Destination choice decisions of retail travellers: results from discrete choice modelling in Brisbane

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Abstract

Retail trips account for approximately 20 precent of all trips in Australian cities and are extremely car dominated. Decisions about retail trip-making are driven by a range of factors such as the attractiveness of shopping destinations (their size, composition, level of service etc.); their accessibility (including travel costs, parking, public transport, walking and cycling access); traveller characteristics; and the nature of the shopping trip itself. Many retail trips are part of trip chains including trips for other purposes, such as shopping trips made on the way home from work, which further affects destination and mode choice decisions. The flexible nature of retail trips in comparison to other major trip types makes it challenging to understand how decision makers' preferences, destination attributes and accessibility affect destination choice.

This paper applies discrete choice modelling, using multinominal logit-based models, to explore how the attributes of individual travellers and destinations choice alternatives influence travellers' choice of shopping destination. The model uses the *2009 SEQ Household Travel Survey* dataset from the Queensland Department of Transport and Main Roads. Shopping centre locations and characteristics for greater Brisbane were geocoded and assigned using secondary data. The model's results are based on the level of utility associated with each choice for different types of shopping trip including groceries, clothes, eating or drinking, alcoholic drinks and household goods. Seven explanatory variables have been included in the model: car distance, number of retail jobs at site, site area and the existence of food court and socio-demographic characteristics of travellers, namely age, gender and income. The results show significant relationships between site attributes and socio-demographic characteristics for most of these trip types.

The model results are the first step towards calculating the probability that particular types of customers will choose particular shopping destinations for their retail trips. This knowledge will help transport and land use planners to better target interventions, including possible retail planning strategies, to encourage more sustainable travel behaviour in South-East Queensland – a rapidly expanding conurbation.

Key words: Retail trips, Destination choice, Discrete choice modelling, Utility and Attractiveness

1. Introduction

Retail destination choices are complicated trip types to study since in many cases they are combined to other trip tasks such as work and education. A few studies such as Limanond et al. (Limanond et al., 2005) have considered shopping trips in tour based or activity pattern models considering that factors which affect these trip tasks result from the decisions made to schedule activities in a daily pattern. But the number of these studied is very limited, acknowledging the complexity of the data and models required and the cost of preparing

them. Other studies available in this area have mostly relied on aggregated and disaggregated, trip-based analysis, which only consider separated trips, to understand the retail trip behaviour of travellers.

Retail trips have been given less focus in Australian cities compared to commuting and school trips. Retail trip patterns have been significantly modified throughout the last few decades (Baker and Wood, 2010) due to changes in the form and structure of Australian cities and also the expanding affluence and wealth of city households. Australian cities have experienced a substantial transformation from transit-supportive main street environments towards large enclosed shopping malls that rely on private car access and provide significant parking capacity. New locations for shopping centres are typically proposed by developers or the owners of existing centres, rather than planning agencies. Most of these decisions focus on factors such as distance to customers and surrounding population cost elements. Other factors affecting retail destination choices are not generally considered. Yamashita et al. suggest that Australian shopping centres have the same functions as 'central places' in Christaller's theory (Yamashita et al., 2006), based on the hierarchical grouping of functions into centres to service the surrounding population. The theory of functional arrangement was used up until the 1970s by planners to promote optimal spatial environments to service urban communities (Walmsley and Weinand, 1990). Dawson (1983) indicated that: "traditionally decisions pertaining to the location and type of shopping centre result from interactions amongst four organizations: developer, architect, property consultant and land use planner… the [latter] is to some extent the custodian of the consumer interest." (Innes et al., 1990). Individual preferences and the factors that affect people's retail choice destinations, what they expect or require from a retail destination and which features and factors directly or indirectly affect their destination choices are mainly ignored. How can we bring the customers' preferences into our planning decision process and consider those factors that drive the selection of one particular shopping destination among the other available destination choices? This study focuses on retail shoppers in Brisbane and aims to identify major influences on their choice of destination for particular types of shopping trip

The paper takes the following structure. A brief review of major approaches applied to identify the retail destination choice of trip-makers focusing more on the discrete choice models and some of the research which have been done using this method since 1960s. The methodology adopted and the datasets applied are then described. Data analysis is then explained and the results of the model are described. A discussion follows and a conclusion then addresses the limitations of the study and avenues for future research.

