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Classifying pedestrian shopping behaviour according to implied heuristic choice rules

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Abstract. Our aim in this paper is to build and test a model which classifies and identifies pedestrian shopping behaviour in a shopping centre by using temporal and spatial choice heuristics. In particular, the temporal local-distance-minimising, total-distance-minimising, and global-distance-minimising heuristic choice rules and spatial nearest-destination-oriented, farthest-destination-oriented, and intermediate-destination-oriented choice rules are combined to classify and identify the stop sequences and route choices of shopping pedestrians. First, several linear networks with a single entry node and a few stop nodes are investigated. For these networks, the global-distance-minimising and spatial choice heuristics classify and identify the sequences of stops very well. Although the local-distance-minimising choice rule identifies pedestrian route choice quite well, another heuristic is needed to improve the identification. In this paper a new, attractive-street-oriented heuristic is suggested to improve the identification ability of the model. This choice rule suggests that shopping pedestrians will never leave the attractive shopping streets before completing their shopping. The model is then applied to empirical data of pedestrian shopping behaviour in Veldhoven City Centre in The Netherlands. The findings of this application suggest that the model based on choice heuristics might be useful to classify and identify the sequences of stops and route choice behaviour of shopping pedestrians in a shopping centre.

Introduction

An understanding of the shopping choice behaviour of pedestrians in shopping centres constitutes an important topic of spatial analysis. The behaviour of pedestrians ultimately dictates the sales levels of shops and also represents a key component in better assessing the likely economic impact of land-use and transportation planning on retailing. Even by the early 1970s, research showed that the commercial viability of inner-city shopping streets is highly influenced by pedestrian movement and that the impact of new retail developments or changes in the transportation network is closely related to the locational patterns of magnet stores and the distribution of transport termini (Bennison and Davies, 1977a; 1977b; Johnston and Kissling, 1971; Lorch and Smith, 1993; Pacione, 1980; Walmsley and Lewis, 1989). The continued relevance of this research topic is indicated by the recent trend, observable in many advanced countries, to reduce car use and mobility in city centres and around large shopping centres. Restricted parking, increased parking fees, one-way streets, and other policy measures aim at reducing car use in city centres and around shopping centres. Retailers are not particularly in favour of such policies as they fear that consumers will decide to shop elsewhere. Planners should thus be interested in trying to predict the likely impact of such policies on pedestrian behaviour and hence on sales.

In general, pedestrian shopping behaviour in a shopping centre depends on knowledge about shops, the street network, the distribution of shops, and the choice mechanisms that are involved in deciding where to shop, in what order, and which route to take. In previous studies (Borgers and Timmermans, 1986a; 1986b; Butler, 1978;

Hagishima et al, 1987; Sandahl and Percivall, 1972) gravity models, sometimes embedded in Markov chains, have been used to predict pedestrian movement. Thus, either explicitly or implicitly, researchers have assumed that pedestrian destination and route choice can be viewed as the result of utility-maximising behaviour, in which pedestrians trade off the attractiveness of stores or shopping streets and the distance or time it takes to visit that store. The assumption of utility-maximising behaviour may, however, be rather strong. It assumes that pedestrians have full information about the stores in their shopping environment and also know exactly which stores they wish to visit before entering the shopping centre. A less rigorous assumption would be that pedestrians do not necessarily behave in such an optimal way, but rather apply particular choice heuristics in their destination and route choice. If this is true, it would be of interest to investigate whether a model of pedestrian shopping behaviour, based on such choice heuristics, can successfully predict the sequence of store choice and the implied route choice of shopping pedestrians.

Some scant evidence supporting this assumption is available in the literature. For example, Hayes-Roth and Hayes-Roth (1979) examined the heuristics that individuals use when asked to plan a trip. In particular, they asked their subjects to choose the order in which to visit a given set of destinations to conduct a series of activities. Their results suggested that people do not behave according to utility-maximising theory. The majority of their subjects first chose the destination closest to home, then the one closest to the one chosen at the previous step, and so on, until all destinations were visited. This research finding was elaborated in a series of studies conducted by Gärling and his associates. Säisä and Gärling (1987) found, both in a laboratory setting and in real-world environments, that some individuals minimised the distance between the successive destinations of their trip, whereas others considered the total distance travelled, if the minimisation of distances between successive destinations would lead to a substantially longer distance to complete the tour than the minimisation of the total distance travelled. In two other projects (Gärling, 1987; Gärling et al, 1986) they found that the heuristics people use also depend on the cognitive representation of the environment. If individuals possess some map-like mental representation of the environment, they are able to minimise the total distance travelled; otherwise they tend to minimise distance in a sequential decisionmaking process. Empirical evidence for such behaviour was found in another study (Gärling and Gärling, 1988). Given this scattered empirical evidence it would be of interest to investigate whether a model of pedestrian shopping behaviour, based on such choice heuristics, can successfully predict the sequence of store choice and the implied route choice of shopping pedestrians.

