# Extending spatial DSS with spatial choice models of multipurpose shopping trip behaviour

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## ABSTRACT

Spatial choice or interaction models have been widely used in spatial DSS or customised GIS for analysing the impacts of retail location plans. The models typically used, however, do not account for spatial agglomeration effects on spatial choice behaviour. This study develops a model system for analysing the impacts of retail plans based on a choice model of multipurpose behaviour developed in earlier work. The model system is implemented in the spatial DSS called Location Planner. An empirical study demonstrates the empirical estimation and use of the model for analysing the impacts of an expansion of floor space in the major shopping centre of a middle-sized city in The Netherlands. The results indicate that agglomeration effects as predicted by the model can have substantial impacts on the performance of retail systems. Therefore, it is argued that when incorporated in a spatial DSS, the more complex models have the potential to improve the use of these systems for impact analysis.

## 1 INTRODUCTION

The use of spatial choice/interaction models for analysing the impact of location plans for retail or service facilities is a well-established area of research. The models serve to predict the spatial choice behaviour of consumers, dependent on the location and attributes of shopping centres/stores and sometimes also socio-economic characteristics of consumers. To facilitate the integration in the planning process, models of the multinomial logit and spatial interaction type have been incorporated in spatial DSS or customised GIS. Examples of such systems have been described in Roy and Anderson (1988), Borgers and Timmermans (1991), Grothe and Scholten (1992), Kohsaka (1993), Birkin *et al.* (1994, 1996), and Clarke and Clarke (1995).

It has been argued on many occasions, however, that the typically used models fall short in predicting spatial choice behaviour under influence of spatial agglomeration forces (e.g., Fotheringham 1985, 1986; Pellegrini *et al.* 1997). Spatial agglomerations of stores are potentially more attractive, as they facilitate comparison and multipurpose shopping. In the present study, we focus on the latter form of spatial behaviour. When engaged in multipurpose shopping, consumers buy items of different goods on the same trip, so as to save the efforts/costs of a separate trip. Delleart *et al.* (1998) developed a discrete choice model of multipurpose shopping and showed that the generalised model outperformed a conventional MNL-based shopping model in a choice experiment. Arentze, Oppewal and Timmermans (1998) developed and tested a multipurpose shopping model that has specific advantages for use in applied settings. They estimated and tested the model based on a large-scale consumer survey. Also in that case, it was shown that the model was better able to reproduce shopping centre choice of individuals.

The purpose of the present study is to develop a model system to account for multipurpose shopping behaviour in retail impact analysis. The proposed model system is implemented in an operational generic DSS called Location Planner. Location Planner is a windows-95 application, which allows users to define the attribute variables and parameter settings of a shopping model and to link the resultant model with an existing geographic and spatial data base (e.g., stored in a GIS). Location Planner offers facilities for graphic and interactive data representations, scenario management and optimisation of retail network configurations. The system design is discussed in more detail in earlier work (Arentze *et al.* 1998, Arentze *et al.* 1997).

The present study focuses on the specification and an empirical application of the proposed model system. We use the mentioned multipurpose shopping model proposed by Arentze, Oppewal and Timmermans (1998). The model simultaneously predicts the purpose and destination of shopping trips for each consumer location. Hence, the output of the model consists of a three-dimensional matrix of choice probabilities. Clarke and Wilson (1994) developed a set of performance indicators to analyse two-dimensional interaction matrices generated by conventional spatial interaction models. The present study involves a generalisation of their work, to deal with three-dimensional interaction matrices. We focus on the two major issues in most retail impact studies, namely the amount of travel required for shopping (travel demands) and the economic performance of shopping centres (market shares).

The remainder of this paper is structured as follows. In Section 2, we first briefly describe the multipurpose trip model that represents the core of the proposed system. Then, in Section 3 we discuss the proposed complementary models for extracting information about travel demand and economic performance. In Section 4, we then consider a case-study to demonstrate the use of the model system. We will highlight the comparison with conventional single-purpose shopping models. Finally, we conclude the paper with outlining the major conclusions and identifying directions of future research.

