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\title{Shopping Online}

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\section*{Abstract}

Personal travel and activities have undergone significant modifications as a result of the growth of e-commerce. We extensively analysed empirical evidence on the connection between personal travel behaviour and internet shopping. The evidence for four different types of effects on a variety of travel outcomes, such as trip frequency, journey distance, trip chaining, mode choice, and time consumption, was synthesised and evaluated. We looked over 42 publications and found more proof that travelling for shopping is no longer necessary. The majority of research conducted thus far have ignored other travel consequences in favour of trip frequency. The modification effect, which has important implications for managing travel demand, has been the subject of very few studies. In conclusion, previous research has not been able to agree on the primary impact of online purchasing, in part because of the variety in variance

\section{Introduction}

The quantity of online shopping portals, the range of items offered online, and the availability of fast internet have all increased steadily during the past ten years. This transition has had a significant impact on people's purchasing habits as well as the maturation of online shopping as a retail channel. Online sales were predicted to reach 3.36 trillion in 2019, accounting for 13.6percent of all retail sales globally, a 20.2percent rise from 2018. (Cramer-Flood et al., 2020). This includes 11.5percent in the US, 21.8percent in the UK, and 34.1percent of all retail sales in China. Online sales are anticipated to have increased much more as a result of the COVID-19 outbreak.

These changes in traffic, pollution, and energy use by private household cars and delivery trucks have had significant effects on how households move. Furthermore, the growth of fulfilment centres, the closure or downsizing of physical stores, the alteration of land use patterns, and the reduction in accessibility to shopping opportunities, particularly for vulnerable populations that might not have access to the necessary banking services and technology, are all consequences of online shopping. A thorough knowledge of the nature of the effects of online shopping on travel, which have been the topic of a fast growing and developing body of research, is necessary to address the associated land use, environmental, and social concerns.

The body of knowledge on online buying is part of a larger body of knowledge on how information and communication technologies (ICT) affect travel behaviour. According to Salomon (1985, 1986), Mokhtarian (1988, 1990, 2002), and Mokhtarian and Meenakshisundaram (1999), there are four distinct sorts of effects that internet buying may have on travel behaviour. Shopping online has the potential to change the nature and patterns of shopping visits, to replace them, to complement them, to expand them, or to have no impact at all (i.e. no effect). Studies from all across the world have discovered actual evidence for one or more of these effects of internet shopping on travel, with the type of effect determined by factors including product characteristics, geography, and culture, among others.

\section{background Overview }

\section*{2.1. Definitions of concepts}

In this article, we referred to online purchasing, also known as B2C, as a purchase made by a customer from a business through an online channel. Prior to making a purchase, customers may or may not conduct an internet information search. This definition is more limited than the one used in a previous review article by Rotem-Mindali and Weltevreden (2013), which focused on consumer and business-to-consumer (C2C) transactions as well as passenger and freight transportation Our definition's more limited emphasis aids in defining the paper's scope and is in accordance with the purview of many other transportation-online shopping investigations (e.g Cao, 2009; Zhou & Wang, 2014).

According to a number of criteria, such as trip frequency, mode preference, journey distance, trip chaining behaviour, and time spent travelling, the quantity and kind of personal travel, which at a global level forms travel demand, is often quantified. Trip frequency measures how often a person goes shopping, independent of the length, location, or other factors. Studies on online buying have used a variety of methods to calculate trip frequency, including travel diaries.

(for instance, Ferrell, 2005) to the respondents' subjective impressions (e.g. Lee, Sener, Mokhtarian, & Handy, 2017). The travel distance measure refers to the overall distance covered by any mode of transportation for shopping (e.g., Holgun-Veras, & Sánchez-Daz, 2016), whereas the mode choice metre focuses on the mode utilised for a trip (e.g., Suel, & Polak, 2017). The trip chaining statistic measures whether a traveller connected a trip for shopping with another journey (e.g. Ferrell, 2005). The journey time metric counts the amount of time a person spent travelling in order to buy, and it is frequently assessed in conjunction with other activity periods, such as the time spent shopping (e.g. Farag, Schwanen, Dijst, & Faber, 2007).

\section*{2.2. Effects of ICT on travel}

Salomon (1986) and Mokhtarian were the first to explore replacement and complementarity impacts, where ICT usage was hypothesised to either replace travel (substitution) or produce more travel (complementarity) (1988, 1990). Journey patterns that have changed as a result of the usage of ICTs include destinations, routes, means of transportation, travel times, and shopping durations (Mokhtarian & Meenakshisundaram, 1999; Salomon, 1985). Finally, neutrality characterises the situation where ICT use has no impact on travel (Mokhtarian, 1990; Salomon, 1985).

Depending on the activity being engaged in or the sort of goods or service purchased, ICT's impact on travel behaviour will vary (Mokhtarian, Salomon, & Handy, 2006). A trip-based activity won't always be replaced by one done via ICT, and Mokhtarian (1990) stated that even in cases when ICT replaces travel, demand for travel may still rise overall due to expanding underlying markets and efficiency improvements. In addition to the direct consequences mentioned below, changes in buying habits may also have indirect and long-term implications on travel behaviour (Salomon, 1985).

The rebound effect, which maintains that as an activity becomes more efficient, the money and time saved from that efficiency may promote further consumption, is another impact noted in the ICT literature (Masanet & Matthews, 2010). Therefore, while online shopping improves the efficiency of the buying process, rebound effects might result in a reallocation of or an increase in travel demand, which could have a detrimental effect on the environment and the transportation networks. A subset of the complementarity and modification effects is the rebound effect.