2. Literature review

Since the early 20th century different approaches have been applied and improved to understand the various ways in which people travel between existing retail destinations separated in space; such as Reilly's (1931) Gravitation law and Christaller's Central Place Theory (1933). These studies were based on Newton's Gravitation model and considered that factors such as distance and the population of catchment areas affected peoples' destination choice (Roy and Thill, 2003) (Bates, 2003). Since the 1960s, due to the growth in the number of large regional shopping centres, researchers have sought to explain competition between multiple urban regional centres and Central Business Districts (Roy and Thill, 2003). New techniques such as Huff's (1963) spatial interaction models have developed to analyse retail market areas and to model consumers' store choice processes. These models acknowledge the competitive and probabilistic nature of retail trips and consider the utility that customers obtain by shopping at a specific retail centre (Yrigoyen and Otero, 1998). About one decade later, discrete choice analysis based on disaggregated datasets found its way into the study of retail outlet choice and made a considerable improvement in this area. These attraction models aimed to predict the probability of individuals choosing one alternative among various discrete alternatives based on the utility that they derived from their visit. Discrete choice models can include additional factors, in

comparison to previous models, and are usually used when the dependant variable is discrete, such as travel destination and mode choice, activity participation location choice, residential location choice and route choice. McFadden initially used these logit-based models in the 1970s and 1980s to understand the transportation mode choices of the trip-makers (Athey and Imbens, 2007).

In 1974 Richards and Ben-Akiva developed their disaggregated simultaneous destination and mode choice model for shopping trips based on the multinominal logit model. Based on the result, they concluded that the disaggregated models can be statistically satisfactory, even when calibrated from a limited number of observations, and suggested further study to justify their results (Richards and Ben-Akiva, 1974). Recker and Kostiniuk (1978) limited their study to destination choice for grocery shopping trips. They believed that grocery shopping destination choices were strongly influenced by three factors: the individual's perception of the destination, the individual's accessibility to the destination and the number of opportunities available in the choice decision. They used a multinominal logit (MNL) model to test their hypothesis. The results confirmed that accessibility was the main factor influencing the destination choice of grocery customers (Recker and Kostyniuk, 1978). Multinominal logit analysis was also applied by McCarthy (1980) to study the qualitative characteristics of travel behaviour and the alternative destinations associated with a traveller's shopping activity and how these combine to influence the destination choice behaviour of customers. McCarthy's model was developed separately for a city centre and suburban areas, with both destination and mode-choice of the travellers considered in the suburban model. The dimensions McCarthy considered in his study included generalized trip convenience (trip time, trip cost, trip arrival time, etc.), generalized trip comfort (cleanliness of travel, protection from bad weather, ride comfort, opportunity to stop at other places on the way to the shopping area, etc.), generalized trip safety (safety from accident during trip, etc.), generalized shopping area attraction (good variety of merchandise, low price of merchandise, etc.) and generalized shopping area mobility (easy to park at shopping area, cleanliness of shopping area, etc.). McCarthy found that consumers' attitudinal information in addition to the trip time, safety and availability of parking could significantly affect the pattern of the shopping trips (McCarthy, 1980). Gautschi (1981) and Bucklin and Gautschi (1983) considered retail centre characteristics and transportation mode characteristics for a set of planned suburban shopping centres and traditional, unplanned downtown centres. Results indicated that both retail centre characteristics and transportation mode characteristics were major factors affecting trip makers' decisions. Safety from accident, safety from crime, convenience, reliability, flexibility, travel atmosphere, comfort of ride, protection from weather, transportation cost and parking cost were all considered in their study (Gautschi, 1981). Gautchi claimed that based on the results consumers consider a combination of retail centre and transportation mode characteristics in their decisions to patronize alternative retail centres (Gautschi, 1981). Innes et al. (1990) used a binary logit disaggregated behavioural model to identify the major factors affecting destination choice of automobile users for shopping trips. The most influential factors found in their study were store hours of operation, quality of goods offered, availability of parking, price of goods, accessibility of the shopping area, selection of goods offered and protection from environmental influences (Innes et al., 1990). In other studies, Agyemang-Duah et al. (1996) and Lee (1997) used disaggregated data applied through discrete choice models to quantify the relationship between land use and trip generation (Limanond et al., 2005). They found that people's decisions about home-based shopping trip frequency were directly affected by land use patterns. Carrasco (2008) investigated the choice process of individuals' destination choice for grocery shopping by applying a discrete choice modelling technique and generating a choice set based on the travel time budget of the individuals and a choice set constructed as a random sample from a fixed number of alternative potential destinations. MNL models were constructed separately for walking and car trips. For car-based trips, store size and travel distance were found to be the most relevant attributes in the destination choice