In the present paper we report the first findings of such an attempt, and build on previous research of the Urban Planning Group of the Eindhoven University of Technology (Van der Hagen et al, 1991) to identify choice heuristics underlying pedestrian movement. In that study, the authors identified several temporal and spatial choice heuristics and examined empirically to what extent such heuristics reflect actual pedestrian movements. In the present paper we take this research a step forward. The specific contributions of this paper are twofold. First, a new choice heuristic is suggested. Second, a model incorporating various choice heuristics is developed and applied to theoretical shopping environments and to the Veldhoven City Centre in the Netherlands. The theoretical part serves to understand better the relevance, potential, and limitations of the choice heuristics for theoretical spatial systems with known properties. The application to actual data on pedestrian shopping behaviour serves to assess the ability of a model for classifying and identifying, based on choice heuristics. Thus the theoretical analysis elaborates our fundamental understanding of the relationship between land use, choice heuristics, and pedestrian movement. Based on this understanding, the empirical analysis tests the classification and identification ability of the rule-based model, which will be developed in this paper.

To this end, the paper is organised as follows. First, we shall discuss the theoretical underpinnings of the study, leading to a rule-based model of pedestrian movement. Then, we shall examine theoretically the properties of the model by investigating theoretical linear retail structures. Next, the performance of the suggested model is tested by using data on actual pedestrian shopping behaviour in Veldhoven City Centre. Finally conclusions are drawn and some avenues for future research discussed.

Introduction of heuristics

Consider the problem that a shopping pedestrian has to decide which stores to visit, in which order, and which route to take, given a list of items to buy and some non-store-related goals of visiting the shopping area. Following common theoretical reasoning, we may assume that the combined choice of store, sequence, and route choice is influenced by spatial (distance) considerations, in addition to physical and nonphysical properties of the stores. Conventional theories typically assume that pedestrians arrive at their ultimate choice by maximising their overall utility function, incorporating these factors, perhaps subject to some time constraints. Examples of such approaches can be found in Borgers and Timmermans (1986a; 1986b) and Hagishima et al (1987).

In the present study we follow an alternative conceptual framework, which suggests that individuals do not necessarily behave in such an optimal manner, but rather use simplifying mechanisms to cope with the complex decision problem. We use the term 'heuristic' for this idea. A heuristic in this paper can be viewed as a rule which describes some principle underlying the choice behaviour of pedestrians. It is a heuristic because the principle is not necessarily one derived from utility-maximising theory, describing an optimal choice. We assume that the choice heuristics of interest can be represented by tools stemming from artificial intelligence.

Assume that the list of stores to be visited is known. Some rules serve to address the problem of which route should be chosen to visit these stores. We shall call these route choice heuristics, to reflect the notion that they describe mechanisms of how pedestrians move from one store to the next. Examples are the local-distance-minimising (LDM), total-distance-minimising (TDM), and global-distance-minimising (GDM) choice rules. The LDM choice heuristic states that a pedestrian will invariably take the shortest route between successive stores on a shopping trip. In contrast, in the TDM heuristic it is assumed that pedestrians are minimising the total distance implied in their route choice. Note that, ceteris paribus, this rule can be derived from utility-maximising choice theory. In the GDM heuristic it is assumed that pedestrians do not necessarily minimise the total distance travelled, but the sequence of stops is consistent with that of the TDM. Hence, globally the choice of stops is based on some principle of optimal store choice, but there are local deviations from a truly optimal route.

Route choice heuristics on their own, however, will not completely solve the decision problem. If a shopping pedestrian knows which stores to visit, and has decided on which route to follow by applying one of these heuristics, then the problem in which sequence to visit the stores still remains. The combination of store and route choice still leaves open alternative sequences in which the stores can be visited. Alternative sequential patterns are unrelated to the total distances involved. Hence we assume that, in addition to route choice heuristics, pedestrians will apply specific sequencing heuristics. Examples of such sequence heuristics are the nearest-destination-oriented (NDO) and the farthest-destination-oriented (FDO) choice rules. The NDO heuristic states that pedestrians first visit the store which is nearest from the point where they entered the shopping area. In contrast, in the FDO it is assumed that the first stop is made at the store farthest from the entry point.

The latter rules were tested empirically in our previous work. However, these two rules leave open the possibility that pedestrian behaviour cannot be described by any of these rules. Pedestrians may decide to start their shopping trip somewhere in between the closest and farthest store from the point where they entered the shopping area. Therefore we formulated another heuristic, called the intermediate-destination-oriented (IDO) heuristic. The IDO heuristic states that pedestrians first visit a store between the nearest and the farthest store from their entry point in their schedule.

