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Incorporating online shopping into travel demand modelling: challenges, progress, and opportunities

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ABSTRACT

There is a large body of literature, spanning multiple disciplines, concerned with the relationship between traditional (physical) shopping and associated travel behaviour. However, despite the recent rapid growth of digital retailing and online shopping, the impact on travel behaviour remain poorly understood. Although the issue of the substitution and complementarity between conventional and virtual retail channels has been extensively explored, few attempts have been made to extend this work so as to incorporate virtual retail channels into modelling frameworks that can link shopping and mobility decisions. Here, we review the existing literature base with a focus on most relevant dimensions for personal mobility. How online activity can be incorporated into operational transport demand models and benefits of such effort are discussed. Existing frameworks of shopping demand are flexible and can, in principle, be extended to incorporate virtual shopping and the associated additional complexities. However, there are significant challenges associated with lack of standard ontologies for crucial concepts and insufficiencies in traditional data collection methods. Also, supply-side questions facing businesses and policy-makers are changing as retailing goes through a digital transformation. Opportunities and priorities need to be defined for future research directions for an assessment of existing tools and frameworks.

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KEYWORDS

Transport planning; demand models; online shopping; e-commerce

1. Introduction

1.1. Research context

In recent years the pace of innovation in the retail industry has accelerated dramatically, with a proliferation of new retail channels and store formats as well as new service offerings (e.g. deliveries, click and collect, virtual stores). In response, the nature of shopping activity is changing from the consumer side. The share of online retailing in the UK reached 12.5% of all sales in 2015 compared to 0.3% in 1998 and 2.1% in 2002 (ONS, 2015). In the USA e-commerce retail sales accounted for 7% of all sales in 2015, up from 2.8% in 2006 (Bucchioni, Liu, & Weidenhamer, 2015). Governments, retailers, transport,

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and town planning professionals are increasingly interested in understanding implications of these trends for personal travel and logistics.

Since the early 1900s, long before the emergence of e-commerce, researchers aspire to better understand how shopping activity changes over time and in response to interventions as shopping is one of the most common purposes for personal trips (19% of all trips in England in 2014 (Department for Transport, 2017) and 20% in US in 2009 (Santos, McGuckin, Nakamoto, Gray, & Liss, 2011)). Numerous conceptual and quantitative models have been developed specifically for shopping travel focusing on different dimensions. Accordingly, travel demand models often treat shopping separately. The literature on online shopping, however, is mostly separate from this traditional shopping literature and focused on quantifying the overall net effects (Section 2). Incorporating new online forms of shopping into conventional and widely applied demand models has received little attention. Yet, doing so might provide additional insights to the substitution or complementarity question. Moreover, emerging temporal and spatial demand profiles can be studied to help answer today's pressing business and policy questions. There is a rich body of work associated with shopping behaviour as it is an important subject of research in multiple fields including transport research, applied geography, urban planning, competition economics, marketing research, and retail studies. In this paper, we review relevant literature with a view on if and how online shopping can be incorporated within traditional frameworks. We limit our focus to modelling personal travel, hence the discussion on freight transport models is limited.

1.2. Conceptual framework

The retail sector is characterised by the complex integration of multiple agents involved in different decision-making processes. Retail transformation is driven by the interaction of these agents: consumers, retailers, government, and many others such as developers,

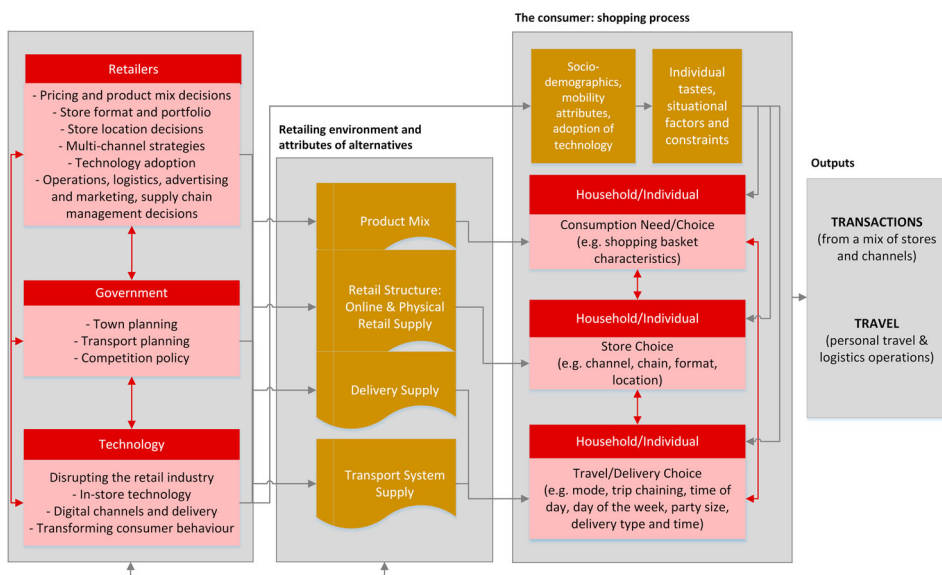


Figure 1. Retail market: conceptual framework.

land markets. Technology is also acting as an agent of change (Figure 1). Supply-side decision-making has long relied on demand side models, hence there is a rich literature on consumers' decision-making processes. The individual will make a series of decisions when shopping, these include but are not limited to: timing, retail chain/firm, channel (online vs. in-store), store location and format, choices related to product purchases, shopping alone vs. with others, travel mode to store, home delivery vs. collection from store when shopping online, route choice, and trip chaining. As the retailing environment becomes more complex, the number of options is increasing. Further, equipped with new technology (e.g. smart phones, price comparison capabilities, and access to online reviews), consumers have access to more information in real-time. It is often not possible to capture data on all these different dimensions. Also, treating each dimension as endogenous will complicate the model structure and create problems in estimation. Therefore, models in practice often focus on modelling selected dimensions of choice. For the present review, we focus on the dimensions that are most relevant for mobility implications.

The remainder of this paper is organised as follows. In the next section, we review studies that are specifically focused on impacts of changes in retailing on personal travel. Next, we classify the literature by application areas corresponding to different dimensions of shopping behaviour that are most relevant for mobility implications. For each category, we present a review of previous studies summarising aims, data sets and methodologies, conclusions, and potential for incorporating online shopping into regional travel demand forecasting models. Lastly, we present a summary and critical assessment of the reviewed literature, and a discussion of priorities and opportunities for future work.

2. Impacts of retail change on personal travel

Impacts of retail change on travel was recognised since the 1980s, where increasing number of out-of-town retail developments led to concerns regarding their impact on personal car use and travel (Department for Transport, 2017; Handy, 1993). As a result, impacts of retail decentralisation on personal travel have been studied extensively (e.g. Cairns, 1998; Cervero, 1989, 1996; DCLG, 2014; Handy, 1992, 1996; Handy & Clifton, 2001; Lowe, 2005; Thomas & Bromley, 2003). Digital innovation and ICT is now driving another important transformation of the retail sector. In response, potential implications of online shopping on personal travel and freight travel have been studied extensively in transportation research and retail geography (Cao, 2010; Cao, Douma, & Cleaveland, 2010; Cullinane, 2009; Golob & Regan, 2001; Mokhtarian, 1990, 2002, 2004; Rotem-Mindali, 2014; Rotem-Mindali & Salomon, 2007; Rotem-Mindali & Weltevreden, 2013; Weltevreden & Rotem-Mindali, 2008, 2009).

Four types of travel impacts of ICT use were identified at the conceptual level: substitution, complementarity, modification, and neutrality (Hjorthol, 2002; Mokhtarian, 2002, 2009; Salomon, 1985, 1986). Building on this taxonomy, numerous studies attempted to quantify net effects on journey frequency and miles travelled. We refer the interested readers to Bhat, Sivakumar, and Axhausen (2003), Rotem-Mindali (2014), Rotem-Mindali and Weltevreden (2013), Weltevreden (2007) for comprehensive reviews. Findings from these studies are diverse and sometimes contradictory. There has also been interest in understanding the relationship between frequencies of in-store and online shopping activity to gain insights to the substitution or complementarity question (Cao, Xu, & Douma, 2012; Circella & Mokhtarian, 2010; Lee, Sener, Mokhtarian, & Handy, 2017; Zhen,

Cao, Mokhtarian, & Xi, 2016; Zhou & Wang, 2014). Cao et al. (2012) presented a detailed review of these studies that use various statistical techniques. Most studies identify complementarity effects, a positive relationship between online and in-store shopping frequency and note causality is hard to determine (Circella & Mokhtarian, 2010; Farag, 2006). More recently, Suel, Daina, and Polak (2016) and Suel, Le Vine, and Polak (2015) reported evidence of substitution effects in the context of grocery shopping in London.

Results from cited studies are highly influenced by assumptions, definitions, and modelling decisions regarding sample selection and methodologies. Also, there are multiple and sometimes counter acting relationships (Golob & Regan, 2001; Keskinen, Delache, Cruddas, Lindjord, & Iglesias, 2001; Mokhtarian, 2004). Shopping as an activity purpose contains a heterogeneous class of activities; shopping for groceries may involve different behavioural mechanisms with different mobility implications than occasional shopping for white goods (Girard, Korgaonkar, & Silverblatt, 2003; Mokhtarian, 2004; Rotem-Mindali & Salomon, 2007; Visser & Lanzendorf, 2004). Different stages of the shopping process are distinct for certain types of products while less so for others (Hsiao, 2009; Mokhtarian, Salomon, & Handy, 2004; Salomon & Koppelman, 1988). The information gathering, for instance, is likely to be relatively long-duration and may involve conducting unique trips for infrequently purchased and high-value items such as personal cars and computers. Grocery shopping, however, mostly does not involve separate visits for information gathering only. Hence, the choice between online and in-store channels for different stages of the shopping process may vary for different product types (Balasubramanian, Raghunathan, & Mahajan, 2005; Farag, 2006; Hsiao, 2009; Mokhtarian & Tang, 2013; Rotem-Mindali & Salomon, 2007, 2009; Weltevreden, 2007). Decisions regarding the delivery of purchased goods (Marker & Goulias, 2007), degree of trip-chaining and multi-purpose shopping (Corpus & Peachman, 2003; Golob & Regan, 2001; Keskinen et al., 2001; Mokhtarian, 2004) will also influence net effects. Online shopping may also lead to generation of new activities with achieved time savings or to increased shopping frequency or spending (Farag, Krizek, & Dijst, 2006; Farag, Schwanen, Dijst, & Faber, 2007; Ferrell, 2005; Gould & Golob, 1997). Due to these complex relationships, a broader perspective of system-wide analysis and a better understanding of individual choice behaviour is required to assess travel impacts of online retailing on travel (Bhat et al., 2003; Mokhtarian & Salomon, 1997). This view also motivated the present review as we believe the rich literature on shopping behaviour offers tools and methodologies to represent complexities needed for a system-wide analysis.

3. Models for different dimensions of shopping

3.1. Shopping location and store choice

The vast literature on shopping location and store choice can be categorised broadly by modelling methodologies, as reviewed in following sub-sections. Differences in models within each category are mostly driven by research aims. Transport researchers, for instance, are often primarily concerned with the geographic location of store alternatives and resulting spatial flows. Market researchers and economists, on the other hand, are more interested in choice with respect to store formats, retail firms or chains, pricing strategies. Such differences influence modelling decisions with respect to formulations, model

structures, data collection, and explanatory variables considered for inclusion as reviewed further below.

