waypoint, which is virtual, the other types of cells all resemble the actual physical environment to be simulated. The physical properties of a place are stored in the variables of the cell representing this place, for example, the area of store floorspace and store type. For computation efficiency, some reusable derivative variables such as the utility of a store are also calculated and stored as cell properties in the beginning of the simulation so that they do not have to be repeatedly calculated by each agent during simulation. Each cell also has some count variables to record the number and time of activities that happen on it, which are very useful for studying aggregate behavior. (4) *Interface* provides a convenient means for controlling the simulation processes and visualizing the real time situation of the simulated environment. In the left of Figure 6.2, the controls include buttons and slides. Here one slide is used for adjusting the number of agents for simulation, and the other slide is for adjusting the walking speed. As assumed in the data processing and model estimation, 1 m/s is the default walking speed for all agents. This means that each simulation step represents 5 seconds in reality. The grid space is put in the middle in which agents are represented by a small triangle with the tip indicating the heading. The space in the right is arranged for output units, including a clock displaying the real time in the simulation, a line graph instantly updating the number of agents conducting different activities at each simulation step, and a text form for outputting required information after the simulation ends.

### 6.1.2 Simulation procedures

Figure 6.3 shows the flowchart of the simulation. The simulation of each agent starts with entering the shopping area at one of the entries. This entry is randomly drawn from the observed distribution of pedestrians' starting locations in the case environment. Also, the time when the agent enters is drawn from the observed time distribution of pedestrians' arrival time. These are the only two given individual conditions in this simulation system. For the three tests that will follow, the actual time distributions are derived by counting the number of pedestrians in each hour. In the simulations, the generation of agents within each hour is set at a constant rate for the ease of operation. However, since the actual hourly distributions are not uniform, some small differences may happen in the final results. Especially, because pedestrians tended to report their arrival time at those integer clock hours or quarters, the actual start time distributions are concentrated around these time spots.

After entering, the first decision that the agent will make is the direction choice decision, based on the direction choice models, if there are alternative directions. The decision is simulated by calculating utilities, generating random factor thresholds and random overall thresholds based estimated probabilities of preference structures. This treatment also applies to simulating all the other decisions. The chosen direction defines the search space of the agent in the following activities. Stores and rest places in the non-chosen directions will be ignored. The heading of the agent is immediately adjusted to the nearest waypoint in the chosen direction.

(See clockwise)

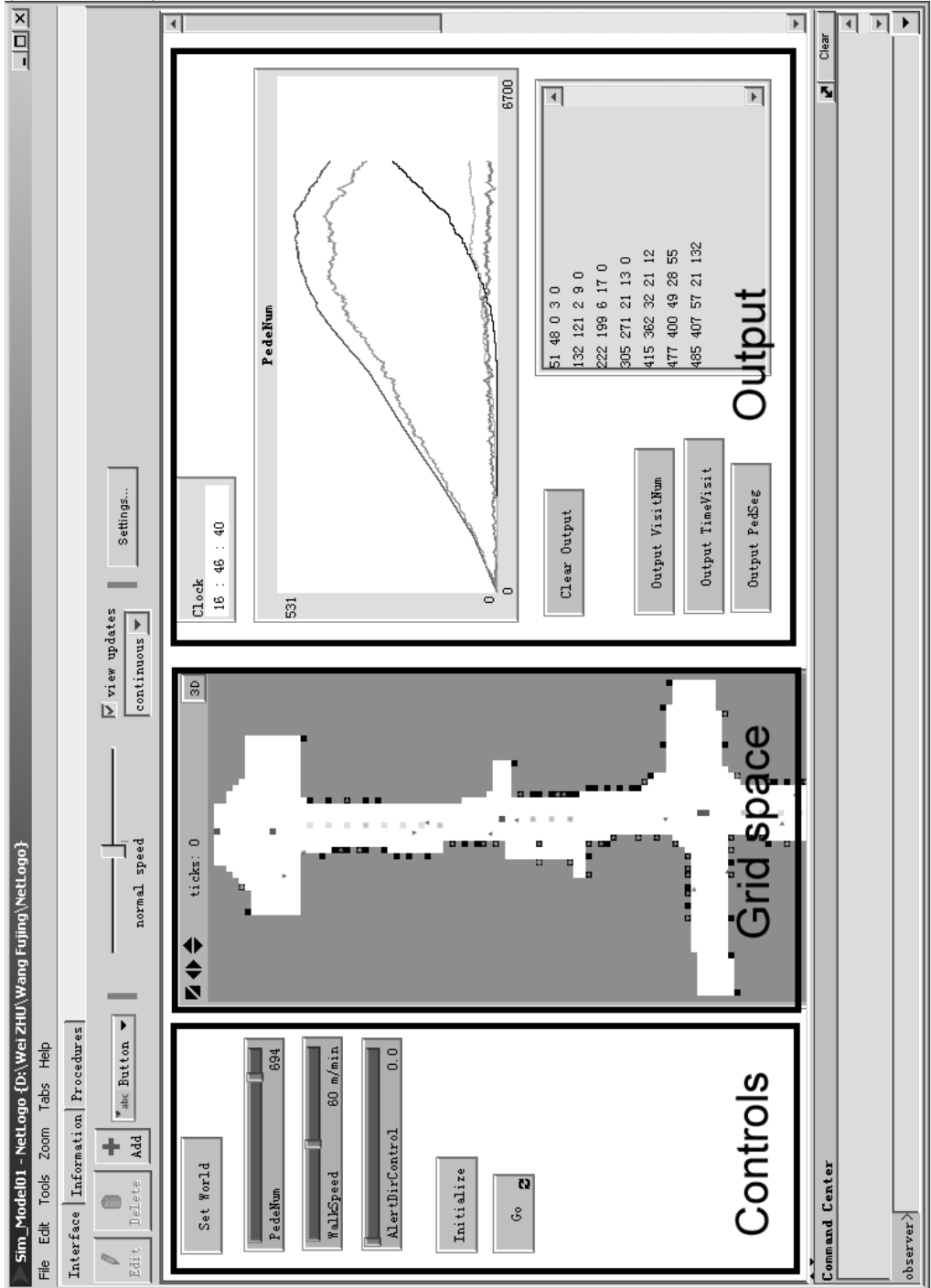
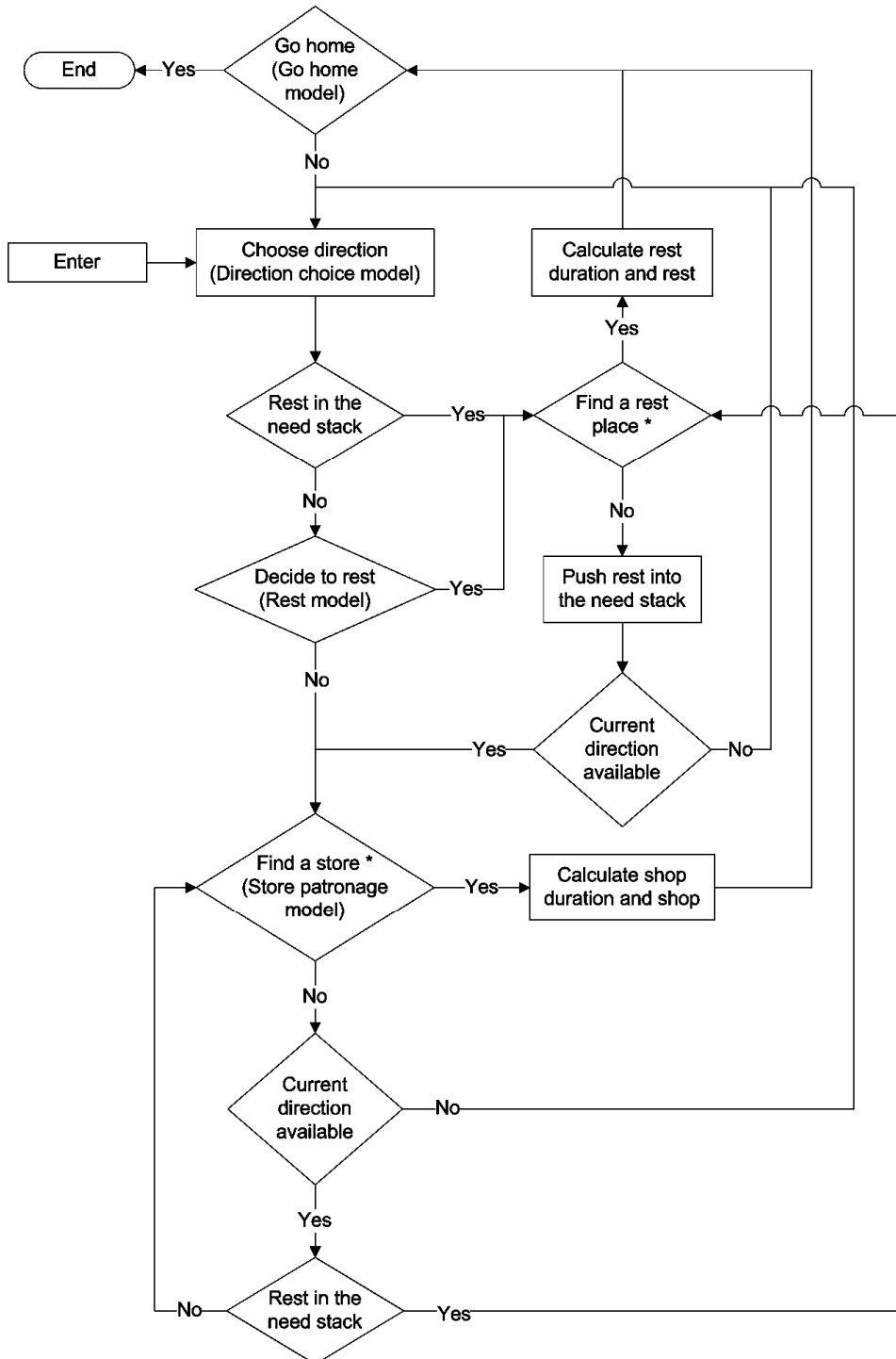


Figure 6.2 Screenshot of the interface



\* Stores and rest places within 100 m search range are searched.

**Figure 6.3 Flowchart of the multi-agent simulation**

Based on the modeling framework in Figure 3.1, the next need of the agent is to rest. This is simulated by first checking whether rest is already in the need stack. Agent's need stack is designed for storing unsatisfied needs which simulates the fact that pedestrians may postpone the pursuit of certain need if it cannot be satisfied under the current situation and give the priority to another need. In this system, only two needs may enter the need stack. Shopping is the default need always in the stack. Rest is the other which may be in or out of the stack depending on related decisions and behaviors. The priorities of the two needs may alternate. The mechanism will be detailed later. Obviously, for agents just entering the area, rest is not in the need stack. Then, an agent will make the rest decision based on the rest models. The proposed rest models require relative and absolute time as explanatory variables. This information can be easily derived based on the current simulation time and the recorded start time of the agent when his/her simulation begins. The positive decision outcome will lead to the same behavior as the agents who already have had rest in the need stack, which is to find a rest place.

The search for a rest place is limited within the chosen direction. Another agent variable has to be mentioned is the search range which can be understood as pedestrian's perceptual distance. The range is arbitrarily set to be 100 m. Note that setting this search range is largely for the simulation efficiency. It imposes very little impact on agent behavior represented by the models. However, reality is not completely ignored since a larger range can always increase computation efficiency. Moreover, the range just suffices to cover some large intersections so that stores in one corner can still be perceived by the agent at the opposite corner. The simulation runs in such a way that if the agent finds that there is a rest place within the search range, he/she will go for the nearest place and rest is removed from the need stack. The assumption here is that the rest place is always available regardless of its capacity and service level, even though many agents could be resting there. By doing so, we may at least identify the potential demands for rest at certain locations. When the agent reaches the rest place, the duration for this rest is predicted from the activity duration model (introduced later). Then, the agent just stays in the rest place until this duration has elapsed. After the rest, the agent thinks about whether to go home, based on the go-home model. A positive outcome will lead to the end of the shopping trip and the agent simply disappears from the environment. A negative outcome leads the agent back to the direction choice decision.

At the node of searching for a rest place, if no place is found within the search range, it is assumed that the agent will push the need for rest into the need stack and at the same time give priority to shopping. The agent will start searching for a store only if there are still stores available in the chosen direction from the current location, otherwise a new direction choice is simulated. The procedure of searching for a store is similar as searching for a rest place. The agent evaluates each store from the nearest to the farthest one within the search range, based on the store patronage model. Once a satisfactory store is found, the agent will head for it. Upon reaching the target, the duration of the shopping activity is predicted from the shopping duration model and the agent will stay there until this time has elapsed. After that, the go-home decision is prompted again. If no satisfactory store is found within the search range, rest will

receive a higher priority if it is in the need stack. Then again, the availability of the current direction is checked. In case that direction is available, the agent will move 20 steps (about 100 m search range) towards the nearest waypoint and start searching for a place to rest at the new location if rest is in the need stack, or start searching for a store when rest is not needed. The unavailability of the chosen direction will lead to a new decision about the direction to take.

### 6.1.3 Comparison statistics

The final step of a validation involves comparing simulated aggregated spatio-temporal agent behavior with the observed aggregate pedestrian behavior. First, the distributions of different types of activities over time are obtained, including shopping, resting, and walking. These statistics can indicate the service levels of corresponding types of space, stores, rest facilities and streets. Aggregating the agents of the three types will give the total number of agents. Furthermore, the cumulative distribution of the number of agents having gone home is a good indication of agents' go-home behavior. The temporal distributions are obtained by taking snapshots of the numbers of agents at 12 integer hours from 10:00 – 21:00, the normal store operation hours. Second, the shopping streets are divided into several segments and the distributions of the numbers of agents in each segment over time are obtained. These spatio-temporal distributions are useful for evaluating the performance of different parts of the shopping environment. Third, the number of visits and the total duration in individual stores are compared with the observations. These statistics are a direct indication of store attractiveness and could be most useful for retail developers. All the statistics are the averages of the results of 20 simulations for each test, in order to average out random fluctuations and obtain stable distributions.

## 6.2 Tests

### 6.2.1 Test 1 – WFS 2004

#### 6.2.1.1 Settings

The map of WFS is simplified for the ease of simulation. The grid space concentrates on the close vicinity to the shopping street. Branch streets which are unlikely to be used are truncated and treated as blocks. The street is divided into 6 segments (Figure 6.4). Segment 1 starts from the southern end of the street to the southern end of the pedestrianized section. Segment 2, 3 and 4 compose the whole pedestrianized section. Segment 5 and 6 are non-pedestrianized. Four main entries are used as the starting

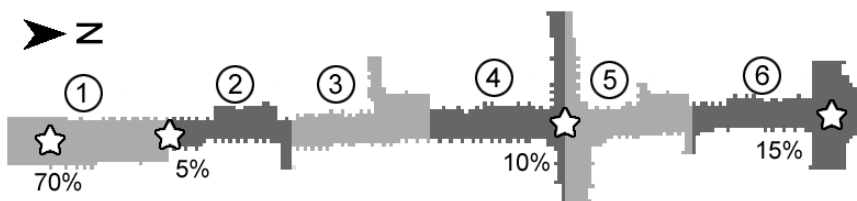
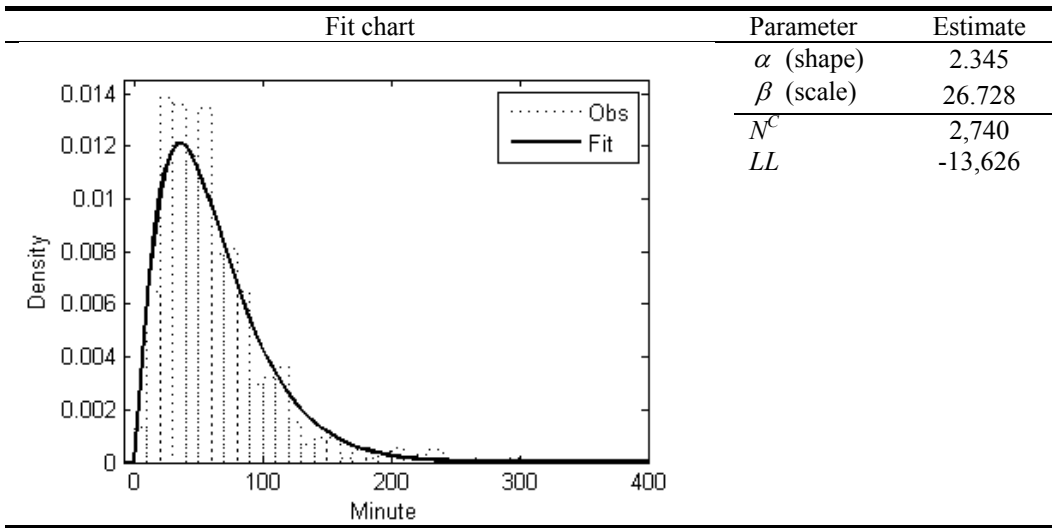


Figure 6.4 Segments of WFS

**Table 6.2 Estimation results of activity duration (WFS)**

points of agents. The numbers of pedestrians entering from the other entries are aggregated into their nearest main entries. From the left to the right of the figure, entry 1 is at the southern end of the street, where 70% of the pedestrians started the shopping trip. Entry 2 is at the southern end of the pedestrianized section where 5% of the pedestrians entered. The other end of the pedestrianized section locates entry 3 where 10% of the pedestrians entered. Entry 4 is at the northern end of the street where 15% of the pedestrians entered.

