Page | 13

Examining the Impact of Omnichannel retailing on Buying Intention Using Binary Models

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How to cite:

Abdelmaged, M. A. M. (2021) 'Examining the Impact of Omnichannel retailing on Buying Intention Using Binary Models', Empirical Quests for Management Essences, 1(1), pp. 13–23.

Article history:

Received: 2021/08/21 Available online: 2021/11/04



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Abstract

The last decade showed that the customer journey is no longer linear and now contains numerous touchpoints. Omni-channel retailing intends to provide a smooth retail experience irrespective of where the consumer is on internet or in-store, and which device they are using, or which channel they are accessing content through. The objective of this study was to check whether the integration of omni-channel has any impact on the buying intention of consumers in retail stores. The study used Probit and Logistic model to fulfill the study objective. The results show that omnichannel integration in retail stores has significant positive impact on the buying intention. Moreover, the results also show that quality of the product, brand image, and social influence have significant positive impact on the buying intention in the context of retail stores. This study recommends that the retail stores can influence the buying intention of consumers by implanting an effective omnichannel strategy.

Keywords: Buying intention, Omni channel, Retailer, Logit, Probit.

1. Introduction

Today's consumers want consistent brand experiences regardless of where they are or whatever channel they use. Customers want a smooth, fluid buying experience regardless of whether they are surfing social media, investigating a website, or shopping in-store. Alternatively, they may just visit a rival and have the seamless experience they want. Retailers that use an omnichannel approach build a single strategy that is implemented across all channels in order to offer a linked, customer-centric experience (Harsha, Subramanian and Ettl, 2019). This means that a shopper who begins their browsing experience on a brand's website will have the same experience regardless of whether they visit the brand's mobile app, social media accounts, or brick-and-mortar store, and regardless of whether they use a mobile phone, or laptop (Flavian, Gurrea and Orús, 2020). Customers may also convert through any of these various online or physical touchpoints with an omnichannel shopping approach.

Omnichannel retailing refers to a business that has minimal, if any, boundaries between online and offline sales. Retailers can react to consumer requirements anywhere and at any time since stocks and supply chains are controlled as a single entity (Gao and Su, 2019). Retailers and consumers have access to information about the availability and location of products. The consumer may visit a store's website to see if a product is in stock at a local location or what the delivery time and cost would be. The consumer has the option of purchasing in a variety of ways (Balakrishnan *et al.*, 2018). The retailer may fulfill the order from a distribution center, a local location, or another location that stocks the item.

Multichannel commerce utilizes many channels concurrently. There is a distinct inventory and supply chain system for brick-and-mortar locations and another for online sales (Balakrishnan *et al.*, 2018). Depending on how things are structured internally, the channels may seem to be self-contained entities. Some older retail enterprises may have constructed their online sales systems ad hoc when the internet took off, resulting in the systems being developed independently (Lim and Srai, 2018).

Customers nowadays are unconcerned about internal organizational hierarchies. They want to be able to communicate with the merchant through the channel of their choice and get the same level of service (Ovezmyradov and Kurata, 2019). It's infuriating to discover an item you want online but cannot locate it in store, especially when the shop workers may be unaware the item exists. The main distinction between omnichannel and multichannel is that omnichannel unifies all customer touchpoints in order to provide a consistent customer experience.

With customers expecting to explore, buy, and return items through a number of channels, the supply chain must accommodate not just the brick-and-mortar store, but also the shopping options available via the customer's mobile device (Ovezmyradov and Kurata, 2019). This functionality necessitates real-time stream visibility of inventory throughout the supply chain, providing consumers with a unified picture as they transition between channels.

As businesses expand their omnichannel and multichannel sales channels, reverse logistics will be critical to their success (Abdelmaged, 2021a). After all, refunds account for a sizable portion of internet purchases. Customers want to be able to return products at their convenience, not the convenience of the corporation (Kleinlercher *et al.*, 2020). If consumers purchase a thing online and pick it up in-store, they may want to return it through parcel pickup rather than returning it in person. Alternatively, if customers choose home delivery, they may choose to drop the package off at a nearby retail store.