3.1.1. Gravity-type models

In line with macroeconomic theory, spatial flows between zones can be modelled by estimating relationships between aggregate travel data and macro-level zonal variables. Gravity and entropy maximisation models, also called spatial interaction models, have been used to compute the total number of trips between zones (Carey, 1867; Haynes & Fotheringham, 1984; Ortúzar & Willumsen, 1994; Sivakumar, 2007; Wilson, 1971). For shopping, magnitude of the aggregate flows are positively associated with shopping zones' attractiveness and negatively associated with the distance between origin zone and shopping zone. These models are estimated using aggregate data on expenditure or trip flows between zones. Early applications can be traced back to Reilly's law of retail gravitation where the point of indifference between two shopping centres is computed (Reilly, 1931). Ortúzar and Willumsen (1994) suggested that the first application of the gravity-type models in transport for analysing shopping trips was the model by Casey (1955), followed by Huff (1963) and Lakshmanan and Hansen (1965). Extensions to the basic gravity-type models attempted to incorporate individuals' perception (Cadwallader, 1975), multiple attributes of shopping centre alternatives (Timmermans, 1981), and competition effects (Fotheringham, 1983; Gibson & Pullen, 1972; Guy, 1987). More recently, Gonzalez-Benito (2005) utilised gravity-type models for studying how different store formats compete over space. Model formulations vary in how they characterise attractiveness of shopping zones (e.g. retail floor space, employment, number of stores, parking, quality and quantity of goods sold) and how they specify the distance function. For models developed by transport researchers trip counts are used for travel flow estimations (Casey, 1955; Guy, 1987; Timmermans, 1981). Retail location planners and economists are more interested in predicting sales volumes and footfall, hence also use consumer expenditure data (Gibson & Pullen, 1972; Gonzalez-Benito, 2005; Lakshmanan & Hansen, 1965; Porojan, 2001). Gravity-type models are criticised for ignoring the heterogeneity between different decision-makers and not incorporating individual consumer characteristics. They are estimated using aggregate data sources (e.g. total number of trips attracted to a shopping zone, total retail expenditure for a given zone, macro-level attributes of spatial zones, and average floor spaces) and do not require data on behaviour of individual decision-makers.

For incorporating online alternatives in a gravity-type model, there is a challenge in representing attractiveness and costs. Physical and online stores do share some characteristics (e.g. quality), yet most commonly used measures of attractiveness in gravity-type models (e.g. floor space) cannot be used for online. Attributes that were found to be influential on channel choice (e.g. payment options) require additional data collection. Similarly, costs associated with in-store alternatives (e.g. travel times) does not apply to online where costs might include delivery fees and times. Further, aggregate data sources often used in estimations will not contain information regarding online shopping activity. Traditional gravity-type models, however, can be attractive for understanding the effects of online shopping on physical retail centres. Some measure of online shopping frequency or expenditure for people living in certain areas may be included as covariates using available data from national travel surveys.

3.1.2. Discrete choice models

Discrete choice models based on random utility maximisation are estimated using disaggregate choice data from individual decision-makers. These models were developed to study individual choice behaviour in situations where decision-makers choose from a set of mutually exclusive and collectively exhaustive discrete alternatives. Rational decision-makers are assumed to select the alternative with the highest indirect utility. The utility has a deterministic part, a function of observable and relevant attributes of alternatives and individual tastes, and a random part. Detailed discussion of discrete choice methods are presented by Ben-Akiva and Lerman (1985) and Train (2009). Numerous applications of discrete choice methods can be found in literature for studying shopping destination and store choice behaviour. Suel (2016) presents a summary list of selected discrete choice models that were developed in the context of shopping location and store choice behaviour (Suel, 2016, p. 50, Table 2.2). Differences result from modelling decisions regarding:

Definition of the choice situation: Some studies model the choice of most frequented store while others are interested in choice of store at each shopping occasion.

Identification of the decision-maker: The decision-maker is generally identified as the individual, or the household (without distinguishing between individual shoppers within the household), or the main shopper (household member who does most of the shopping).

Aggregation of choice alternatives: At the most disaggregate level, it is possible to model the choice of individual stores (Bell & Lattin, 1998; Recker & Schuler, 1981; Rust & Donthu, 1995). However, data on exactly which store was chosen and detailed attributes of each alternative is rarely available especially as choice sets get larger. Most studies in transportation research use zonal aggregates of alternatives (e.g. shopping centres, transportation analysis zones) (Cadwallader, 1975; Koppelman & Hauser, 1978; Miller & O'Kelly, 1983; Thill & Wheeler, 2000). The choice of geographic zones as the unit of aggregation is consistent with the ultimate aim of travel demand models to predict spatial flows between zones and also driven by available data as traditional travel surveys collect specific location information yet do not contain additional information on visited store attributes. Data on attributes of alternatives is more readily available at the zonal level (e.g. total retail employment, total retail floor space, and population). Studies in marketing, retailing, and competition economics typically use aggregates of alternatives based on store types, retail chains, or formats (Aaker & Jones, 1971; Bell, Ho, & Tang, 1998; Bhatnagar & Ratchford, 2004; Burnett, 1978; Fox, Montgomery, & Lodish, 2004; Gonzalez-Benito, 2002; Messinger & Narasimhan, 1997; Reutterer & Teller, 2009; Rust & Donthu, 1995; Schiraldi, Seiler, & Smith, 2011). These approaches are consistent with the aims of research in understanding influence of store format, pricing, branding, and retail chains on store choice.

Model formulation: Different formulations including the basic multinomial logit and its extensions have been used in store choice modelling. Earlier models have adopted the multinomial logit model in its simplest form using a linear specification for the utility function (Dunn & Wrigley, 1985; Fotheringham, 1988; Koppelman & Hauser, 1978; Recker & Schuler, 1981; Richards & Ben-Akiva, 1974; Rust & Donthu, 1995; Timmermans, Van Der Heijden, & Westerveld, 1984; Wrigley, 1988). Linear utility specifications allow for non-

linear spatial effects of agglomeration and competition using different definitions of proximity (Bhat, 1998c; Fotheringham, 1988). More advanced formulations, such as nested logit (Suárez, del Bosque, Rodríguez-Poo, & Moral, 2004; Suel, 2016), cross nested logit (Ding et al., 2014), and mixed logit (Gijbrecchts, Campo, & Nisol, 2008; Popkowski Leszczyc, Sinha, & Sahgal, 2004) have been utilised for more flexible formulations.

Explanatory variables: Many attributes and tastes might affect decision-making in the context of shopping destination choice. Covariates considered for inclusion in the observed part of the utility function is influenced by research aims, hypotheses regarding the underlying choice behaviour, and data availability. Transport researchers typically have a very detailed representation of travel-related attributes and a simpler representation of store attributes. Socio-demographic variables used are also more likely to include mobility attributes (e.g. car ownership) (Bhat, 1998c; Limanond, Niemeier, & Mokhtarian, 2005; Miller & O'Kelly, 1983; Richards & Ben-Akiva, 1974; Timmermans, 1996). Conversely, marketing researchers characteristically have a simplified representation of travel-related attributes (e.g. physical distance) and a detailed representation of store attributes (e.g. store format, pricing and promotions, store ambiance). Socio-demographics might include variables related to consumer behavioural characteristics (e.g. price sensitivity, large basket shoppers vs. small basket shoppers) (Aaker & Jones, 1971; Bell et al., 1998; Gonzalez-Benito, 2002). Explanatory variables may also include objective measures of store attributes and costs (e.g. physical distance, employment, floor area, store type, and presence of other stores within a mile), and/or subjective measures based on individual perceptions of alternatives with respect to various attributes (e.g. quality, cognitive distance, reasonable pricing, and store atmosphere). Data for the former is usually more readily available, while customised surveys are conducted for the latter (Cadwallader, 1975).

Data types: Disaggregate data required for discrete choice models can be collected through stated preference (SP) (Timmermans, 1996; Timmermans, Borgers, & van der Waerden, 1992) or revealed-preference (RP) surveys (Bhat, 1998c; Limanond et al., 2005; Recker & Kostyniuk, 1978). RP data describes actual choices from real life; hence alternatives and attributes are restricted to existing choice sets. SP data, on the other hand, is collected through controlled experiments where respondents are asked to indicate their choices in hypothetical choice situations with real or hypothetical alternatives. The benefit of SP is the ability to design statistically efficient generation processes that are not affected by unwanted correlations which typically is the case for RP data. Further, SP surveys provide opportunities to explore complex behaviours and effects of potential changes in the choice environment. RP data benefits from realism as people often behave differently in real life than when they are responding to surveys. RP data often only includes attributes of chosen alternatives and there is a challenge in collecting information on un-chosen alternative attributes. Also, different from SP data, true choice set is not known and analysts rely on assumptions for choice set construction. SP and RP data can also be jointly utilised (Bhat & Castelar, 2002; Hensher & Bradley, 1993; Ortúzar & Willumsen, 1994). Synthesised data are also used for demonstrating applications of suggested model formulations and frameworks (Borgers & Timmermans, 1987).

Incorporating online alternatives within a discrete choice framework is relatively straightforward in principle. Online stores simply are additional alternatives in choice sets. The attributes of online and in-store alternatives, however, are largely different. This is problematic in practice for data collection and interpreting coefficient estimates. First, travel

surveys typically collect quite limited information regarding online activity, hence the challenge in finding empirical data sources. Second, there is a difficulty in capturing attributes of virtual alternatives due to their highly personalised and dynamic nature. For instance, delivery prices and windows presented to decision-makers at the time of purchase is often highly personalised and depend on unobserved factors (e.g. time of order, delivery requests by other customers). Such dynamic attributes are difficult to capture using traditional survey methods, thus new data collection tools are needed. Data on perceptions regarding online attributes like website design and attractiveness, quality of delivery service are influential and need to be collected. Thus, existing models of channel choice are mostly developed at the level of aggregated channel alternatives where the decision is between online versus in-store, and heterogeneity within each channel is not represented. Two recent exceptions are Chintagunta, Chu, and Cebollada (2012) and Suel (2016); discrete choice models are estimated at the level of individual stores in the context of grocery shopping (see Section 3.5.2 for a detailed review). Such extension allows for a realistic representation of choice behaviour among available shopping options that consist of both in-store and online alternatives.