## 2 THE MULTIPURPOSE SHOPPING MODEL

The model has an hierarchical structure to simultaneously predict the purpose and destination of shopping trips (Figure 1). Trip purpose is defined as a set of one or more goods to be bought on the trip. To define optional trip purposes, consumer goods are classified into a limited set of good categories, which may be bought at different frequencies in time and in different store types. The trip purpose-choice set is defined

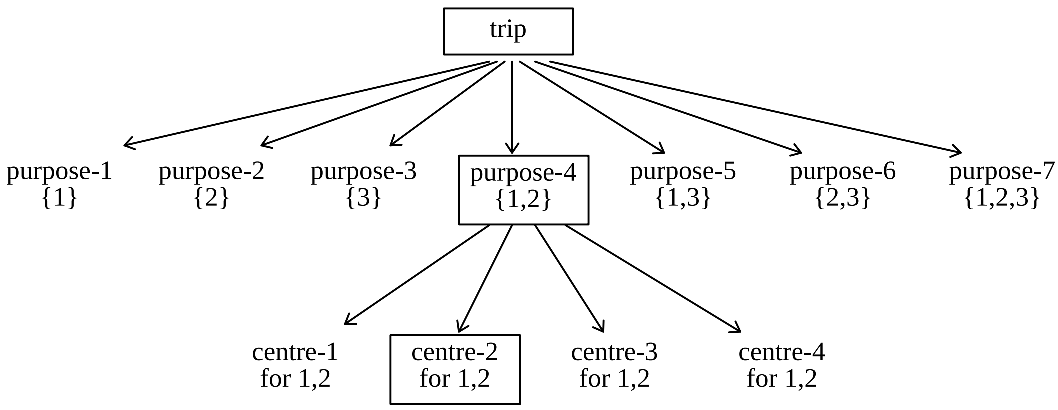


Figure 1**. The Multipurpose Model Structure for a Three-Goods Case (source Arentze, Oppewal, Timmermans 1998).**

as all possible combinations of the distinguished good categories. For example, if the categories food, cloths/shoes, and appliances are distinguished, the purpose choice-set can be written as $\boldsymbol{P}$ = { {1}, {2}, {3}, {1,2}, {1,3}, {2,3}, {1,2,3} }. The destination choice-set of a trip, on the other hand, is defined as the known shopping centres where the required goods for the trip can be bought.

The model predicts the choice probability of a purpose and destination combination using the equation:

$$Pr\left(j,\boldsymbol{p}\right)=Pr\left(\boldsymbol{p}\,\middle|\,\boldsymbol{p}\in\boldsymbol{P}\right)Pr\left(j\,\middle|\,\boldsymbol{p};j\in\boldsymbol{J}^{\boldsymbol{p}}\right) \tag{1}$$

where:

$\boldsymbol{p}$ is a set of one or more goods, $g$;

$\boldsymbol{P}$ is the set of all unique, non-empty sets of goods that can be formed given $g$=1..$n$;

$\boldsymbol{J}^{\boldsymbol{p}}$ is the set of known centres where the set of goods, $\boldsymbol{p}$, can be bought.

A nested-logit model structure is used to define trip-purpose choice probability:

$$Pr(\boldsymbol{p}\,|\,\boldsymbol{p}\in\boldsymbol{P})=\frac{\exp\left(\alpha^{\boldsymbol{p}}+\theta^{p}I^{\boldsymbol{p}}\right)}{\sum_{\boldsymbol{p}'\in\boldsymbol{P}}\exp\left(\alpha^{\boldsymbol{p}'}+\theta^{p'}I^{\boldsymbol{p}'}\right)} \tag{2}$$

where:

$\alpha^{\boldsymbol{p}}$ is a purpose-specific constant representing the systematic utility related to buying the goods involved in ***p***;

$\theta^{\boldsymbol{p}}$ is a scale correction parameter representing the proportion of the scales of the non-systematic utility components between the higher level choice and the lower level choice of a specific purpose ***p***;

$I^{\boldsymbol{p}}$ is the inclusive value of destination alternatives for purpose ***p***.

The inclusive value of destination alternatives within a nest is defined as the expected maximum utility across the alternatives:

$$I^{\boldsymbol{p}} = \ln \sum_{j \in \boldsymbol{J}^{\boldsymbol{p}}} \exp\left(V_j^{\boldsymbol{p}}\right) \tag{3}$$

where $V_j^{\boldsymbol{p}}$ is the systematic utility component of centre $j$ for purpose ***p***.

The choice of a destination $j$ given trip purpose ***p*** is modelled as a conventional MNL-model:

$$Pr\left(j \mid \boldsymbol{p}; j \in \boldsymbol{J}^{\boldsymbol{p}}\right) = \frac{\exp\left(V_j^{\boldsymbol{p}}\right)}{\sum_{j' \in \boldsymbol{J}^{\boldsymbol{p}}} \exp\left(V_{j'}^{\boldsymbol{p}}\right)} \tag{4}$$

Finally, the systematic utility of destination alternatives, $j$, for purpose ***p*** is defined as:

$$V_j^{\boldsymbol{p}} = \chi' \boldsymbol{x}_j + \sum_{g \in \boldsymbol{p}} \beta^{g\,\prime} \boldsymbol{x}_j^g + \delta^{\boldsymbol{p}} d_j \tag{5}$$

where:

$\beta^g$ is a vector of weights and $\boldsymbol{x}_j^g$ a vector of attribute values of stores offering goods $g$;

$\chi$ is a vector of weights and $\boldsymbol{x}_j$ a vector of attribute values of the shopping environment (e.g., the centre’s atmosphere, parking facilities, etc.);

$\delta^{\boldsymbol{p}}$ is a purpose-specific weight and $d_j$ the travel distance or time to reach centre $j$.

