1 Introduction

Across Western nations, online ~~orders of~~ food delivery (OFD) orders are growing rapidly because convenience is coupled with the ease of access afforded by the ubiquity of mobile Internet devices (Pigatto et al., 2017). This rapid growth of online food delivery services ~~led to~~has brought new and powerful intermediaries ~~in~~to the food industry (e.g., just-eat.com, clickdelivery.com, foodpanda.com, UberEATS). These business platforms provide order services, payment, and monitoring of the process but are not necessarily responsible for the food preparation and order delivery operations (Pigatto et al. 2017). Although large fast food chains like McDonald's or Domino's Pizza still offer their own delivery services, most small or medium restaurants are dependent upon the services that these intermediaries provide on their platforms (Yeo et al., 2017).

Food delivery companies offer both online ~~as well as~~and offline service elements, converting the process of food delivery into an omni-channel retail environment. Above and beyond the speed of fast food delivery, consumers experience the interplay of physical product features ~~with~~and multichannel service dimensions. Established concepts of omni-channel service design can thus be transferred from non-food settings to assess the relevant dimensions of food delivery services. However, as Blut et al. (2018) pointed out, the "effectiveness of retail mix instruments differs for retailers carrying food versus non-food items" (p. 116), which ~~makes~~necessitates conceptual adaptations and specific empirical analyses ~~necessary~~ to derive specific implications. ~~Thus~~Therefore, this research draws on a widely established concept of tiers in service mix decisions (SMD) and empirically adapts it to online fast food delivery services.

An effective omni-channel marketing strategy enhances consumer engagement and forms profitable firm-consumer value relationships (Manser Payne et al., 2017). For the omni-channel shopper, the total experience is different ~~from~~to that of the traditional retail customer. Specifically, consumer-company interactions in food delivery platforms differ largely from interaction in traditional restaurant visits. E-WOM and user-generated content are a particularly powerful means ~~to reveal~~of revealing the drivers ~~for the adoption of~~that persuade clients to adopt products and services offered in multichannel environments (Aksoy et al., 2011). Firms such as Just-eat.com, FoodPanda, or DeliveryHero, make ~~widely~~wide use of this communication practice in their online webpages. In contrast ~~hereto~~, to date, scientific evaluations of consumers' experiences with online food delivery services are ~~(yet)~~ scarce. While ~~online food delivery services received the attention of research~~many scholars who employed traditional survey-based techniques have researched online food delivery services (e.g., Pigatto et al., 2017, Yeo et al., 2017), only ~~recently~~a few recent studies started to use a data-driven approach to understand omni-channel services delivery.

Consumers' online ~~feedbacks~~feedback and reviews are promising as unstructured data sources ~~as~~because they influence nearly half of all purchase decisions (Mathwick and Mosteller, 2017). ~~Their~~However, their value only really emerges ~~however only~~ when useful information is extracted from this data to articulate, for example, an effective strategy for multichannel retailers (Thakur, 2018). This study provides a methodological framework that transposes unstructured consumer comments to specific experiential dimensions ~~and derives~~to derive implications for managers and consumer researchers, taking online food delivery services as an example.

Our analysis reveals distinct dimensions of online fast food services based on customers' comments across six fast food product categories. Consumers' reviews that are publicly available from a food delivery services platform are aggregated into word co-occurrence ~~matrixes~~matrices of interconnected concepts. Data are split by a core/periphery network structure (Borgatti and Everet, 2000), and further separated by factor analyses. Altogether, three tiers are identified as the distinct layers of ~~SDM~~SMD in the context of online food delivery: ~~A~~a semantic core (conveying the benefits of using the platform), a tier related to the actual product (product issue and brand satisfaction), and a tier related to the augmented product (payment process and service handling).

The remainder of this paper is organized as follows. ~~Firstly~~First, we introduce the concept of SMD as theoretical background. ~~Hereby~~In doing so, to explain SMDs, we state a set of substantive arguments based on ~~the bases of~~ customers' comments and feedback ~~to explain SMDs.~~. Then, we describe our method with sufficient computational ~~details~~detail, elaborating on both ~~on~~ the data collection and the analysis procedure~~. Results are presented.~~, after which we present results. In the final section of our work, we discuss the theoretical and practical implications ~~for~~that point to future research.