When used in combination, these route choice and sequence heuristics allow one to classify and identify the stop sequences and route choices underlying pedestrian shopping behaviour. To that effect, the heuristics should be represented by some formalism. In the present study, we decided to use the formalism of production systems from artificial intelligence. Simply stated, a production system is a set of 'IF ... THEN' rules. The IF part of the logical expression specifies a series of conditions or facts, whereas the THEN part represents actions or behaviour. Figure 1 displays a basic flowchart of the model.

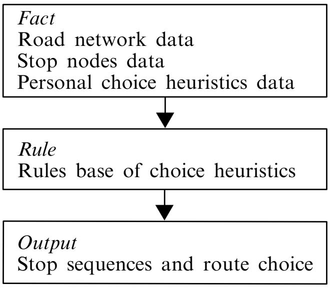


Figure 1. Flowchart of the model.

Explanation

Classifying stop sequences

The above discussion thus implies that, in order to classify pedestrian shopping behaviour, the choice heuristics need to be represented in terms of a set of logical expressions. The system was built in PROLOG. There were two reasons for this choice.
(1) Its declarative semantics make PROLOG ideally suited to the analysis of rule-based systems. The built-in functionality of pattern matching, automatic backtracking, and backward reasoning allows the researcher to identify very efficiently which cases are described by a particular rule, and which are not. Hence, stop sequences and route choice can be predicted by very efficient code.
(2) The tree-based data structure of PROLOG represents a very effective and efficient way of classifying the stores and the street network. Figure 2 shows the flowchart of the PROLOG production system for classifying and identifying stop sequences.

Classifying route choice

In addition to classifying and identifying stop sequences, the system should also classify and identify the route choice behaviour of shopping pedestrians. In particular, route choice is classified by assuming that stop sequences are known. In previous models it has almost invariably been assumed that shopping pedestrians choose the shortest route between successive stops (that is, the LDM choice heuristic), but empirical evidence suggests this is not necessarily true (Van der Hagen et al, 1991).

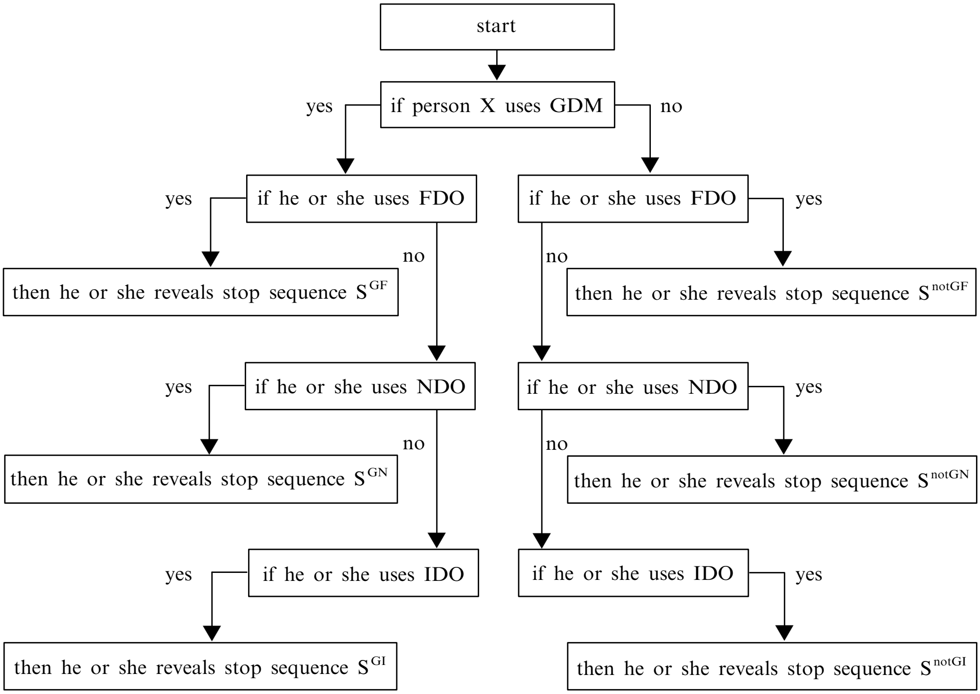


Figure 2. Flowchart of predicting stop sequences.