The model defined by equations 1-5 has suitable features for describing multipurpose shopping behaviour. Spatial agglomeration effects on trip destination choice are covered by determining the choice set and utility of destinations dependent on the selected trip purpose. Specifically, the utility of the available supply is determined as the sum of the utilities of stores matching the trip purpose. Moreover, trip purpose is an endogenous variable of the model. The constants, $\alpha$, and scale values, $\theta$, play different roles in this respect. The constants capture the trip frequency component that does not co-vary with supply factors. Hence, this component can be held constant in impact analysis. The scale values, on the other hand, can be interpreted as a supply elasticity coefficient of trip purpose choice. The coefficient can vary between zero and one. A zero value indicates the absence of an influence of available destinations on trip purpose choice, whereas a value of one suggests maximal sensitiveness to supply factors. Thus, the model is able to predict, for example, the impacts of shopping opportunities on the probability of choosing multipurpose trips.

## 3 MODELS FOR IMPACT ANALYSIS

To use the model for impact analysis, the study area is subdivided into zones that are considered the origin locations of consumers residing in the area. The model is used to predict the choice probability of consumers in zone $i$ selecting purpose $\boldsymbol{p}$ and destination $j$, for each $i$, $j$ and $\boldsymbol{p}$. Note that the predicted probabilities for each zone sum up to one across trip purposes $\boldsymbol{p}$ and destinations $j$:

$$\sum_{p\in P}\sum_{j\in J^p} a_{ij}^{p} = 1 \qquad " \; i \tag{6}$$

where the $a$-variables represent the probabilities predicted by the multipurpose model for each zone $i$. The remainder of this section, derives measures of travel demands by zones and market shares of centres from this three-dimensional matrix of probabilities.

### 3.1 Travel Demand

We conceptualise travel demand as the product of trip frequency and trip length:

$$Z_i = X_i T_i D_i \tag{7}$$

where:

$Z_i$ is the total distance/time travelled by consumers in demand zone $i$;
$X_i$ is the population size in zone $i$;
$T_i$ is the total trip frequency in zone $i$;
$D_i$ is trip length measured as travelled distance/time averaged across shopping trips originating from demand zone $i$.

Average trip length is calculated as a weighted sum of travelled distances/times using trip choice probabilities as weights:

$$D_i = \sum_{p\in P}\sum_{j\in J^p} a_{ij}^{p} d_{ij} \tag{8}$$

where:

$a_{ij}^{\boldsymbol{p}}$ is the predicted probability of consumers in $i$ selecting trip purpose $\boldsymbol{p}$ and destination $j$;

$d_{ij}$ is the travel distance/time from the centroid of demand zone $i$ to the destination location $j$.

It should be noted that this measure accounts only for shopping trips to destinations within the study area. Usually, the proportion of trips to locations outside the area is assumed to be constant in retail impact studies. A measure of demand for travel within the study area, therefore, is still a suitable indicator for impact analysis.

With regard to total trip frequencies, $T_i$, conventional shopping models implicitly assume that this frequency is a given constant. The proposed multipurpose model predicts the distribution of trips across trip types. Although it does not predict trip generation in a strict sense, a supply-sensitive trip generation model can be derived if we assume that individuals select multipurpose trips with the aim to reduce the number of trips required for purchasing goods. Note that by definition the purchase frequency of good $g$ equals the total number of trips involving a purchase of $g$:

$$f_g = T_i \sum_{p \in P^g} a_i^p \tag{9}$$

where:

$f_g$ is the purchase frequency of good $g$;

$T_i$ is the total number of trips originating from zone $i$;

$\boldsymbol{P}^g \in \boldsymbol{P}$ is the subset of trips including a purchase of $g$;

$a_i^{\boldsymbol{p}}$ is the predicted probability of selecting trip purpose $\boldsymbol{p}$ (defined by Equation 2).