Page | 14

Many e-commerce sites, for example, promote returns on garments and footwear, making the reverse flow of items critical. Retailers must be able to return things and replenish or liquidate them cost-effectively (Lazaris *et al.*, 2015). To thrive, reverse logistics must establish itself as a distinct profession with management control and investment. For many major e-commerce firms, the solution is to establish a distinct supply chain that is as transparent as the outgoing process.

Page | 15

The existing literature stresses two fundamental approaches to channel integration: one is to give access to and information about the Internet store at physical locations, and another is to provide access to and knowledge about physical locations at the Internet shop. Thus, integration might occur either from the shop to the Internet or vice versa (Mishra, 2020). Companies deploy self-service totems or aided online terminals in their physical establishments to combine online elements into offline channels. This form of connection may mitigate the negative impact of physical shop unavailability on clients and complement human assistance. Additionally, corporations include a physical shop locator and information about their physical store selection in their online storefronts to combine offline elements. According to client views of online integration, this integration has the potential to mitigate the negative impact of non-availability for online customers (Akter *et al.*, 2019).

Shifting from a multichannel to an omnichannel approach entails significant organizational and operational adjustments. Once multichannel capabilities are in place, the firm may make strategic decisions about its operations that will eventually lead it to become an omnichannel player. Omnichannel merchants may use best practices from both the brick-and-mortar and e-commerce sectors (Ameen *et al.*, 2020). Promotion, transaction management, product and price information management, access to information, order fulfillment, and customer support should all be linked with traditional processes. The first retailer to develop an omnichannel strategy was John Lewis in the United Kingdom, which began its omnichannel journey in the early 2000's and continues to spend heavily in omnichannel management and information technology solutions.

2. Literature review

Frasquet-Deltoro, Molla-Descals and Miquel-Romero, (2021) uses a complete scale creation approach to propose a retailer brand experience scale for the omnichannel environment, with a particular emphasis on single-brand merchants since they may give richer shopping experiences. Our validated measure consists of 19 questions classified as sensory, emotional, intellectual, behavioral, lifestyle, pragmatic, relational, and social. This scale extends the scope of the brand experience construct by including characteristics of experience enabled by the growing number of digital media and channels that have supplemented the physical channel in the omnichannel retail environment. We end by demonstrating that an omnichannel retailer's brand experience improves consumer happiness and loyalty.

The purpose of research Saha and Bhattacharya, (2020) was to examine how markets fragment when an omnichannel store joins a market previously serviced by non-omnichannel merchants. The enhanced value created by omnichannel flexibility is likely to attract more consumers to omnichannel retailers, drawing them away from existing non-omnichannel competitors. Customers, on the other hand, are expected to value omnichannel flexibility differently. Additionally, since attaining omnichannel flexibility includes greater expenditures for service integration, the omnichannel aspirant is likely to charge clients a higher price than non-omnichannel rivals. Our model takes all of these elements into account and provides analytical expressions for the omnichannel retailer's predicted market share as a function of the prices paid by non-omnichannel competitors, the degree of flexibility supplied, and the cost of offering the same. Additionally, we estimate the amount of flexibility that an omnichannel store must provide in order to achieve a certain market share, based on the cost of service integration. The results imply that the accompanying integration cost conseducs the maximum market share that an omnichannel entrant may pursue.

Bell, Gallino and Moreno, (2018) discover that showrooms: (1) increase overall demand and in the online channel; (2) generate operational spillovers to other channels by attracting more customers who, have a higher cost-to-serve; (3) enhance operating efficiency by raising conversion in a sampling channel and reducing rates of return; and (4) amplify these demand and advantages when dealing with customers in the most acute need for the firm's products. Additionally, the benefits we observe continue to intensify over time, since showrooms contribute to not just brand recognition but also to what we refer to as channel awareness. We end by expanding on the underlying consumer dynamics that underpin our results and proposing insights for how online-first companies may implement omnichannel strategies.