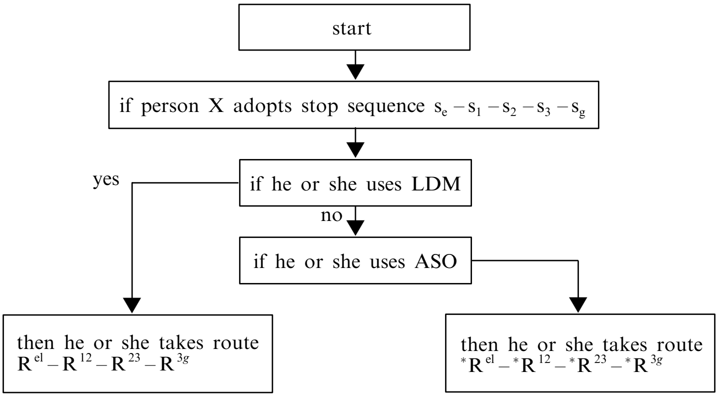


Figure 3. Flowchart of predicting route choice.

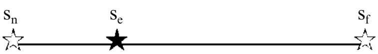
In addition to the alternative formulations, presented in the above discussion, it may be assumed that pedestrians are attracted to streets with many shops, regardless of distance. An additional choice heuristic, which we will call attractive-street-oriented (ASO), thus states that pedestrians will wish to stay as much as possible on attractive streets. Pedestrians who use this ASO heuristic move from an entry point to a gate node which is on the shortest route to the first store to be visited. At the next step, pedestrians move between successive stores only on attractive streets. We assume that they will choose the shortest route following shopping streets only. Hence the ASO heuristic represents a special case of the LDM heuristic. According to the latter rule, pedestrians may use any street, regardless of its functions, whereas in the first rule it is assumed that pedestrians will move along shopping streets only after they have visited the first store. At the last step of their shopping trip, when they leave the shopping area, they are assumed to choose the same route as the one they used to start their shopping trip. If they do not return to the entry point, they are assumed to choose the shortest route to their final destination. Figure 3 shows the flowchart of classifying and identifying route choice.

Detailed explorations of the combinatorial possibilities

Before applying the system to empirical data, we decided to gain a better understanding of the formal properties of the suggested system by applying it to a set of theoretical, hypothetical situations of increasing complexity. All these situations represented a linear shopping street. First, we applied the system to a linear structure, involving a single entry point, and two destinations. The next application involved a linear retail structure with three destinations. This was again made more complicated in the next example involving four destinations. These applications then led to the formulation of the rule-based system for the general linear case.

Linear structure: two-stops case

The least complicated case is the one where a shopping pedestrian is entering a linear shopping street and has to visit two stores. In this case, the pedestrian can decide to visit the nearest store first and then visit the more distant store (NDO heuristic), or decide to go to the store farthest away from the entry point first and visit the second store on the way back to the entry point (FDO heuristic). This is shown in figure 4, where node s_e is the entry and exit point, node s_n is the store nearest to the entry point, and node s_f represents the store farthest away from the entry point. For this simplest case, the route choice heuristics are redundant as they are implied by the sequence heuristics. Thus pedestrians can either apply the NDO or the FDO heuristic. As shown in table 1, each of these heuristics represents a stop sequence pattern.



s_e: starting-point (goal) node
s_n: stop node nearest to node s_e
s_f: stop node farthest from node s_e

Figure 4. Diagram of linear structure: two-stops case.

Table 1. Rules of linear structure: two-stops case.

	Heuristic		Sequence
if	F	then	$s_e - s_f - s_n - s_e$
if	N	then	$s_e - s_n - s_f - s_e$

N, nearest-destination-oriented; F, farthest-destination-oriented.

Linear structure: three-stops case

Let us now consider the case of a linear shopping structure with three stops, as shown in figure 5. Once again, let s_e represent the entry point, s_n the store located nearest to the entry point, s_f the store located farthest away from s_e, and s_h an intermediate store, located between s_n and s_f. For this situation, two cases can be identified for the route

s_h: stop node between node s_n and noe s_f

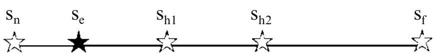
Figure 5. Diagram of linear structure: three-stops case.

choice heuristic. The first case is the one where the GDM rule is true, whereas the second case is the one where the GDM rule is false. Similarly we can identify three cases for the sequence choice heuristics—NDO, FDO, or IDO—where the last implies that the intermediate destination is chosen first. Note, however, that the NDO rule cannot be valid when the GDM heuristic is false. Thus the combination of route choice and sequence choice heuristics for the case of a linear shopping structure with three stops leads to five possible sets of rules. Table 2 represents these cases and the implied stop sequences. Every heuristic exactly represents a unique stop sequence, except the case where GDM and NDO are both true. There are two possible sequences in this case: $s_e - s_n - s_h - s_f - s_e$ and $s_e - s_n - s_f - s_h - s_e$.

Table 2. Rules of linear structure: three-stops case.