Assume the extreme case where individuals keep the total number of purchases constant and adjust the number of required trips. Then, the total trip frequency can be calculated as:

$$T_i = \frac{c}{\sum_g \sum_{p \in P^g} a_i^p} \tag{10}$$

where: $c$ is a constant representing the sum of purchase frequencies of goods. When multipurpose trips occur, the same good $g$ occurs in more than one purpose set, $\boldsymbol{p}$. Consequently, the denominator of the quotient in Equation 10 is normally bigger than one, indicating that the number of trips is a fraction of the number of purchases. This can be illustrated by a simple 2-good system. In that case Equation 10 becomes:

$$T_i = \frac{c}{a_i^{\{1\}} + a_i^{\{2\}} + 2a_i^{\{1,2\}}} = \frac{c}{1 + a_i^{\{1,2\}}} \tag{11}$$

In words, when multipurpose trips occur, the denominator expresses the reduction of trips achieved by making multipurpose trips. The two models - constant number of trips and constant number of purchases - can be thought of as two extremes. In reality, we may assume that consumers adjust both frequencies in response to changes in supply and that, consequently, trip frequency will lie somewhere in between these two extremes.

In summary, the advantage of the above travel demand model over conventional travel demand models is that the measure is sensitive to changes in the choice of trip purpose. This has two effects. First, supply induced shifts for example towards higher probabilities of higher-order trips at the expense of lower order trips may lead to larger average trip lengths. Second, an increase in multipurpose trips implies a reduction of the number of trips required to realise a given set of purchases.

### 3.2 Market Share Allocation

The market share of stores of type $g$ in centre $j$ is defined as the share of available expenditure for good $g$ within the study area attracted by the centre. Following common practice in retail impact studies, we assume that for each demand zone $i$ the available expenditure, $E_i^g$, for good $g$ is a given constant. Possibly, this constant is calculated as the product of population size and a national per capita expenditure rate possibly adjusted for the socio-economic characteristics of the local population. The trip probability matrix, $a_{ij}^{\boldsymbol{p}}$, is used to allocate available expenditure across supply locations, as follows:

$$Z_j^g = \sum_i E_i^g \left( \frac{\sum_{p \in P^g} w_g^p a_{ij}^p \left(1 - a_{i0}^p\right)}{\sum_{p \in P^g} w_g^p a_i^p} \right) \qquad (12)$$

where:

$Z_j^g$ is the market share of stores $g$ in centre $j$;

$E_i^g$ is the given amount of expenditure for good $g$ in zone $i$;

$a_{i0}^{\boldsymbol{p}}$ is a given zone and purpose-specific proportion of trips having a destination outside the study area;

$w^{\boldsymbol{p}}_g$ is a weight expressing the relative amount of expenditure for $g$ on trips of type $\boldsymbol{p}$;

and other variables are defined as above. Usually, the share of trips to locations outside the study area, $a_{i0}^{\boldsymbol{p}}$, is estimated based on rules of thumb and specific knowledge of the area. For example, zones located near the borders of the study area will have higher shares of external trips than more centrally located zones. The weights, $w^{\boldsymbol{p}}_g$, are specific for the multipurpose trip model. Inclusion of this parameter reflects the notion that the amount of expenditure per trip for a good may be

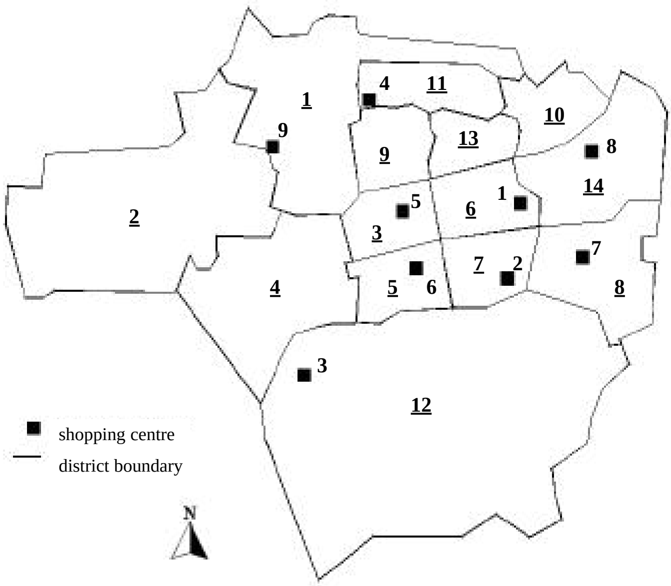


Figure 2. **Spatial Arrangement of Districts and Shopping Centres of Veldhoven**.

dependent on trip type. For example, we may assume that expenses for a good are less on trips where the good is combined with other goods.