2 Conceptual basis of Service Mix Decisions (SMDs)

Consumers ~~are~~do not ~~buying~~buy goods or services as an end ~~by~~in itself; rather, they seek them as means to fulfill their needs and to achieve satisfaction (Grönroos, 1978). While this interpretation ~~remains~~is largely ~~hidden~~obscured in the traditional product concept, the term “service” accentuates the assistance function and benefit provision which is ~~more~~ consistent with a consumer orientation (Vargo and Lusch, 2004). The specification of service mix components thus becomes ~~thus~~ a core issue in service marketing (Berry et al., 1983; Swartz and Brown, 1989). Marketers can design products and services by both ~~by~~ their tangible and intangible ~~aspects~~features (Levitt, 1980). Lovelock (1995) introduced a supplementary services model which emphasizes augmented elements of a product to enhance customer values. By integrating the product and services model, Kotler and Armstrong (2014~~),~~) propose that “product planners need to think about the products and services on three levels” (p. 249) in which all levels add different customer value. ~~According to this~~Following the latter model, this study proposes the three tiers of SMDs (figure 1), which include semantic core benefits, actual product, and augmented product as the layers of ~~SDMs~~SMDs of online food delivery services.

Figure 1. Tiers of Service Mix Decisions: Conceptual Framework

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2.1 Semantic core benefits

According to ~~Kotlers'~~Kotler and ~~Armstrongs'~~Armstrong’s (2014) model, the most basic service level is the core customer value that results from the problem-solving benefits of a product or service, being the basic reason for purchase ~~reason~~ (Lovelock, 1995). The core service component is ~~even~~ “the basic motivation for the customer to get in touch with a service provider” (Dimitriadis and Koritos, 2014). ~~A higher~~Higher core-service satisfaction influences consumers’ future decisions, and results in ~~a~~ higher ~~repurchase~~repurchasing behavior (Jones et al., 2000). From a managerial point of view, some service elements are needed to enable products’ ~~usage~~use, while others are designed to enhance the appeal and usefulness of the core service (Lovelock, 1995). ~~Complementary hereto~~In addition, literature shows that consumers’ experiences are not limited to the product consumption as such, but that they occur when the consumer begins to search for a product, when they actually shop, and even after ~~it has been consumed.~~consumption. Accordingly, retailers found that shopping is not just a matter of procuring tangible products~~ but rather~~; even more, it ~~is about~~entails experiential, enjoyment and entertainment aspects of retail.

In this context~~ it remains questionable~~, whether sensory products such as fast food can be suitably characterized in online settings., remains questionable. The inability to touch has proven to be a particularly salient reason for why consumers remain hesitant to buy products online (Overmars and Poels, 2015; van den Heuvel et al., 2007). McCabe and Nowlis, (2003) postulate that only non-sensory attributes can be described verbally, or communicated digitally. In contrast ~~hereto~~, Kopalle and Assunção (2000) suggest that search costs for obtaining information about the non-sensory attributes listed in an online market are lower than for sensory attributes, and consumers ~~even~~ have more information about sensory attributes than about the non-sensory when ~~making~~they make choices. The wide-spread use of Instagram to depict food items hints ~~towards~~at the possibilities ~~to transfer~~of transferring sensory experiences in online environments. Transferring these insights into the realm of online fast food delivery services, the core benefits of online food deliveries can be identified by revealing the commonly shared set of attributes mentioned across various online reviews. Then, ~~it~~we can ~~be explored~~explore which specific product or service attributes are core from the consumers' point of view;, considering whether consumers primarily base their evaluation of fast food deliveries on the speed of delivery or whether they take other aspects of product and service offerings into account (and if so, which).

2.2 Actual product

The core product is not always enough to create competitive results, thus, "the ability of the firm to manage its resources to create a holistic offering over time that evolves into an acceptable perceived customer value" is critically important (Grönroos, 1997). Vargo and Lusch (2004) claim that "goods and service are not mutually exclusive (e.g., tangible versus intangible) subsets of a common domain, that is, products" (p. 326). According to ~~Kotlers'~~Kotler and ~~Armstrongs'~~Armstrong's (2014) model, product planners must turn the core benefits into an actual product. Differentiation is most readily apparent in branded, packaged consumer goods; in the design, operating character, or composition of industrial goods; or in the features or "service" intensity of intangible products (Levitt, 1980). ~~A previous study (~~Earlier, Kopalle and Assunção~~,~~ ~~(~~2000) hypothesize that when attributes listed in the online store are relevant ~~for~~to choice, the price will have a smaller impact on choices in online supermarkets.