\section{related work}

\section*{3.1-Online shopping cart abandonment}

Online merchants suffer significant revenue losses due to the phenomena of abandoned shopping carts (Huang et al, 2018; Rajamma et al, 2009), which weakens their standing in the market. As a result, existing marketing literature addressed this issue by using a behavioural perspective to identify and understand the key factors that contribute to online shopping cart abandonment. Rajamma et al (2009) concentrated on potential barriers at the checkout stage and discovered that high perceived risk and increased perceived transaction inconvenience at the checkout stage contribute to online shopping cart abandonment. These findings appear to be partially for new consumers who aren't familiar with the checkout procedure. Similar research by Kukar-Kinney and Close (2010) shows that customers are more likely to choose to purchase a product from a stationary offline store when privacy and security concerns are present. In addition, they discovered that shopping carts' amusement value, their use as a tool for organising, the wait for a sale, and concerns about expenses were all precursors to cart abandonment (Kukar-Kinney & Close, 2010). Close and Kukar-Kinney (2010), who demonstrated that customers' propensities to add products to the online shopping cart for reasons other than imminent purchase are—among other things—due to organisational aims, provided support for their stated determinants.In their study, Huang et al (2018) concentrated on mobile shopping cart abandonment.They discovered that both intrapersonal (ie., conflicts over the attributes of mobile shopping and low self-efficacy regarding mobile shopping) and interpersonal (i.e., discrepancies from the other's attitudes to self-attitudes) conflicts disturb consumers' emotions during mobile shopping, implying the abandonment of shopping carts. Overall, their findings suggest that buying behaviour may also be impacted by the online shopping device used. Cho et al. (2006) shown that factors such as information overload, high value consciousness, unpleasant prior experiences, plans to compare prices, and untrustworthy websites are likely to cause customers to quit their online shopping carts.

\section{Methodology}

\section*{4.1-Preprocessing and preliminary data analysis}

This study's objective is to apply machine learning to predict shopping cart abandonment. The best classifier for this assignment is determined by comparing the machine learning models described in section "Machine learning techniques for classification." The server log files of a well-known German online store that predominantly sells fashion were used to collect the clickstream data. The data were produced by the online store by taking the sequential log files containing the consumers' chronological online shopping activity and Each entry in the log file represented a single customer action or activity (such as a click), such as adding an item to the shopping basket or selecting an item to examine its details. Then, each client's session-specific actions were allocated to summary variables. As a result, all of a customer's behaviours were combined into a single observation with several characteristics defining the session. Thus, a session is a time of continuous web surfing or a series of page views by a user up until that user leaves an online store (Montgomery et al., 2004). 3,511,037 observations or sessions made between February 1, 2019, and the data are included.extracting them.

and April 30, 2019, or three months. The data also include 18 explanatory factors for each observation or session, which are reported in Table 1 and many of which support the findings of Van den Poel and Buckinx (2005). Only site visitors who used the virtual shopping cart during the session—that is, those who added items to their cart—are of interest to us. According to Close and Kukar-Kinney (2010), using a shopping cart is an essential prerequisite for abandoning one. Consequently, we eliminated customers who were referred to as "simply browsing" consumers since they did not add any things to their shopping basket throughout the session, and 821,048 observations (23.38) were still present. Shopping cart abandonment was modelled as a dummy variable utilising data from the customer's assembled and ordered shopping carts (variables BASKETS BB and BASKETS) during the session.

\section{Experiment results}

\section*{5.1 Sales differences among different types of food souvenirs}

To analyse the variations in sales of several food-related souvenirs, we utilised an ANCOVA. Online sales were seen as the dependent variable, whereas product categories were seen as independent factors. As controlled factors, we took into account price, listing duration, and promotional activity. We utilised the modified sales volume as the dependent variable after a logarithmic adjustment of the volume of the souvenirs' online sales. The findings indicated that the four different categories of food souvenirs sold significantly differently online.F (3,6056) = 152.104, partial 2 = 0.070, p 0.0005. The findings of a post hoc analysis with a Bonferroni correction revealed that TCFS had the largest selling volume, which was noticeably larger than that of NCCFS, LFS, and OFS (see Tables 2 and 3). H1 was therefore

\section{Conclusion}

Online shopping cart abandonment can hinder corporate growth and, as a result, undermine a company's ability to succeed in a cutthroat market. In addition, as commercial use of the Internet grows, it becomes possible to follow customer online activity and activities, producing clickstream data.Therefore, we suggested several machine learning algorithms to identify online shopping cart abandoners by extracting useful information from such clickstream data. We examined 821,048 observations from a German online retailer's data, and we fitted the models using 10-fold cross validation. As a result, our work adds to the body of literature by fusing machine learning techniques with the academic domains of clickstream data and online shopping cart abandonment.Our data show that compared to buyers, who typically add more goods to their shopping carts and explore more pages on average, consumers who abandon their shopping carts are more likely to be new customers and mobile shoppers. With an AUC of 0.8182, an F1-Score of 0.8569, and an accuracy of 82.29, our comparative results further demonstrate that gradient boosting with regularisation is an effective strategy for differentiating between abandonments and buyers. A decision tree or boosted logistic regression, however, may be viable alternatives that are computationally more practical and produce just slightly less accurate prediction results.

Even said, research on clickstream data and machine learning techniques is still in its infancy, especially in the context of marketing. In order for e-commerce enterprises to succeed over the long run, machine learning will thus be necessary, and the analysis offered in this article will encourage more study on the subject.

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\section{Timetable}

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     background Overview & 2.5\\
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     related work & 1.5\\
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