In sum, the proposed model makes sure that available expenditure is allocated to centres proportionally to the probability of selecting the centre, while taking into account the weights of trip types and trips with an external destination. Turnover volumes can be found by adding to the market share the attracted expenditure from locations outside the study area. Again, the amount of incoming expenditure flows is usually estimated for each centre based on rules of thumbs and knowledge of the area. The specific advantage of the above model is that it takes into account possible differences in amounts of expenditure between trip types as well as differences in the weight of trip types between origin zones.

## 4 EMPIRICAL APPLICATION

### 4.1 The Study-Area

The data used to illustrate the model system were collected in Veldhoven, a city in The Netherlands with 41,000 inhabitants in 1996. Veldhoven is located closely to Eindhoven, a larger city with a population of almost 190,000 persons. Figure 2 shows a map of the Veldhoven area. The area is subdivided into districts, which correspond to the major neighbourhoods. As typical for Dutch retail systems, most retail facilities are concentrated in planned district centres with a local function. The major shopping centre in the inner city has an above local function. In addition, several shopping centres in Eindhoven play a role. These include local shopping centres in districts adjacent to Veldhoven and two larger shopping centres, of which the major shopping centre of Eindhoven is the most important. The relevant shopping centres of Eindhoven were included in the analysis.

In 1997 a large-scale expansion of the major shopping centre of Veldhoven - called the City Centre - was opened. The expansion involved almost a doubling of retail floor space in both the daily and the non-daily sector. After expansion, the total floor space amounted to 8,800 m2 (daily goods) and 10,800 m2 (non-daily goods). To analyse the impacts of this development on the shopping and travel behaviour of the population of Veldhoven, a consumer survey was held before and after the expansion of the centre. The after-survey provided suitable data for estimating the multipurpose trip model. In the remainder of this section we discuss the results of estimation and application of the model for analysing the impacts of the expansion.

### 4.2 Model Estimation

The data used to estimate the model describe shopping trips of a random sample of 498 households collected in the area. Each respondent was asked to describe maximally three shopping trips they had made during the last week. Shopping trips were described in terms of the transport mode used, the destination and the items bought. For each trip, respondents could specify maximally three destinations. Thus, a trip could involve visits to several centres. Visits to a centre rather than trips were taken as the unit of analysis here. By choosing a week as the time-frame, possible day-of-the-week effects on trip choice were controlled for. Hence, we may assume that the resultant sample of trips (i.e., shopping centre visits) is representative.

Considering the general information needs of local government in retail impact analysis, the purchased items reported by the respondents were exhaustively classified into daily goods (food and personal care) and non-daily goods (all other goods). Given this 2-good system, three trip types based on trip purpose could be distinguished, namely single purpose daily-good trips, single purpose non-daily good trips and multipurpose trips where items of both categories were bought during the same visit to the centre. In total 1369 visits to shopping locations were reported, 53 % involved daily only, 27 % non-daily only, and 20 % were multipurpose. This means that, given the used categorisation of goods, a considerable portion of trips is multipurpose in this case.

Distance was measured as the length in meters of the shortest route across the road network. Respondents were assigned to the node of the network that was closest to the 5-position zip code of their home address. Similarly, the shopping centres/streets were assigned to the nodes closest to the centroid of the centre/street. The relevant shopping areas in Eindhoven were linked through a major road with the network. The GIS package TransCAD was used to digitise the geographic data and to generate a demand $\times$ supply distance matrix using a shortest path routine. Each shopping location was described in terms of the total floor space of stores in the daily and non-daily sectors, respectively. Furthermore, the presence of a low-price level image of the centre was encoded by means of a binary variable. Other generally relevant variables, such as parking facilities and atmosphere of the centre, were left out of consideration, as the main purpose of the study was to illustrate the potential of the modelling approach.

The destination choice set for each of the three trip types was defined as the set of centres known to the individual where stores required by the trip type under concern were available (daily, non-daily or both). The software HieLow was used for full-information estimation of the hierarchical multipurpose model (Bierlaire 1995). The results are shown in tables 1 and 2. The Mc Fadden's Rho bar squared value of 0.163 indicates a satisfactory goodness-of-fit of the model considering the limited set of variables used to measure the attractiveness of shopping locations. All parameter values that were tested against zero were statistically significant and had values as expected. First, two distance parameters were used to account for a possible difference in the disutility of travel between low-order trips (daily goods only) and high-order trips (involving non-daily goods as single purpose or in combination with daily goods). As expected, the distance weight is significantly more negative for the low-order trips. Second, the constants, $\alpha$, are negative, given the fact that single purpose daily good trips were taken as the base alternative (zero constant value). This indicates, as expected, that the base-frequency of higher-order trips is lower. Finally, the scale parameters for the trip types, q, all fall within the zero-one range indicating that the hierarchical structure of the model fits the data. The *t*-values of the scale parameters refer to a test of the parameters against one. Only, the theta related to the single purpose daily good trips differs significantly from one (alfa is 5 %). As said, the scales can be interpreted in terms of the elasticity of trip choice for available supply. Interpreted that way, the scale values suggest that, at least in this case, the relative frequency of single purpose daily good trips are the least sensitive to supply factors, which is as we would expect.