	Heuristic		Sequence
if	G, F	then	$s_e - s_f - s_h - s_n - s_e$
if	G, N	then	$s_e - s_n - s_h - s_f - s_e$ or $s_e - s_n - s_f - s_h - s_e$
if	G, I	then	$s_e - s_h - s_f - s_n - s_e$
if	^{n}G, F	then	$s_e - s_f - s_n - s_h - s_e$
if	^{n}G, I	then	$s_e - s_h - s_n - s_f - s_e$

I, intermediate-destination-oriented; G, global-distance-minimising; ^{n}G, not G; F, farthest-destination-oriented; N, nearest-destination-oriented.



s_{h1}: stop node second nearest to node s_e
s_{h2}: stop node third nearest to node s_e

Figure 6. Diagram of linear structure: four-stops case.

Table 3. Rules of linear structure: four-stops case.

Case		Heuristic		Sequence
1	if	G, F	then	$T_1 = 1$
2	if	G, N	then	$T_2 = 4$
3	if	G, I	then	$T_3 = 3$
4	if	^{n}G, F	then	$T_4 = 5$
5	if	^{n}G, N	then	$T_5 = 2$
6	if	^{n}G, I	then	$T_6 = 9$

Note: Possible sequences are as follows.

Case 1 $s_e - s_f - s_{h2} - s_{h1} - s_n - s_e$.

Case 2 $s_e - s_n - s_{h1} - s_{h2} - s_f - s_e$, $s_e - s_n - s_f - s_{h2} - s_{h1} - s_e$, $s_e - s_n - s_{h1} - s_{h2} - s_f - s_e$, $s_e - s_n - s_{h2} - s_f - s_{h1} - s_e$.

Case 3 $s_e - s_{h1} - s_{h2} - s_f - s_n - s_e$, $s_e - s_{h1} - s_f - s_{h2} - s_n - s_e$, $s_e - s_{h2} - s_f - s_{h1} - s_n - s_e$.

Case 4 $s_e - s_f - s_n - s_{h1} - s_{h2} - s_e$, $s_e - s_f - s_n - s_{h2} - s_{h1} - s_e$, $s_e - s_f - s_{h1} - s_{h2} - s_n - s_e$, $s_e - s_f - s_{h1} - s_n - s_{h2} - s_e$, $s_e - s_f - s_{h2} - s_n - s_{h1} - s_e$.

Case 5 $s_e - s_n - s_{h2} - s_{h1} - s_f - s_e$, $s_e - s_n - s_f - s_{h1} - s_{h2} - s_e$.

Case 6 $s_e - s_{h1} - s_n - s_{h2} - s_f - s_e$, $s_e - s_{h1} - s_f - s_n - s_{h2} - s_e$, $s_e - s_{h1} - s_n - s_{h2} - s_f - s_e$, $s_e - s_{h1} - s_n - s_f - s_{h2} - s_e$, $s_e - s_{h2} - s_f - s_n - s_{h1} - s_e$, $s_e - s_{h2} - s_f - s_{h1} - s_n - s_e$, $s_e - s_{h2} - s_n - s_{h1} - s_f - s_e$, $s_e - s_{h2} - s_n - s_f - s_{h1} - s_e$, $s_e - s_{h2} - s_{h1} - s_f - s_n - s_e$.

See table 2 for an explanation of the notation.

Linear structure: four-stops case

Adding another store or stop further complicates the analysis. This is shown in figure 6, where node s_{h1} is the second nearest stop from s_e, and s_{h2} is the third nearest. For this situation, there are two possible route choice rules, and three possible sequence choice heuristics, leading to a total of six possible combinations. These possible combinations are listed in table 3, where T_i represents the total number of possible sequences for case i. Table 3 clearly demonstrates that there are many possible sequences for each case. Thus the rule-based system will no longer exactly identify a particular sequence, but the system can reduce the possible sequences for each case. In other words, the system can estimate only the probability that a particular stop sequence will occur.

Linear structure: the general case

Assume a linear shopping structure with $k+2$ stops and one entry or exit point. Figure 7 shows the street network, and the distribution of stops implied by this situation. Table 4 lists the relevant rules and number of possible stop sequences in this situation. The number of possible sequences, as indicated in tables 1–3, based on the linear structure situations are special situations of this general formulation. For example, the situation with two stops in table 1 is represented by two cases (1 and 2). Similarly, the situation with three stops in table 2 is represented by five cases (1, 2, 3, 4, 6) in table 4, and the situation involving four stops is represented by all six cases in table 4. Note that the sum of the T_i of six cases equals $(k+2)!$, where $k+2$ represents the number of stop nodes. As in the previous situations, the rules cannot uniquely define a stop sequence, but they can effectively reduce the possible stop sequences and estimate the probability of a particular stop pattern. These six cases represent the basic frame for classifying and identifying stop sequences of pedestrians, and they may be useful in other situations where the street network and the distribution of stops are different. Based on a particular street network and distribution of stops, the stop sequences of shopping pedestrians can be classified by applying these six rules. The street network and distribution of stops may be different from the linear structure. However, the

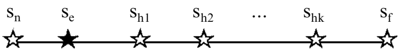


Figure 7. Diagram of linear structure: the general case.