2. Factors affecting buying intention and research hypotheses

Traditionally, Given the abundance of research on the conventional elements influencing consumer purchasing choices, this study will concentrate only on brand image, social influence, socioeconomic status, and the quality of items offered in hypermarkets (Ayad, Ainous and Maliki, 2016) (Ameen *et al.*, 2020) (Motwani, 2016). These characteristics were considered for this research because they are mostly neglected in situations (Islam and Daud, 2011). In this research, we will examine how these indicators might be used to elicit clients' purchasing intentions. supermarkets. As a result, a short summary of these elements is provided below.

a) Quality of the product

Customer happiness is influenced significantly by the quality of products and services supplied in shops. The ability of a product to meet particular client desires is referred to as its quality. Perceived quality relates to how consumers perceive items or brands that live up to their expectations. Individuals evaluate items based on their experience with two businesses' brands. Product quality contributes to a firm's competitive advantage. In compared to private companies, customers choose national brands because they are more known, trustworthy, and get more media attention. Generally, the quality of a product is determined by its features, advantages, and capacity to meet specified demands (Li *et al.*, 2021) (Abdul Rahman, Maaruf and Abdul Rahman, 2018). It is regarded to be a significant predictor of consumers' purchase intentions. Thus, it may be anticipated that:

H1: Product quality has a positive and substantial effect on consumers' inclination to shop.

Page | 16

b) Brand image

The brand image refers to how a business or product is perceived by the public. Brand image can be defined as an individual's mental impression of a brand based on their connections with it. Organizations strive to develop a strong brand associated with a particular product. Apart from establishing brand awareness in general, most businesses want their product or service to have a certain image or to be seen in a particular manner. Thus, brand image refers to the entire impression generated in customers' minds as a result of all encounters with the firm. This brand image may be used to describe how a product is introduced, the sort of product released, the type of advertising they perform, and the type of clients they serve (Park, Dayarian and Montreuil, 2021). The provenance of a product, such as the country in which it was manufactured and the manufacturer, has an effect on how people perceive a brand. This implies that the recall process is based on past knowledge of the firm, brand reputation, and product qualities, all of which may have an effect on customers' response and buying behavior. Positive brand image consistently outperforms consumer expectations. (Gao, Agrawal and Cui, 2021) (Yang *et al.*, 2019) A positive brand image boosts an organization's goodwill and brand value. Thus, we may postulate that:

H3: A favorable and substantial link exists between brand image and purchase intention of buyers.

C) Socioeconomics

Socioeconomic status is a critical factor in determining a customer's buying choice. Individual income is a critical aspect in socioeconomics; it classifies persons according to their social status by calculating their quantity and source of money. Due to their limited means, poor clients choose to shop at discount shops and make little purchases in supermarkets. Customers make purchasing choices based on their personal attributes such as their age, employment, and financial situation (Piotrowicz and Cuthbertson, 2019). These variables have a direct effect on consumer behavior. This socioeconomic status of purchasers has a significant impact on their purchasing choices. As a result, marketers take socioeconomic variables into account when developing goods and promotional campaigns. As a result, we may postulate that:

H4: There is a positive and substantial association between a customer's socioeconomic status and their inclination to shop.

d) Social influence

Social influence is the process through which an individual's actions, emotions, ideas, attitudes, or behaviors change as a result of contact with other people or groups. It is seen in socialization, peer pressure, and familial pressure. It is often used in social psychology to refer to the effect of societal norms on the altering of individual behavior and attitudes. Purchasing decisions are influenced by social values stemming from a desire to be respected and to attain desired social standing (de Borba *et al.*, 2020). According to various observations, the majority of customers do not shop alone. Individuals' purchasing decisions are strongly influenced by their peers, family members, and other organizations. These reference organizations sell themselves by word of mouth. They may have a direct influence on the views of others. This influencing effect might work against or in favor of a certain organization's interests. As a result, we postulated the following:

H4: There is a considerable link between social impact and the purchase intention of consumers.

Page | 17

e) Omnichannel

omnishoppers, and they want a consistent experience across all media. For instance, an omnishopper may investigate a product's attributes using a mobile app, compare pricing on other

Page | 18websites using a laptop, and eventually purchase the thing in a physical store. This consumer 3.0
makes use of new technologies to do research, express views, explain experiences, make purchases,
and communicate with brands. In an omnichannel context, channels are utilized fluidly and
interchangeably throughout the search and purchase process, making store management difficult,
if not impossible. As a result, we postulated the following:

H5: There is a considerable link between omnichannel experience and the purchase intention of consumers.