process. Among the socio-demographic characteristics of the travellers, household size was found to be more important than age or gender (Carrasco, 2008).

Almost all of these discrete choice models are based on the Random Utility Maximization (RUM) hypothesis in which it is assumed that a decision maker selects the alternative which delivers them the highest utility among the options available at the time that the choice is made. The randomness arises because the analyst cannot observe all the influences which individuals take into account when maximizing their utility. The choice set from which an individual chooses their decision is considered to be mutually exclusive, collectively exhaustive and the number of alternatives is finite (Nerella and Bhat, 2004). A major practical issue which arises in RUM-based discrete choice modelling is the preparation of the choice-set of available alternatives, since in many activity- and travel-related dimensions the number of alternatives in the choice set will be very large. For example, for residential choice situations or shopping trip destinations, a decision maker can potentially have up to a few hundred choice alternatives to choose from (Nerella and Bhat, 2004). In the earlier models, it was assumed that all possible alternatives were evaluated by an individual before selecting the preferred alternative (Fotheringham, 1988). Later this assumption was challenged because of its infeasible data processing requirements and also the practical limitations that confine the number of alternatives (Carrasco, 2008). Different methods have been developed to help with the selection of alternatives available for choice makers such as the Space-time prism by Hagerstrand (1970), the Competing destinations model by Fotheringham (1988), and Random-choice formation by Manski (1977) (Thill, 1992). Moshe Ben_Akiva and Steven R. Lerman proposed a practical way to manage large choice sets called "Simple random sample of alternatives" which is based on a subset of alternatives [17]. Based on this method, a simple random sample of alternatives will be drawn from all the available alternatives excluding the chosen one, and then the chosen alternative is added into the constructed sample choice set (Akiva and Lerman, 1985). Different numbers of alternatives can be considered in this method. Neralle and Bhat (2004) in their research on the systematic numerical study of the effect of sample size on empirical accuracy and model performance for both MNL and mixed multinominal logit model (MMNL) indicated that the MNL always guarantees consistency with a subset of alternatives, but concluded that it was always advisable to consider sample sizes that are not too small (Yang et al., 2009). Yang et al. (2009) claimed that 50 is a pretty good number for the size of the destination choice-set for shopping trips in an MNL model to generate good estimations (Yang et al., 2009) while Termansen et al. (2003) showed that in their recreation choice application: "as choice set increases, the variation in estimated parameters between different choice sets decreases" (Termansen et al., 2004).

As discussed above, the influence of various factors on the retail trip destination/mode choice of travellers has been studied using discrete choice analysis till today. Some of these studies focussed on the spatial characteristics of the destination, such as the size of the centre, or the number of parking areas available, whereas others investigated the impacts of travellers' attributes (such as age, gender, household size, having a driving license and affordability for having a car). Trip attributes such as distance and travel time or travel cost, the comfort and convenience of the trip have also been considered separately. Discrete choice analysis have become important tools for analysing the destination and mode choice of travellers, as it has the ability to consider the dis-aggregated characteristics of travellers and, as will be explained later, also provide a measurable and meaningful way of quantifying people's retail travel behaviour.