3.1.3. *Conjoint analysis*

Historically, conjoint analysis and discrete choice methods co-evolved and influenced one another (Gustafsson, Herrmann, & Huber, 2013; Louviere, 1988; Louviere, Flynn, & Carson, 2010; Louviere, Hensher, & Swait, 2000). Initially, conjoint analysis methods were used to elicit preference through SP, where respondents are asked to provide a rating of preference for a set of hypothetical alternatives using a bounded integer scale. Ratings for each alternative were used as the dependent variable for estimating taste coefficients for different attributes (Louviere & Meyer, 1981). In later applications, respondents were asked to rank their preference for a set of hypothetical alternatives and provide ratings for selected attributes of each alternative. Collected rankings data were then converted to choice data with the assumption that the highest ranked alternative is chosen among all others, the second ranked is chosen among all others except the first ranked and so on (Ben-Akiva, Morikawa, & Shiroishi, 1991). Resulting data were then used to estimate separate contributions of different attribute levels to overall utility. The underlying assumption is similar to discrete choice: overall utility can be represented as a function of part-worth utilities associated with different levels of alternative attributes. It is also assumed that individuals will choose the alternative that yields the maximum utility; choices of individuals can be predicted based on different assumptions on unobserved utilities and decision rules (e.g. logit model) (Louviere et al., 2010). The main problem with using ranking data is that it is less reliable for lower ranked alternatives; respondents will provide better information on their most preferred alternative yet spend less effort with lower ranked alternatives (Ben-Akiva et al., 1991). Over the years, a choose-one approach emerged as the preferred survey format where respondents are asked to choose one among several alternatives they are presented with to mimic actual choice behaviour closely (Boyle, Holmes, Teisl, & Roe, 2001). Conjoint analysis methods, also called multi-attribute preference models, have been applied in the context of store preferences and related choice behaviour (Koppelman & Hauser, 1978; Recker & Schuler, 1981; Timmermans, 1982, 1984; Timmermans et al., 1984; Timmermans, Van der Heuden, & Westerveld, 1982). Results consistently indicate that prices, variety and quality of products,

speed and quality of service, store atmosphere, parking availability, number of shops within a retail complex, and travel distances affect preferences for shopping location and store.

Incorporating online shopping in conjoint analysis studies is rather straightforward as online stores are additional alternatives in the choice sets as is the case with discrete choice. Doing so will offer ways to start quantifying how shoppers value attributes of online alternatives and measuring trade-offs between them in relation to attributes of physical stores. Attributes of online alternatives are characteristically very different from in-store and there exists a rich literature focusing on identifying influential characteristics (Section 3.2). Based on such background, surveys can be designed using conjoint methods. This will allow researchers, for instance, to quantify relative value of delivery times and prices compared to parking costs and travel times.

3.1.4. Markov chain

Store loyalty or store switching behaviour can be formulated as a Markov-chain model. Markov-chain models are used for modelling sequences of random variables that are representative of states of a stochastic process $X^{(t)}$, $t = 0, 1, 2, \dots$ where the state at time t depends only on the state at time $t - 1$. In this context, the recurrent activity of store choice can be considered as a two state process where $X^{(t)} = 1$ if the consumer shops from the most frequently visited store (e.g. defined by chain, format, and specific store), and $X^{(t)} = 0$ if any other store is visited in a given shopping occasion. Such representation is used to study store loyalty and switching behaviour (Aaker & Jones, 1971; Burnett, 1977). The probability that the process will make a transition to one state given the current state can be specified to be dependent on selected covariates including socio-demographics or situational factors (Burnett, 1978).

Incorporating online alternatives when estimating of Markov-chain models requires using online and in-store purchase data. Intuition suggests store switching will involve different behavioural mechanisms in the physical and online worlds. To test this hypothesis, it is possible estimate Markov-chain models using online and in-store purchase data separately and compare results. These models can also be used to study switching behaviour between channels. For instance, for a given product category with recurring purchases, effects of personalised advertising, promotions, delivery availability, delivery fee reductions, etc. on switching channels can be studied using Markov-chain models.

3.1.5. Heuristics

Heuristic-based models take an alternative approach to modelling decision processes, where individuals may adopt rule-based strategies (as opposed to utility maximisation) to guide their decision-making. For instance, the decision-making process can be represented as a set of if-then rules (e.g. elimination by aspects proposed by Tversky (1972)) that can then be expressed as a decision tree when modelling choice behaviour. This approach is particularly attractive for complex choice situations involving high numbers of alternatives (e.g. spatial choice, activity scheduling) where it is often cognitively impossible for individuals to gather and evaluate detailed information on each alternative. Heuristics methods also allow for modelling non-compensatory decision strategies where negative attributes of an alternative cannot be compensated by its positive attributes (Johnson & Meyer, 1984; Recker & Golob, 1979). In the context of shopping

location choice, Thill and Wheeler (2000) employed a decision tree induction algorithm to produce spatial decision trees for home-based shopping trips. Independent variables in the choice model included travel distance and time, destination attributes (e.g. population, employment), zonal type (e.g. central city, developed area, and outlying business district), and socio-demographics (e.g. age, gender, income, household size, presence of children, and number of cars). They found attributes of destinations and measures of travel distance are the most discriminating variables, and socio-demographics become important predictors at lower levels of the tree. The destination or location model for shopping in Albatross (Arentze & Timmermans, 2000), an agent-based transport model, also uses decision trees (Arentze, Ettema, & Timmermans, 2011). A combination of heuristic and discrete choice methods can also be used. For example, a deterministic rule based on a distance threshold (e.g. all stores within a certain distance from home (Beynon, Griffiths, & Marshall, 2002; Black, 1984) or maximum number alternatives considered (e.g. nearest n stores (Schiraldi et al., 2011)) can be used to define the choice set. Decision-making processes may then be modelled using discrete choice methods using the generated choice set.

Incorporating and including online stores to decision trees and other heuristic-based models will help shed some light into potential rule-based strategies people use for channel choice. For instance, there may be a threshold value for delivery time (next available delivery slot) or delivery fees for individuals over which they are reluctant to order online similar to travel time thresholds.

3.1.6. Activity generation and scheduling

Decisions regarding shopping can be studied in the context of the activity scheduling problem. How people plan and schedule their daily activities and trips have been studied extensively in transport literature for developing activity-based travel demand models (see Bhat and Koppelman (1999) for a comprehensive review). Activity scheduling models aim to predict which activities are conducted, where, at which sequence, for how long, with whom, etc. They incorporate travel behaviour to link activities in space. Examples of activity-based models in transport include Albatross (Arentze & Timmermans, 2000), Famos (Pendyala, Kitamura, Kikuchi, Yamamoto, & Fujii, 2005), and Tasha (Roorda, Miller, & Habib, 2008). In this context, shopping activities compete with other activities and fit into individual daily schedules. Hence, activity-based models offer a framework for studying how shopping activity interacts with other activities. Recently, Rasouli and Timmermans (2013) demonstrated how shopping location choice can be analysed using activity generation and scheduling models using Albatross, where shopping trips are embedded in the prediction of daily activity-travel patterns.

Incorporating in-home (online) and out-of-home (in-store) shopping activity within activity-based models is again relatively straightforward when detailed data on both types of activity is available. Moreover, online shopping activity can actually be conducted while at home, at work, or while travelling. This will fully or partially satisfy the need to do shopping, hence there will be less of a need for a shopping trip. In this framework, it is also possible to account for trip-chaining and multi-purpose shopping when studying effects of online shopping on total number of trips or miles travelled. Data may become available from detailed time-use surveys where respondents are specifically asked about types of online activity they conduct when filling in diaries.

3.2. Travel mode choice

There is a vast amount of literature that studied travel mode choice in general and for specific activity purposes. One of the earliest applications of logit models was in commuters' mode choice by McFadden et al. (1977), and since then numerous studies have attempted to model travel mode choice for work trips using the discrete choice framework (Ben-Akiva & Lerman, 1985; Bhat, 1998b, 2000; Horowitz, 1993; Swait & Ben-Akiva, 1987; Train, 1980, 2009). Mode choice for shopping trips, and non-work trips more generally, have been studied separately from work trips due to their comparatively flexible nature and potential for managing peaks (Koppelman & Bhat, 2006; Kumar & Levinson, 1995; Steed & Bhat, 2000). Discrete choice have been widely applied to mode choice problems for shopping trips (Ibrahim & McGoldrick, 2003; Jiao, Moudon, & Drewnowski, 2011; Recker & Stevens, 1976; Schmöcker, Quddus, Noland, & Bell, 2008; Timmermans, 1996; Uncles, 1987). Covariates frequently considered and found to be significant include socio-demographics (e.g. income, household size, employment status, and age), individual attitudes towards available modes collected through ad-hoc survey instruments (e.g. value associated with the flexibility of the car mode, perceived safety), and distinctive characteristics of available travel modes (e.g. travel times, costs, parking availability, and costs). Higher street density, accessibility to stores, and other amenities have been found to positively correlate with not driving.

Joint or sequential models of destination and travel mode choice are common in literature. Timmermans (1996) developed a model for sequential choice of mode and destination using the basic multinomial logit form using SP data. Shopping centre attributes included prices, distance, size, and parking facilities; transport mode attributes included travel and parking, travel time, and frequency of service. Limanond et al. (2005) developed a mode and destination choice model for shopping trips using a nested logit form. Joint choice models for travel mode and departure time were developed for shopping trips using nested logit, mixed logit, and generalised extreme value models (Bhat, 1998a, 1998c).

For incorporating online shopping, additional modes for travel or delivery need to be considered. It is possible to get home deliveries, buy online and collect from stores or designated pick up locations using traditional travel modes. Amazon, for instance, have been experimenting with conveniently located collection lockers (Campbell, 2012; Goldfingle, 2014). Uber started using its fleet of cars to offer express deliveries through partnerships with retailers (Hawkins, 2016). Volvo, Daimler, and DHL experimented with the idea of using parked cars as delivery locations (Etherington, 2016; Winter, 2014). Little is known about user acceptance, the level of potential demand, and willingness to pay for these services. Incorporating emerging delivery services as new modes of travel and delivery within existing destination and mode choice models will be valuable to better understand consumer preferences and behaviour.

3.3. Shopping frequency

One approach to studying shopping frequency is to assume individuals allocate monetary and time budgets to competing activities where shopping is one. In the framework suggested by Blaylock (1989) households maximise their overall utility by allocating their monetary budgets to food and non-food purchases and their time budgets to labour participation, grocery shopping, and other activities (e.g. leisure, home production,

and other shopping). Grocery shopping is treated separately from other types of shopping, as it is assumed to have less recreational value when compared to non-maintenance shopping. With more frequent shopping, individuals reduce opportunity costs (i.e. costs associated with inventory holding and not having desired products at a given time) yet increase travel costs and time spent shopping. Similar constrained optimisation models of consumers optimising shopping frequency as a function of non-shopping trip frequencies, inventory costs, and travel costs have been suggested by Bacon (1995) and Bawa and Ghosh (1999). These studies found household size, access to stores, and income level are all positively associated with shopping frequency. Households with all adults employed have lower frequency of shopping due to time constraints. Lundevaller (2009) used Poisson regression to study effects of travel costs, region, income, and frequency of conducting other activities on frequency of grocery shopping. He found a negative correlation between number of shopping and recreational trips, potentially due to time budget constraints. The idea of allocating time between competing activities is also used in activity scheduling models (Section 3.1.6), hence offer a framework for studying shopping frequency (Bhat & Koppelman, 1999; Pinjari & Bhat, 2011).