A rising proportion of clients shop through several platforms. These consumers are referred to as

2. Methodology

We investigated our hypothesis using binary models. The dependant variable can only have two possible values in this kind of model. Y might be a dummy variable representing the chance of a scenario occurring or a choice between two alternatives. For example, the outcomes of each match in a league sample may be useful in modeling (whether successful project or not). The teams differ in a variety of quantifiable characteristics that we refer to as x. The objective is to establish a correlation between team characteristics and the probability of project success. y is a binary variable with a range of 0 to 1. Because the observed conditional average model imposes insufficient constraints on the model's residuals, just virtually regressing y on x is insufficient. Additionally, the value of y is not constrained to zero in a simple linear regression. Rather than that, we use a specification to address the fundamental demands of binary regressors. (Long and Mustillo, 2021). Assume that the probability of seeing 1 is as follows:

$$\Pr(y_i = 1 | x_i, \beta) = 1 - F(-x_i'\beta),$$

The kind of binary model that is chosen is given by the function F, which is a pure rising continuous function that accepts a true value and returns a number between 0 and 1. (Lei, 2021).

$$\Pr(y_i = 0 | x_i, \beta) = F(-x_i'\beta)$$

As a resut:

Maximum likelihood approaches may be used to find the values of this model given this specification. (Rass, König and Schauer, 2021). The likelihoods function is denoted by the

$$l(\beta) = \sum_{i=0}^{n} y_i \log(1 - F(-x_i'\beta)) + (1 - y_i) \log(F(-x_i'\beta)).$$

following notation:

Due to the nonlinear nature of the first-order criteria for this probability, an iterative solution is required to get parameter estimates. This standard offers two opposing viewpoints that need consideration. In many cases, binary models are utilized to define latent variables. Assume a latent component y* exists that is linearly connected to x.

Page | 19

$$y_i^* = x_i'\beta + u_i$$

y* determines whether the measured response variable reaches a specified value, where u denotes random fluctuations:

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \le 0. \end{cases}$$

The threshold is set to zero in this case, however the threshold value is irrelevant if x contains a constant term (Musa 2013). The marginal impact of a distinctive x factor on a single conditional probability associated with the objective y is computed as follows:

$$\frac{\partial \mathbf{E}(y_i | x_i, \beta)}{\partial x_{ij}} = f(-x_i'\beta)\beta_j.$$

If the consumer buys, the variable "purchase"=1.

If the consumer does not buy, the variable "purchase"=0.

Other variables' data consist of PCA components derived from diverse responses based on five attributes. The data were collected from shoppers of different omni-channel retail stores. The final sample size is 569 retail shoppers.

2. Results

Table 1 presents the results from binary probit model. As discussed in the previous section we have included five independent variables in the model. They are, 1) quality, 2) Brand 3) Socioeconomic, influence, and finally, Omni. The result shows that the p-value for Quality is less than 5 percent. This implies that quality of product significantly impacts the intention to buy. the p-value for the variable Brand is less than 5 percent. This implies that influence significantly impacts the intention of product significantly impacts the intention to buy. Moreover, the p-value for Influence variable is less than 5 percent. This suggests that influence significantly impacts the intention to buy. However, the p-value for Quality is 0.99 which is greater than 5 percent. This implies that socioeconomic factors do not significantly impacts the intention to buy.