Brisbane as the largest city in South East Queensland (SEQ) is experiencing rapid population growth and expansion in its footprint area, followed by an increase in the number of automobile trips resulting into an unsustainable transport environment. Retail trips comprise about 20 precent of total trips per week (Shobeirinejad et al., 2012), and can therefore have a massive impact on Brisbane's sustainable transport system. Study of the cities' retail structure and the ways people travel to these destinations is therefore of the

utmost importance for current and future planning of the city. This study applies a preliminary discrete choice model to study the travel behaviour of consumers in Brisbane and to investigate important factors which affect retail travel behaviour. Results from this model will provide a basis for the development of more sophisticated destination choice models which can help inform current and future policy making.

3. Methodology

As mentioned previously, discrete choice analysis has been applied using different forms of logit models to study and predict the probability of individuals choosing a particular alternative among various discrete alternatives based on the utility that they derive from their choice decision. The multinomial logit model (MNL) is the most widely used discrete choice model when more than two choice alternatives are available. An important property of the MNL is its assumption of independence from irrelevant alternatives (IIA), which means that the likelihood of selecting one alternative over the other is independent of the presence of any other alternative(s) in the choice set. This IIA property renders MNL models inappropriate for some choice applications. In practice, however, a simple MNL model is almost always developed to provide a 'starting point' description of choice behaviour, from which more sophisticated models which relax the IID assumption can be developed. This study presents results from an initial MNL model of destination choice by retail trip makers in Brisbane. These results will inform development of more flexible models and also provide an initial indication of which destination-specific, trip-specific and individual-specific attributes appear to influence retail destination choice among Brisbane shoppers.

In an RUM framework, Equation [1] represents the utility of chosen alternative i in the choice set C_n of decision-maker n (U_{ni}).

[1] $U_{ni} = V_{ni} + \epsilon_{ni}$

This utility consists of an observed systematic component (V_{ni}) and a randomly distributed unobserved component (ϵ_{ni}) capturing the uncertainty.

Systematic utility V_{ni} is expressed as a function of X_{ni} attributes of alternative i and decision-maker n and corresponding estimated coefficients, β_{ni}. The general form of systematic utility is:

[2] $V_{ni} = \sum \beta_{ni} X_{ni}$

It is assumed that the alternative with highest utility is chosen. The probability P_{ni} of decision maker n choosing alternative i from choice set C_n is given as:

[3] $P_{ni} = Prob\left(V_{ni} + \epsilon_{ni} > V_{nj} + \epsilon_{nj}\right) where\ j \neq i\ and\ i,j\ \in C_n$

$P_{ni} = Prob\left(\epsilon_{nj} - \epsilon_{ni} > V_{ni} - V_{nj}\right)$

The logit model is obtained by assuming that error components ($\epsilon_{nj} - \epsilon_{ni}$), are independently and identically Gumbel distributed across alternatives, which means there is no covariance between errors for alternatives i and j, i.e. $COV\ \epsilon_{nj} - \epsilon_{ni} = 0$ and error structure is identical for decision maker n across both alternatives i and j. The Logit model for two alternatives is as follow:

[4] $P_{n1} = \exp(V_{n1}) / exp\ (V_{n1}) + \exp(V_{n2})$

$P_{n2} = 1 - P_{n1} = \exp(V_{n2}) / exp\ (V_{n1}) + \exp(V_{n2})$

With more than two alternatives, the model expands to the Multinominal Logit (MNL) model, with choice probability for alternative i and decision maker n given by (Train, 2003, Koppelman and Bhat, 2006):

[4] $P_{ni} = \exp(V_{ni}) / \sum j \neq i\ C_n\ \exp(V_{nj})$

Socio-demographic characteristics of individual n can be incorporated by interacting dummy variables for socio-demographic categories D_n^k with a destination-specific or trip-specific attribute Z_{ni} as:

[5] $V_{ni} = \sum \beta_{ni} X_{ni} + \sum_{k=1}^{k=K-1} D_n^k Z_{ni}$

3.1. Data

Three datasets have been used in combination for this study:

1-South East Queensland household travel survey data (SEQ-HTS): The 7-day 2009 SEQ-HTS provides records on shopping trips that have been considered here as the trips started from home for doing shopping and terminated at home (home-based shopping trips). A total of 4165 home based shopping trips for individuals over 5 years old are reported in the dataset.