Shopping frequency can also be studied using a needs-based approach or hazard-based duration models. In the needs-based framework, the frequency of a certain activity is predicted using an underlying growth function for selected human needs. Need levels are reduced after completion of activities that help satisfy the need, and grow again with time. Activities can impact multiple need levels, for example, shopping primarily satisfies the need for replenishing stock but also reduces needs for socialising, entertainment, and physical exercise to some extent (Pattabhiraman, 2012). Building on activity-based ideas, Arentze and Timmermans (2009) developed a need-based modelling framework for activity generation, which can be used to study shopping frequency. In a similar vein, Kim and Park (1997), Schonfelder and Axhausen (2001), and Bhat, Frusti, Zhao, Schonfelder, and Axhausen (2004) applied hazard-based models to analyse inter-shopping duration. The base line hazard function is used to model the increasing likelihood of participation to shopping with increase in time passed without participation due to inventory depletion effects. The models differ in how they define the baseline hazard, selected explanatory variables, and in how they account for heterogeneity across individuals. Bhat et al. (2004) and Kim and Park (1997) distinguish between routine and erratic shoppers. For erratic shoppers, the hazard function is constant over time hence the probability of a shopping event is independent of the time elapsed. For routine shoppers, the propensity to shop increases as time elapsed since last shopping increases. Explanatory variables found to be significant in determining inter-shopping duration include gender, age, employment details, income, household type, income, number of vehicles, car use for shopping, and percentage of shopping episodes chained with other activities. For instance, longer working hours are associated with higher inter-shopping durations in line with expectations. Shoppers who use cars as their primary travel mode for shopping trips have larger inter-shopping durations potentially due to the ability to carry and hence stock more items. Interestingly, different variables were found to be significant for erratic and routine shopper groups when separate models are estimated.

Activity generation, needs-based and hazard-based models can be extended to incorporate online shopping activity to understand the interrelationship between in-store and online shopping frequency. In an activity generation framework, as above, online shopping

may be modelled as a type of shopping activity. Similarly, online shopping can be represented as an alternative to satisfy the need to go for shopping in a needs-based framework (Schonfelder & Axhausen, 2001) and as a shopping event in a hazard-based model (Suel et al., 2016).

3.4. Multi-purpose multi-stop shopping and trip chaining

Individuals may choose to combine purchases of different types of goods when shopping (Arentze et al., 2011; Baker, 1996). This might involve single-stop or multi-stop shopping trips (Brooks, Kaufmann, & Lichtenstein, 2008). Shopping activities might also be chained or combined with other activities (Adler & Ben-Akiva, 1979; Strathman, Dueker, & Davis, 1994; Thill & Thomas, 1987). Multi-purpose multi-stop shopping and trip chaining is likely to influence store choice, hence should ideally be incorporated in shopping location and store choice models (Arentze et al., 2011). These aspects might be especially interesting when studying effects of virtual channels on activity and travel patterns; online shopping will not necessarily replace a full length trip if physical shopping trips are combined or chained with other activity purposes.

In earlier gravity-type models, benefits of agglomeration resulting from consumers' desire to do multi-purpose shopping was recognised. In Ghosh (1986)'s suggested framework, shoppers are allowed to combine trips to minimise the total cost of shopping for multiple goods. Total cost included travel, purchased goods, and inventory costs. For modelling trip-chaining behaviour in a discrete choice framework, Kitamura (1984) characterised the prospective utility for each chain of destinations as the sum of their individual utilities for modelling multi-stop trips. Building on this framework and Arentze, Borgers, and Timmermans (1993)'s work on multi-purpose trip making, Dellaert, Arentze, Bierlaire, Borgers, and Timmermans (1998) proposed a utility-based model for multi-purpose and multi-stop shopping. The utility for each destination is computed as a weighted sum of individual store utilities based on types of products and their frequencies of purchase giving them an order of importance. Yun and O'Kelly (1997) used a three-level nested logit model to model whether to participate in shopping at all on a given day, scheduling of the trip, and the number of shopping stops. Arentze and Timmermans (2001) and Arentze, Oppewal, and Timmermans (2005) developed nested logit models for trip purpose and destination choice where the purpose is defined based on different product categories to capture multi-purpose shopping. Popkowski Leszczyc and Timmermans (2001) reported results from a conjoint choice experiment for understanding how shoppers choose from different shopping strategies when organising their weekly shopping allowing multi-stop multi-purpose trips to smaller convenience stores and single-stop trips to larger stores, concluding the former is preferred in the sampled set of consumers. Popkowski Leszczyc et al. (2004) showed their multi-purpose shopping model outperformed the single-purpose model and the former brought out effects not revealed in the latter. Activity-based models account for interdependencies between different activity types and multiple activity purposes combined in a single location, hence can be used to study multi-purpose multi-stop shopping trips and chaining with other activities (Arentze & Timmermans, 2000; Pendyala et al., 2005; Rasouli & Timmermans, 2013; Roorda et al., 2008). Accounting for the often ignored dimensions related to combining trip purposes and chaining of activities improves behavioural realism as single-stop single-purpose

shopping trips assumption is often violated in reality. This is especially important for quantifying the effects of online shopping on travel frequency and miles travelled as discussed.

3.5. Channel choice

Retailers and market researchers are interested in channel choice behaviour to find optimal multi-channel strategies as consumers use an increasing variety of shopping channels (Dholakia, Zhao, & Dholakia, 2005; Schoenbachler & Gordon, 2002). Urban planners are primarily interested due to potential negative effects of online shopping on physical stores which might in turn have implications for land use patterns and built environment attributes (Couclelis, 2009). Travel implications of online retailing for personal travel and freight logistics have also attracted significant attention in transport research. Researchers have developed a number of conceptual frameworks for behavioural mechanisms involved in choice of shopping channel (Balasubramanian et al., 2005; Bosnjak, Galesic, & Tuten, 2007; Broekhuizen & Jager, 2004; Couclelis, 2009; Dholakia et al., 2010; Nagurney, Dong, & Mokhtarian, 2001; Salomon & Koppelman, 1988; Schoenbachler & Gordon, 2002). Distinctive benefits (e.g. reducing uncertainty, value of physical assessment, recreational aspects, time savings, lower prices, comparison capabilities, and gratification for additional information) and costs (e.g. travel to store, delivery costs, and browsing time) associated with in-store and online shopping were identified. Attributes of available shopping channels (e.g. prices, quality, intra-personal service quality, store design and ambiance, delivery service quality, user friendliness of the online interface, delivery times, and windows) are also hypothesised to influence choice behaviour. Individual preferences and recreational aspects of conventional in-store shopping also play an important role.

Building on conceptual studies, empirical work in this area have focused on modelling (i) adoption of online shopping and (ii) choice of channel for a specific shopping occasion. The focus of studies in the first group is to develop models for understanding whether an individual adopts the channel (i.e. does any shopping via the online channel). Previous work in the second group is limited and has been separate from shopping destination and store choice literature that was discussed in Section 3.1.

3.5.1. Adoption of online shopping

Liao and Cheung (2001) presented a comprehensive review of empirical studies that aim to identify determinants of online shopping adoption. Variables frequently considered include internet's distinctive characteristics as a retailing channel (e.g. degree of privacy, security, convenience, delivery service attributes, comparison capabilities, ability to access additional information, prices, and recreational value), characteristics of individual retailer websites and apps (e.g. available products, brands, reputation, website and app design, and payment options), and consumer socio-demographics (e.g. gender, income, age, experience with online shopping, internet use, and time availability). Liao and Cheung (2001) found perceptions regarding transaction security, prices, level of internet usage, and vendor quality significantly affect initial willingness to shop online in Singapore. Lee and Tan (2003) reported perceived service risks are higher for online shopping and found no significant difference in perceived product risks between channels. Numerous other studies in marketing and transportation literature use different statistical methods to explore potential factors for adoption using ad-hoc survey data (Bellman,

Lohse, & Johnson, 1999; Crocco, Eboli, & Mazzulla, 2013; Ha & Stoel, 2009; Huang & Oppewal, 2006; Liu & Forsythe, 2011; Pauwels & Neslin, 2011; Rhee, Riggins, & Kim, 2009; Schröder & Zaharia, 2008; Soopramanien & Robertson, 2007; Teltzrow, Meyer, & Lenz, 2007). Most studies find a positive relationship between income, education level, time pressures, and adoption. Males and younger adults are more likely to be online shoppers, while most online grocery shoppers are female (Farag et al., 2006). Farag (2006) found that accessibility to physical stores is a significant determinant for adoption in addition to socio-demographic and attitudinal variables. Studies in this part of the literature are not intended to identify how online shopping interacts with in-store shopping. Furthermore, findings regarding the impacts of specific covariates are frequently mixed or inconclusive (Figure 1 in Chang, Cheung, and Lai (2005).

3.5.2. Channel choice for specific shopping occasions

A separate segment of the literature investigated choice of shopping channel for specific shopping occasions. These models, in fact, are store choice models that use aggregates of alternatives based on channel (Section 3.1). All types of conventional physical stores including corner shops, convenience stores, big-box stores are categorised under a single in-store category. Mobile stores, web-based stores of different chains, and other types of virtual stores are categorised under a single online category. Cao (2012), Chocarro, Cortiñas, and Villanueva (2013), and Hsiao (2009) used binary logit models. Data are either sourced from stated-preference experiments with simulated attributes (e.g. website design, in-store atmosphere, prices, travel and delivery costs, delivery times) and contextual variables (e.g. time pressure, presence of other decision-makers) (Chocarro et al., 2013; Hsiao, 2009), or from revealed-preference surveys where respondents are asked about the channel used for their most recent purchase of a given product category (Cao, 2012; Mokhtarian & Tang, 2013). Additional data on behavioural covariates (e.g. online purchase frequencies, choice of channel in pre-purchase stages, and experience with internet) and socio-demographics are also often collected, and have been found to significantly correlate with channel choice. For instance, Mokhtarian and Tang (2013) and Zhai, Cao, Mokhtarian, and Zhen (2016) studied interactions between pre-purchase and purchase channels for clothes and books shopping using revealed-preference data, where respondents were asked about channel choice for different shopping stages on their most recent purchase. Similarly, Weltevreden (2007) examines the links between channel choice at information gathering and buying stages. Chocarro et al. (2013) reported differences in channel choice behaviour for different product categories (e.g. books, clothing, IT, and airline tickets). With a slightly different focus, Rotem-Mindali and Salomon (2007) focused on choice between different delivery methods for online shopping. Ad-hoc survey data, often used in this line of work, is not always readily available. Use of a novel dataset was introduced by Chintagunta et al. (2012), who analysed channel choice for grocery shopping using scanner data from a single retail chain. They found that choice of channel is significantly influenced by what is being bought (e.g. total basket cost, heavy/bulky, or perishable items in the basket) in addition to situational variables (e.g. weekday/weekend, time of day, weather conditions, delivery costs, and in-store promotions).

The literature on channel choice for a specific choice occasion, crucially, has largely focused on modelling the choice between online and in-store using aggregated

alternative categories. In reality, however, shoppers choose from a set of alternatives that include both online and in-store alternatives available to them. Using aggregated alternatives based on channel, therefore, ignores the heterogeneity within each channel.