| Attribute | Parameter estimate | t-value |
|---|---|---|
| Floor space daily goods ($\beta$) | 17.69 e-05 | 20.66 |
| Floor space non-daily goods ($\beta$) | 4.38 e-05 | 11.69 |
| Low price image ($\chi$) | 1.35 | 7.27 |
| Travel distance daily ($\delta$) | -5.92 e-04 | -14.48 |
| Travel distance non-daily ($\delta$) | -4.02 e-04 | -12.04 |
| Trip constant, non-daily ($\alpha$) | -1.07 | -3.03 |
| Trip constant, multipurpose ($\alpha$) | -1.60 | -2.56 |
| Trip scale, daily ($\theta$)* | 0.34 | -2.30 |
| Trip scale, non-daily ($\theta$)* | 0.64 | -1.09 |
| Trip scale, multipurpose ($\theta$)* | 0.53 | -1.21 |

*Significance of scale parameters is tested against one.

Table 1. **Parameter Estimates of the Multipurpose Trip Model.**

| Statistic | value |
|---|---|
| Number of observations | 1339 |
| Number of coefficients | 10 |
| Log-likelihood model | -3440.47 |
| Log-likelihood null model | -3605.57 |
| Mc Fadden’s Rho bar squared | 0.1633 |

Table 2. **Estimation Statistics of the Multipurpose model.**

### 4.3 Using the Model for Impact Analysis

Location planner was used to predict shopping trips and impacts of the expansion of the City Centre in terms of travel demand and economic performance of the centres. Using the same zoning system as in estimating the model, the study area was subdivided into 5-position zip code areas resulting in a total of 89 zones. Demographic data were available only at the level of districts (14 areas). For determining market shares of centres and aggregating travel demand to the district level, it was assumed that populations within districts were evenly distributed across zones. For each trip type, destination choice-sets were defined based on the availability of appropriate floor space only. In addition, for single purpose daily good trips the resultant choice-sets were further reduced by imposing a maximum travel distance of 5,000 meter. The model was applied to both the before and the after situation for analysing the impacts of the expansion.

*4.3.1 Trip Type Choice*

The question considered in this section is whether the prediction of trip type choice is sensitive to changes in supply factors (over time or space). Overall averages are calculated across zones using population size as weight. As it appears, the average trip frequencies after expansion of the City Centre are 51.5 % (daily only), 30.2 % (non-daily only) and 18.3 % (multipurpose trips). The corresponding minimum and maximum frequencies are 45.9-53.0 % (daily only), 28.3-33.6 % (non-daily only) and 17.9-20.5 % (multipurpose trips). The variance in trip frequencies reflects differences in the utility of available shopping locations. Generally, zones nearby large concentrations of shopping facilities are characterised by higher shares of higher-order trips, as these trips are more supply sensitive than daily good trips. For example, relatively high shares of multipurpose trips are predicted for zones nearby the City Centre or the major shopping centre of Eindhoven.

The same mechanism is apparent when we consider the impact of the expansion of the City Centre. Before expansion the predicted overall average trip frequencies are 51.8 % (daily only), 30.4 % (non-daily only) and 17.8 %

| district | population $X_i$ | total frequency $T_i$ | av. triplength, $D_i$ | total travel, $Z_i$ * |
|---|---|---|---|---|
| 1 | 1560 | 99.6 | 99.0 | 98.5 (99.5) |
| 2 | 210 | 99.5 | 98.7 | 98.3 (99.3) |
| 3 | 3225 | 99.5 | 97.9 | 97.6 (98.7) |
| 4 | 160 | 99.6 | 99.6 | 99.1 (99.9) |
| 5 | 3900 | 99.5 | 98.5 | 98.0 (99.2) |
| 6 | 4690 | 99.6 | 99.7 | 99.3 (100.0) |
| 7 | 3920 | 99.5 | 96.4 | 95.9 (97.6) |
| 8 | 2430 | 99.5 | 96.4 | 95.9 (97.6) |
| 9 | 5060 | 99.6 | 96.3 | 95.9 (97.6) |
| 10 | 560 | 99.6 | 96.3 | 95.9 (97.5) |
| 11 | 1500 | 99.5 | 98.1 | 97.6 (98.9) |
| 12 | 4800 | 99.6 | 98.6 | 98.1 (99.2) |
| 13 | 2975 | 99.6 | 98.1 | 97.6 (98.9) |
| 14 | 5985 | 99.5 | 94.8 | 94.3 (96.4) |
| average | | 99.5 | 97.5 | 97.1 (98.5) |

*Percentages between brackets refer to conventional MNL-model predictions.