2-Zenith strategic transport/land use model: This is a strategic transport and land use model, provided by Veitch Lister Consulting Company, calibrated with household travel survey data from the Queensland Department of Transport and Main Roads. It includes zonal data for 2512 geographical zones covering the Brisbane statistical division. It includes data such as number of retail jobs in each zone, walking, car and public transport distance, time and cost incurred in trips between centroid of each geographical zone. The models fine-grained zonal structure provides a useful platform for retail trip analysis.

3- Directory of Shopping Centres/Queensland 2011(SCD): This dataset has been produced by Property Council of Australia. It provides the spatial characteristics of shopping destinations in Brisbane. We applied and linked this dataset, including 389 shopping centres comprising more than 4.6 million square meters of retail floor space, to our retail trip dataset. The SCD follows the classification of shopping centres employed in all of the Property Council's shopping centre directories, including the city centre, super-regional, major regional, sub-regional, regional, neighbourhood, themed and bulky goods categories.

All these datasets were arranged and linked to form one composite dataset for destination choice analysis. Rubymine5.1 scripting software was applied to attach and link the composite dataset. The shopping trips from HTS were associated with available attributes of the destination zone and also with attributes of the shopping centre located in that zone (for those zones for which relevant data were available). The 4165 home-based shopping trips, covering trip attributes such as trip-id, trip origin and destination zones, in addition to socio-demographic characteristics of the trip makers, such as age, gender, etc. were all extracted from the HTS. The origin and destination zones of the trips (based on Census Collection Districts numbers (CCDs)) were then compared and matched with the zone-numbers in Zenith model and assigned an appropriate zoning number and characteristics. Zonal

attributes such as the number of retail employees and also distances between the zones' centroids (walking distance and car distance) were incorporated into the dataset based on information available in Zenith model. The 389 geocoded shopping centres available in the SCD were then overlayed and matched with the Zenith zones and spatial characteristics of the shopping centres were assigned to the Zenith zones that surrounded them.

As discussed in the literature, preparation of the choice-set of available alternatives is an important issue that arises in the RUM_based destination choice modelling. In this study two datasets were created and applied for modelling, one contained 50 random alternatives, and the other contained 150 random alternatives for each retail trip. Initial results indicated that the larger choice-set produced improved model fit (as reported by log-likelihood comparison). Therefore choice sets of 150 randomly selected alternative destinations were created separately for each trip, picking up relevant data for each potential destination zone. The final dataset comprised 624,751 rows and contained different characteristics of travellers, various attributes of alternative destination zones and alternative attributes of trips.

3.2. Variables

The generated dataset provides 13 site attributes (*site area, number of major tenants in a centre, major tenets Gross Lettable Area-Retail (GLAR), number of specialty store, specialty store GLAR,GLAR of the centre of the centre, total number of parking, parking location, the retail centre type (regional, sub-regional, neighbourhood), number of retail employees, having a food court, having a cinema, total centre Gross Lettable Area (GLA)*), 8 individual-specific characteristics (age, income, gender, having a car licence, number of cars, worker or dependent, household size, household structure of the trip makers) and 4 trip-specific attributes (distance, cost and time of the traveling between different zones). Some of these variables are highly correlated as indicated by initial scatter plots and R^2 correlations between pairs of independent variables, which will end the model with some error. To avoid potential collinearity problems, only seven variables out of the original 25 were retained for modelling after measuring the collinearity between them, namely age, gender and income (as individual characteristics of the retail trip maker), number of retail employees, site area and existence of a food court (as characteristics of the destination zones), and the car distance (as a trip-specific attribute) travelled from the origin to the destination zone.

Dummy variables were created for the categorical socio-demographic variables (age, income and gender) and interacted with the car distance variable. Five groups were created for age of the travellers: less than 18, 18 to 30, 30 to 45, 45 to 60 and 60 or above. Weekly income was categorised into five groups: very low (less than 200 A\$ per person), low (200 to 500 A\$ per person), medium (500 to 1000 A\$ per person), high (1000 to 1500 A\$ per person) and very high (more than 1500 A\$ per person).