4. Priorities, opportunities, and conclusions

In this paper, we have examined how shopping behaviour has been addressed by the travel demand modelling community and closely related disciplines such as marketing and retail studies. Our review has highlighted the existence of a huge body of knowledge on conventional shopping and related travel behaviour, covering multiple inter-related dimensions. Moreover, the existing modelling frameworks used in practice and for research are flexible and can, in principle, be extended to incorporate online shopping and associated complexities. However, the review also demonstrated that the bulk of the work carried out on the mobility impacts of online shopping has been undertaken largely separately from the research on conventional shopping and shopping-related mobility behaviour. Whilst this parallel development is perhaps understandable in circumstances where online shopping was a minority and fringe behaviour, as online shopping has become increasingly mainstream, it becomes necessary to integrate these two bodies of work. In particular, there is an urgent need to develop practical approaches to incorporating online shopping into operational transportation planning models. This integration raises a number of significant challenges. In this section, we identify these challenges and lay out a road map of key developments that need to be made to enable better accommodation of new digital modes of shopping in operational travel forecasting models.

The first requirement is at a conceptual level. We do not yet have standard ontologies for relevant concepts and elements used in quantitative models. This is a problem for the shopping literature in general, but becomes more severe for online shopping. Individual studies use different definitions for crucial concepts, e.g. online shopper, shopping trip, main shopper, store availability, attribute measurements (accessibility, retail mix, population, or employment density). Empirical results are heavily influenced by assumptions and definitions; it becomes impossible to reach conclusions or comment on the degree of consistency that exists between different studies. Being a relatively new field of research, there is an urgent need for convergence onward to some sort of typology of concepts and appropriate definitions.

Second, capturing the interaction between online and physical shopping requires modelling shopping patterns over multiple days and even weeks as there are temporal interactions between them coupled by replenishment. To capture these dependencies, activity-based models of travel demand (Section 3.1.6) need to span longer periods for activity generation. This will require collecting detailed empirical data covering longer periods, which we highlight below under the fourth point.

Third, online alternatives need to be introduced as part of the choice sets in destination choice to offer a realistic representation of the choice situation involved in store choice. Additionally, customers often have the option to obtain home deliveries, or to collect from stores or designated pick up locations. These services need to be modelled as new modes of travel or delivery within existing destination and mode choice frameworks. As reviewed in Sections 3.1 and 3.2, existing discrete choice frameworks are sufficiently flexible in principle to accommodate online alternatives as well as new delivery modes

as part of existing choice sets. The challenge here is again finding the empirical data sources for model estimation as we detail below under the fourth point.

Fourth, existing data collection procedures and methods need to be extended in a variety of ways. In particular, diary-based instruments should ideally cover longer periods of time (to capture temporal links between online and physical shopping occasions) and record online shopping occasions and details of the delivery modes used. This will enable the incorporation of online stores and delivery modes into existing choice sets in operational transport planning models. Currently, most regional and national travel surveys collect data on online shopping activity through questions on frequency or last purchase as part of the survey and not of the detailed travel diary. We note that attributes of digital options are highly dynamic and personalised. The amount of data needed for estimations also increases with additional dimensions and complexity. Emerging capabilities of digital data collection should be better utilised to make relevant data available as part of travel diaries or other instruments.

Fifth, traditional travel demand models and developed capabilities for traditional shopping assume that individuals will make trips to stores for their purchases. With online shopping, delivery of goods becomes much more complex. Individual trips to stores may be replaced by home deliveries by retailers or third party carriers. Alternatively, ordered goods might be delivered to designated pick up locations for collection hence will generate individual trips to these collection points. Shopping travel needs, therefore, can be fulfilled by logistics or individual trips or a combination of the two. Traditionally, however, freight demand models have been entirely separate from personal travel models and this separation makes it difficult for practitioners to model interdependencies. Transport agencies are interested in bringing freight components into travel forecasting models as they recognise the growing importance of urban logistics in planning with increasing digitalisation of services (Lee & Ross, 2016). It is crucial for such efforts to continue to develop modelling frameworks that successfully can combine urban logistics and individual travel demand models. Such capability will also serve to answer some of the emerging and pressing questions from the business side. For example, understanding preferences for delivery slots and how their availability influences physical trip decisions is important to manage peaks in demand both for efficient logistics operations and reducing trucks on urban roads. Similarly, peer-to-peer business models in retailing and logistics will give rise to new questions regarding demand and supply relationships.

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References

- Aaker, D. A., & Jones, J. M. (1971). Modeling store choice behavior. *Journal of Marketing Research (JMR)*, 8(1), 38–42. doi:10.2307/3149723
- Adler, T., & Ben-Akiva, M. (1979). A theoretical and empirical model of trip chaining behavior. *Transportation Research Part B: Methodological*, 13(3), 243–257. doi:10.1016/0191-2615(79)90016-X
- Arentze, T. A., Borgers, A., & Timmermans, H. J. P. (1993). A model of multi-purpose shopping trip behavior. *Papers in Regional Science*, 72(3), 239–256. doi:10.1007/BF01434275
- Arentze, T., Ettema, D., & Timmermans, H. (2011). Location choice in the context of multi-day activity-travel patterns: Model development and empirical results. *Transportmetrica*, 9(April 2014), 1–17. doi:10.1080/18128602.2010.538870
- Arentze, T. A., Oppewal, H., & Timmermans, H. J. P. (2005). A multipurpose shopping trip model to assess retail agglomeration effects. *Journal of Marketing Research (JMR)*, 42(1), 109–115. doi:10.1509/jmkr.42.1.109.56884
- Arentze, T. A., & Timmermans, H. J. P. (2000). *Albatross: A learning based transportation oriented simulation system*. Eindhoven: Eirass.
- Arentze, T. A., & Timmermans, H. J. P. (2001). Deriving performance indicators from models of multi-purpose shopping behavior. *Journal of Retailing and Consumer Services*, 8(6), 325–334. doi:10.1016/S0969-6989(00)00038-2
- Arentze, T., & Timmermans, H. J. P. (2009). A need-based model of multi-day, multi-person activity generation. *Transportation Research Part B: Methodological*, 43(2), 251–265. doi:10.1016/j.trb.2008.05.007
- Bacon, R. W. (1995). Combined trips and the frequency of shopping. *Journal of Retailing and Consumer Services*, 2(3), 175–183. doi:10.1016/0969-6989(95)00034-8
- Baker, R. G. V. (1996). Multi-purpose shopping behaviour at planned suburban shopping centres: A space-time analysis. *Environment and Planning A*, 28(4), 611–630. doi:10.1068/a280611
- Balasubramanian, S., Raghunathan, R., & Mahajan, V. (2005). Consumers in a multichannel environment: Product utility, process utility, and channel choice. *Journal of Interactive Marketing*, 19(2), 12–30. doi:10.1002/dir.20032
- Bawa, K., & Ghosh, A. (1999). A model of household grocery shopping behavior. *Marketing Letters*, 10(2), 149–160. doi:10.1023/A:1008093014534
- Bell, D. R., Ho, T.-H., & Tang, C. S. (1998). Determining where to shop: Fixed and variable costs of shopping. *Journal of Marketing Research (JMR)*, 352–369. doi:10.2307/3152033
- Bell, D. R., & Lattin, J. M. (1998). Shopping behavior and consumer preference for store price format: Why “large basket” shoppers prefer EDLP. *Marketing Science*, 17(1), 66–88. doi:10.1287/mksc.17.1.66
- Bellman, S., Lohse, G. L., & Johnson, E. J. (1999). Predictors of online buying behavior. *Communications of the ACM*, 42(12), 32–38. doi:10.1145/322796.322805
- Ben-Akiva, M., & Lerman, S. R. (1985). Discrete choice analysis: Theory and application to travel demand. *Journal of Business & Economic Statistics*, 6. doi:10.2307/1391567
- Ben-Akiva, M., Morikawa, T., & Shiroishi, F. (1991). Analysis of the reliability of preference ranking data. *Journal of Business Research*, 23(3), 253–268. doi:10.1016/0148-2963(91)90033-T
- Beynon, M., Griffiths, B., & Marshall, D. (2002). A prototype store choice and location modelling system using Dempster–Shafer theory. *Expert Systems*, 19(5), 273–284. doi:10.1111/1468-0394.00214
- Bhat, C. R. (1998a). Accommodating flexible substitution patterns in multi-dimensional choice modeling: Formulation and application to travel mode and departure time choice. *Transportation Research Part B: Methodological*, 32(7), 455–466. doi:10.1016/S0191-2615(98)00011-3
- Bhat, C. R. (1998b). Accommodating variations in responsiveness to level-of-service measures in travel mode choice modeling. *Transportation Research Part A: Policy and Practice*, 32(7), 495–507. doi:10.1016/S0965-8564(98)00011-1
- Bhat, C. R. (1998c). Analysis of travel mode and departure time choice for urban shopping trips. *Transportation Research Part B: Methodological*, 32(6), 361–371. doi:10.1016/S0191-2615(98)00004-6

- Bhat, C. R. (2000). Incorporating observed and unobserved heterogeneity in urban work travel mode choice modeling. *Transportation Science*, 34(2), 228–238. doi:10.1287/trsc.34.2.228.12306
- Bhat, C. R., & Castelar, S. (2002). A unified mixed logit framework for modeling revealed and stated preferences: Formulation and application to congestion pricing analysis in the San Francisco Bay area. *Transportation Research Part B: Methodological*, 36(7), 593–616. doi:10.1016/S0191-2615(01)00020-0
- Bhat, C. R., Frusti, T., Zhao, H., Schönfelder, S., & Axhausen, K. W. (2004). Intershoppping duration: An analysis using multiweek data. *Transportation Research Part B: Methodological*, 38(1), 39–60. doi:10.1016/S0191-2615(02)00093-0
- Bhat, C. R., & Koppelman, F. S. (1999). Activity-based modeling of travel demand. In Randolph Hall (Ed.), *Handbook of transportation science* (Vol. 56, pp. 35–61). New York, US: Springer.
- Bhat, C. R., Sivakumar, A., & Axhausen, K. W. (2003). An analysis of the impact of information and communication technologies on non-maintenance shopping activities. *Transportation Research Part B: Methodological*, 37(10), 857–881. doi:10.1016/S0191-2615(02)00062-0
- Bhatnagar, A., & Ratchford, B. T. (2004). A model of retail format competition for non-durable goods. *International Journal of Research in Marketing*, 21(1), 39–59. doi:10.1016/j.ijresmar.2003.05.002
- Black, W. C. (1984). Choice-set definition in patronage modeling. *Journal of Retailing*, 60(2), 63–85.
- Blaylock, J. R. (1989). An economic model of grocery shopping frequency. *Applied Economics*, 21(6), 843–852. doi:10.1080/758520277
- Borgers, A., & Timmermans, H. J. P. (1987). Choice model specification, substitution and spatial structure effects: A simulation experiment. *Regional Science and Urban Economics*, 17(1), 29–47. doi:10.1016/0166-0462(87)90067-6
- Bosnjak, M., Galesic, M., & Tuten, T. (2007). Personality determinants of online shopping: Explaining online purchase intentions using a hierarchical approach. *Journal of Business Research*, 60(6), 597–605. doi:10.1016/j.jbusres.2006.06.008
- Boyle, K. J., Holmes, T. P., Teisl, M. F., & Roe, B. (2001). A comparison of conjoint analysis response formats. *American Journal of Agricultural Economics*, 83(2), 441–454. doi:10.1111/0002-9092.00168
- Broekhuizen, T. L. J., & Jager, W. (2004). *A conceptual model of channel choice: Measuring online and offline shopping value perceptions*. Groningen, The Netherlands: University of Groningen.
- Brooks, C. M., Kaufmann, P. J., & Lichtenstein, D. R. (2008). Trip chaining behavior in multi-destination shopping trips: A field experiment and laboratory replication. *Journal of Retailing*, 84(1), 29–38. doi:10.1016/j.jretai.2008.01.009
- Bucchioni, P., Liu, X., & Weidenhamer, D. (2015). *Retail E-commerce sales*. US Census Bureau of the Department of Commerce.
- Burnett, P. (1977). Tests of a linear learning model of destination choice: Applications to shopping travel by heterogeneous population groups. *Geografiska Annaler. Series B, Human Geography*, 59(2), 95–108. doi:10.2307/490961
- Burnett, P. (1978). Markovian models of movement within urban spatial structures. *Geographical Analysis*, 10(2), 142–153.
- Cadwallader, M. (1975). A behavioral model of consumer spatial decision making. *Economic Geography*, 339–349. doi:10.2307/142918
- Cairns, S. (1998). Promises and problems: Using GIS to analyse shopping travel. *Journal of Transport Geography*, 6(4), 273–284. doi:10.1016/S0966-6923(98)00026-X
- Campbell, L. (2012). *Amazon partners with co-op for collection lockers*. The Bookseller.
- Cao, X. J. (2010). E-Shopping, spatial attributes, and personal travel. *Transportation Research Record: Journal of the Transportation Research Board*, 2135(1), 160–169. doi:10.3141/2135-19
- Cao, X. J. (2012). The relationships between e-shopping and store shopping in the shopping process of search goods. *Transportation Research Part A: Policy and Practice*, 46(7), 993–1002. doi:10.1016/j.tra.2012.04.007
- Cao, X. J., Douma, F., & Cleaveland, F. (2010). Influence of E-shopping on shopping travel. *Transportation Research Record: Journal of the Transportation Research Board*, 2157(1), 147–154. doi:10.3141/2157-18