The distribution of entry time directly uses the observation as in Figure 4.5, from which an agent's start time of the shopping trip is drawn. In order to predict the activity duration, the observation is fitted using a gamma distribution (Table 6.2). The fit is good in general, except that it is less peaked than the observation. Because the activity duration is averaged across all activities, the difference in time use by different activity types cannot be identified. The activity duration is predicted by simply drawing a random number from this distribution. The four major decisions are simulated based on the best heuristic models in terms of CAIC (Table 5.12). The simulation of a decision is implemented as such in general. First, a factor is selected for consideration based on the search sequence suggested by the heuristic. For the conjunctive model, the sequence does not matter. Second, factor threshold values are randomly drawn from respective estimated threshold distributions. Third, factor values are compared with the thresholds and judgments can be made according to the heuristic. Drawing random thresholds every time an agent is making a decision may be unrealistic since individual's judgment standards are relatively stable, if not constant. However, because, to keep the models simple, we estimated the models under the assumption of independent decision cases, the simulation has to follow the models. To correct the problem requires modeling more complex correlation structures within each individual. The total number of simulated agents is 694, which is the number of respondents with complete shopping diaries.

### 6.2.1.2 Results

The distributions of agents conducting different activities over time are shown in Figure 6.5, where the x-axis lists the 12 clock hours. Figure-a compares the simulated and observed total numbers of agents in the street. The fit appears to be very good and the single modal shape peaked around 15:00 is well captured. The simulated numbers before 15:00 almost match the observations perfectly, while after this point, there is evidence of some overestimation, suggesting that the go-home model does not generate agents' go-home decisions early enough.

In Figure-b, the match between the simulated and the observed numbers of in-store agents is good, too, except for some minor underestimations and overestimations that occur before and after 15:00. The number of agents who are taking a rest is compared in Figure-c. The simulated distribution is slightly flatter compared to the observed distribution. The simulation fits the observation well before 14:00 and after

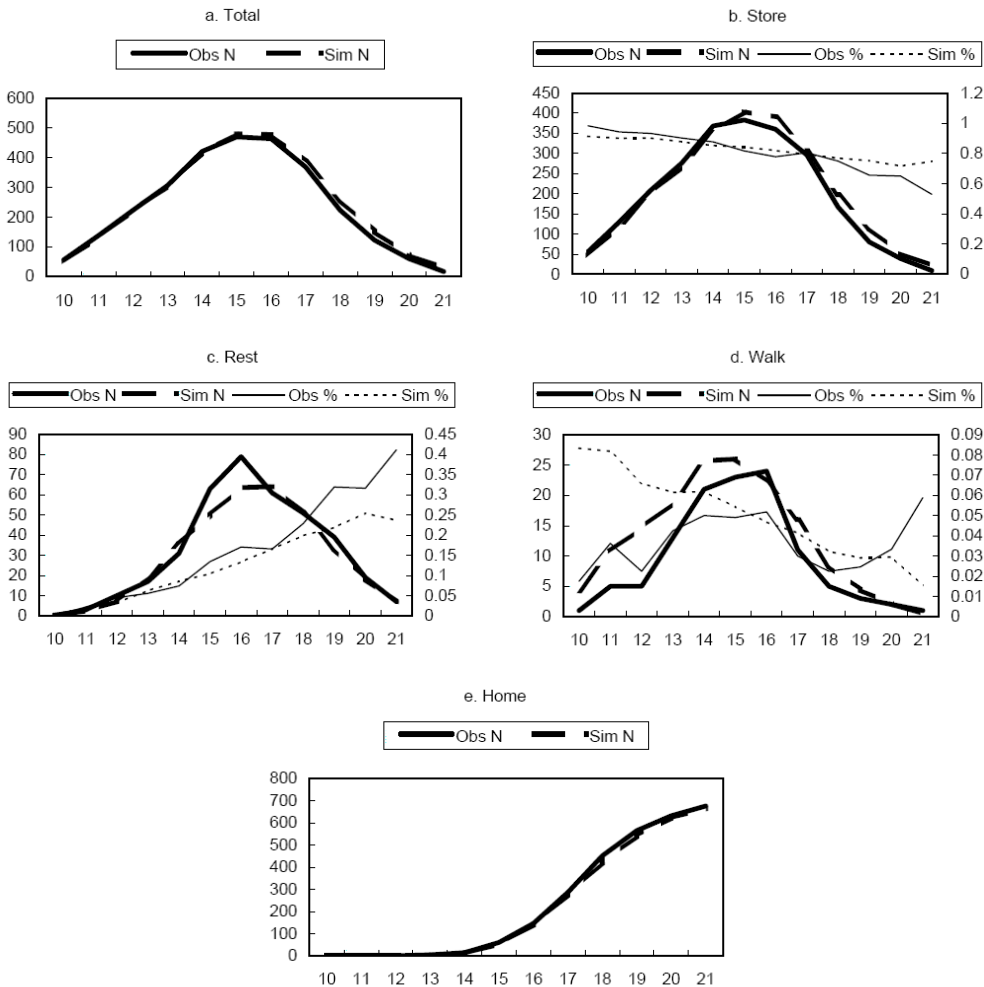


Figure 6.5 Distributions of agents by activities over time (WFS)



17:00. However, it does not capture the fast increase at 15:00 and the peak at 16:00.

The fit between the simulated and observed numbers of walking agents is the worst among all, although the general trend is right. However, this could be partially tolerated as the numbers of observation are small compared to other activities. Therefore, the distribution is more sensitive to random fluctuations and more difficult to capture.

Finally, the two cumulative distributions of agents who have gone home stay very close in Figure-e. The slight bend-down in the simulation confirms the conjecture from Figure-a that the thresholds estimates should be a little more relaxed in the go-home model.

In Figure-b – d, the percentages of agents conducting different activities are also shown, with the right y-axis being their scales. One interesting phenomenon from the observation is that the percentage of in-store activities constantly drops and the

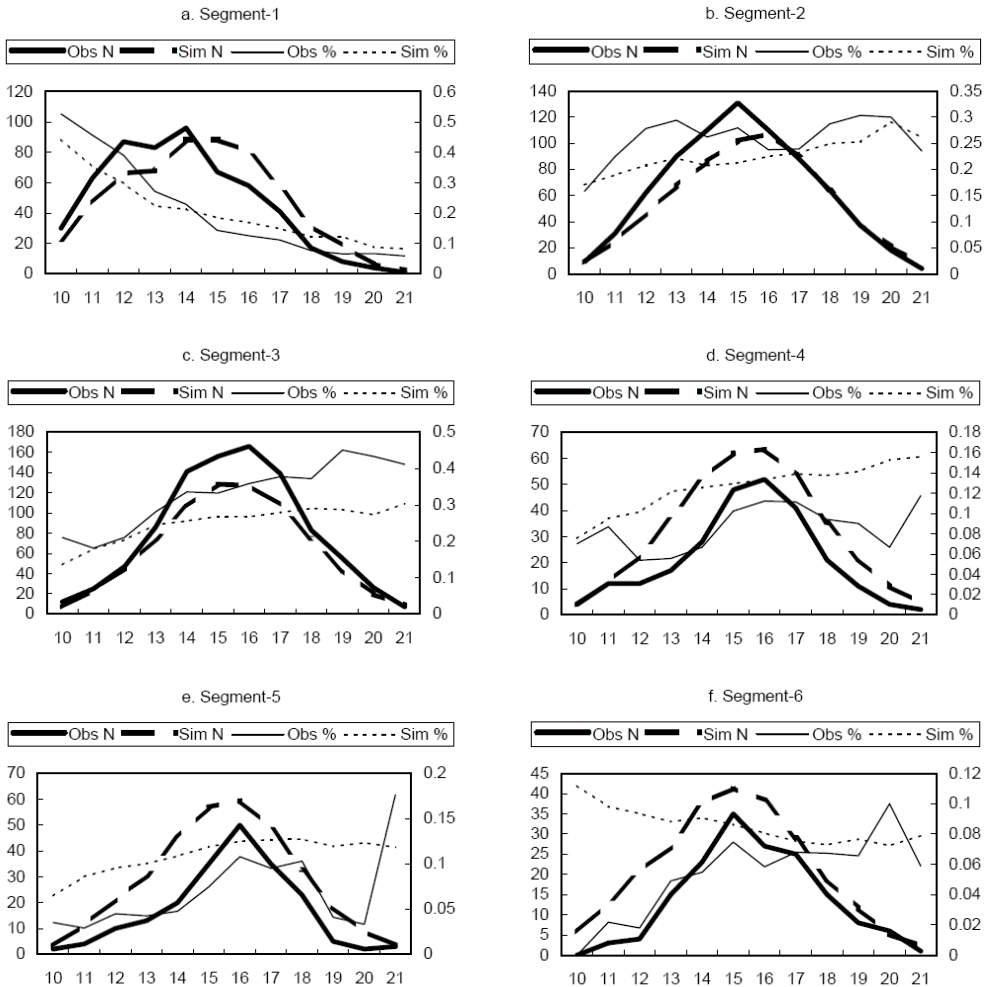
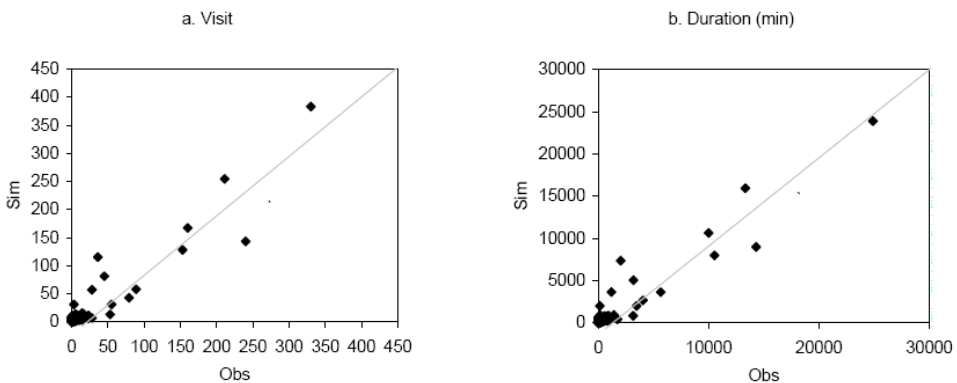


Figure 6.6 Distributions of agents in segments over time (WFS)

percentage of rest keeps rising as time goes by. This can be reasonably explained as the result of high motivation for shopping in the early stage of the trip, which becomes lower in the later stage as the pedestrian could have fulfilled the needs or feels fatigue or bored. The simulated percentages for both activities are flatter than the observations. This could be a result of averaging duration across all activity types, which cannot reflect the influence of shopping habits on changes of duration. The distribution of the percentage of walking agents is actually random, while a downward trend is simulated.

The distributions of agents in segments over time are shown in Figure 6.6. Although the simulation captures the general trends in the observations, there is increased evidence of more under- and overestimations. Segment 1 is the closest segment to the southern entry where most agents enter. The number of agents in this segment increases fast before 12:00 in the observations. However, the simulation underestimates the numbers before 14:00 and overestimates these after this point. Segments 2 and 3 are the two segments with the highest peak in the numbers of pedestrians. This is reflected in the simulation but with some underestimations. In contrast, the simulated numbers of agents in segments 4, 5 and 6 which actually have much fewer pedestrian activities are overestimated. This result suggests that the store patronage model seems to have made the stores in segments 4 – 6 more attractive than they really are. In the simulation, these stores absorbed the agents entering at the two northern entries and reduced the probability of the agents searching stores in segments 1 – 3. On the other hand, the influence of walking environment seems to be limited than it actually is since it is the last factor for consideration in the lexicographic direction choice model. As a result, the behavior that the pedestrians walking northwards in the pedestrianized section and then turn back at the end of this section is weakened in the simulation, while the probability of agents continuing walking into the northern segments becomes higher.

The final comparison is between the simulated and observed numbers of agents and total durations that the agents spend in each store (Figure 6.7). Figure-a shows the numbers of visits. The scatter points gather close to the iso-value line, suggesting a good match. It seems that the number of agents in the large stores has been overestimated, implying that the store patronage model overemphasizes the



**Figure 6.7 Number of visits and duration in stores (WFS)**

attraction of large stores. The observed total number of in-store visits is 2,293, while the simulated number is 2,364. The overestimation is 3.1%. In Figure-b, the dispersion of total duration is smaller. The simulated sum across all stores is 148,226 minutes. Compared to the observations (141,075 minutes), there is a 5.1% overestimation. The average in-store duration is 61.5 minutes in the observations and 62.7 minutes in the simulation.

## 6.2.2 Test 2 – ENR 2007

### 6.2.2.1 Settings

The map of ENR in 2007 is divided into 12 segments (Figure 6.8), with the smaller numbers representing segments near the western end and the larger numbers near the eastern end. Thus, the pedestrianized section starts from segment 2 to 8. Some branch streets are also counted as segments if there are at least 50 m of stores along the street, such as Segments 3, 7, 9 and 11. The surrounding less relevant streets are truncated, assuming that the agents only walk in these remaining main segments, which is consistent with the behavior of most pedestrians in reality. All the entries are kept as they are and no aggregation is implemented on the entry distribution. The original distribution as in Figure 4.17 is directly used for drawing at random the entries for the agents.

Unlike the treatment in WFS, activity durations were asked from the respondents and corrected. It is possible to differentiate duration between activity types. Their differences are shown in Figure 4.16. Four models are estimated to the durations for the four activity types: shopping, meal, rest, and tourism. Each model is specified as,

$$D = \alpha + \beta^q q + \beta^R t^R + \beta^A t^A + \Gamma(\alpha^g, \beta^g) \quad (5.32)$$

Here, duration,  $D$ , is assumed to be a linear function of the following variables: (1)  $\alpha$ , an intercept which serves as a type-specific parameter adjusting the average duration; (2)  $q$ , the retail floorspace of a store. Hypothesizing that large stores can attract pedestrians to stay longer, its parameter should be positive; (3)  $t^R$ , relative time could also have some effect considering the changes of pedestrian's shopping motivation and need for rest during different stages of the shopping trip; (4)  $t^A$ , absolute time

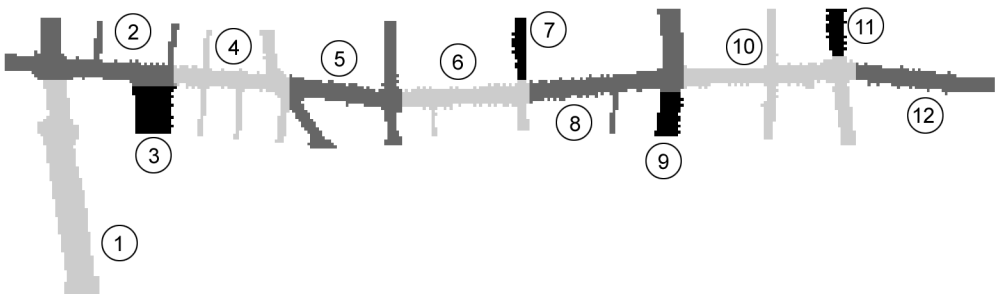


Figure 6.8 Segments of ENR 07

may have an impact if pedestrians are faced with external scheduling constraints; (5)  $\Gamma$ , a gamma distribution, representing the unobservable random part. Because the function includes time variables, the subsample of respondents with complete diaries is used so that the time distributions are not biased due to incomplete trips, however, at the risk of reducing completeness due to small sample size.