Table 4. Rules of linear structure: the general use ($k \geqslant 1$).

Case		Heuristic		Sequence
1	if	G, F	then	$T_1 = 1$
2	if	G, N	then	$T_2 = 1 + \sum_{n=0}^{k-1} 2^n$
3	if	G, I	then	$T_3 = \sum_{n=0}^{k-1} 2^n$
4	if	$^{\mathrm{n}}$G, F	then	$T_4 = (k+1)! - 1$
5	if	$^{\mathrm{n}}$G, N	then	$T_5 = (k+1)! - \left(1 + \sum_{n=0}^{k-1} 2^n\right)$
6	if	$^{\mathrm{n}}$G, I	then	$T_6 = k(k+1)! - \sum_{n=0}^{k-1} 2^n$

See table 2 for an explanation of the notation.

framework is valid for any street network and distribution of stops. If the framework of six cases for particular combinations of route choice and sequence heuristics is true, every combination of stop nodes can be classified according to these six cases. In the following section we will demonstrate the potential of the suggested framework in a study of pedestrian shopping behaviour in Veldhoven City Centre.

Empirical results

Data

To understand better the potential of the suggested production system of route choice and sequence choice heuristics, the system was applied to data collected for Veldhoven City Centre, located close to Eindhoven in the Netherlands. The shopping centre, where car traffic is prohibited, is a typical Dutch subregional shopping centre with a primary market area with approximately 40 000 customers. The purpose of this application is to investigate how well the system is capable of classifying the stop sequences and route choice behaviour of shopping pedestrians in this shopping centre.

The data for the present application on pedestrian shopping behaviour were collected in 1993. Pedestrians were invited to participate in the survey when leaving the shopping centre. Those who agreed were asked to list where they shopped, in what order, and the route they took. A total of 895 pedestrians participated in the study, but the model is based on only 408 pedestrians as the remainder visited one store only, and hence their shopping data are irrelevant for the present study.

To apply the system to Veldhoven City Centre, we adapted the system as shown in figure 8 (see over) which shows the flowchart of the developed system. There are six steps for classifying stop sequences, and two steps for classifying route choice. We will explain each of these steps in turn.

Procedure

Step 1: Prepare data

The street network of Veldhoven City Centre was coded in terms of nodes and links. Entry points and street crossings were used as nodes, whereas the streets were coded as links. Stores were assigned to the nearest node. Distances between links were measured and saved in a separate data file. Observed stop sequences and route choices were derived from the survey for each pedestrian separately.

Step 2: Calculate the minimum distance route and the corresponding distance

A shortest route algorithm was used to identify the shortest distance between all possible pairs of stores. These data, together with a coding of the involved route, were stored in a separate data file.

Step 3: Calculate TDM sequences and identify GDM and non-GDM sequences

The shortest total distances associated with all possible permutations of stops were calculated for each pedestrian, given the stops. Based on these distances, the TDM stop sequence was identified for all respondents, and then saved as the TDM sequence data. GDM heuristics and non-GDM heuristics can then be identified based on the similarity of stop sequences.

Step 4: Classify stops

The nodes of the observed stop sequence were classified separately for each respondent as a s_n, s_f, s_{h1}, or s_{h2} node.

Step 5: Identify heuristics

This step is the most central of the model as it involves identifying the rule that best describes the observations. First, the TDM sequence is compared with the observed stop sequence to differentiate the GDM and non-GDM heuristics (see step 3). Next, by use of the minimum distance data, a distinction was made between the LDM and the