- Cao, X. J., Xu, Z., & Douma, F. (2012). The interactions between e-shopping and traditional in-store shopping: An application of structural equations model. *Transportation*, 39(5), 957–974. doi:10.1007/s11116-011-9376-3
- Carey, H. C. (1867). *Principles of social science* (Vol. 3). Philadelphia: JB Lippincott & Company.
- Casey, H. J. (1955). Applications to traffic engineering of the law of retail gravitation. *Traffic Quarterly*, 9(1), 23–35.
- Cervero, R. (1989). *Land-use mixing and suburban mobility*. Berkeley: University of California Transportation Center.
- Cervero, R. (1996). Mixed land-uses and commuting: Evidence from the American housing survey. *Transportation Research Part A: Policy and Practice*, 30(5 PART A), 361–377. doi:10.1016/0965-8564(95)00033-X
- Chang, M. K., Cheung, W., & Lai, V. S. (2005). Literature derived reference models for the adoption of online shopping. *Information and Management*, 42(4), 543–559. doi:10.1016/S0378-7206(04)00051-5
- Chintagunta, P. K., Chu, J., & Cebollada, J. (2012). Quantifying transaction costs in online/off-line grocery channel choice. *Marketing Science*, 31(1), 96–114. doi:10.1287/mksc.1110.0678
- Chocarro, R., Cortiñas, M., & Villanueva, M.-L. (2013). Situational variables in online versus offline channel choice. *Electronic Commerce Research and Applications*, 12(5), 347–361. doi:10.1016/j.elerap.2013.03.004
- Circella, G., & Mokhtarian, P. L. (2010). *Complementarity or substitution of online and in-store shopping: An empirical analysis from Northern California*. In Transportation Research Board 89th Annual Meeting.
- Corpus, G., & Peachman, J. (2003). *Measuring the impacts of internet usage on travel behaviour in the Sydney Household Travel Survey*. In Australasia Transport Research Forum Conference, Wellington, October.
- Couclelis, H. (2009). Rethinking time geography in the information age. *Environment and Planning A*, 41(7), 1556. doi:10.1068/a4151
- Crocco, F., Eboli, L., & Mazzulla, G. (2013). Individual attitudes and shopping mode characteristics affecting the use of E-shopping and related travel. *Transport and Telecommunication*, 14(1), 45–56. doi:10.2478/ttj-2013-0006
- Cullinane, S. L. (2009). From bricks to clicks: The impact of online retailing on transport and the environment. *Transport Reviews*, 29(6), 759–776. doi:10.1080/01441640902796364
- DCLG. (2014). *Planning practice guidance: Ensuring the vitality of town centres*. London: Department for Communities and Local Government.
- Dellaert, B. G. C., Arentze, T. A., Bierlaire, M., Borgers, A., & Timmermans, H. J. P. (1998). Investigating consumers' tendency to combine multiple shopping purposes and destinations. *Journal of Marketing Research (JMR)*, 35(2), 177–188. doi:10.2307/3151846
- Department for Transport. (2017). National Travel Survey, 2002–2015. [data collection]. 11th Edition. UK Data Service. SN: 5340, <https://doi.org/10.5255/UKDA-SN-5340-7>.
- Dholakia, U. M., Kahn, B. E., Reeves, R., Rindfleisch, A., Stewart, D., & Taylor, E. (2010). Consumer behavior in a multichannel, multimedia retailing environment. *Journal of Interactive Marketing*, 24(2), 86–95. doi:10.1016/j.intmar.2010.02.005
- Dholakia, R. R., Zhao, M., & Dholakia, N. (2005). Multichannel retailing: A case study of early experiences. *Journal of Interactive Marketing*, 19(2), 63–74. doi:10.1002/dir.20035
- Ding, C., Xie, B., Wang, Y., Lin, Y., Chuan, D., Binglei, X., ... Yaoyu, L. (2014). Modeling the joint choice decisions on urban shopping destination and travel-to-shop mode: A comparative study of different structures. *Discrete Dynamics in Nature and Society*, 2014, doi:10.1155/2014/492307
- Dunn, R., & Wrigley, N. (1985). Beta-logistic models of urban shopping center choice. *Geographical Analysis*, 17(2), 95–113. doi:10.1111/j.1538-4632.1985.tb00831.x
- Etherington, D. (2016). *Daimler begins testing Smart car trunk delivery service with DHL*. Tech Crunch.
- Farag, S. (2006). *E-shopping and its interactions with in-store shopping*. Utrecht: Utrecht University.
- Farag, S., Krizek, K. J., & Dijst, M. (2006). E-shopping and its relationship with in-store shopping: Empirical evidence from the Netherlands and the USA. *Transport Reviews*, 26(1), 43–61. doi:10.1080/01441640500158496

- Frag, S., Schwanen, T., Dijst, M., & Faber, J. (2007). Shopping online and/or in-store? A structural equation model of the relationships between e-shopping and in-store shopping. *Transportation Research Part A: Policy and Practice*, 41(2), 125–141. doi:10.1016/j.tra.2006.02.003
- Ferrell, C. E. (2005). *The effects of teleshopping on travel behavior and urban form*. Berkeley: University of California.
- Fotheringham, A. S. (1983). A new set of spatial-interaction models: The theory of competing destinations. *Environment and Planning A*, 15(1), 15–36. doi:10.1068/a150015
- Fotheringham, A. S. (1988). Note – consumer store choice and choice set definition. *Marketing Science*, 7(3), 299–310. doi:10.1287/mksc.7.3.299
- Fox, E. J., Montgomery, A. L., & Lodish, L. M. (2004). Consumer shopping and spending across retail formats. *The Journal of Business*, 77(S2), S25–S60. doi:10.1086/381518
- Ghosh, A. (1986). The value of a mall and other insights from a revised central place model. *Journal of Retailing*, 62(1), 79–97.
- Gibson, M., & Pullen, M. (1972). Retail turnover in the East Midlands: A regional application of a gravity model. *Regional Studies*, 6(2), 183–196. doi:10.1080/09595237200185161
- Gijsbrechts, E., Campo, K., & Nisol, P. (2008). Beyond promotion-based store switching: Antecedents and patterns of systematic multiple-store shopping. *International Journal of Research in Marketing*, 25(1), 5–21. doi:10.1016/j.ijresmar.2007.07.001
- Girard, T., Korgaonkar, P., & Silverblatt, R. (2003). Relationship of type of product, shopping orientations, and demographics with preference for shopping on the internet. *Journal of Business and Psychology*, 18(1), 101–120. doi:10.1023/A:1025087021768
- Goldfingle, G. (2014). Amazon launches click-and-collect lockers in London Tube stations. *Retail Week*.
- Golob, T. F., & Regan, A. C. (2001). Impacts of information technology on personal travel and commercial vehicle operations: Research challenges and opportunities. *Transportation Research Part C: Emerging Technologies*, 9(2), 87–121. doi:10.1016/S0968-090X(00)00042-5
- Gonzalez-Benito, O. (2002). Overcoming data limitations for store choice modelling. Exploiting retail chain choice data by means of aggregate logit models. *Journal of Retailing and Consumer Services*, 9(5), 259–268. doi:10.1016/S0969-6989(01)00035-2
- Gonzalez-Benito, O. (2005). Spatial competitive interaction of retail store formats: Modeling proposal and empirical results. *Journal of Business Research*, 58(4), 457–466. doi:10.1016/j.jbusres.2003.09.001
- Gould, J., & Golob, T. F. (1997). Shopping without travel or travel without shopping? An investigation of electronic home shopping. *Transport Reviews*, 17(4), 355–376. doi:10.1080/01441649708716991
- Gustafsson, A., Herrmann, A., & Huber, F. (2013). *Conjoint measurement: Methods and applications*. New York: Springer Science & Business Media.
- Guy, C. M. (1987). Recent advances in spatial interaction modelling: An application to the forecasting of shopping travel. *Environment and Planning A*, 19(2), 173–186. doi:10.1068/a190173
- Ha, S., & Stoel, L. (2009). Consumer e-shopping acceptance: Antecedents in a technology acceptance model. *Journal of Business Research*, 62(5), 565–571. doi:10.1016/j.jbusres.2008.06.016
- Handy, S. L. (1992). Regional versus local accessibility: Neo-traditional development and its implications for non-work travel. *Built Environment (1978)*, 18, 253–267.
- Handy, S. L. (1993). *Regional versus local accessibility: Implications for nonwork travel*. Berkeley: University of California Transportation Center.
- Handy, S. L. (1996). Methodologies for exploring the link between urban form and travel behavior. *Transportation Research Part D: Transport and Environment*, 1(2), 151–165. doi:10.1016/S1361-9209(96)00010-7
- Handy, S. L., & Clifton, K. J. (2001). Local shopping as a strategy for reducing automobile travel. *Transportation*, 28(4), 317–346. doi:10.1023/A:1011850618753
- Hawkins, A. J. (2016). Uber wants to be your express delivery service for everything. *The Verge*.
- Haynes, K. E., & Fotheringham, A. S. (1984). *Gravity and spatial interaction models* (Vol. 2). Beverly Hills: Sage.
- Hensher, D. A., & Bradley, M. (1993). Using stated response choice data to enrich revealed preference discrete choice models. *Marketing Letters*, 4(2), 139–151. doi:10.1007/BF00994072