The estimation results are shown in Table 6.3. The models have been tested to be much better than the conventional linear regression model with a normally distributed random part and a pure gamma distribution. The positive  $\beta^q$  in the shopping and meal model is consistent with the hypothesis. The magnitude of this parameter in the shopping model is much smaller because there are more larger stores for shopping activities than for meal activities, implying that the parameter cannot be too high. The parameters for  $t^R$  are all positive, which means that pedestrians spend more time on activities during the later stage of the trip probably due to the diminishing tendency to switch between stores and accumulating fatigue or boredom. In contrast, the parameters for  $t^A$  are ubiquitously negative, which could be explained as absolute time approaching some schedule deadline, the pedestrian has to limit the duration in order to meet the deadline.

The major decisions are simulated based on the four HHM models. Although in reality it is much easier for the pedestrian to search factors sequentially based on selected decision heuristics, operationally it is more convenient to simulate decision outcomes based on overall value (utility). The treatment is that, in the initialization of a simulation, the overall value set is calculated based on the value (weight) parameters of each model, and the estimated probability distribution of preference structures is input. For some static factors such as floorspace, their values are calculated and stored during the initialization. To generate a decision outcome during simulation, the overall threshold is drawn from the overall value set according to the distribution of preference structures. Then, the overall value of the alternative is calculated or retrieved from the storage. The outcome is simply derived by checking the overall value against the overall threshold. The number of simulated agents is 236, the same as the subsample size of near-the-end respondents.

**Table 6.3 Estimation results of activity duration (ENR 07)**

Parameter	Estimate			
	Shopping	Meal	Rest	Tourism
$\alpha$	23.238	28.843	32.761	94.653
$\beta^q$	1.360e-4	0.003	-	-
$\beta^R$	0.025	0.026	0.014	0.079
$\beta^A$	-0.028	-0.028	-0.036	-1.000
$\alpha^g$	1.384	0.968	1.272	0.838
$\beta^g$	43.633	72.690	39.600	131.781
$N^C$	549	90	142	21
$LL$	-2,784	-471	-696	-113

### 6.2.2.2 Results

Figure 6.9 shows the activity-time distributions. The simulated total number of agents fits the observations quite well. The distribution has the similar shape as in WFS case with 15:00 being the single peak. Slight underestimation can be found before this time mainly because the agent generation procedure, based on constant hourly generation rates, does not generate as many agents as in reality near the clock hours which in fact are more frequently reported by respondents as their arrival time. The mismatches become more apparent in the in-store distributions when the numbers of agents are fewer. Nevertheless, almost every turning-point is well captured. The number of agents taking rests rises steeply from 12:00 to 15:00, which was well reproduced by the simulation. After 15:00, the simulated numbers drop too fast.

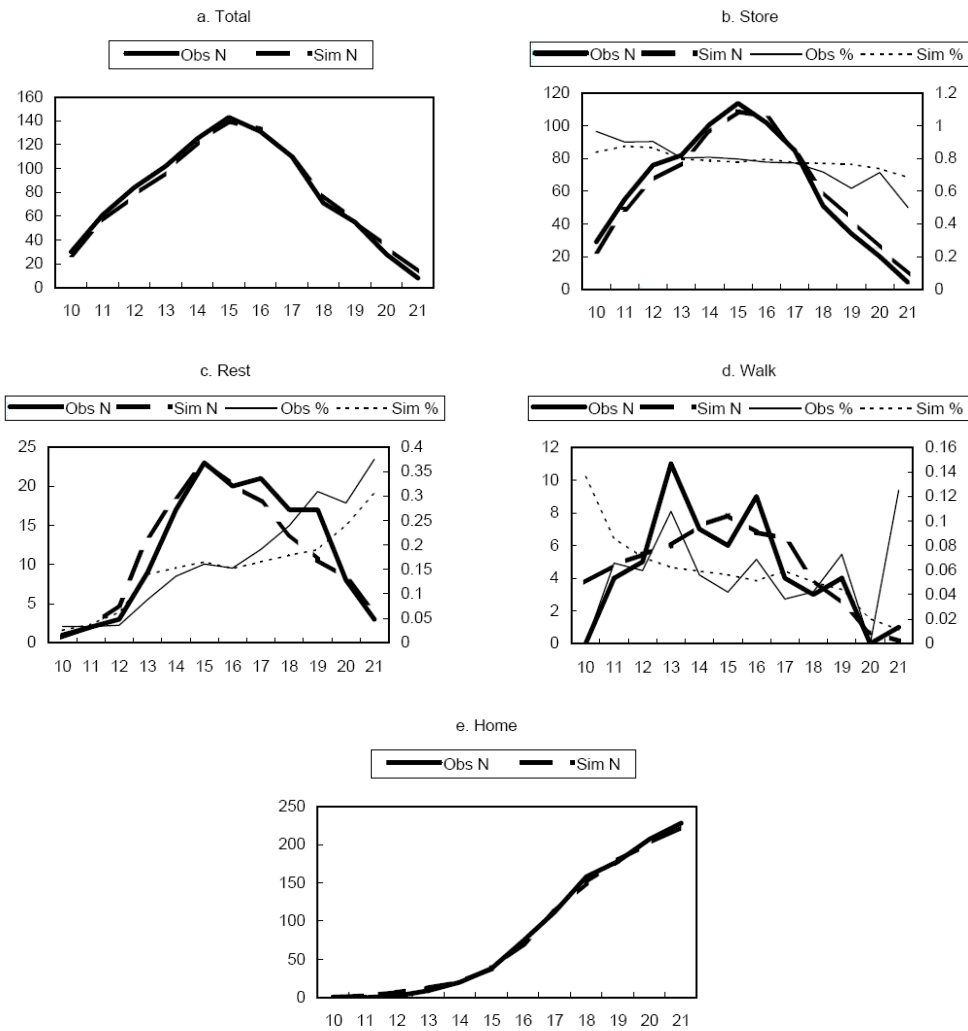


Figure 6.9 Distributions of agents by activities over time (ENR 07)

The fit between the simulated and observed number of walking agents is poor, largely due to the small numbers in the sample. The two distributions of the cumulative number of agents who have gone home are very close. The changes of the activity percentages over time display very similar patterns as in the WFS case. The percentage of in-store activities drops from about 90% in the beginning to about 60% in the end; the percentage of resting keeps increasing from none to about 40%. The percentage of walking is the smallest most of the time.

The magnitudes of the simulated number of agents in segments are largely correct (Figure 6.10), although with more severe under- and overestimation. The fits in the segments with very small numbers of pedestrians, such as Segments 1, 3, 7, 9 and 11, are poor. This is what one should expect for small numbers. However, at least they reflect the fact that branch streets are not very competitive compared to the main shopping street. Actually the under-development of branch streets has been a topic for the local planning authority for quite some time. The distributions in Segments 2 and 4, the two segments closest to the western end, are simulated relatively well. The numbers in the two segments in the middle, Segments 5 and 6, are underestimated, mainly because the attractiveness of some stores of special fame in these segments are not represented in the store patronage model. Thus, the probability of agents just walking through these segments becomes higher in the simulations. In the non-pedestrianized section, as the number of pedestrians drops, the simulated numbers appear to be more erratic, with the numbers in Segment 10 overestimated and those in Segment 12 underestimated.

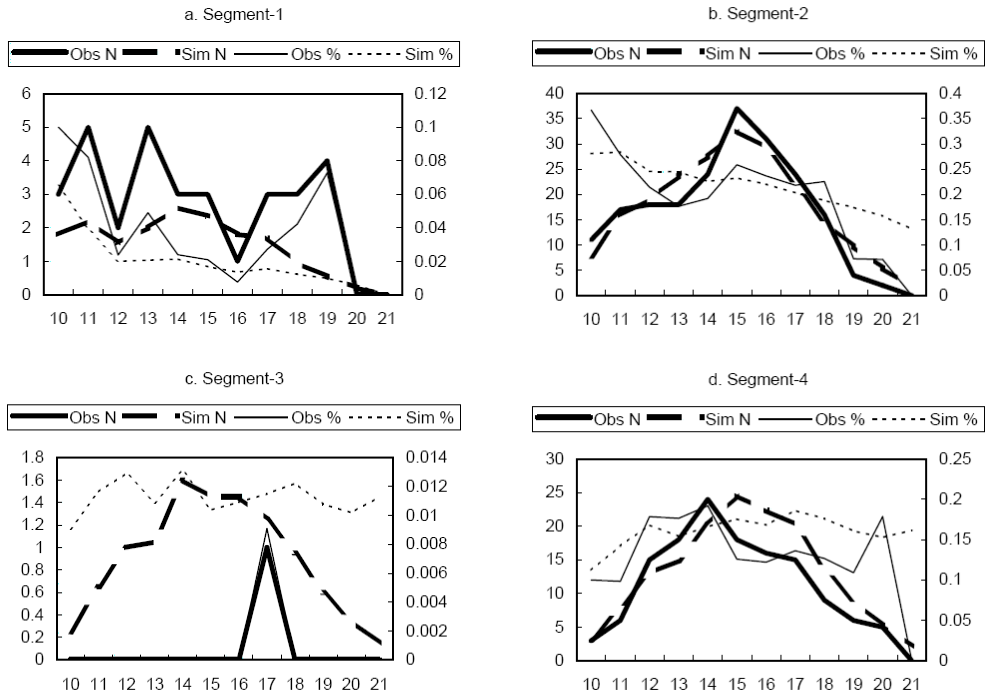


Figure 6.10 Distributions of agents in segments over time (ENR 07)

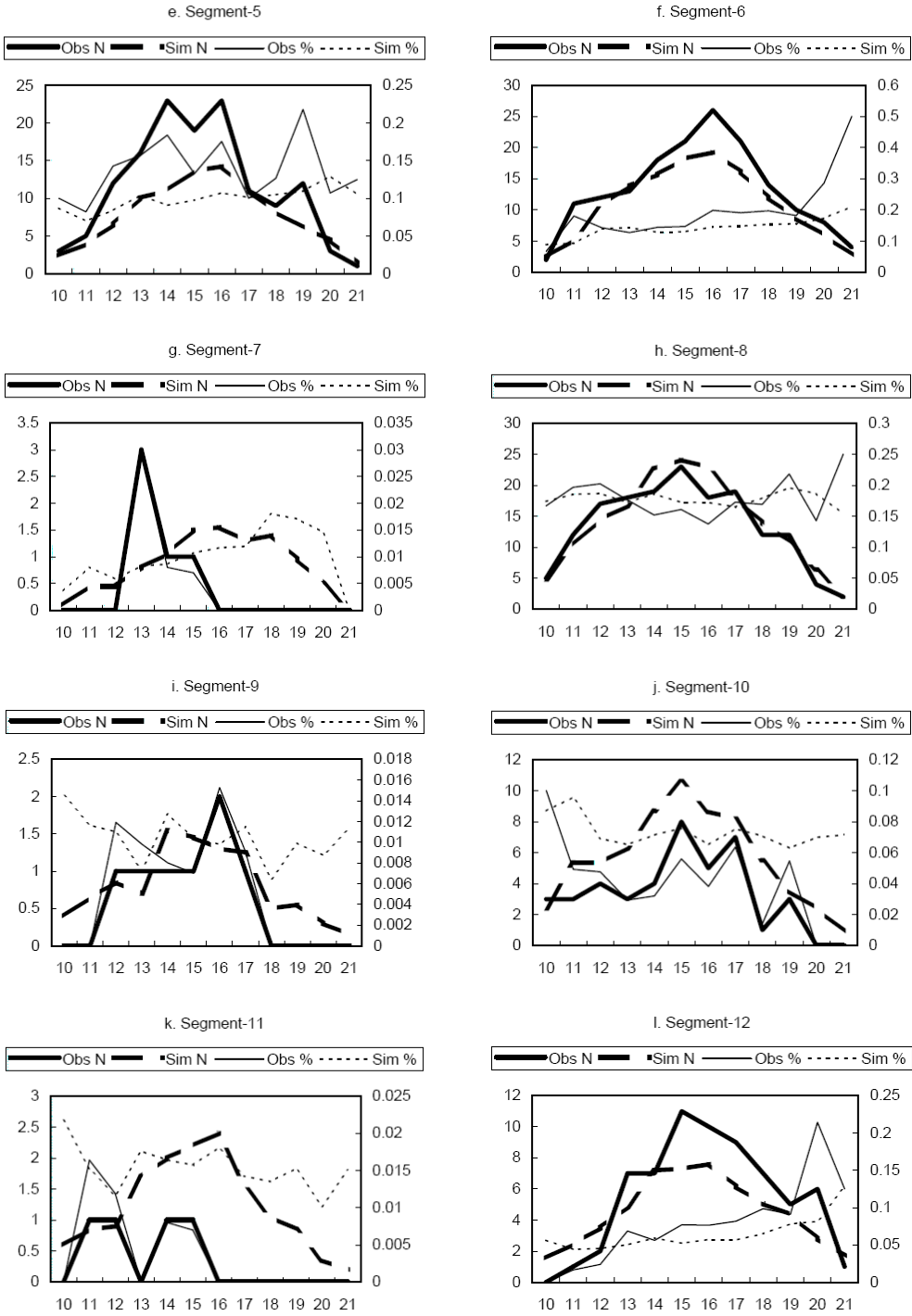
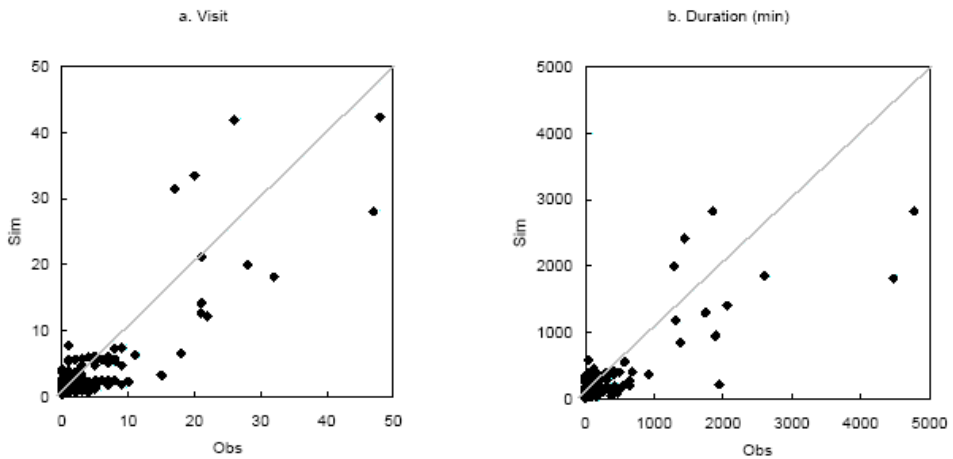


Figure 6.10 Distributions of agents in segments over time (ENR 07) (continued)



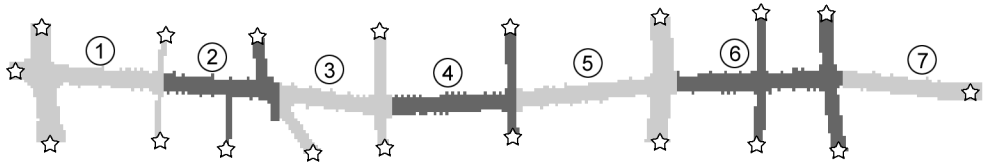
**Figure 6.11** Number of visits and duration in stores (ENR 07)

Figure 6.11-a shows that the simulated number of visits in stores reflect the general trend, however, with more dispersion compared with the WFS case. This is not very surprising since the shopping environment in ENR is more prosperous and complicated than the one in WFS, and pedestrians are more heterogeneous as ENR's stronger regional fame attracts diverse consumer groups from within the area. Moreover, the inability of the store patronage model to consider more specific decision factors such as store reputation, retail strategy, window display, and atmosphere could also be responsible (e.g., Sen, *et al.*, 2002; Teller and Reutterer, 2008). The overall observed number of visits is 655, while the simulated number of visits is 682, indicating overestimation of 4.1%. In Figure-b, most scatter points gather closer to the iso-value line except two points representing two large stores. The simulated overall in-store duration is 46,019 minutes, compared to the observation 44,083 minutes. The mean simulated duration is 67.5 minutes, which is very close to the observed 67.3 minutes.