Table 1. Binary Probit model results

Dependent Variable: Purchase Method: ML - Binary Probit (Newton-Raphson / Marquardt steps) Sample: 1 569 Included observations: 569 Convergence achieved after 7 iterations Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Quality	0.008017	0.003591	2.232549	0.0256
Socioeconomic	8.71E-06	0.000208	0.002326	0.0000
Influence Omni	0.824898 0.218936	0.102930 0.031456	8.014177 6.960028	0.0000 0.0000
С	24.18480	2.387374	10.13030	0.0000
McFadden R-squared	0.757774	Mean dependent var		0.627417
S.D. dependent var Akaike info criterion	0.483918 0.340981	S.E. of regres Sum squared	sion resid	0.223774 28.19221
Schwarz criterion	0.386787	Log likelihood		-91.00921
Restr. deviance	0.358855 751.4400	Restr. log like	lihood	-375.7200
LR statistic Prob(LR statistic)	569.4216 0.000000	Avg. log likelil	nood	-0.159946
Obs with Dep=0 Obs with Dep=1	212 357	Total obs		569
	Variable Quality Brand Socioeconomic Influence Omni C McFadden R-squared S.D. dependent var Akaike info criterion Schwarz criterion Hannan-Quinn criter. Restr. deviance LR statistic Prob(LR statistic) Obs with Dep=0 Obs with Dep=1	VariableCoefficientQuality0.008017Brand0.783112Socioeconomic8.71E-06Influence0.824898Omni0.218936C24.18480McFadden R-squared0.757774S.D. dependent var0.483918Akaike info criterion0.340981Schwarz criterion0.358855Restr. deviance751.4400LR statistic569.4216Prob(LR statistic)0.000000Obs with Dep=0212Obs with Dep=1357	VariableCoefficientStd. ErrorQuality0.0080170.003591Brand0.7831120.080208Socioeconomic8.71E-060.003744Influence0.8248980.102930Omni0.2189360.031456C24.184802.387374McFadden R-squared0.757774Mean dependerS.D. dependent var0.483918S.E. of regressAkaike info criterion0.340981Sum squaredSchwarz criterion0.358855DevianceRestr. deviance751.4400Restr. log likeProb(LR statistic)0.0000000.000000Obs with Dep=0212Total obsObs with Dep=1357357	Variable Coefficient Std. Error z-Statistic Quality 0.008017 0.003591 2.232549 Brand 0.783112 0.080208 9.763569 Socioeconomic 8.71E-06 0.003744 0.002326 Influence 0.824898 0.102930 8.014177 Omni 0.218936 0.031456 6.960028 C 24.18480 2.387374 10.13030 McFadden R-squared 0.757774 Mean dependent var S.D. dependent var 0.483918 S.E. of regression Akaike info criterion 0.340981 Sum squared resid Schwarz criterion 0.358855 Deviance Restr. deviance 751.4400 Restr. log likelihood Hannan-Quinn criter. 0.358855 Deviance Restr. deviance 751.4400 Restr. log likelihood Prob(LR statistic) 0.000000 0.000000

The binary logistic model's findings are summarized in Table 2. It shows that the p-value for Quality is less than 5%. This means that the quality of the product has a substantial effect on the intention to purchase. Brand has a p-value of less than 5%. This suggests that the brand of a product has a major influence on the purchase intention. Additionally, the p-value for the Influence variable is less than 5%. This indicates that influence has a major effect on the desire to purchase. The p-value for Quality, on the other hand, is 0.86, which is larger than 5%. This indicates that socioeconomic considerations have little effect on the propensity to purchase.

Table 2. Binary Logistic model results

Dependent Variable: Purchase Method: ML - Binary Logit (Newton-Raphson / Marquardt steps) Sample: 1 569 Included observations: 569 Convergence achieved after 8 iterations Coefficient covariance computed using observed Hessian

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Quality	0.013536	0.006415	2.109962	0.0349
Brand	1.417766	0.157218	9.017815	0.0000
Socioeconomic	0.001153	0.006790	0.169759	0.8652
Influence	1.491630	0.195312	7.637179	0.0000
Omnichannel	0.398820	0.059381	6.716294	0.0000
С	43.74793	4.701918	9.304274	0.0000
McFadden R-squared	0.756928	Mean depend	ent var	0.627417
S.D. dependent var	0.483918	S.E. of regression		0.223204
Akaike info criterion	0.342099	Sum squared resid		28.04873

	Schwarz criterion Hannan-Quinn criter. Restr. deviance LR statistic Prob(LR statistic)	0.387904 0.359972 751.4400 568.7860 0.000000	Log likelihood Deviance Restr. log likelihood Avg. log likelihood	-91.32702 182.6540 -375.7200 -0.160504
Page 21	Obs with Dep=0 Obs with Dep=1	212 357	Total obs	569

5. Conclusion

Omnichannel shopping is all about giving consumers with a seamless experience that allows them to visit a company whenever and wherever they choose. This may include buying things online while in-store, shipping products between locations using their phone, and package delivery to a safe and secure area while resting on the beach. Essentially, everything that can be done in a physical and mortar business can be done just as readily and conveniently somewhere else.

In today's environment, omnichannel retail promotes consumer choice and creates a smooth shopping experience. Many individuals feel this undermines the concept of conventional brickand-mortar establishments. However, this is not true. Stores are evolving. They're growing more efficient as the internet purchasing experience improves.

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 Page | 23
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