Table 3. **Travel Demand Impacts of Expansion City Centre (Before Expansion is 100).**

(multipurpose trips). These figures indicate that the expansion has lead to a slight increase in the share of multipurpose trips (to the City Centre). The increased availability of daily and non-daily good stores in this centre is responsible for this effect.

*4.3.2 Travel Demand Analysis*

The impact of the expansion of the City Centre was determined by comparing predictions of trip frequency, average trip lengths as well as the resultant total travel distance in the situation before and after the change. Moreover, a comparison is made with predictions that are obtained when an equivalent system of MNL-based shopping models is used. For this, a MNL-model was specified for both the daily and the non-daily sector using the parameter estimates of the multipurpose model concerning the distance, floor space and low price image variables. Because the same parameters were used the differences between the two sets of predictions can be attributed exclusively to the influence of agglomeration effects in the multipurpose model.

Table 3 shows at the district level the analysis results for the after-situation as a percentage of the outcomes for the before-situation. The predictions of the MNL-based model system are placed between brackets. The multipurpose model predicts for each zone a small decrease in the total trip frequency (on average 0.5 %). Assuming that the sum of purchases of daily and non-daily goods remains constant, the decrease is attributable to the predicted increase in the share of multipurpose trips due to the

| Centre | size daily (m2) | size non-daily (m2) | low price image | Market share daily $Z_j^1$ * | Market share non-daily $Z_j^2$ * |
|---|---|---|---|---|---|
| 1. City Centre | 8800 | 10800 | 0 | 137.9 (133.7) | 131.6 (122.1) |
| 2. Burg van Hoof | 1198 | 1745 | 0 | 93.4 (94.1) | 94.9 (96.4) |
| 3. Kromstraat | 1534 | 4148 | 0 | 94.1 (94.8) | 95.1 (96.6) |
| 4. Heikant | 775 | 30 | 0 | 93.8 (94.4) | 95.0 (96.5) |
| 5. t Look | 610 | 0 | 0 | 93.8 (94.4) | |
| 6. Zonderwijk | 1340 | 230 | 0 | 93.7 (94.4) | 94.9 (96.5) |
| 7. Mariaplein | 115 | 745 | 0 | 93.3 (93.9) | 95.0 (96.4) |
| 8. Zeelst | 657 | 1146 | 0 | 93.2 (93.8) | 94.9 (96.4) |
| 9. Oerle | 100 | 0 | 0 | 93.3 (93.9) | |
| 10. EH inner city | 4273 | 88273 | 0 | 92.6 (94.6) | 94.6 (96.5) |
| 11. EH Woensel | 7780 | 12139 | 0 | 92.5 ( [1] ) | 94.0 (96.5) |
| 12. De Hurk | 1225 | 3163 | 1 | 92.8 (93.5) | 95.0 (96.5) |
| 13. Kast. Plein | 1653 | 2318 | 0 | 93.2 (94.3) | 94.9 (96.5) |
| 14. Trudoplein | 207 | 2189 | 0 | 93.0 (94.9) | 95.0 (96.5) |

*Percentages between brackets refer to conventional MNL-model predictions.

[1] There are no daily shopping trips to this centre in the MNL-model, given the used maximum distance of 5,000 m to delineate choice-sets.

Table 4. **Market Share Impacts of Expansion City Centre (Before Expansion is 100).**

expansion of the City Centre (on average 3.1 %). Note that MNL-based models of travel demand implicitly assumes that total trip frequency remains the same.

Also, the predicted average trip length has decreased for each zone (on average 2.5 %). A closer look at the destination choice probability matrices learns that this decrease is the result of two counter-acting effects. First, the City Centre tends to distract to a larger extend trips from the local district centres inducing more travel inside Veldhoven. At the same time, the expansion of the City Centre is responsible for a decrease of relatively long trips to the larger centres in Eindhoven. The net result of these two opposite effects is a decrease of average trip length.