### 6.2.3 Test 3 – ENR 2003

In August of 2003, a pedestrian survey was carried out in ENR. The survey methods and questions were similar to the WFS case. The interviewers, in two normal days from 13:00 – 20:00, invited respondents who were near the end of their shopping trips to participate. Respondents' shopping diaries were recorded, however, without rest behavior. The sample size is 809. The physical environment of the street in 2007 was not fundamentally different from the situation in 2003, except that two large department stores and a new metro line had been opened at the western end, and some other smaller scale retail redevelopments took place at other places along the street. To test the temporal transferability of the proposed approach, the models estimated from the ENR 07 data will be directly used to simulate agent behavior in the simulated





**Figure 6.12 Segments of ENR 03**

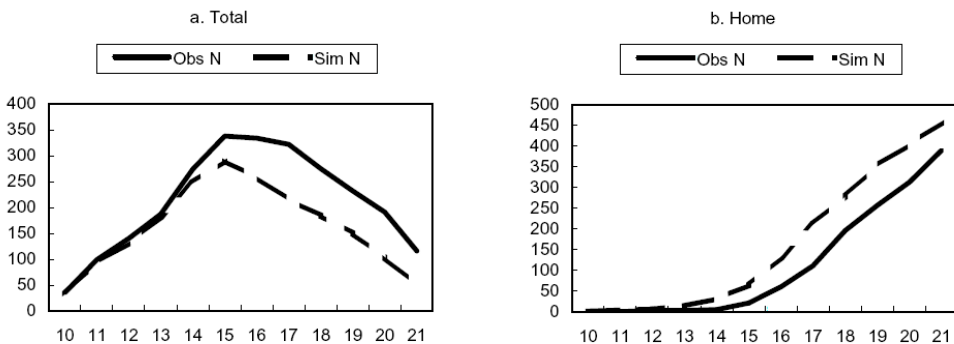
environment of ENR 03. The simulated aggregate behavior will be compared with observed data collected in 2003.

**6.2.3.1 Settings**

Because the stores in the branch streets were not taken into account in the 2003 survey, the simulated environment is simpler than the one for the ENR 07 case with 7 segments (Figure 6.12). Nineteen entries surrounding ENR were used as agents’ starting points. The entry distribution and starting time distribution were derived from the 2003 data. The simulation models were completely transferred from the 07 case. The number of agents to simulate is 508; the same as the number of the respondents with complete shopping diaries.

**6.2.3.2 Results**

The test was run in three rounds. The first round completely used the ENR 07 models to simulate the ENR 03 situation, except that the rest decision module was taken out. The result is not satisfactory. Figure 6.13 shows that after 15:00 the simulated total number of agents drops much faster and the number of agents having gone home accumulates much faster than the observations. The go-home model based on the 07 data generates go-home behavior too early, which in turn decreases the accuracy of all other distributions. Therefore, the HHM go-home model was estimated again, this time using the 03 data. This newly estimated model replaced the 07 go-home model in the second round. This modification solved the problem in the sense that the go-home data were much better predicted. However, another problem occurred in that the total



**Figure 6.13 Distributions of agents by activities over time using the ENR 07 models (ENR 03)**

number of store visits was heavily overestimated because the mean in-store duration is about 62 minutes in the 07 data, while it is about 81 minutes in the 03 data. This large difference is partially due to the difference between the two data collections. Recall that rest behavior was not recorded separately during the survey in the 03 data, but mixed with in-store duration. To avoid this bias, the duration model was re-estimated using the 03 data. The third round of tests was run with replacing the 07 duration model with the 03 version.

After these two rounds of corrections, the distributions of the simulated total number of the active agents and the gone-home agents fit the observations almost perfectly (Figure 6.14). Without the simulation of rest behavior, in-store activity accounts for over 90% of the activities, while walking behavior represents only a small proportion. The direction model and store patronage model were not modified. In Figure 6.15, the distributions of agents in segments display similar patterns as in the 07 case. The distributions of the two segments closest to the western end (Segments 1 and 2) are reproduced relatively well. The distributions in Segments 3 and 4, the two middle segments, are still underestimated, even more. Much stronger overestimation can be seen in Segments 5 – 7. These results suggest that pedestrians in the 03 case had stronger preferences for the stores in the pedestrianized section than the pedestrians in the 07 case. The store patronage model based on the 07 data fails to capture this trend. At the same time, the direction choice model could not have emphasized the 03 pedestrians' preference for the pedestrianized section enough.

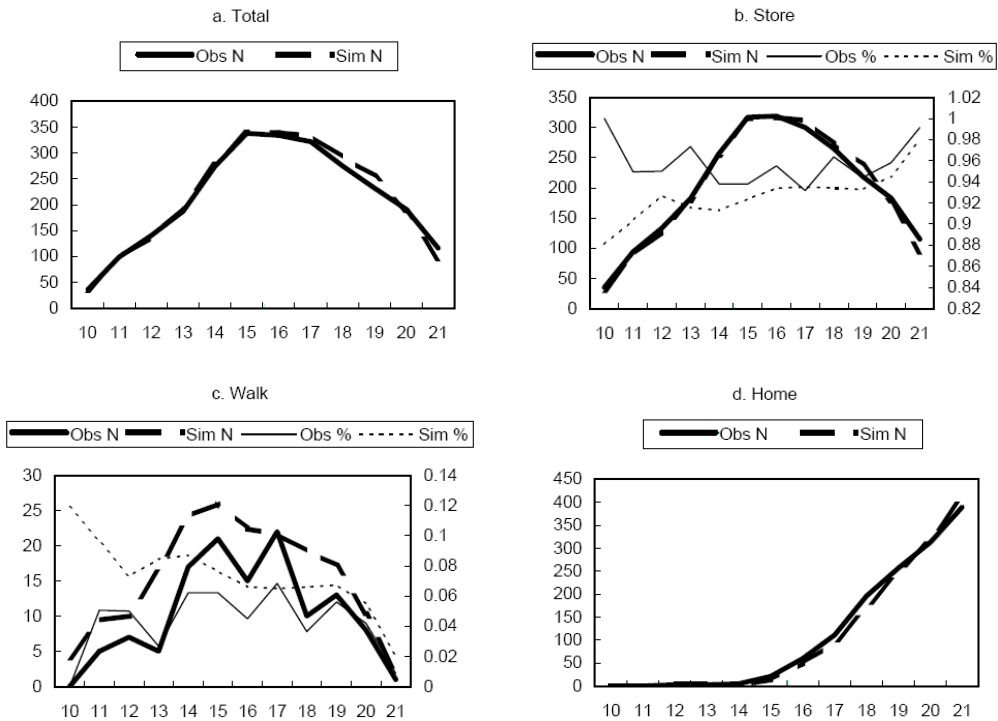


Figure 6.14 Distributions of agents by activities over time (ENR 03)

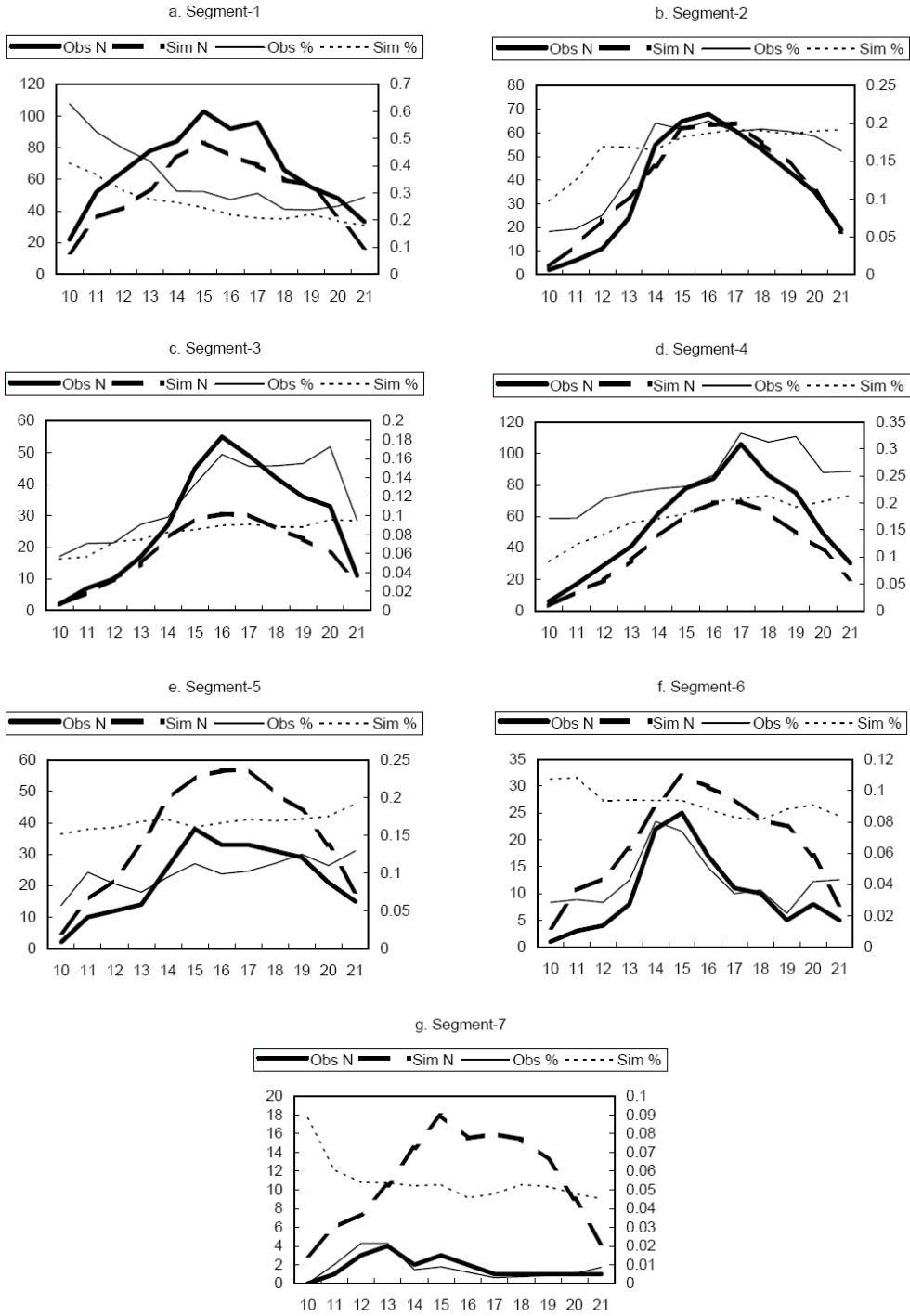
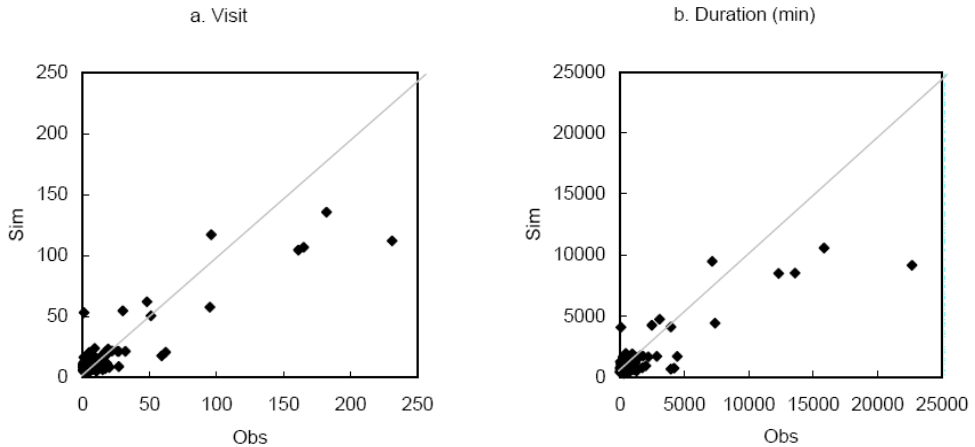


Figure 6.15 Distributions of agents in segments over time (ENR 03)



**Figure 6.16 Number of visits and duration in stores (ENR 03)**

The correction of the duration model leads to significant improvement (Figure 6.16). The simulated total number of store visits is 1,878, almost the same as the observed 1,877. The simulated aggregate overall in-store duration is 147,275 minutes, compared to the observed 151,245 minutes an underestimation of only 2.6%. The mean durations are 78 minutes in the simulation and 81 minutes in the observations.

Although the overall durations are well predicted, comparisons of individual stores do not show that good consistency. Both the number of visits of and total durations in large stores seem to be underestimated. Since the overall sums are very close to observations, it implies that activities in small stores are overestimated. This renders further proof of our conjecture that the direction choice model underestimated the attraction of the pedestrianized street and the store patronage model underemphasizes the larger stores most of which are located in the pedestrianized street.

### 6.3 Summary

This chapter first introduced the construction and operation of a multi-agent pedestrian simulation platform, which was specifically developed to incorporate the bounded rationality models that were estimated. The purpose of this multi-agent simulation, although this can be viewed as a model in its own right, was primarily to validate the *joint* predictive ability of these models, which were formulated and estimated independently as a first prototype. The validation is based on a comparison of aggregated simulated agent behavior and observed aggregated behavior in the original data. The comparison statistics include the number of agents conducting different activities over time, the number of agents in street segments over time, the number of agents visiting individual stores, and the total duration of activities that the agents conduct in individual stores.

Three tests were run for this purpose. The first and second test simulated the environment of WFS in 2004 and ENR in 2007. In general, the comparisons suggested

good predictive abilities of the heuristic models and the HHM models. In particular, the distributions of activities by type over time were reproduced very well. The models also performed very well for the go-home decision. The simulations of rest behavior were only slightly worse, while walking behavior seems to be the most difficult to predict accurately. However, there was reason to believe that these tests would not perform very well due to the larger random fluctuations in the small numbers of observations. The two tests showed consistent percentages of activities over time, suggesting the general characteristics of pedestrians' temporal behavior and also the stability of the survey method. The percentage of in-store activity decreases over time and the percentage of rest behavior increases over time. In-store activity is the dominant activity throughout the whole shopping trip with an average percentage about 80%. These trends were also captured well in both tests, except the changes were not sharp enough as the observations, largely due to the averaging effects of the model estimations. The averaging effects in the store patronage models and direction choice models caused more discrepancies in the comparisons of activity distributions in street segments, even though the general percentages of the activity numbers in segments were right. The simulations overestimated the activities in the stores along the non-pedestrianized sections and underestimated the activities in the stores along the pedestrianized sections. Again, distributions in segments with large number of activities were predicted better than those segments with a limited number of activities. Roughly, 50 should be the smallest number for an activity distribution to represent stable trends. The overall sums of the simulated number of visits and duration in individual stores, as well the average duration, were very close to observations. However, more specific factors have to be included in the store patronage model for higher predictive accuracy at the individual store level.

The third test was meant to validate the temporal transferability of the HHM models by simulating the ENR 03 situation using the ENR 07 models. The transferability turned out to be very limited as the simulation results deviated substantially from the observation on all statistics under the original models. One of the obvious reasons was that the interviewing protocols between the two data collection differed substantially on some questions. Once this was taken into account, results improved significantly. However, the results also suggest that pedestrian behavior changed as a result of the change in the retail environments around ENR during three years between the two surveys. Within ENR, new developments and redevelopments of small but special stores has intensified competition and reduced the dominance of magnet stores. Therefore, the store patronage model derived from the 07 data over-emphasized small stores. Outside ENR, retail developments in nearby areas may also have competed with ENR, implying that pedestrians stayed shorter in ENR to visit other shopping areas. Considering these complications, the transferability test cannot be conclusive.

However, after accounting for some effects, the transferability test did provide insight into the function of each model within the whole model system. The go-home model seems to be the most important model for predicting aggregate behavior on all aspects. If the model generates the go-home decision outcome too early or too late, significant under- or overestimation must happen in other activities as the pool size is

already wrong. Although not as influential as the go-home model, the duration model should be the second most important model to be studied carefully. This is because, on the one hand, based on the assumption of independence of each decision, every go-home decision has the probability to generate a positive outcome. On the other hand, as it is assumed that the go-home decision is made after each shopping or rest activity, activity duration is the factor directly influencing the frequency of the go-home decision. For example, if the duration is underestimated as in the first round of test 3, the frequency of the go-home decision will increase, causing the probability of going home to increase accordingly. Another apparent effect of the duration model is on the number of store visits, less duration, more visits, and vice versa.