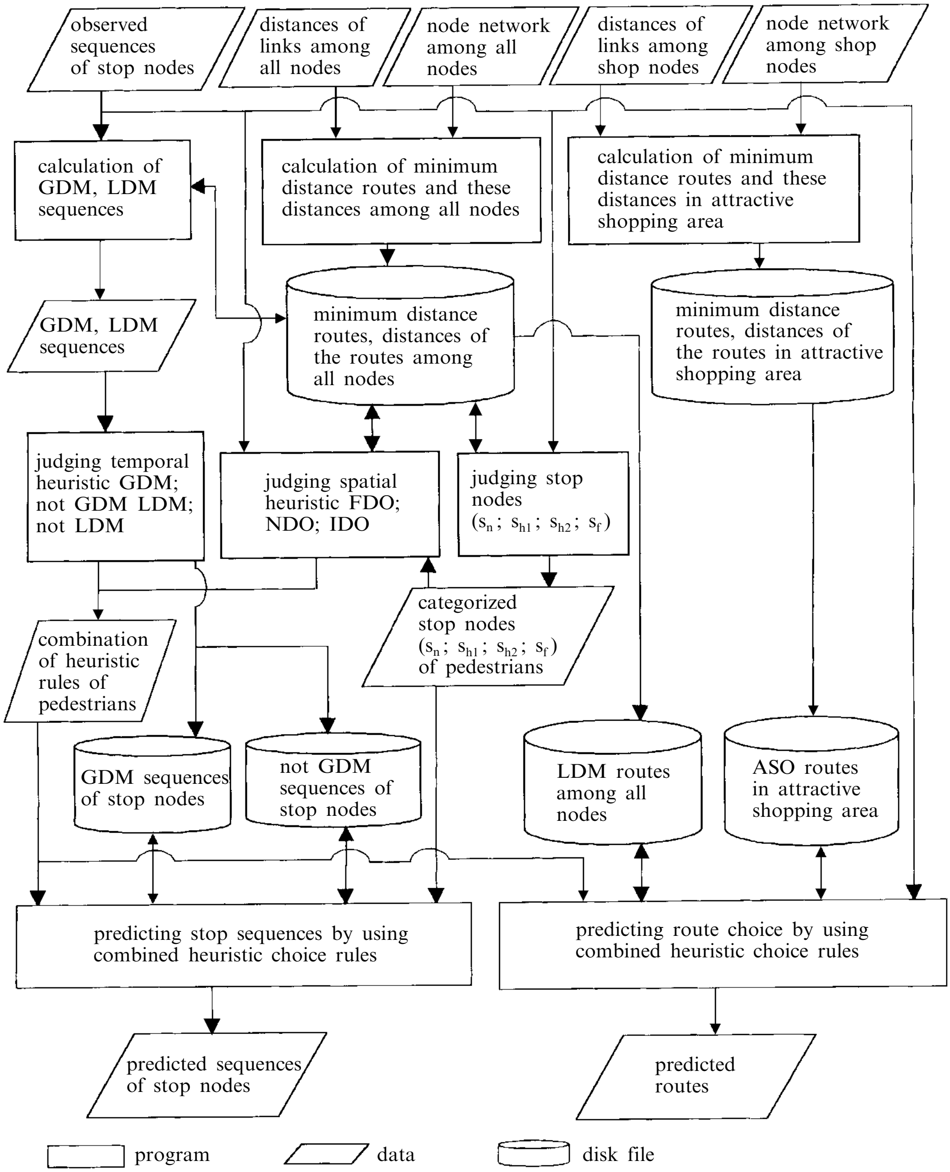


Figure 8. Flowchart of the model applied to Veldhoven City Centre.

non-LDM heuristics. If the first stop of an observed sequence is the nearest one, s_n, the heuristic is NDO. If the first stop is the farthest one, s_f, the heuristic is FDO, otherwise it is IDO.

Step 6: Predict stop sequence

In this step the heuristic is applied to a specific stop sequence. The principle can be best illustrated by using a simple example:

$1: = s_e, s_n, s_h, s_f, s_e$ $\qquad$ $2: = s_e, s_n, s_f, s_h, s_e$

$3: = s_e, s_h, s_n, s_f, s_e$ $\qquad$ $4: = s_e, s_h, s_f, s_n, s_e$

$5: = s_e, s_f, s_n, s_h, s_e$ $\qquad$ $6: = s_e, s_f, s_h, s_n, s_e$

Now suppose the pedestrian applies a combination of GDM and FDO heuristics. From the latter we know that he or she must first stop at s_f, leaving open options 5 and 6. The first option, however, is inconsistent with the GDM choice heuristic, hence we can by deductive reasoning and using PROLOG easily predict the stop sequence that is consistent with the choice heuristics.

Having predicted the stop sequence, we required two additional steps to predict the route choice of pedestrians.

Step 7: Identify ASO routes

From the street network of Veldhoven City Centre, attractive streets along which stores are located were identified, resulting in a new street network with attractive streets only. For this network, the minimum distance routes were identified and saved as ASO routes in a separate file.

Step 8: Predict route choice

Finally, route choice was predicted. In the case when the pedestrian used a LDM heuristic, the route consistent with this heuristic, given the stop sequence, was identified. Obviously all predictions in this case are perfectly correct, by definition. This is not true if pedestrians do not use the LDM heuristic. In all these cases we identified the route that was consistent with the ASO heuristic.

Results

First, we assessed the ability of the rule-based model to classify and identify the stop sequences of the 408 shopping pedestrians. As our theoretical analysis has shown, the model cannot uniquely identify a single-stop sequence when a pedestrian visits more than two stores. In this situation we can only probabilistically identify a particular stop sequence. Assuming that the stop patterns are equally likely, these average probabilities can be derived by dividing 1.0 by the number of possible stop sequences.