- Hjorthol, R. J. (2002). The relation between daily travel and use of the home computer. *Transportation Research Part A: Policy and Practice*, 36(5), 437–452. doi:10.1016/S0965-8564(01)00012-X
- Horowitz, J. L. (1993). Semiparametric estimation of a work-trip mode choice model. *Journal of Econometrics*, 58(1–2), 49–70. doi:10.1016/0304-4076(93)90113-J
- Hsiao, M.-H. H. (2009). Shopping mode choice: Physical store shopping versus e-shopping. *Transportation Research Part E: Logistics and Transportation Review*, 45(1), 86–95. doi:10.1016/j.tre.2008.06.002
- Huang, Y., & Oppewal, H. (2006). Why consumers hesitate to shop online: An experimental choice analysis of grocery shopping and the role of delivery fees. *International Journal of Retail and Distribution Management*, 34(4/5), 334–353. doi:10.1108/09590550610660260
- Huff, D. L. (1963). A probabilistic analysis of shopping center trade areas. *Land Economics*, 81–90. doi:10.2307/3144521
- Ibrahim, M. F., & McGoldrick, P. J. (2003). *Shopping choices with public transport options: An agenda for the 21st century*. Ann Arbor: Ashgate.
- Jiao, J., Moudon, A. V., & Drewnowski, A. (2011). Grocery shopping. *Transportation Research Record: Journal of the Transportation Research Board*, 2230(1), 85–95. doi:10.3141/2230-10
- Johnson, E. J., & Meyer, R. J. (1984). Compensatory choice models of noncompensatory processes: The effect of varying context. *Journal of Consumer Research*, 528–541. doi:10.1086/208989
- Keskinen, A., Delache, X., Cruddas, J., Lindjord, J. E., & Iglesias, C. (2001). *A purchase and a chain. Impacts of E-commerce on transport and the environment*. Report of Working Group, 3.
- Kim, B.-D., & Park, K. (1997). Studying patterns of consumer's grocery shopping trip. *Journal of Retailing*, 73(4), 501–517. doi:10.1016/S0022-4359(97)90032-4
- Kitamura, R. (1984). Incorporating trip chaining into analysis of destination choice. *Transportation Research Part B: Methodological*, 18(1), 67–81. doi:10.1016/0191-2615(84)90007-9
- Koppelman, F. S., & Bhat, C. R. (2006). *A self instructing course in mode choice modeling: Multinomial and nested logit models*.
- Koppelman, F. S., & Hauser, J. R. (1978). Destination choice behavior for non-grocery-shopping trips. *Transportation Research Record: Journal of the Transportation Research Board*, 673, 157–165.
- Kumar, A., & Levinson, D. (1995). Temporal variations on allocation of time. *Transportation Research Record: Journal of the Transportation Research Board*, 1493, 118–127.
- Lakshmanan, J. R., & Hansen, W. G. (1965). A retail market potential model. *Journal of the American Institute of Planners*, 31(2), 134–143. doi:10.1080/01944366508978155
- Lee, D. J.-H., & Ross, C. L. (2016). *Bringing freight components into statewide and regional travel demand forecasting*. Atlanta: Georgia Tech Research Corporation.
- Lee, R. J., Sener, I. N., Mokhtarian, P. L., & Handy, S. L. (2017). Relationships between the online and in-store shopping frequency of Davis, California residents. *Transportation Research Part A: Policy and Practice*, 100, 40–52. doi:10.1016/j.tra.2017.03.001
- Lee, K. S., & Tan, S. J. (2003). E-retailing versus physical retailing: A theoretical model and empirical test of consumer choice. *Journal of Business Research*, 56(11), 877–885. doi:10.1016/S0148-2963(01)00274-0
- Liao, Z., & Cheung, M. T. (2001). Internet-based e-shopping and consumer attitudes: An empirical study. *Information and Management*, 38(5), 299–306. doi:10.1016/S0378-7206(00)00072-0
- Limanond, T., Niemeier, D. A., & Mokhtarian, P. L. (2005). Specification of a tour-based neighborhood shopping model. *Transportation*, 32(2), 105–134. doi:10.1007/s11116-004-6992-1
- Liu, C., & Forsythe, S. (2011). Examining drivers of online purchase intensity: Moderating role of adoption duration in sustaining post-adoption online shopping. *Journal of Retailing and Consumer Services*, 18(1), 101–109. doi:10.1016/j.jretconser.2010.10.004
- Louviere, J. J. (1988). Conjoint analysis modelling of stated preferences: A review of theory, methods, recent developments and external validity. *Journal of Transport Economics and Policy*, 22, 93–119.
- Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. *Journal of Choice Modelling*, 3(3), 57–72. doi:10.1016/S1755-5345(13)70014-9
- Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). Stated choice methods: Analysis and application. *Journal of Applied Econometrics*, 17(6), 701–704. doi:10.1002/jae.701

- Louviere, J. J., & Meyer, R. J. (1981). A composite attitude-behavior model of traveler decision making. *Transportation Research Part B: Methodological*, 15(6), 411–420. doi:10.1016/0191-2615(81)90025-4
- Lowe, M. (2005). The regional shopping centre in the inner city: A study of retail-led urban regeneration. *Urban Studies*, 42(3), 449–470. doi:10.1080/00420980500035139
- Lundevaller, E. H. (2009). The effect of travel cost on frequencies of shopping and recreational trips in Sweden. *Journal of Transport Geography*, 17(3), 208–215. doi:10.1016/j.jtrangeo.2008.05.002
- Marker Jr, J. T., & Goulias, K. (2007). Framework for the analysis of grocery teleshopping. *Transportation Research Record: Journal of the Transportation Research Board*, 1725(1), 1–8. doi:10.3141/1725-01
- McFadden, D., Talvitie, A., Cosslett, S., Hasan, I., Johnson, M., Reid, F., & Train, K. E. (1977). *Demand model estimation and validation* (Vol. 5). Berkeley: Institute of Transportation Studies, University of California.
- Messinger, P. R., & Narasimhan, C. (1997). A model of retail formats based on consumers' economizing on shopping time. *Marketing Science*, 16(1), 1–23. doi:10.1287/mksc.16.1.1
- Miller, E. J., & O'Kelly, M. E. (1983). Estimating shopping destination models from travel diary data. *The Professional Geographer*, 35(4), 440–449. doi:10.1111/j.0033-0124.1983.00440.x
- Mokhtarian, P. L. (1990). A typology of relationships between telecommunications and transportation. *Transportation Research Part A: General*, 24(3), 231–242. doi:10.1016/0191-2607(90)90060-J
- Mokhtarian, P. L. (2002). Telecommunications and travel. The case for complementarity. *Journal of Industry Ecology*, 6(2), 43–57. doi:10.1162/108819802763471771
- Mokhtarian, P. L. (2004). A conceptual analysis of the transportation impacts of B2C e-commerce. *Transportation*, 31(3), 257–284. doi:10.1023/B:PORT.0000025428.64128.d3
- Mokhtarian, P. L. (2009). If telecommunication is such a good substitute for travel, why does congestion continue to get worse? *Transportation Letters*, 1(1), 1–17. doi:10.3328/TL.2009.01.01.1-17
- Mokhtarian, P. L., Salomon, I., & Handy, S. L. (2004). *A taxonomy of leisure activities: The role of ICT*.
- Mokhtarian, P. L., & Salomon, I. (1997). Chapter 7: Emerging travel patterns: Do telecommunications make a difference? In Hani S. Mahmassani (Ed.), *Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges* (pp. 143–182). Pergamon Press/Elsevier, 2002.
- Mokhtarian, P. L., & Tang, W. L. (2013). Trivariate probit models of pre-purchase/purchase shopping channel choice: Clothing purchases in Northern California. *Choice Modelling: The State of the Art and the State of Practice, Chapter 12*, 243–273.
- Nagurney, A., Dong, J., & Mokhtarian, P. L. (2001). Teleshopping versus shopping: A multicriteria network equilibrium framework. *Mathematical and Computer Modelling*, 34(7), 783–798. doi:10.1016/S0895-7177(01)00099-1
- Office for National Statistics. (2015). *Retail sales 2014*.
- Ortúzar, J., & Willumsen, L. G. (1994). *Modelling transport*. Sussex, England: Wiley.
- Pattabhiraman, V. R. (2012). *A needs-based approach to activity generation for travel demand analysis*. Cambridge, MA: Massachusetts Institute of Technology.
- Pauwels, K., & Neslin, S. A. (2011). Building with bricks and mortar: The revenue impact of opening physical stores in a multichannel environment. *Working Paper*, 603, 1–29. doi:10.1016/j.jretai.2015.02.001
- Pendyala, R. M., Kitamura, R., Kikuchi, A., Yamamoto, T., & Fujii, S. (2005). Florida activity mobility simulator: Overview and preliminary validation results. *Transportation Research Record: Journal of the Transportation Research Board*, 1921(1), 123–130. doi:10.3141/1921-14
- Pinjari, A. R., & Bhat, C. R. (2011). Activity-based travel demand analysis. *A Handbook of Transport Economics*, 10, 213–248.
- Popkowski Leszczyc, P. T. L., Sinha, A., & Sahgal, A. (2004). The effect of multi-purpose shopping on pricing and location strategy for grocery stores. *Journal of Retailing*, 80(2), 85–99. doi:10.1016/j.jretai.2004.04.006
- Popkowski Leszczyc, P. T. L., & Timmermans, H. J. P. (2001). Experimental choice analysis of shopping strategies. *Journal of Retailing*, 77(4), 493–509. doi:10.1016/S0022-4359(01)00054-9
- Porojan, A. (2001). Trade flows and spatial effects: The gravity model revisited. *Open Economies Review*, 12(3), 265–280. doi:10.1023/A:1011129422190