Compared to the go-home and duration models, other models are not really effective in controlling the overall number of active agents and they do not even have to be very accurate in order to predict the proportions of activity types. The latter point is supported by the result that, in the third round, even though the store patronage model was not estimated to the 03 data, the distribution of in-store activity was still simulated well. This means, for this task, that the store patronage model or rest model only have to capture the general probability that the behavior of interest will occur, no matter where it occurs. However, for predicting spatial distributions, the store patronage model and direction choice model are fully responsible for allocating the “resources” in the pool to different places, and must be fitted well to the local conditions.



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*Chapter*

## **7 CONCLUSION AND DISCUSSION**

Understanding pedestrian decisions is an important task for urban and retail planning as planning decisions influence pedestrian behavior which in turn affects spatial usage, retail turnover, and the vitality of particular urban areas. Pedestrian decision research dominantly relies on rational choice models which typically assume that pedestrians are rational agents who have complete knowledge about the choice set, use all factors relevant to characterize the choice alternatives, aggregate their part-worth into an overall utility, and choose the alternative with the highest overall utility. A substantial amount of counterevidence has accumulated over the years to indicate that these assumptions are rarely satisfied in reality. In contrast, due to the fact that their cognitive capacity and computation ability are limited, people often use simplifying decision strategies which allow them to use information selectively, process information in non-compensatory manners, make choices with simple rules-of-thumb, and accept satisfactory alternatives which may not be optimal. This evidence and these conjectures are founded on the theory of bounded rationality.

Guided by the motivation to investigate pedestrian behavior using behaviorally more realistic modeling approaches, the aim of this thesis is to test the validity of models, incorporating principles of bounded rationality, to explain spatio-temporal pedestrian behavior in meso-level shopping environments. Under the proposed general framework for modeling spatio-temporal decisions, most emphasis was put on exploring, extending, estimating, and validating heuristic decision models. Comparing the estimation results of conventional rational choice models and bounded rationality models on real-world pedestrian shopping diary data suggested the promising theoretical and empirical potential of the latter for pedestrian modeling. To support this overall conclusion, we will complete this thesis by discussing the main findings of each chapter (which also serves as a summary), reflect on these findings and articulate some directions of future research.

### **7.1 Findings**

In the literature review (Chapter 2), we focused on the two realms of models that are directly related to our research project: models of pedestrian behavior and models of bounded rationality. Over the decades, models of pedestrian behavior have become increasingly more complex in terms of detail, content of pedestrian behavior, and the modeling techniques. Aggregate models have been replaced by various, multi-disciplinary individual-based models and techniques that allow much more detailed and flexible analyses of individual behavior and underlying mechanisms. Examples are discrete choice models, physics-analogous models, cognitive and psychological models, cellular automata models, and multi-agent systems. It should be noted that behavioral realism in these alternative approaches differs dramatically. In comparison, approaches of bounded rationality are much more diverse and concentrate around decision heuristics. Different compensatory or non-compensatory, alternative-based or attribute-based, singular or combined decision heuristics which more or less deviate



from rational choice principles, or are completely based on different principles, have been proposed and tested. More importantly, endeavors have been made to explain the choice of decision strategies, contingent upon personal and environmental characteristics involved in a decision. Although most research only revealed the general relationships between strategy use and influencing factors and very few operational formal models are available, they have opened a door which leads to much deeper understanding of human decision making.

Based on this review, it was argued that bounded rationality models have never been empirically tested in pedestrian research and that it will therefore be of value to make such an attempt. In this context, the heterogeneity of decision strategies, although being an old idea, is still an infant research topic. Hence, developing a formal model of this process may not only benefit the understanding of complex pedestrian behavior but also decision research at large. Moreover, the content of meso-level pedestrian research can be enriched by considering the influence of time on pedestrian behavior and decisions, which however was at most modeled as discrete stops. Multi-agent simulation can be a useful validation tool with the support from concrete calibration results against real-world data.

Consequently, based on these main findings of the literature review, we set out to explore the potential of developing and applying pedestrian models based on principles of bounded rationality in general. More specifically, one of the main goals is to examine how the idea of heterogeneous decision strategies can be incorporated in such a modeling approach. This also defines the major contributions of this thesis to the international state-of-the-art in modeling pedestrian behavior at the meso level. Some other minor contributions and relatively unique aspects of this study will be articulated later on.

Given this objective, Chapter 3 discussed the conceptual framework of this thesis for modeling pedestrian behavior. It started by proposing a modeling framework which consists of four inter-dependent decisions, namely the go-home, direction choice, rest, and store patronage decision, based on which, aggregate spatio-temporal pedestrian activities can largely be recovered. The go-home decision determines the duration of each pedestrian's shopping trip and affects the aggregate number of activities in the whole shopping area. The direction choice model determines the activity space of each pedestrian and in turn the aggregate activity levels in different parts of the shopping area. The rest decision determines the occurrence of rest taking behavior, which also takes space and time and obviously competes with shopping behavior. The store patronage decision determines which stores are visited by the pedestrian and is most relevant for retail development. This is followed by introducing the rationales of three model prototypes that are to be specified for each decision. The first prototype is the multinomial logit model. It is representative of rational choice models and serves as a benchmark in this study. The second prototype includes three typical decision heuristics: conjunctive rule, disjunctive rule, and lexicographic rule. Extensions were made based on the original logic of each rule by incorporating threshold heterogeneity and deriving probabilistic formulations. The third prototype, the heterogeneous heuristic model (HHM), is the major methodological contribution of this thesis. It models selective consideration of factors in decision making by

incorporating factor thresholds as filtering mechanism, and translation of these factors into limited discrete states. By attaching values to each factor state and weights to each factor and aggregating factor values into an overall value in an assumed linear combination manner, it constructs a mental representation of the decision problem by individuals. Checking the overall value against some overall threshold leads to a judgment. Although this is a semi-compensatory process, it was shown that under reasonable assumptions of a stochastic overall threshold, heterogeneous non-compensatory decision heuristics can be exactly identified through logical inference, including the three rules of the second prototype.

Based on this finding, the choice of heuristic was modeled, assuming that each individual has a repertoire of decision strategies and chooses the decision strategy probabilistically in proportion to the joint influence of mental effort, risk perception, and expected outcome. Finally, a latent class structure was used to estimate the choice outcome. With HHM, the diversity of decision processes can be explicitly studied by estimating the probability of each decision strategy with different sequence of information search, which is completely impossible for rational choice models and limited in separately specified heuristic models.

The data used for empirical model tests were introduced in Chapter 4. They include two pedestrian shopping dairy datasets collected in two shopping centers in China. We decided to use real-world behavioral data instead of experimental data mainly based on the consideration that there are still many aspects such as sense of time and fatigue that cannot be realistically replicated in virtual environments, but which, by no means, are negligible when modeling spatio-temporal behavior. The first dataset was collected in Wang Fujung Street, Beijing, in 2004 and the second dataset was collected in East Nanjing Road, Shanghai, in 2007. Questionnaire-based surveys were used to record pedestrians' socio-demographics and shopping dairies. In addition to this information, temporal information corresponding to each activity was estimated for modeling time related decisions using a grid-based estimation approach. Although the two cities are in different regions in China and pedestrians are somehow different in socio-demographics, their behaviors in general are similar in terms of the number of store visits, the number of rests, activity duration, the relationship between the entry distribution and public transport, the relationship between the activity distribution and store type and walking environment, which suggests underlying consistency of pedestrian behavior and validates the survey method to some extent.

In Chapter 5, the three prototype models were tailored to each four decision problems. The models were estimated against the two datasets in order to compare their statistical performances. The heuristic models were estimated against the WFS data and the HHMs were estimated against the ENR data. The MNL models were estimated against both datasets. It was found that, for the WFS case, all the MNL models were outperformed by the heuristic models in terms of log-likelihood (LL) and Consistent Akaike Information Criterion (CAIC). In particular, disjunctive models were never the optimal strategy for all the decisions, suggesting that pedestrians' decision standards are not low in general. Except that the go-home decision was best modeled by a conjunctive model, the other three decisions were all best modeled by lexicographic models. However, none of the lexicographic models were in the pure

lexicographic form, but rather a combination with other rules. Especially for the store patronage decision, the model implies a complex combination of conjunctive, disjunctive, lexicographic, and other unnamed rules. However, it should be noted that the goodness-of-fit statistics of some other non-optimal models (sometimes heuristics models and sometimes MNL models) was sometimes very close to that of the best fitting model.

The advantage of HHM to estimate such coexisting heuristics was further demonstrated by the model estimations for the ENR case. Although all the HHMs on the four decisions were the best in terms of LL, only the two for the direction choice decision and the store patronage decision were the best in terms of CAIC, and the go-home decision and the rest decision were best modeled by MNL. This was mainly caused by the small sample size for the go-home and rest decision and the extra parameters in the HHMs for modeling choice of strategies. Considering the latter reason along with the unresolved difficulty in comparing non-nested models, the statistical advantage of HHMs is still acceptable.

The estimated decision processes by the HHMs suggested some interesting implications. It was found that the preference structures underlying pedestrians' go-home, rest, and store patronage decisions (the three binary rejection/acceptation decisions) share some similar characteristics, with strict and simple decision strategies being preferred in general. However, extremely risky strategies are avoided, except the unconditional rejection strategy which is almost effortless. In contrast, pedestrians turned out to be risk-averse for the direction choice decision, which is a comparative decision. The probabilities of using mild decision standards (discriminant thresholds for differentiating two alternatives) appeared to be high as the implied heuristics tend to make the individual uncertain about the comparison at each stage of factor search, which therefore stimulates more information search. Heuristics with too small discriminant thresholds which lead to easy differentiation between alternatives and those with too large discriminant thresholds which lead to random choice were not preferred, except the effortless unconditional random choice strategy.

The sequences of factor search were also estimated. For the go-home and rest decision in which time factors are influential, absolute time is more frequently searched first than relative time, at least under mid and high level decision standards. For the direction choice decision, the length of the pedestrianized street and whether the direction is the same as the previous direction are more frequently searched first than retail floorspace and the location of landmark. For the store patronage decision, pedestrians seemed to care about store type most, followed by retail floorspace of that store and its dominance within the vicinity. These findings are direct indications of factor importance in each decision.

Although the influence of time on direction choice and store patronage decision was also investigated by incorporating time factors into the choice of strategies in order to test the change of strategy usage over time, temporal influence was tested to be insignificant, which is contradictory with the findings by Zhu, *et al.* (2006a) where an MNL with time variables was specified. The statistical explanation is that the heterogeneity in the data was well captured without time factors, since the

numbers of factor thresholds were not set a priori but estimated to the largest number that the CAIC allows.

Chapters 3 and 5 showed the theoretical and empirical advantages of the bounded rationality models. To validate the modeling framework and the bounded rationality models as a practically useful tool, Chapter 6 described the results of a multi-agent simulation, using NetLogo, for testing the predictive ability of the model system. The estimated models were incorporated into the platform to simulate agents' decisions and behaviors. The simulated individual behavior was aggregated into aggregate behavior in space and time and compared with observed behavior in order to evaluate the models. Three aspects of aggregate behavior were generated, the distribution of the different types of activities over time, the distribution of the activities in street segments over time, and the number of visits and duration in individual stores. Three tests were conducted. The first test tested the heuristic models on WFS data. The second test tested the HHMs on ENR data. The third test tested the temporal transferability of the HHMs on another data collected in ENR in 2003. Test 1 and 2 demonstrated that the distributions of activity types over time were very close to the observations, especially for those activities with a large number of observations like the total number of pedestrians, the number of in-store pedestrians, and the cumulative number of gone-home pedestrians. When the number of observations was low as for resting and walking behavior, more mismatches appeared as these observations are more susceptible to random fluctuations. The distributions of spatial activities over time were simulated less well, although still satisfactory in general. Similarly, the matches in segments where a large number of pedestrian activities were observed were better than those in segments with smaller numbers of observations. Different degrees of under- and overestimation were found mainly due to the averaging effects of the models. Such effects also affected the simulation of store visits. Numbers in large stores were underestimated, while numbers in small stores were overestimated. However, the simulated total number of store visits, the total amount of in-store duration, and the average in-store duration were very close to the observations.

Test 3 suggested limited transferability of the HHMs to the new data. However, many other aspects, besides the model itself, must be taken into account, such as potential biases caused by survey administration, changes in the shopping environment over the years, and changes in pedestrian behavior. Nevertheless, with some corrected simulations, the results did reflect the different functionalities of each decision model in the whole system. The go-home decision appeared to be the most important decision for predicting aggregate behaviors accurately, because it determines the pool of pedestrians at any time from which activities are generated. The duration model is also important since it determines the frequency of the go-home decision as assumed in the simulation framework. If only the number of activities is concerned, the rest and store patronage model does not have to be estimated very accurately as long as they may predict the average occurrence rate of these behaviors well. To this effect, the transferability of these models to a new environment should be satisfactory, as it has been shown in Chapter 4 that pedestrian behaviors are generally consistent on these aspects. But if the spatial activities should also be predicted well,

then the store patronage model and direction choice model must be carefully fitted to the local conditions.

## 7.2 Discussion

Pedestrian behavior is the result of complex interactions between individuals and the environment. From the standpoint of a pedestrian, such complexity is mainly due to the objective environment in the sense that he/she is constantly exposed to all kinds of information, large number of stores, advertisements, window displays, lights, sounds, and the behavior of other pedestrians. Moreover, pedestrians need to make a series of decisions under such circumstances. However, that does not necessary mean that such objective complexity is subjectively experienced by the pedestrian. Actually, we argue this will be rarely the case since we believe that most people will agree that shopping is among the most relaxed activities in life and is often experienced as “time out”. Then why is shopping still thought as more relaxed than many other decisions such as for example choosing a holiday destination, although it potentially involves tons of information? We conjecture it is logical to infer that most information must be ignored by pedestrians, that their actual decision making is probably very simple and requires limited involvement and information processing. This inference already qualitatively justifies the argued need to develop models of bounded rationality instead of rational decision models for pedestrian decision modeling. And fortunately, the model estimation and validation results in this thesis also gave quantitative support for this conjecture.

This is the first contribution of this thesis to the state-of-the-art in research on pedestrian behavior. Although comparing goodness-of-fit statistics of models is not sufficient as proof of the true underlying mechanisms, the results at least suggest that BR models are statistically as competitive as rational choice models, at least the MNL in this case, to predict pedestrian behavior. Whether this will open a new line of research and practice depends largely on the practical effectiveness of the policy measures that are developed from the results of BR models. In theory, BR models may suggest quite different policies from rational choice models. In terms of the evaluation of alternative, under the typical compensatory rule, rational choice models may suggest enhancing one factor as long as the improved utility may cover the disutility from other factors. In contrast, BR models may suggest that several factors must satisfy certain criteria in order to make the alternative acceptable to the consumer, and after reaching the criteria any enhancement may not be virtually effective at all. The continuous utility functions in conventional choice models suggest gradual changes in choice probabilities along with factor changes. In threshold-based mechanisms, however, choice probabilities will only change after factor shifts into another state. For example, to attract more pedestrians to visit a store, in theory, increasing the same amount of retail floorspace could help store patronage rate or be ineffective at all, depending on whether the additional floorspace can lead the status-quo into a higher state in individual’s mind. In terms of the choice from a choice set, rational choice models will not suggest any extra policy or marketing measure for guiding consumers’ search priority since the models assume each alternative will be evaluated anyhow. BR models, however, suggest that extra eye-catching measures could determine the

success or failure of an alternative since consumers' evaluation may not be complete and some alternatives may be ignored.

However, despite the theoretical and empirical advantage of BR models, the difficulty of operationalizing these models may be a large barrier deterring their application. The classic MNL model is mathematically succinct and has a regular objective function, which is easy to estimate using mature and widely available algorithms. BR models often have irregular objective functions which easily cause conventional algorithms to get trapped in local optima. Using more sophisticated global search algorithms no doubt cost much more computation and time and in principle cannot guarantee a global optimum. Solving such technical problems either by improving the formulation of BR models or the estimation algorithms is a fundamental prerequisite for the future of BR models in pedestrian research and practice.