Table 1: Explanatory variables considered in the MNL model

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Car_dist (Km)[1]	624750	0.08	465.11	93.37	64.92
Ret_jobs[2]	624750	0	2274	75.67	156.56
Site_ar (Ha)[3]	624750	0	38	0.34	2.11
Food_c[4]	624750	0	1	---	---
Per_age[5]	624750	5	90	49.63	17.72
Income (per person)	624750	0	3000	655.58	477.15
Gender	624750	0	1	---	---

[1]Car distance, [2]Number of retail jobs, [3]Site area, [4]Having a food court, [5]Person age

4. Data Analysis

The Mlogit package (contained within the R software) was used to run three separate MNL models with gender, age and income as interaction terms (Equation (5)) to identify individual-specific, destination-specific and trip-specific factors which affect retail destination choice. Parameter estimates are produced by maximum likelihood methods, knowing the observed destinations and given randomly synthesised choice sets for each trip. Parameter estimates are produced for the influence exerted by the seven explanatory variables of Table 1 in various categories of shopping trips based on the type of items purchased: 'groceries', 'clothes', 'eat or drink', 'alcoholic drink' and 'household goods'. Model results and parameter estimates are shown in Table 2 and discussed for each type of shopping trip in the following subsections.

Grocery shopping:

For grocery shopping, car distance, number of retail jobs at the destination, the existence of a food court and the site area of the destination all significantly affect destination choice. The parameter coefficients for car distance and site area are both negative, indicating that – all else being equal – a destination becomes less attractive as travel distance increases and as its size increases. This suggests that grocery shoppers generally prefer smaller, more local destinations such as neighbourhood shopping centres for their grocery necessities. The number of retail jobs and a food court at the destination location both act to make a destination more attractive to grocery shoppers. In terms of the socio-demographic characteristics of the customers, it is noticeable that the aversion to trip distance increases as age increases and that lower income groups as significantly more averse to travel distance than medium or high income groups. For grocery shoppers over 45 years old, the attractiveness of a destination decreases rapidly as travel distance increases. Distance aversion appears to be unaffected by gender for grocery shopping trips.

Clothes shopping:

For purchasing clothes, travel distance is still a major determinant of the attractiveness of destination sites for trip-makers. The relationship is again negative, i.e. all else being equal, a site becomes less attractive to clothes shoppers as trip distance increases. The results also show that, ceteris paribus, the attractiveness of the site increases as the number of retail jobs at the site increases, but site attractiveness decreases cet. par. as site area increases. This suggests that if clothes shoppers are confronted with two otherwise identical destination choices, they will prefer the smaller site, but when comparing sites of similar size they will prefer the location with more retail jobs. More retail jobs in the same floor area might indicate a higher concentration of clothing and shoe shops, both of which have higher staffing per unit floor area than grocery or household good outlets. Thus a smaller shopping centre, which provided the same opportunities for clothes shopping as a larger regional or sub-regional centre would appear to be preferred by clothing shoppers. A food court at the destination can also significantly increase the attractiveness of a destination for clothing shoppers. This can perhaps be explained by the longer hours travellers spend in shopping centres when buying clothes. Looking across the different trip types, gender only interacts significantly with travel distance for clothing trips. Men seem to be prepared to travel greater distances to do their clothes shopping than do women. The aversion to travel distance for clothes shopping trips appears to be sensitive to age and income. The highest income group are clearly willing to travel further than the other income groups for an equivalent clothes shopping experience. Aversion to travel distance is also affected by age. Under 18s appear willing to travel further for clothes shopping, followed by 30 – 45 year olds, but all other age groups are distinctly more averse to longer travelling distances. This might be because under 18s are very fashion conscious. Clothing trip choices of 18 – 30s, and to a lesser extent 30 – 45s, could perhaps be constrained by young children in the family, whereas the two oldest age groups display their normal increasing aversion to travel distance with age.