The results are shown in table 5, which shows that on average the system correctly classifies 85% of the observed stop sequences. Table 5 also shows that the classifying success decreases as we move from the simpler cases to the more complex ones. This finding supports the idea prevalent in the literature on wayfinding that the success of reaching a destination is related to plan complexity and legibility (Miller, 1992; Passini, 1984; Weisman, 1981). The average probability of correctly identifying the observed stop sequence of pedestrians decreased from 0.99 for case 1, to 0.86 for case 2, to 0.84

Table 5. Results of classifying and identifying stop sequences.

Case	Heuristic					Number of stops			Total	Average
	temporal		spatial			2	3	4		
	G	not G	F	N	I					
Case 1	127		127			96	22	9	127	0.99
Case 2	182			182		109	53	20	182	0.86
Case 3	36				36		25	11	36	0.84
Case 4		15	15			1	11	3	15	0.64
Case 5		28		28		1	13	14	28	0.57
Case 6		20			20		13	7	20	0.46
Total	345	63	142	210	56	207	137	64	408	
Average	0.91	0.55	0.96	0.82	0.71	1.00	0.81	0.47		0.85

G, global-distance-minimising; F, farthest-destination-oriented; N, nearest-destination-oriented; I, intermediate-destination-oriented; Total, total number of pedestrians; Average, average probability.

for case 4, to 0.46 for case 6. This is not surprising as the number of possible stop sequences also increases. It also shows that the classifying success decreases with an increasing number of stop nodes.

The frequencies listed in table 5 indicate that the majority of pedestrians use the GDM heuristic. This finding is consistent with results obtained elsewhere (for example, see Zacharias, 1993). The NDO heuristic is applied more often than the FDO heuristic and especially the IDO heuristic. The frequency of the number of stops also decreases rapidly with an increasing number of stops, suggesting that the vast majority of the paths through the shopping centre were simple loops or straight lines.

A second analysis involved examining the success of the system in classifying and identifying pedestrian route choice. The probability of success was measured by dividing the number of correctly identified links by the number of observed total links in a route. For example, if the model identified four correct links, and there were five links in total in the observed route, the probability is 80%. The results are listed in table 6, which shows that the system correctly identified links in each route with an average probability of 78% in total. It indicates, as expected, that the success in identification is perfect if pedestrians use the LDM heuristic. When pedestrians use the ASO heuristic, the average probability is 68%.

Table 6. Results of classifying and identifying route choices.

LDM or ASO heuristic	Heuristic					Number of stops			Total	Average
	temporal		spatial			2	3	4		
	G	not G	F	N	I					
LDM heuristic	106	17	48	58	17	77	31	15	123	1.00
ASO heuristic	239	46	94	152	39	130	106	49	285	0.68
Case 1	81		81			56	18	7	81	0.66
Case 2	133			133		73	46	14	133	0.65
Case 3	25				25		18	7	25	0.75
Case 4		13	13			1	9	3	13	0.78
Case 5		19		19			8	11	19	0.73
Case 6		14			14		7	7	14	0.79
Total	345	63	142	210	56	207	137	64	408	
Average	0.77	0.84	0.79	0.75	0.84	0.76	0.79	0.80		0.78

LDM, local-distance-minimising; ASO, attractive-street-oriented; G, global-distance-minimising; F, farthest-destination-oriented; N, nearest-destination-oriented; I, intermediate-destination-oriented; Total, total number of pedestrians; Average, average probability.

Conclusion and discussion

In the present paper we report the progress made in building a rule-based system of choice heuristics to classify pedestrian shopping behaviour. After obtaining some new knowledge about the behaviour of the system, derived from theoretical shopping structures, we applied the system to the observed shopping behaviour of pedestrians in Veldhoven City Centre. The results of this study indicate that, when the shopping trip involves two stops only, the exact stop sequence is inevitably identified by the model. A set of six rules, representing a combination of route and sequence choice heuristics seems to be effective in reducing the possible stop sequences of each shopping pedestrian. Applied to Veldhoven City Centre, the model identified the stop sequences with an average probability of 85%, and the routes with an average probability of 78%.

These findings demonstrate the potential of the suggested model in classifying pedestrian shopping behaviour in a shopping centre.

Notwithstanding these promising results, the model can be further improved in various ways to classify micro-shopping behaviour better. First, there is a need for specification. The choice of heuristic might, for example, depend on the type of stores that are visited. Such conditions might be incorporated in the production system representation of the choice rules. Second, the present model does not discriminate between stop sequence and routes that differ slightly from the conditions implied by the heuristic and more remote stop sequences and route. It would be interesting to investigate whether fuzzy rules could adequately incorporate this information and improve the identification ability of the rule-based model. Third, the approach taken in the present paper is one of testing the performance of prespecified rules. Alternatively, one may try to derive the choice heuristics from the observations by applying learning algorithms.

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