The second contribution of this thesis is the heterogeneous heuristic model which, we argue, will not only contribute to the pedestrian behavior research but also to decision research at large. Although we also proposed some new specifications for the conventional heuristic models, these are relatively minor contributions compared to the more theoretically general HHM. The contribution can be understood in two ways. First, it is shown that some common decision heuristics can be *exactly* inferred from a single model. It is assumed that the heuristics are inferred by the individual from the preference structures under the stochastic overall threshold. A decision rule is formalized when the individual logically goes through the preference structure and checks whether the information gathered at each stage of factor search may lead to a definitive decision outcome under some factor search sequence. Although a complete cognitive structure (preference tree) may include many factors and factor states, only parts of these may be actually used under the certain overall threshold. Therefore, the model automatically leads to heterogeneous decision heuristics.

Incorporating heterogeneity in rational choice models has been suggested, as for instance exemplified by the mixed logit model (e.g., Hensher and Green, 2003) which represents decision heterogeneity by assuming that parameters are random distributions. However, in fact, these model are based on the assumption that the nature of the decision making process represented by the functional form is invariant across individuals; only the relative weights of the attributes differs. In HHM, the decision making process in itself can also differ between individuals. Although the approach currently cannot embody many other decision heuristics such as frequency of good/bad features rule (Alba and Marmorstein, 1987) and the majority of confirming dimensions rule (Russo and Doshier, 1983), it provides a potential systematic, semi-unified framework which explains the origin of heuristics and can be used for proposing new heuristics.

It must be noted that components of HHM have been suggested and examined in other contexts before. Threshold effect has long been discovered and incorporated in decision models, although most of the time only a single threshold is specified for each factor. We elaborated and generalized this notion by allowing multiple thresholds, which enables more graded mental states. This is similar to multiple activation thresholds in artificial neural network models (ANN). In this sense, HHM possesses

some properties similar to data mining tools. However, the basic model form is still largely bounded by the theoretical assumptions rather than highly nested and layered value functions in ANN which sometimes are just used as concept-free equations to generate accurate predictions. A linear combination function is assumed for aggregating the weighted factor values, which may be viewed as a discrepancy with the main theme of the thesis. Choosing such formalism does not mean that we consider it as a way of representing a decision *process* (which is the subject of heuristics) but a cognitive (value) *structure* that has been established for some time and serves as the reference for inferring decision heuristics. Actually only the relative relationships, be it compensatory or non-compensatory, between the factor state values matter. Therefore, using linear combination is largely a mathematical convenience. Other forms of representations such as multiplication value functions can serve the same purpose. Having said that, as an alternative, a process-oriented modeling approach can be examined in future research.

The second aspect of HHM's contribution is that we provided an operational framework to explain the distribution of heterogeneous heuristics as the outcome of a choice process. Although theories which state that people select a decision strategy contingent upon factors such as implementation effort, decision accuracy, personal characteristics, and decision context have been proposed before (e.g., Beach and Mitchell, 1978; Payne, 1976, 1982) and general relationships between these influencing factors and the usage of decision strategy have been verified, very few formal models that may at least reproduce the choice outcomes are available (e.g., Swait and Adamowicz, 2001). The diversity of decision heuristics is the major cause of this problem. Because the decision heuristics were proposed sporadically from observations rather than systematically derived from a bundle of theorems, it becomes much more difficult to find some common rationales that are shared by the heuristics, based on which an integrated framework can be established and operated. The lack-of-backbone problem really hits BR modeling at this point. Since the inference mechanism in HHM provides a potential backbone for identifying heterogeneous heuristics from preference structures, it naturally provides a platform for systematically studying the problem of heuristic choice.

We assumed that the distribution of the usage of heuristics can be modeled by a multinomial logit model. It should be noted however that the choice of the MNL model does not imply that we implicitly and certainly not explicitly explain the choice process based on random utility theory. Similar to other choice models, we do assume that individuals demonstrate probabilistic choice behavior, proportional to the value of the heuristic, jointly composed of effect of mental effort, risk perception and expected outcome. This proportionality is depicted by the MNL specification for convenience and robustness.

According to the information processing flow implied in a heuristic, the definition of mental effort is more systematic and consistent than some existing measures such as EIP (e.g., Bettman, *et al.*, 1998). And more valuable, it can be empirically estimated and tested, even though it may just be an indirect estimate of the true mental effort. However, the definition concentrates on the effort inflicted during factor search and ignores the mental operations which are the major concern of EIP.

Although it may not be complete, we believe that information search behavior usually costs significantly more effort (due to engagement, attention, and using auxiliary equipments), than mental operations which manipulate the collected information in the brain, only costing little electronic-chemical neural activities. The definition of risk perception can achieve a similar effect as decision accuracy, as low-risk strategies imply extensive information search and therefore guarantee accuracy, and vice versa, although the formalization using information entropy may be disputable. As for expected outcome, which is usually not considered under the conventional effort-accuracy framework, it was also tested to be influential in strategy choice. This is not surprising because except the general influence from effort and accuracy, the context of a decision is often more important. Although the expected outcome, which represents an individual's value bias and inclination for decision goals in general, may just be an element of the decision context, more elements can be incorporated in this modeling framework, such as time pressure, involvement, and socio-demographics. However, our definitions and specifications of these three elements may just be alternatives among other candidate representations. It can also be seen that the specifications inherits a lot of notions of expected utility. Whether these or other simpler definitions are more appropriate for representing decision maker's real evaluations of these elements, can be a topic of future research.

Thus, our two-level two-stage decision modeling framework provides a powerful structure which allows testing many interesting elements, which are not realizable through most existing decision models: (1) individual's cognitive structure; (2) heterogeneous decision heuristics; (3) influences of endogenous and contextual factors on the usage of heuristics. The estimation of these elements may have profound practical implications. Since the rational choice models do not provide insights into information search, they give no suggestions on how information should be provided as long as it is provided. In contrast, knowing the individuals' decision processes, the preferences for information search, and the relationships between strategy usage and explanatory factors, practitioners may utilize this as reference for providing information in a way that is more accessible and acceptable by individuals or even may guide the usage of strategies and pattern of information search, which may in turn benefit the intended policy target. According to some strategies, not all information needs to be provided, which may save operation costs. It also provides a better basis for developing customization policies in which different customers are provided with different sets of information, information quality, and information priority.

The third contribution of the thesis is that it is the first time that the role of real time is reflected in a formal modeling of the meso-level pedestrian behavior. It was shown that by only including two time-related decisions, go-home and rest decision, the model system can already predict the aggregate spatio-temporal activity distributions quite well. Compared to the existing stop-based time representation, the proposed approach is closer to pedestrian behavior and more meaningful for practice. Urban planners and retailers may know during what time period, how many pedestrians will be in certain public space, using certain rest facilities, and visiting certain stores; therefore they may develop plans and allocate resources more



effectively by taking the advantage of the spatio-temporal usage patterns. We also provided time estimation procedures based on spatial information and respondent's estimation, which are simple to administrate and robust for reflecting the general time use pattern. However, this must have caused more or less errors in the data and reduce the credibility of the empirical results. More advanced survey methods, such as GPS or RFID, are required for obtaining accurate time information.

Although the empirical results of the case studies suggested interesting and reasonable behavioral characteristics and practical implications, considering this is the first time that models of bounded rationality are applied to meso-level pedestrian behavior modeling and only two cases in one corner of the world were studied, we are not going to conclude that the empirical findings obtained in these studies represent general rules of pedestrian behavior. Rather, we prefer qualifying these findings as tentative modeling results, shedding some light on further research endeavors.

At a more detailed level, we should also emphasize that we often made simplifying *operational* definitions and assumptions for ease of computation and to set a benchmark. Examples are the independent judgment of thresholds, the assumed independence of decisions in the full visit to the street and the corresponding formulation of the log likelihood function. Variations on these decisions, which would make the models more complex and difficult to estimate, could be examined.

### 7.3 Future Directions

The thesis is no exception and in itself also a product of bounded rationality. Limitations of time, knowledge, computation ability and data availability were instrumental in proposing an approach to modeling bounded rational pedestrian behavior that should improve behavioral realism, while at the same time should produce results that are at least competitive to those of commonly used approaches. The decision was to focus first on principles with a limited number of explanatory variables as these can be easily included in further research without the need of changing the basic, underlying principles. Although we argue that we have established some degree of success, much more is still waiting to be explored, studied, and integrated. It should also be emphasized that we used the MNL model with a limited number of explanatory variables as a benchmark. More complex specifications, still consistent with the random utility theory could be chosen as a comparison. In addition, even within the MNL framework, interactions and other principles to cope with observed problems could have been applied. It is even possible, as argued in the literature review, to use multiplicative specifications, apply the usual principles of random utility theory, and arrive at model specifications that very closely approximate the models that we developed in this thesis. Thus, from a mathematical and model specification perspective, the difference between rational choice models and models of bounded rationality is smaller than often debated. However, there will always remain differences in overall framework and the key concepts that are assumed to be captured by the mathematical expressions. If one relies on empirical observations only, interpretations in terms of decision strategy by definition are limited.

As for the further development and application of HHM, the following paths may be interesting to explore. First, context factors and socio-demographics can be

easily incorporated into the model of strategy choice so that their influence on the distributions of strategy usage can be tested. For example, the effect of gender can be included in the relevant function such that the parameters for mental effort, risk perception, and expected outcome will reflect taste variations due to gender. Then, it will be possible to develop group-specific measures according to respective preferences on decision strategies.

Second, although heterogeneous decision heuristics can be inferred from the cognitive structure, for the ease of operation, the model still assumes that each respondent's cognitive structure is the same, which however may not be true. A more realistic improvement could assume that people have different cognitive structures and therefore different repertoires of decision strategies. For example, individual A's cognitive structure may just be part of a more complex structure of individual B. Then it is possible that even though the involved factor states are the same for a decision, the inferred lexicographic heuristic for individual B could be a conjunctive heuristic for individual A. Such consideration may result in a quite complicated model specification.

Third, the model can be extended to other decision problems than the binary rejection/acceptation decision and comparative decision. It will be relatively straightforward to use the model for categorization problems in which an object is designated into a category usually by judging whether it possesses some properties (e.g., factor states). The optimization of property search sequence also applies as the processing of an important property earlier may obliterate the need for searching for minor properties. A similar extension may apply to the formation and evolution of concepts, which can be understood as a wrap of elements, properties, and relations. It will also be interesting to extend the elicitation of factor search sequence to decision sequences. People sometimes make a series of decisions for satisficing some general goal, such as to go shopping at a near shopping street by foot or at a far away shopping center by car. There may be several combinations of sub decision outcomes that lead to a similar degree of satisfaction in light of the general goal. Through repetition, people may develop an optimized decision sequence that costs least information search effort, like forming a habit.

Finally, but above all, the approach must be validated against real human decision processes. That means that the actual processes, information representation and search must be observed first in order to compare them with the processes estimated by the model, which is never an easy task. Indirect methods may be easier to implement but with less reliability. For example, the processes may be obtained from protocol analysis, which has been found to be accurate for justifying qualitative aspects like using or not using some factors or thresholds when these factors require conscious cognition, but very inaccurate for identifying usage and quantitative threshold values when the decision involves unconscious and automatic information processing (e.g., Weitz and Wright, 1979). Computer-based process tracking can be useful. Experiments are often implemented by tracking click behaviors of the user when they use the mouse to open some closed information tags containing factor values. The major disadvantage is that by breaking the information about an object down into pieces, some sense of realism is lost because actual information is often

holistically available and people do not engage searching information consciously. To replicate the experiment environment with good realism and reduce the bias caused by measurement equipments, techniques like eye-fixing may be used for capturing focusing behavior and infer decision processes, if it can be assumed that these concepts are strongly related, which needs evidence in its own right. The imperfection is that focus does not necessarily mean that only the focal information is processed. Much other information in the non-focal visual area may also be processed but maybe with little accuracy and effort if the information is quite salient. Direct measurements into the neural activities in the human brain such as through MRI have the potential to be reliable indications for information processing. However, as brain activities are so complex and intertwined, how to separate the activities of interest with other noisy activities and linking these activities with mental processes constitutes enormous technological and theoretical challenges. Some combination of these measurement techniques overcoming the cons and utilizing the pros of each may be valuable for validation. However, as discussed earlier, it is an open question whether this increased amount of detail is required to better predict the impact of urban planning scenarios, as long we have found a robust way of capturing the basic principles underlying pedestrian behavior in different environments.

Because our main objective of this thesis is to test the validity of BR models in pedestrian research and minor effort was made to develop a full-fledge framework for modeling meso-level pedestrian behavior, this still leaves many opportunities for enhancing the four-decision framework. First, the interdependencies between decisions have not been modeled. The go-home decision may not only depend on time factors, but also on the attractiveness of the environment. Pedestrians may suppress the influence of time pressure with a positive impact of an interesting street or store nearby. Considering interesting directions may be part of the go-home decision process and serves as the screening phase for direction choice later. The continuous unsatisfactory judgments on stores, when accumulated to some extent, may also stimulate the go-home decision. The shopping duration in the street may also be linked to the larger area where the street is located. The development of other attractive places within the area may compete with the street. As a result, pedestrians may lessen the trip duration in the street.

Second, replacing the simultaneous store choice framework with a sequential satisficing framework avoided the still unsolved, or at least not very convincingly solved, choice set problem in the store patronage model. However, it may have led to another arbitrary extreme which assumes that only one store is evaluated each time. If a pedestrian is faced with two adjacent, identical stores, both meeting all satisfaction thresholds, our model predict that the closest one will be invariably chosen, which may not be very realistic. The decision to use this conceptualization was that it would serve as a benchmark. It may be possible that pedestrian use a bound of spatial indifference. A more general model which estimates such a bound, the size of choice set and its distribution, may increase the realism of the store patronage model.

Third, the temporal effects on the choice of decision strategies were tested to be insignificant, which is counter-intuitive. Nevertheless, whether this is prevalent requires more tests on more cases.

Fourth, for the simplicity of the study, we did not include many other explanatory variables in the models which may also be useful for urban and retailing planning, such as width of street, density of stores, window displays, price levels, and level of service. It will be interesting to test their influences under the BR models and compare different implications with the results under the rational choice models.

Fifth, our modeling of the spatial decisions still largely follows traditional treatments, selecting some explanatory factors based on past experiences or intuition, obtaining their physical measurements as factor values, and directly linking these values with some mapping mechanisms. Pedestrian's perceived factors and values were not included. Making this step explicit may improve the model.

Sixth, the survey methods need to be diversified in order to obtain detailed behavioral and contextual information if more ambitious researched goals are expected. Questionnaire-based survey methods, although not very accurate in recording all the activities that are conducted by the pedestrian, still suffice for reflecting and studying general sample characteristics, movement patterns, the occurrence and content of different types of activities, and choice preferences, and most of all, can guarantee a large sample size for a relatively small budget. To get higher-quality individual shopping diary data, techniques such as manual, cell-phone, and GPS tracking may be applied. However, for a fixed budget, the resulting sample size may be too small. Moreover, there may be ethical issues and the data collection may need cooperation of respondents which in turn may introduce sample biases. Nevertheless, these technologies can be valuable as a complementary survey method.

Finally, with the help of more detailed survey methods, it is possible to study pedestrian's learning behavior and the adaptation of decision strategy. In this thesis, pedestrians were assumed to be homogeneous agents in terms of their degree of knowledge about the shopping environment and use decision strategies from the same repertoire of strategies all the time. All these assumptions can be challenged and the proposed model could and perhaps should be elaborated along each of these lines. Pedestrians have different knowledge levels (e.g., cognitive structures, beliefs), may use different decision strategies and may change the usage as they learn. For example, strangers in a shopping street may ponder much for visiting a store in the beginning of the shopping trip as they know little about the place and their cognitive structure is yet to be established or modified based on some old structure. That may take several rounds of trial-and-error. After they have visited the street more often, their cognitive structure will become more or less stable, implying their decision will be quick and easy. In contrast, local pedestrians with good knowledge who know where the shops are, may apply completely different decision heuristics such as visit the store that was visited last time and probably optimize visit sequence. Their behavior tends to be more routinized as opposed to the explorative behavior of strangers. Studying such dynamics and heterogeneity is an interesting topic of pedestrian behavior research, but also complicated and require more subtle input information.