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Table 2: Model results and parameter estimates

	Variables	Estimate	Std. Error	t-value	Pr(>|t|)
Groceries	car_dist	-0.390	0.025	-15.56	< 2.2e-16 ***
	ret_jobs	0.001	0.001	4.398	1.092e-05 ***
	food_c	0.348	0.036	9.467	< 2.2e-16 ***
	site_ar	-0.025	0.012	-2.135	0.032 *
	Age_18to30	0.039	0.031	1.239	0.215
	Age_30to45	-0.005	0.028	-0.196	0.844
	Age_45to60	0.081	0.026	3.136	0.001 **
	Age_60&more	0.063	0.026	2.424	0.0153 *
	female	-0.020	0.013	-1.481	0.138
	Income_Cat1	-0.159	0.039	-4.053	5.039e-05 ***
	Income_Cat2	-0.103	0.023	-4.337	1.443e-05 ***
	Income_Cat3	-0.075	0.023	-3.226	0.001 **
	Income_Cat4	-0.065	0.028	-2.274	0.022 *
	Log-likelihood : -3219.5				
Clothes	car_dist	-0.051	0.012	-4.001	6.291e-05 ***
	ret_jobs	0.003	0.001	12.738	< 2.2e-16 ***
	food_c	0.433	0.092	4.676	2.917e-06 ***
	site_ar	-0.160	0.028	-5.537	3.063e-08 ***
	Age_18to30	-0.100	0.032	-3.065	0.0021717 **
	Age_30to45	-0.040	0.017	-2.363	0.0181057 *
	Age_45to60	-0.089	0.023	-3.861	0.0001 ***
	Age_60&more	-0.073	0.025	-2.871	0.004 **
	female	-0.031	0.015	-2.058	0.039 *
	Income_Cat1	-0.162	0.074	-2.198	0.027 *
	Income_Cat2	-0.087	0.016	-5.402	6.559e-08 ***
	Income_Cat3	-0.092	0.017	-5.207	1.911e-07 ***
	Income_Cat4	-0.121	0.033	-3.632	0.0002802 ***
	Log-likelihood : -495.06				
Eat_or_Drink	car_dist	-0.351	0.040	-8.599	< 2.2e-16 ***
	ret_jobs	0.001	0.001	3.259	0.001118 **
	food_c	0.543	0.071	7.623	2.465e-14 ***
	site_ar	-0.054	0.026	-2.083	0.037 *
	Age_18to30	0.141	0.047	2.998	0.002 **
	Age_30to45	0.143	0.041	3.509	0.0004 ***
	Age_45to60	0.211	0.039	5.388	7.099e-08 ***
	Age_60&more	0.014	0.055	0.259	0.794945
	female	0.022	0.020	1.095	0.273
	Income_Cat1	-0.300	0.147	-2.036	0.041 *
	Income_Cat2	0.114	0.038	2.964	0.003 **
	Income_Cat3	0.005	0.044	0.124	0.901
	Income_Cat4	0.191	0.037	5.158	2.488e-07 ***
	Log-likelihood : -779.24				
Alcoholic_ Drinks	car_dist	-0.614	0.106	-5.779	7.497e-09 ***
	ret_jobs	0.002	0.001	2.951	0.003 **
	food_c	0.180	0.199	0.903	0.366
	site_ar	-0.211	0.113	-1.854	0.063
	Age_18to30	0.280	0.130	2.151	0.031 *
	Age_30to45	0.115	0.139	0.828	0.407
	Age_45to60	0.412	0.098	4.203	2.628e-05 ***
	Age_60&more	0.309	0.091	3.372	0.0007 ***
	female	0.083	0.056	1.490	0.136
	Income_Cat1	-2.633	1.784	-1.475	0.139
	Income_Cat2	0.296	0.079	3.747	0.0001 ***
	Income_Cat3	0.286	0.072	3.930	8.479e-05 ***
	Income_Cat4	0.238	0.093	2.550	0.010 *
	Log-likelihood : -120.43				
Household_Goods	car_dist	-0.254	0.031	-8.217	2.220e-16 ***
	ret_jobs	0.001	0.001	7.288	3.140e-13 ***
	food_c	0.317	0.063	5.030	4.895e-07 ***
	site_ar	-0.096	0.025	-3.749	0.0001 ***
	Age_18to30	-0.021	0.044	-0.488	0.625
	Age_30to45	0.109	0.031	3.509	0.0004 ***
	Age_45to60	0.021	0.034	0.632	0.527
	Age_60&more	0.089	0.031	2.816	0.004 **
	female	0.007	0.015	0.493	0.621
	Income_Cat1	0.152	0.031	4.814	1.478e-06 ***
	Income_Cat2	0.060	0.029	2.078	0.037 *
	Income_Cat3	0.093	0.027	3.418	0.0006 ***
	Income_Cat4	0.042	0.035	1.195	0.232
	Log-likelihood : -1216.2				