- Rasouli, S., & Timmermans, H. J. P. (2013). Assessment of model uncertainty in destinations and travel forecasts of models of complex spatial shopping behaviour. *Journal of Retailing and Consumer Services*, 20(2), 139–146. doi:10.1016/j.jretconser.2012.05.001
- Recker, W. W., & Golob, T. F. (1979). A non-compensatory model of transportation behavior based on sequential consideration of attributes. *Transportation Research Part B: Methodological*, 13(4), 269–280. doi:10.1016/0191-2615(79)90019-5
- Recker, W. W., & Kostyniuk, L. P. (1978). Factors influencing destination choice for the urban grocery shopping trip. *Transportation*, 7(1), 19–33. doi:10.1007/BF00148369
- Recker, W. W., & Schuler, H. J. (1981). Destination choice and processing spatial information: Some empirical tests with alternative constructs. *Economic Geography*, 57(4), 373–383. doi:10.2307/144216
- Recker, W. W., & Stevens, R. F. (1976). Attitudinal models of modal choice: The multinomial case for selected nonwork trips. *Transportation*, 5(4), 355–375. doi:10.1007/BF00151097
- Reilly, W. J. (1931). *The law of retail gravitation*. New York: Knickerbocker Press.
- Reutterer, T., & Teller, C. (2009). Store format choice and shopping trip types. *International Journal of Retail and Distribution Management*, 37(8), 695–710. doi:10.1108/09590550910966196
- Rhee, H.-S., Riggins, F. J., & Kim, C. (2009). The impact of product type and perceived characteristics of the web on multifaceted online shopping behavior. *Journal of Organizational Computing and Electronic Commerce*, 19(1), 1–29. doi:10.1080/10919390802198907
- Richards, M. G., & Ben-Akiva, M. (1974). A simultaneous destination and mode choice model for shopping trips. *Transportation*, 3(4), 343–356. doi:10.1007/BF00167965
- Roorda, M. J., Miller, E. J., & Habib, K. (2008). Validation of TASHA: A 24-h activity scheduling micro-simulation model. *Transportation Research Part A: Policy and Practice*, 42(2), 360–375. doi:10.1016/j.tra.2007.10.004
- Rotem-Mindali, O. (2014). E-Commerce: Implications for travel and the environment. In *Handbook of sustainable travel* (pp. 293–305). London: Springer.
- Rotem-Mindali, O., & Salomon, I. (2007). The impacts of E-retail on the choice of shopping trips and delivery: Some preliminary findings. *Transportation Research Part A: Policy and Practice*, 41(2), 176–189. doi:10.1016/j.tra.2006.02.007
- Rotem-Mindali, O., & Salomon, I. (2009). Modeling consumers' purchase and delivery choices in the face of the information age. *Environment and Planning B: Planning and Design*, 36(2), 245. doi:10.1068/b34013t
- Rotem-Mindali, O., & Weltevreden, J. W. J. (2013). Erratum to: Transport effects of e-commerce: What can be learned after years of research? *Transportation*, 40(5), 867. doi:10.1007/s11116-013-9457-6
- Rust, R. T., & Donthu, N. (1995). Capturing geographically localized misspecification error in retail store choice models. *Journal of Marketing Research (JMR)*, 32(1), 103–110.
- Salomon, I. (1985). Telecommunications and travel: Substitution or modified mobility? *Journal of Transport Economics and Policy*, 219–235. doi:10.1080/09595238100185051
- Salomon, I. (1986). Telecommunications and travel relationships: A review. *Transportation Research Part A: General*, 20(3), 223–238. doi:10.1016/0191-2607(86)90096-8
- Salomon, I., & Koppelman, F. S. (1988). A framework for studying teleshopping versus store shopping. *Transportation Research Part A: General*, 22(4), 247–255. doi:10.1016/0191-2607(88)90003-9
- Santos, A., McGuckin, N., Nakamoto, H. Y., Gray, D., & Liss, S. (2011). Summary of travel trends: 2009 national household travel survey, Washington: US Department of Transportation.
- Schiraldi, P., Seiler, S., & Smith, H. (2011). Supermarket choice with multi-store shopping: Measuring the effect of format regulation, London: Unpublished manuscript.
- Schmöcker, J. D., Quddus, M., Noland, R. B., & Bell, M. G. H. (2008). Mode choice of older and disabled people: A case study of shopping trips in London. *Journal of Transport Geography*, 16(4), 257–267. doi:10.1016/j.jtrangeo.2007.07.002
- Schoenbachler, D. D., & Gordon, G. L. (2002). Multi-channel shopping: Understanding what drives channel choice. *Journal of Consumer Marketing*, 19(1), 42–53. doi:10.1108/07363760210414943
- Schonfelder, S., & Axhausen, K. W. (2001). *Analysing the rhythms of travel using survival analysis*. Transportation Research Board 80th Annual Meeting, 137–162.

- Schröder, H., & Zaharia, S. (2008). Linking multi-channel customer behavior with shopping motives: An empirical investigation of a German retailer. *Journal of Retailing and Consumer Services*, 15(6), 452–468. doi:10.1016/j.jretconser.2008.01.001
- Sivakumar, A. (2007). *Modelling transport: A synthesis of transport modelling methodologies*. London: Imperial College of London.
- Soopramanien, D. G. R., & Robertson, A. (2007). Adoption and usage of online shopping: An empirical analysis of the characteristics of “buyers” “browsers” and “non-internet shoppers”. *Journal of Retailing and Consumer Services*, 14(1), 73–82. doi:10.1016/j.jretconser.2006.04.002
- Steed, J., & Bhat, C. (2000). On modeling departure-time choice for home-based social/recreational and shopping trips. *Transportation Research Record: Journal of the Transportation Research Board*, 1706, 152–159. doi:10.3141/1706-18
- Strathman, J. G., Dueker, K. J., & Davis, J. S. (1994). Effects of household structure and selected travel characteristics on trip chaining. *Transportation*, 21(1), 23–45. doi:10.1007/BF01119633
- Suárez, A., del Bosque, I. R. d. B., Rodri’guez-Poo, J. M., & Moral, I. (2004). Accounting for heterogeneity in shopping centre choice models. *Journal of Retailing and Consumer Services*, 11(2), 119–129. doi:10.1016/S0969-6989(03)00011-0
- Suel, E. (2016). *Modelling the relationship between multi-channel retail and personal mobility behaviour* (PhD Dissertation). Imperial College London.
- Suel, E., Daina, N., & Polak, J. W. (2016). A hazard-based approach to modelling effects of online shopping on inter-shopping duration. In Universities’ Transport Study Group (UTSG) Conference January 2016. Bristol.
- Suel, E., Le Vine, S., & Polak, J. W. (2015). Empirical application of expenditure diary instrument to quantify relationships between in-store and online grocery shopping: Case study of greater London. *Transportation Research Record: Journal of the Transportation Research Board*, 2496, 45–54. doi:10.3141/2496-06
- Swait, J. D., & Ben-Akiva, M. (1987). Empirical test of a constrained choice discrete model: Mode choice in São Paulo, Brazil. *Transportation Research Part B: Methodological*, 21(2), 103–115. doi:10.1016/0191-2615(87)90010-5
- Teltzrow, M., Meyer, B., & Lenz, H.-J. (2007). Multi-channel consumer perceptions. *Journal of Electronic Commerce Research*, 8(308277), 18–31.
- Thill, J., & Thomas, I. (1987). Toward conceptualizing trip-chaining behavior: A review. *Geographical Analysis*, 19(1), 1–17. doi:10.1111/j.1538-4632.1987.tb00110.x
- Thill, J.-C., & Wheeler, A. (2000). Knowledge discovery and induction of decision trees in spatial decision problems. In *Spatial economic science. Advances in Spatial Science*. (pp. 188–205). Berlin, Heidelberg: Springer.
- Thomas, C. J., & Bromley, R. D. F. (2003). Retail revitalization and small town centres: The contribution of shopping linkages. *Applied Geography*, 23(1), 47–71. doi:10.1016/S0143-6228(02)00068-1
- Timmermans, H. J. P. (1981). Multiattribute shopping models and ridge regression analysis. *Environment and Planning A*, 13(1), 43–56. doi:10.1068/a130043
- Timmermans, H. J. P. (1982). Consumer choice of shopping centre: An information integration approach. *Regional Studies*, 16(3), 171–182. doi:10.1080/09595238200185201
- Timmermans, H. J. P. (1984). Discrete Choice Models versus Decompositional Multiattribute Preference Models: A Comparative Analysis of Model Performance in the Context of Spatial Shopping-behaviour. In: D. E. Pitfield (Ed.), *Discrete choice models in regional science* (pp. 88–102). London: Pion, ISBN 0-85086-113-6. (British section of the Regional Science Association annual conference; 1993).
- Timmermans, H. J. P. (1996). A stated choice model of sequential mode and destination choice behaviour for shopping trips. *Environment and Planning A*, 28(1), 173–184. doi:10.1068/a280173
- Timmermans, H. J. P., Borgers, A., & van der Waerden, P. (1992). Mother logit analysis of substitution effects in consumer shopping destination choice. *Journal of Business Research*, 24(2), 177–189. doi:10.1016/0148-2963(92)90060-O
- Timmermans, H. J. P., Van der Heuden, R., & Westerveld, H. (1982). The identification of factors influencing destination choice: An application of the repertory grid methodology. *Transportation*, 11(2), 189–203. doi:10.1007/BF00167931

- Timmermans, H. J. P., Van Der Heijden, R., & Westerveld, H. (1984). Decision making between multi attribute choice alternatives: A model of spatial shopping-behaviour using conjoint measurements. *Environment and Planning A*, 16(3), 377–387. doi:10.1068/a160377
- Train, K. E. (1980). A structured logit model of auto ownership and mode choice. *The Review of Economic Studies*, 47(2), 357–370. doi:10.2307/2296997
- Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge: Cambridge University Press.
- Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review*, 79(4), 281. doi:10.1037/h0032955
- Uncles, M. D. (1987). A beta-logistic model of mode choice: Goodness of fit and intertemporal dependence. *Transportation Research Part B: Methodological*, 21(3), 195–205. doi:10.1016/0191-2615(87)90003-8
- Visser, E., & Lanzendorf, M. (2004). Mobility and accessibility effects of B2C e-commerce: A literature review. *Tijdschrift Voor Economische En Sociale Geografie*, 95(2), 189–205. doi:10.1111/j.0040-747X.2004.00300.x
- Weltevreden, J. W. J. (2007). Substitution or complementarity? How the internet changes city centre shopping. *Journal of Retailing and Consumer Services*, 14(3), 192–207. doi:10.1016/j.jretconser.2006.09.001
- Weltevreden, J. W. J., & Rotem-Mindali, O. (2008). Mobility effects of b2c and c2c e-commerce: A literature review and assessment. In *Third international specialist meeting on ICT, everyday life and urban change* (pp. 16–19). Briston, UK.
- Weltevreden, J. W. J., & Rotem-Mindali, O. (2009). Mobility effects of b2c and c2c e-commerce in the Netherlands: A quantitative assessment. *Journal of Transport Geography*, 17(2), 83–92. doi:10.1016/j.jtrangeo.2008.11.005
- Wilson, A. (1971). A family of spatial interaction models, and associated developments. *Environment and Planning A*, 3(1), 1–32. doi:10.1068/a030001
- Winter, C. (2014, February 27). Volvo wants your parked car to accept deliveries. Bloomberg. Retrieved from <https://www.bloomberg.com>.
- Wrigley, N. (1988). *Store choice, store location and market analysis*. London: Routledge.
- Yun, D.-S., & O'Kelly, M. E. (1997). Modeling the day-of-the-week shopping activity and travel patterns. *Socio-Economic Planning Sciences*, 31(4), 307–319. doi:10.1016/S0038-0121(97)00010-4
- Zhai, Q., Cao, X., Mokhtarian, P. L., & Zhen, F. (2016). The interactions between e-shopping and store shopping in the shopping process for search goods and experience goods. *Transportation*, 1–20. doi:10.1007/s11116-016-9683-9
- Zhen, F., Cao, X. J., Mokhtarian, P. L., & Xi, G. (2016). Associations between online purchasing and store purchasing for four types of products in Nanjing, China. *Transportation Research Record: Journal of the Transportation Research Board*, 2566, 93–101. doi:10.3141/2566-10
- Zhou, Y., & Wang, X. C. (2014). Explore the relationship between online shopping and shopping trips: An analysis with the 2009 NHTS data. *Transportation Research Part A: Policy and Practice*, 70, 1–9. doi:10.1016/j.tra.2014.09.014