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## SUBJECT INDEX

### A

absolute time, 84-85, 98, 110, 112, 116, 118, 128, 134-135, 150  
 action time, 98-99, 116  
 activity, 2, 4-5, 7, 10, 16, 18-19, 21-22, 24, 39, 42-43, 65, 67-72, 74-75, 77, 79, 81-82, 84, 92, 95, 98, 101, 104, 109, 114, 117, 123-125, 128-137, 140-141, 143-145, 148-149, 151-152, 155, 158-159  
 activity chain, 69  
 agent, 2, 6, 10, 24-27, 123-125, 128-143, 145, 147-148, 151, 159  
 aggregate behavior, 2, 5, 123-125, 140, 144, 151  
 aggregate model, 11, 13  
 algorithm, 24, 26, 71, 77, 88  
 attribute, 3-4, 14-16, 18, 28-33, 37-38, 41, 44, 46, 49-50, 52, 94, 96, 147, 153

### B

behavior characteristic, 156  
 belief, 30, 34, 110  
 bounded rationality, 3-5, 10, 24, 32, 38, 41, 44, 49, 52, 58, 66, 83, 103, 109, 123, 143, 147-148, 151-152, 154, 156

### C

calibration, 20, 40, 148  
 cell, 20-21, 25-26, 71, 123, 124, 159  
 choice alternative, 3-4, 10, 13-15, 17, 19, 28-34, 36-39, 41-50, 53-60, 62-65, 83, 85, 92, 94-96, 98, 102-104, 106, 109, 113-114, 119, 125, 135, 147, 150, 152, 154-155  
 choice behavior, 4, 6, 9-10, 13, 15, 17, 25, 31, 33, 35, 38, 43, 154  
 choice probability, 6, 17, 31, 33, 37, 45, 47, 50, 64, 88, 93, 114, 152  
 comparison, 7, 17, 28-29, 34, 36, 44, 46, 48-49, 62-65, 84, 94-96, 114, 122, 133, 143, 147, 150, 156  
 compensatoriness, 3, 28-29, 31-32, 35-36, 41, 49, 85, 89, 147, 149, 152, 154  
 computation ability, 4, 24, 147, 156  
 conjecture, 4, 132, 143, 147, 152

conjunctive heuristic, 6, 29, 32, 35, 41, 45-47, 49, 55, 66, 84-87, 91-95, 98, 101, 104-106, 108-109, 122, 130, 148-149, 157

Consistent Akaike Information Criterion, 89-91, 96-97, 100-101, 107-108, 112-115, 117, 119-122, 130, 149-151

### D

data, 4, 6, 13, 16, 19, 21, 25, 27, 31, 35, 38-40, 50, 66-68, 76, 82-83, 86, 90-92, 97, 99-100, 106, 111, 122-123, 125, 139-141, 143-145, 147-151, 154, 156, 159

decision, 1-6, 10-11, 13, 16-19, 21, 23-29, 31-32, 34-62, 64-67, 75, 83, 85-88, 91-94, 96-99, 101-106, 109-111, 113, 115-116, 118-119, 121-125, 128-130, 135, 139, 145, 147-159

decision heterogeneity, 5-7, 10, 14, 21, 27, 32-33, 35, 42, 45, 47, 49-51, 55, 64, 66, 68, 75, 83, 85, 110, 111, 122, 139, 148, 150, 153-155, 157, 159

decision heuristic, 4-6, 11, 18, 22, 24, 27, 31, 34-35, 37, 41, 44-45, 48-51, 55-59, 61, 63, 65-67, 83-84, 88, 95, 101, 110-115, 117, 121-123, 130, 135, 144, 147-151, 153-155, 157, 159

decision process, 3-4, 10, 17, 21, 28, 32, 34-35, 38, 41, 44, 46, 48-49, 55-57, 60, 83, 87, 91, 93-94, 96, 98, 101, 109, 115, 149, 150, 154-155, 157-158

decision strategy, 5-6, 10, 26-28, 31, 34-36, 39, 42, 49, 60, 66, 92, 96, 110, 112, 121, 147-150, 154, 156-159

direction choice decision, 44, 92-93, 96, 114, 122, 125, 128, 150

discrete choice model, 3, 5-6, 9, 14, 19, 25, 32, 34, 62, 147

disjunctive heuristic, 6, 29, 35, 41, 45, 47, 49, 56, 66, 84, 86-87, 91-92, 94-95, 99, 101, 105-106, 108, 122, 148-149

distribution, 2, 6-7, 9, 11, 13, 15-17, 19, 23-25, 32-33, 39, 42-43, 45-46, 48, 58, 60, 65-66, 69, 72-75, 77-83, 85-88, 91, 93-95, 98-99, 101, 104-106, 109-111,

---

113-117, 122, 125, 129-137, 140-141, 144-145, 149, 151, 153-155, 157-158  
duration, 25, 71-75, 77, 79-82, 101, 124, 128-130, 133-135, 139, 141, 143-145, 148-149, 151, 158

## E

East Nanjing Road, 6-7, 67, 75-76, 78-83, 109, 112-113, 115, 117, 119-123, 134-144, 149-151  
expectation, 6, 18-19, 26, 28, 33-34, 37, 39, 47, 50, 58-66, 68, 70, 75, 77, 92, 111, 114, 149, 154-155, 157, 159  
expected outcome, 6, 50, 59, 61-62, 65-66, 111, 114, 149, 154-155, 157

## F

factor, 1, 3-5, 15, 17-18, 20, 24, 28, 33, 36, 38-39, 42-57, 59-61, 63-66, 68, 83, 85-88, 91-96, 98-99, 101-102, 104-107, 109-111, 113-120, 122, 125, 130, 133, 135, 139, 144-145, 147-148, 150, 152-159  
factor state, 53, 55-56, 60-61, 65, 110-111, 122, 149, 153-154, 157  
floorspace, 12-13, 17, 69, 77, 92-93, 95-96, 102, 104, 106, 109, 114, 116, 118-120, 125, 134-135, 150, 152

## G

genetic algorithm, 18, 27, 88  
go-home decision, 42, 44, 83-85, 87, 91-93, 98, 110, 117, 128, 131, 144, 148-151, 158  
goodness-of-fit, 6, 15, 32, 34-35, 89, 92, 95, 101, 109-111, 114, 122, 150, 152  
gravity model, 11-15, 17, 25  
grid-space, 20, 70-71, 124-125, 129

## H

heterogeneity, 5-7, 10, 14, 21, 27, 32-33, 35, 42, 45, 47, 49-51, 55, 64, 66, 68, 75, 83, 85, 110-111, 122, 139, 148, 150, 153-155, 157, 159  
heterogeneous heuristic model, 6-7, 50, 66, 83, 88, 109-117, 119, 121-123, 135, 140, 144, 148-150, 153-154, 156

## I

independence, 12, 15, 18, 39, 45, 88, 123, 130, 145-156  
inference, 17, 29, 31, 35, 51, 56, 82, 110, 149, 152-154, 157  
information, 1-2, 4, 21, 26, 28-31, 34-35, 37-39, 41, 45-47, 49-50, 52, 55, 57, 59-61, 63-64, 66-68, 70-71, 77-78, 82-83, 87, 91, 97, 102, 115, 119, 122, 124-125, 128, 147, 149-150, 152-157, 159  
information processing, 28-29, 34, 38-39, 41, 50, 152, 154, 157  
information search, 29, 34-35, 37-38, 45-47, 49-50, 57, 61, 63-64, 87, 91, 115, 120, 122, 149-150, 155, 157  
inter-dependence, 2, 48, 148

## J

judgment, 30, 31, 33, 35, 44-46, 48, 51-55, 59-62, 64, 87-88, 91, 93, 95-96, 103-107, 109, 112-113, 122, 130, 149, 156-158

## L

latent class, 37, 50, 66, 111, 149  
learning, 26, 41, 52, 159  
lexicographic heuristic, 6, 30, 41, 45-49, 56-57, 63, 66, 84, 87-88, 91, 94-96, 99-101, 105-107, 109, 120, 122, 133, 148-149, 157  
Log-likelihood, 88, 90-91, 95-97, 100-101, 106-108, 112-117, 119-122, 130, 135, 149-150

## M

maximizing, 3, 18, 28, 34, 36, 66, 93  
mental effort, 6, 50, 59-60, 65-66, 97, 110-111, 114, 122, 149, 154, 157  
meso level, 2, 6, 18, 25, 38, 147-148, 155-156, 158  
mixed logit model, 153  
model comparison, 47, 122  
model estimation, 30, 66, 82, 87, 91, 95, 100, 114, 119, 122, 125, 135, 144, 147, 150, 152  
model selection, 89, 111, 119, 122  
multi-agent modeling, 6, 10, 24, 39-40, 123, 127, 143, 147, 151  
multinomial logit model, 6, 10, 14-19, 31-35, 38-39, 41, 43, 65-66, 83-85, 88, 90-

91, 93-96, 98, 100, 103-104, 106-107,  
110-122, 148-150, 152-154, 156

**N**

nested logit model, 15-17, 19  
NetLogo, 6, 27, 123, 151  
non-compensatoriness, 4, 28, 31, 35, 41,  
44, 49, 147, 149, 154

**O**

observation, 13, 15, 17, 19-20, 23, 27-28,  
33, 35, 40, 88, 92, 129-134, 136, 139-  
141, 143-144, 151, 154, 156  
optimization, 3, 18, 27, 30, 37, 41, 47, 88-  
89, 91, 96, 109, 111, 122, 147, 149, 157  
overestimation, 131, 133-134, 137, 139,  
141, 144, 151

**P**

parameter, 11-12, 14, 17-18, 20-21, 32-33,  
39-40, 43, 49, 53, 62, 84-95, 98, 100,  
102, 104-107, 110-114, 116, 118-119,  
122, 124, 134-135, 150, 153, 157  
pedestrian, 1-6, 9-14, 17-25, 27, 38-39, 41-  
44, 65-72, 75-79, 81-88, 91-94, 96-99,  
101-106, 109-111, 113-119, 121-125,  
128-130, 133-135, 137, 139, 141, 143-  
144, 147-153, 155-156, 158-159  
pedestrian behavior, 1-6, 9-13, 17-18, 22-  
25, 38-39, 41, 43, 65-67, 75, 82-83,  
121-123, 129, 144, 147-149, 151-153,  
155-156, 158-159  
pedestrian street, 68-69, 71, 75-77, 82, 92-  
93, 95-96, 114-115, 129, 133-134, 137,  
141, 143-144, 150  
prediction, 9-11, 15-16, 32, 37, 122, 128,  
130, 140, 143-144, 151, 154  
preference, 4, 14-15, 20, 23-24, 36-37, 41,  
51-62, 64, 66, 71, 111-113, 115-118,  
120-122, 125, 135, 141, 150, 153-155,  
157, 159  
preference structure, 51, 54-59, 61-62, 64,  
66, 111-113, 115-118, 120-122, 125,  
135, 150, 153-154  
probability, 13, 15-17, 21, 25, 32-33, 37,  
44-48, 50, 58-62, 65, 85-88, 91, 93-95,  
97, 99, 101, 103-107, 109-113, 115, 117,  
120, 125, 133, 135, 137, 145, 149-150,  
152

**Q**

questionnaire, 67, 69, 77, 82

**R**

random utility theory, 3, 4, 6, 9-10, 14,  
154, 156  
rational choice model, 3-4, 11, 34, 38, 41,  
44, 50, 66, 83, 147-149, 152-153, 155-  
156, 159  
rationality, 3-6, 10, 14, 27-28, 30, 32, 34,  
36, 38, 41, 44, 50, 66, 83, 115, 121, 123,  
147-149, 151-153, 155-156, 159  
relative time, 84, 110, 112, 116, 118, 134,  
150  
repertoire, 36-37, 51, 58, 149, 157, 159  
representation, 18-20, 24-26, 32, 50, 52-54,  
66-67, 123, 149, 154-155, 157  
rest decision, 44-45, 97-99, 105, 116, 118,  
120, 122, 128, 140, 148, 150, 155  
retailing, 1, 2, 5, 9, 12-13, 16-18, 25, 39,  
43, 68-69, 75-76, 92, 95, 103-104, 109,  
114, 118, 123, 129, 134, 139, 144, 147-  
148, 150, 152, 159  
risk, 6, 38, 50, 59-62, 65-66, 110-112,  
114-115, 117, 120, 122, 135, 149-150,  
154-155, 157  
risk perception, 50, 59, 61-62, 65-66, 111,  
114-115, 117, 149, 154-155, 157  
rule-of-thumb, 147, 183

**S**

satisfaction, 3, 11, 29, 31, 33, 40, 44-46,  
48, 56, 58, 60-62, 86-87, 91, 93-95, 97,  
99, 102-107, 109, 114, 120, 128, 140,  
147, 151, 157-158  
satisficing, 3-4, 44, 48, 87, 93-94, 103, 122,  
157, 158  
selection, 6, 30-31, 37-38, 41-42, 47, 49-  
50, 59, 61, 65, 69, 75, 84, 89-90, 114,  
130, 135  
sequence, 13, 17-18, 25, 29-30, 34-35, 37,  
45-50, 52, 59-61, 63, 65, 68, 75, 87, 91,  
94-96, 99, 103, 105, 107, 109, 113, 115,  
122, 130, 149-150, 153, 157-159  
shopping, 2, 4-6, 9, 11-18, 23-25, 31, 35,  
41-44, 67-69, 71-72, 75-77, 79, 82-85,  
87-88, 91-92, 96, 98-99, 101-103, 110-  
112, 123-125, 128-130, 133-135, 137,  
139-140, 144-145, 147-149, 151-152,  
157-159

---

shopping behavior, 12-13, 67, 71, 123, 148  
shopping diary, 13, 68, 82, 130, 139-140,  
147, 159  
simulation, 6, 10, 12-13, 17-18, 20-21, 23-  
24, 26-27, 33, 37, 40, 123-125, 127-133,  
135-137, 139-141, 143-145, 148, 151  
social force model, 10, 19, 20, 26  
socio-demographics, 14, 32, 67-68, 78,  
149, 155-156  
space, 1, 5-7, 9, 11-13, 15-17, 19-23, 25-  
27, 39, 42-44, 60, 65, 67, 69-71, 75, 77,  
83, 102, 106, 122-125, 129, 145, 147-  
149, 151, 155, 158-159  
space syntax, 22-23  
spatial behavior, 12, 23  
store patronage decision, 6, 43-44, 102-  
103, 106, 118, 148, 150  
store type, 104, 106-107, 109, 118-119,  
124-125, 149-150

## T

threshold, 6, 24, 29-30, 32-34, 37, 44-50,  
52-58, 60, 62-63, 65-66, 85-87, 89, 91-  
95, 97-99, 101, 104-106, 109-112, 114,  
117, 119, 122, 125, 130, 132, 135, 148,  
150-153, 156-158  
time, 2, 4-7, 9, 11-13, 17-18, 20-21, 25-29,  
36, 38-43, 50, 52, 62, 65, 67-72, 75, 77-  
79, 82-85, 89, 91-92, 98-103, 110-111,  
113, 115-118, 122-125, 128-133, 135-  
144, 147-153, 155-156, 158-159

## U

uncertainty, 18, 59, 61, 150

underestimation, 131, 133, 136, 143  
urban planning, 1-5, 9-10, 15, 22, 25, 38,  
123, 147, 158-159  
utility, 3-4, 10, 12, 14-20, 26, 28, 32-34,  
36, 39, 41, 43-44, 49-50, 53, 62, 66, 84-  
85, 91, 93-94, 98, 102-104, 106, 111,  
113-114, 116, 118-119, 122, 124-125,  
135, 147, 152, 155-156

## V

validation, 3, 5, 15, 19, 30, 34, 39, 70, 77,  
82, 103, 111, 122-123, 129, 143-144,  
147-148, 151-152, 158  
value, 3-4, 14, 26, 28-30, 32-34, 41, 43-46,  
48, 50-66, 72, 85-88, 93, 95, 97, 99-100,  
108, 110-112, 114, 116-119, 122, 130,  
133, 135, 139, 148-149, 154-155, 157,  
159  
visibility graph analysis, 10, 23

## W

walking, 1, 18-19, 20, 23, 25, 27, 42-43,  
71, 76-77, 92, 95, 97, 103, 113-114, 116,  
119, 125, 129, 132-133, 137, 141, 144,  
149, 151  
walking speed, 20, 27, 71, 77, 125  
Wang Fujing Street, 6, 67-70, 72-75, 77-  
79, 82-83, 90, 92, 96-97, 100, 106-111,  
113-114, 116, 118-123, 129-134, 136-  
137, 139, 143, 149, 151  
weight, 14, 28, 53, 62, 110-112, 122, 135,  
149, 153