Finally, travel demand is the product of total trip frequency and average trip length. The multipurpose model systematically predicts larger decreases in travel demand than the MNL-based model system does (on average 2.9 versus 1.5 %). This is due to the fact that the conventional model system ignores agglomeration effects and, therefore, underestimates the increase in competitive strength of the centre, in particular, relative to the inner city centre of Eindhoven. A smaller decrease in long trips to Eindhoven centre implies a smaller decrease of average trip length.

### *4.3.3 Market Share Analysis*

To derive market shares it was assumed that the amount of expenditure for a good is twice as much on single purpose trips than on multipurpose trips. This assumption was made for both daily and non-daily goods. The validity of this assumption is not the main issue here. The purpose here is to evaluate the potential impact of agglomeration forces on the economic performance of centres. Therefore, we will highlight the comparison with the MNL-based model system.

Table 4 shows the results of the analysis of the after situation as a percentage of the outcomes in the before situation. As we would expect, the market share of the City Centre has increased considerably in both the daily (38 %) and non-daily sector (32 %). The decrease in market share of competing centres is almost evenly distributed across the centres in the daily (6.9-7.5 %) as well as the non-daily sector (4.9-6.0 %). Also, the competition with the major centre of Eindhoven is of interest. In the daily and non-daily sector the decrease in market share of the inner city centre of Eindhoven is 7.4 % and 5.4 %.

The MNL-based model system predicts smaller impacts, namely an increase of the market share of the City Centre of 34 % (daily sector) and 22 % (non-daily) and a decrease of market share of Eindhoven inner city of 5.4 % (daily) and 3.5 % (non-daily). Clearly, the MNL-based models underestimate the increased competitive strength of the City Centre in the multipurpose trips segment. Differences in predictions would even be stronger if higher weights of multipurpose trips in expenditure rates per good were assumed.

### *4.2.4 Concluding Remarks*

Comparison with a conventional, MNL-based model system indicates that the proposed model system predicts bigger impacts of the expansion both in terms of travel demand and market share allocation. The reason for this difference is that the model assigns a higher increase in competitive strength of the centre, as it takes into account the increased spatial agglomeration of stores. Specifically, the model re-assigns to a bigger extent trips from competing local centres as well as the larger centres in Eindhoven towards the own city centre resulting in bigger shifts in terms of average trip lengths as well as market shares.

## 5 CONCLUSIONS AND DISCUSSION

This paper developed a model system for retail impact analysis based on a choice model of multipurpose shopping behaviour. The choice model simultaneously predicts the choice of trip purpose and trip destination dependent on the location and attributes of shopping centres. In contrast to conventional MNL-based shopping models, the multipurpose model accounts for spatial agglomeration effects on spatial choice behaviour. The system is implemented as a generic analytic framework in Location Planner. A case-study showed the use of the model system for retail impact analysis. The study highlighted the comparison with conventional MNL-based shopping models in analysing the impacts of a relatively large-scale expansion of the major shopping centre in a middle-sized Dutch city. The results of this case-study indicates that spatial agglomeration effects as predicted by the model have measurable impacts on the performance of retail systems. The expansion of the centre led to a bigger increase in the competitive strength of the centre and consequently to stronger impacts for both the allocation of market shares across centres and travel demand. We conclude, therefore, that the increased sensitivity of the model system can improve the use of spatial DSS for impact analysis.

The case-study showed the application of the multipurpose model when a distinction is made between daily and non-daily goods. Although the model structure in Location Planner more generally allows one to define an *n*-good model system, there are several limitations to assuming finer categorisations of goods. First, the number of trip types soon becomes very large when the number of good categories increases. The size of the sample of trips required to derive reliable estimates of the trip-type specific constants and scale parameters of the model may become prohibitive. Second, the 2-good system matches the information needs and available data sources in typical Dutch applied retail research. Nevertheless, a 3-good system allows one to define more homogenous good categories and it seems worthwhile to investigate whether this would improve the goodness-of-fit of the model.

Besides the categorisation of goods, specification of the model system requires several other choices. First, for predicting travel demand an assumption must be made about how consumers adjust their shopping pattern. In the present case study, the number of purchases was held constant and the number of trips was derived dependent on the relative frequency of multipurpose trips. Alternatively, consumers could adjust purchase frequencies while keeping the number of trips constant or they could adjust both in combination. In future research, it seems interesting to estimate elasticity coefficients of trip and purchase frequencies based on shopping trip data. Possibly, this can be done within the framework of the multipurpose trip model. Second, for predicting market share allocation across centres, an assumption must be made about how consumers distribute their expenditure for the concerned good across trip types. In the case-study, it was rather arbitrarily assumed that multipurpose trips weight less in that respect. Future research could focus on further refining the model by incorporating and empirically estimating an appropriate coefficient also for this aspect of behaviour.

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