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Eat-or-Drink Shopping:

Reassuringly, the attractiveness of destinations for eat and drink trips (defined as visits to fast food outlets, restaurants or coffee-shops), is significantly affected by the presence of a food court in the shopping outlet, and also by the number of retail jobs. Travel distance exerts its usual adverse effect, and again – all else being equal - smaller shopping centres appear to be preferred. This might again indicate a preference for neighbourhood centres rather than major shopping centres for this type of trip. Generally as age increases, aversion to travel distance decreases, although over 60s are again the exception. This could be due to limited independent mobility for under 18s and a diminishing influence of young families across the 18 to 60 age range. With regard to income, the lowest income group are significantly more averse to travel distance in selecting their eat-or-drink destinations than are the other income groups.

Alcoholic-Drinks Shopping:

Car distance and the number of retail jobs at the destination are both significant influences over the attractiveness of destinations for the purchase or consumption of alcoholic drinks. People do not appear to like travelling long distances for their alcohol purchases, but they do appear to prefer locations which offer more options and more stores. Among different income categories, the lowest income group are very significantly more averse to travel distance than all other groups, perhaps emphasising the importance of travel convenience for a higher prevalence of alcohol purchase for consumption at home. Aversion to travel distance is less variable across the age categories. As expected, site area and a food court do not influence destination choice for alcohol purchase trip-makers.

Household-Goods Shopping:

All three site attributes and travel distance exert significant influence over shopping trips for household goods. Influences here are very similar to those reported earlier for clothes shopping, with, all else being equal, aversions to increased distance and increased site area and preferences for more retail jobs and a food court food at the destination. The similarity with clothes shopping might arise because purchasing furniture, curtains and bedding, for example, entails similar subjective choices to purchasing clothes: personal preferences regarding colour, fit and style are important in both cases. Aversion to travel distance is similar across income and age categories.

5. Discussion and Conclusion

Results from MNL models with socio-demographic interaction terms show meaningful relationships between destination-specific, trip-specific and individual-specific attributes and destination choice for all the different categories of shopping trip. This suggests that – even allowing for potential misspecification of the MNL models - site attributes and socio-demographic characteristics do play a role alongside accessibility (distance) in destination choice, in accordance with the literature review. Site area generally exerts a negative effect on site attractiveness, indicating that travellers generally prefer smaller shopping destinations if they can still provide the same number of options. Longer travel distances almost always reduce the attractiveness of a destination, all else being equal. A food court is an important positive influence for trips such as buying clothes or household goods where the time spent at the destination is longer. Gender does not typically interact significantly with site or trip characteristics except for clothes shopping, whereas income and age do typically interact significantly with the aversion to travel distance, although the strength of these interactions varies between the different types of trip. Interestingly, men are travelling further for clothes shopping than women, which may relate to the limited retail offer provided to men in Australian cities and the limited number of franchise stores in shopping centres here (Burke, 2012).

Other individual-specific variables such as having a car license and household structure, as well as other attributes of the destination location such as the density of alternative shopping destinations in the region still need to be examined in further research. Simultaneously, the substantial expansion in the number of e-commerce shopping and its impacts on the travel behaviour of customers are of an utmost importance and should be considered in later studies. Alternative methods for selection of the choice sets including space/time prism may also change the set of available alternatives considerably, and the specification of the number of alternatives in the choice set can also be examined in more detail. Additional research has to be done to consider other types of logit models which relax the IIA property of the MNL models presented here. This could be particularly important when seeking to predict choice probabilities based on site characteristics and location. Nested logit, mixed logit and/or latent class models will all be investigated.

These findings are still relevant and important since it gives us the opportunity to basically understand how the different individual-specific, site-specific and trip-specific attributes substantially influence the destination choice of consumers while traveling for their shopping requirements.

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