## AUTHOR INDEX

### A

ABC Research Group, 163-164, 166  
 Adamowicz, 37, 50, 154, 172  
 Adler, 21, 162  
 Alba, 29, 49, 153, 161  
 Albert, 162  
 Ali, 25, 161  
 Allenby, 33, 35, 166  
 Antonini, 18, 161-162  
 Arentze, 13, 16, 161, 164  
 Aschenbrenner, 162  
 Aumann, 3, 161

### B

Badler, 170  
 Bandini, 21, 27, 67, 161, 165, 171  
 Barlas, 173  
 Batty, 18, 20-21, 23, 27, 39, 161-162, 165,  
 169  
 Beach, 36, 58, 154, 162  
 Beecham, 162  
 Beijing Dong Cheng District Government,  
 69, 162  
 Ben Zur, 38, 162  
 Ben-Akiva, 14, 41, 162  
 Benedikt, 23, 162  
 Berrou, 27, 162  
 Berry, 12, 162  
 Bettman, 28, 33, 36, 49, 60, 154, 162, 170  
 Bharathy, 171  
 Bierlaire, 17, 161-162, 164  
 Block, 171  
 Blue, 21, 162  
 Boccara, 32, 41, 162  
 Bockenholt, 38, 162  
 Boer, 168  
 Book, 104, 118, 166  
 Borgers, 13, 15, 17-19, 32, 43, 67, 161-  
 164, 169, 172-173  
 Borges, 31, 163  
 Bovy, 18, 20, 26, 163-164, 168  
 Bozdogan, 89, 163  
 Breznitz, 38, 162  
 Brooks, 13, 163  
 Browne, 89, 163  
 Burstedde, 21, 163

Bussemeyer, 89, 163, 173

### C

Cadwallader, 12-13, 163  
 Cantillo, 32-33, 35, 164  
 Cao, 1, 164  
 Cervero, 1, 164  
 Chan, 169  
 Chandran, 171  
 Chang, 22, 164  
 Chen, 173  
 Cheung, 25, 169  
 Choi, 170  
 Chu, 28, 37, 50, 164  
 Conlisk, 36, 164  
 Cooper, 33, 167  
 Cornwell, 171  
 Crask, 12, 164  
 Cutting, 89, 164  
 Czerlinski, 34, 164

### D

Daamen, 2, 25, 164, 168  
 Dai, 173  
 Dawes, 28, 49, 164  
 Dayton, 90, 164  
 Dellaert, 13, 16, 164  
 Desyllas, 161  
 Dijkstra, 18, 24, 164-165  
 Dios, 164  
 Dong, 173  
 Dorso, 20, 170  
 Doshier, 29, 49, 153, 171  
 Doxa, 172  
 Duxbury, 161

### E

Einhorn, 49, 165  
 Embrechts, 162  
 Epistein, 162

### F

Farkas, 167  
 Federici, 161  
 Fehler, 169  
 Foerster, 5, 34, 165  
 Forster, 89, 165  
 Fotheringham, 12, 15, 165-166, 170  
 Franz, 23, 166



---

**G**

Gärling, 18, 22, 166  
Gartner, 67, 170  
Gattermann, 162, 164, 168, 173  
Gautschi, 101, 166  
Gensch, 49, 166  
Gerodimos, 162  
Ghosh, 12, 162, 166  
Gibson, 12, 166  
Gigerenzer, 30-31, 49, 163-164, 166  
Gilbride, 33, 35, 166  
Gilliland, 38, 166  
Gjersoe, 173  
Gloor, 20, 26, 166  
Goh, 25, 166, 169  
Goldstein, 30-31, 163-164, 166, 173  
Golledge, 11, 21-22, 163, 166, 172  
Golob, 13, 167  
Gottardi, 173  
Grajewski, 167  
Greene, 167  
Grether, 4, 49, 167  
Gupta, 33, 167  
Guy, 12, 167

**H**

Haab, 41, 167  
Hagen, 18, 173  
Hagishima, 12-13, 167, 169  
Haklay, 2, 24-25, 167, 170  
Han, 33, 167  
Handerson, 19, 167  
Handy, 164  
Hanson, 12, 22, 167  
Havard, 173  
Helbing, 19-20, 27, 41, 167-168  
Hensher, 153, 167  
Herrler, 169  
Herzog, 21, 167  
Heydecker, 164  
Hicks, 41, 167  
Hill, 27, 32, 68, 167-168  
Hillier, 22, 167  
Hine, 25, 168  
Ho, 169  
Hochmair, 22, 168  
Hoogendoorn, 2, 18, 20, 25-26, 38, 67,  
163-164, 168  
Huang, 173

**I**

Irie, 170  
Ishibashi, 17, 102, 171

**J**

Jessurun, 164-165  
Jiang, 162  
Joh, 162  
Johansson, 27, 168  
Johns, 171  
Johnson, 170  
Johnston, 9, 168

**K**

Kagarlis, 162  
Kahneman, 4, 10, 33, 168, 172  
Kau, 32, 168  
Kaufman, 163  
Keltsch, 167  
Kemperman, 162  
Kerridge, 25, 168, 173  
Kirchner, 21, 168  
Kissling, 9, 168  
Kitamura, 13, 16, 168-169  
Kitazawa, 18, 169  
Klauck, 163  
Knoflacher, 162, 164, 168, 173  
Kostyniuk, 15, 171  
Krichner, 171  
Krishnan, 33, 169  
Kukla, 173  
Kurose, 13, 18, 162, 167, 169

**L**

Lam, 25, 166, 169, 173  
Landman, 168  
Lee, 25, 27, 169  
Lehmann, 167  
Lerman, 14, 162  
Leszczyc, 16, 170  
Lewis, 9, 173  
Li, 173  
Lichtenstein, 163  
Limanond, 16, 169  
Lin, 90, 164, 170  
Lindberg, 166  
Lippert, 171  
Liu, 173  
Lorch, 9, 169  
Luce, 162

Lynch, 21, 169

## M

Ma, 173  
 Manrai, 30, 169  
 Manzoni, 161  
 Marmorstein, 29, 49, 153, 161  
 Martignon, 34, 169  
 McFadden, 3, 10, 14, 91, 170  
 Meyer, 34, 170  
 Miller, 13, 170  
 Millonig, 67, 170  
 Mitchell, 36, 58, 154, 162  
 Mitsuyoshi, 167  
 Mokhtarian, 164, 169  
 Molnar, 19, 167  
 Morishita, 170  
 Morrall, 169  
 Moulin, 25, 161  
 Muramatsu, 21, 170  
 Myung, 89, 170

## N

Nagatani, 170  
 Nagel, 166  
 Nakashima, 173  
 Narimatsu, 21, 170  
 Newell, 50, 170  
 Niemeier, 169  
 Nishinari, 168, 171

## O

O'Brien, 170, 171  
 O'Kelly, 12, 13, 166, 170  
 O'Sullivan, 24, 167, 170, 172  
 Oppewal, 15, 161, 170  
 Ortmann, 163  
 Ortuzar, 32, 102, 164, 173

## P

Pacione, 9, 170  
 Parisi, 20, 170  
 Parr, 162  
 Payne, 4, 28, 31, 36-37, 49, 58, 154, 162,  
 170  
 Pelechano, 26, 170  
 Pelligrini, 170  
 Pendyala, 173  
 Penn, 22-23, 167, 170, 172  
 Peoponis, 170

Phipps, 34, 170  
 Plott, 4, 167  
 Pullen, 12, 166

## Q

Quaglia, 162

## R

Radisch, 1, 164  
 Ratti, 22, 171  
 Read, 22, 171  
 Recker, 15, 31, 49, 171  
 Research Center of Shanghai Commercial  
 Economy, 76, 171  
 Reutterer, 139, 172  
 Russo, 29, 49, 153, 171

## S

Saarloos, 162  
 Saisa, 166  
 Saito, 17, 102, 171, 173-174  
 Schadschneider, 21, 163-164, 168, 171  
 Schmalhofer, 162  
 Schmitt, 34, 166, 169  
 Schreckenberg, 162, 164, 168, 171, 173  
 Scott, 12, 171  
 Sen, 139, 171  
 Seyfried, 20, 171  
 Shiraishi, 170  
 Shu, 173  
 Shugan, 37, 50, 171  
 Silverman, 26, 170, 171  
 Simon, 3-4, 10, 29, 50, 170-171  
 Simone, 27, 161  
 Simonson, 4, 172  
 Sinha, 30, 169  
 Smeets, 162  
 Smith, 9, 162, 169  
 Spires, 28, 37, 50, 164  
 Steffen, 171  
 Stucki, 166  
 Svestka, 49, 166  
 Swait, 33, 35, 37, 41, 49-50, 154, 171, 172

## T

Tan, 67, 172  
 Teklenburg, 23, 172  
 Teller, 139, 172  
 Thurstain-Goodwin, 162, 167

---

Timmermans, 5, 11, 13, 15-18, 21, 24, 35,  
43, 101, 122, 161-166, 169-170, 172-  
174  
Todd, 163-164, 166  
Train, 14, 168, 172  
Trew, 15, 166  
Turner, 23, 172  
Tversky, 4, 29-30, 33, 41, 49, 168, 172

## V

Vaatstra, 168  
Veldhuisen, 13, 163, 172  
Vicsek, 167  
Vizzari, 161  
Vries, 165, 172

## W

Waerden, 16, 19, 172-173  
Wagenburg, 172  
Waldau, 1, 162, 164, 168, 173  
Walmsley, 9, 25, 173  
Wang, 6, 17, 34, 67-68, 82, 89, 149, 162-  
163, 173-174, 183  
Weber, 29, 161-162, 173  
Weitz, 34, 157, 173  
Wiener, 23, 166  
Wigan, 168  
Wilde, 49, 167

Williams, 173  
Willis, 25, 71, 173  
Wilson, 11, 173  
Wong, 169, 173  
Wood, 166  
Wooler, 28, 174  
Wright, 34, 36-37, 157, 173

## X

Xia, 20, 173  
Xu, 167

## Y

Ye, 16, 173  
Young, 31, 49, 72, 79, 173  
Yu, 20, 173

## Z

Zacharias, 21, 174  
Zakay, 28, 174  
Zhang, 162, 173  
Zhu, 17, 82, 150, 162, 173-174, 184  
Zimring, 170  
Zittartz, 163  
Zucchini, 89, 174

## **SUMMARY: BOUNDED RATIONALITY AND SPATIO-TEMPORAL PEDESTRIAN SHOPPING BEHAVIOR**

Understanding pedestrian decisions is an important task for urban and retail planning as these decisions affect spatial usage, retail turnover, and the vitality of particular urban areas. Pedestrian decision research dominantly relies on conventional rational choice models which assume that pedestrians are rational agents who have complete knowledge about the choice set, use all factors relevant to characterize the choice alternatives, aggregate these in a compensatory manner into an overall utility, and choose the alternative with the highest overall utility. A substantial amount of counterevidence has accumulated over the years to indicate that these assumptions are rarely satisfied in reality. In contrast, due to the fact that their cognitive capacity and computation ability are limited, people often use simplifying decision strategies which allow them to use information selectively, process information in non-compensatory manners, make choices with simplified rules-of-thumb, and accept satisfactory alternatives which may not be optimal. This evidence and these conjectures are founded on the theory of bounded rationality.

Guided by the motivation to investigate pedestrian behavior in meso-level shopping environments using behaviorally more realistic modeling approaches, the aim and the contribution of this thesis is three-fold: (1) to develop and test a model of pedestrian behavior based on principles of bounded rationality; (2) to develop a modeling approach that allows heterogeneity among pedestrians in terms of the decision heuristics they use; (3) to systematically examine time-dependent aspects of behavior.

To that end, the emphasis of the thesis is put on exploring, extending, estimating, and validating heuristic decision models. Chapter 2 reviews the state-of-the-art in modeling pedestrian behavior and bounded rationality. As for the pedestrian models, the focus is especially on individual-based models and techniques. We limited the review of bounded rationality models to the realm of decision heuristics. Based on this review, it is argued that bounded rationality models have never been empirically tested in pedestrian research and that it will therefore be of value to make such an attempt. In this context, the heterogeneity of decision strategies, although being an old idea, is still an infant research topic and developing a formal model of this process may not only benefit the understanding of complex pedestrian behavior but also decision research at large. The content of meso-level pedestrian research can be enriched by considering the influence of time on pedestrian behavior and decisions.

Chapter 3 discusses the conceptual framework for modeling pedestrian behavior. It starts by proposing a modeling framework which consists of four inter-dependent decisions, namely the go-home, direction choice, rest, and store patronage decision, based on which, aggregate spatio-temporal pedestrian activities can largely be recovered. This is followed by introducing the rationales of three model prototypes that are to be specified for each decision. The first prototype is the multinomial logit model, as the representative of rational choice models and a benchmark for comparison. The second prototype includes three typical decision heuristics: the

conjunctive, disjunctive, and lexicographic rule. Extensions are made by incorporating threshold heterogeneity and deriving probabilistic formulations. The third prototype, the heterogeneous heuristic model (HHM), is the major methodological contribution of this thesis. In HHM, (1) factor thresholds are introduced as the fundamental cognitive mechanisms for information representation and factor selection; (2) heterogeneous non-compensatory decision heuristics can be identified under the assumption of stochastic individual decision standards; (3) choice of heuristics is modeled by estimating mental effort, risk attitude, and expected outcome involved in the evaluation of heuristics under decision uncertainty.

The data used for empirical model tests are introduced in Chapter 4. They include two pedestrian shopping dairy data sets, one collected in Wang Fujung Street (WFS) in 2004, Beijing, and the other collected in East Nanjing Road (ENR) in 2007, Shanghai. The data collection procedure, estimation of temporal information, and the basic characteristics and pedestrian behavior of the samples are discussed.

In Chapter 5, the three prototype models are tailored to each decision problems. The models are estimated against the two data sets in order to compare their statistical performances. The heuristic models are estimated against the WFS data and the HHMs are estimated against the ENR data. The MNL models are estimated against both data sets. It is found that, for the WFS case, all MNL models are outperformed by the heuristic models in terms of log-likelihood (LL) and the Consistent Akaike Information Criterion (CAIC). The advantage of HHM to estimate the coexisting heuristics is further demonstrated by the model estimations for the ENR case. In addition, HHM provides more insight into the decision process by estimating the distribution of pedestrian's preference on decision heuristics of different degrees of strictness and risk, and the sequence of information search. These properties are discussed for each of the four decision problems.

To validate the modeling framework and the bounded rationality models as a practically useful tool, Chapter 6 describes the results of a multi-agent simulation, using NetLogo, for testing the predictive ability of the model system. The estimated models are incorporated into the platform to simulate agents' decisions and behaviors. The simulated individual behavior is aggregated into aggregate behavior in space and time and compared with observed behavior in order to evaluate the models. The results show that the observed aggregate spatio-temporal pedestrian behavior can be simulated satisfactory by both the heuristic models and HHMs. However, the temporal transferability of the models is limited when they are used for simulating new data.

In conclusion, the research suggests that models of bounded rationality may be a better representation of pedestrian behavior than rational choice models. This may have profound implications for planning practice as the decision processes implied in the models may lead to policy measures which are established on satisficing instead of maximizing, partial information rather than full information. The proposed modeling approach provides a theoretical perspective on the formation of decision heuristics, which may push forward a more systematic endeavor of proposing and testing heuristics. In practice, the estimation of heterogeneous decision heuristics may be valuable for developing more customized, effective, and efficient strategies in urban and retail planning.

## **CURRICULUM VITAE**

Wei Zhu was born in 1978 in Shanghai, China. He started his bachelor program in urban planning in 1996 at Tongji University, China. After earning the Bachelor's Degree in Urban Planning in 2001, he continued the master program at the same university and completed his Master's Degree in Urban Planning in 2004. During these three years, his major research project concerned the application of discrete choice models to simulate pedestrian behavior in East Nanjing Road, the shopping center of Shanghai.

In November, 2004, Wei Zhu joined the Urban Planning Group at the Eindhoven University of Technology as a PhD candidate. His research still focused on pedestrian behavior, examining alternative modeling approaches, especially those established on the theory of bounded rationality. He will start as a post-doctorate researcher in the Center for Adaptive Behavior and Cognition of the Max-Planck-Institute for Human Development, Germany, in November 2008.

His current research interests are modeling human decision processes, theories and models of bounded rationality, decision heuristics, and model applications in urban planning, retailing, transportation, and various other domains.

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