Lehtinen and Lehtinen (1991) suggest that physical quality is the dimension of quality originating in the physical elements of service ~~including~~which include both physical product and physical support. “In a transactional situation the core product is exchanged for money, and not much more in terms of additional services or additional sacrifice is supposed to influence the perceived customer value of the transaction” (Grönroos, 1997, p. 413). Acquaintance ~~about~~with goods quality is insufficient to recognize service quality (Parasuraman et al., 1985). An essential characteristic is the production-consumption interaction (Grönroos, 1978). According to Assimilation-Contrast theory, Anderson (1973) hypothesized that product perceptions vary directly ~~with~~parallel to expectations ~~about~~of actual product performance, but product perceptions might vary inversely ~~with~~to the level of consumer expectations. McCabe and Nowlis (2003) hypothesize that consumers are likely to choose products with pleasant material properties in examining the actual products, more so than ~~when~~in examining pictures and written descriptions or only written descriptions.

Transferring these thoughts to food delivery services, we expect that consumers will refer to relative food qualities when describing their experiences with the actual product in their online reviews. Thus, ~~it is expected~~we expect that consumers will write about their experiences ~~about~~of the relative food quality with referenced criteria ~~being~~ contingent on the specific fast food category.

2.3 Augmented product

According to ~~Kotlers'~~Kotler and ~~Armstrongs'~~Armstrong's (2014) model, “product planners must build an augmented product around the core benefit and actual product by offering additional consumer services and benefits” (p. 249). Frow et al. (2013) ~~indicate that~~mention other terms by which the augmented product is also known in current literature ~~as~~, namely supplementary services, extended product, auxiliary services, peripheral services, or product services. Physical support is a framework which facilitates the production of a service that can be ~~alienated~~divided into two categories: the environment and instruments (Lehtinen and Lehtinen, 1991).

According to Lovelock (1995), supplementary services "facilitate the augmentation of the core product~~,~~; nonetheless, supplementary services are not explicitly a part of the core offer". Auxiliary or augmented services are developed in order to enhance the sales or profitability of primary services (de Brentani, 1989). This holds for products with material properties such as clothing and home furniture (McCabe and Nowlis, 2003). Transferring the concept of augmented product to the realm of fast food deliveries, one might expect issues of order handling to be mentioned ~~within~~in consumers' reviews.

3 Methods and analysis

This study proposes a Web data driven approach that we regard as a rather new complement to surveys. Although this ~~approach~~ is a well-known ~~by~~approach among data scientists who are trained ~~for analyzing~~to analyze data from different sources like social networks or institutional repositories (Russell, 2014), it remains unknown ~~by~~among applied ~~marketer~~marketing researchers. ~~This has~~Thus, having been acknowledged elsewhere (Danneman and Heimann, 2014; Landers et al., 2016~~) but~~), this approach presents unique opportunities for omni-channel ~~strategist~~strategists.

3.1 ~~E-WoM~~e-WOM as secondary data

E-WOM is defined as any positive or negative customers' statement which is available to a multitude of consumer segments via the Internet (Wangenheim, 2016). Unlike traditional WOM, ~~whose message disappears~~in which messages disappear almost instantaneously, e-WOM remains visible ~~by~~to the members of an online community (Trifts and Häubl, 2003). E-WOM ~~badges~~prompts the (potential) consumers to engage in social interaction with each other, trade product-related information (Fink et al. 2018), and make purchase decisions through computer-mediated communication (Chen and Xie, 2008~~), the users~~). The user-generated content and e-WOM becomes a key factor in services offering (Cheong and Morrison, 2008; Flanagin and Metzger, 2013). Typical forms of e-WOM include blogs, ratings, online reviews, social media posts, and messages posted on online groups (Hennig-Thurau et al., 2004), thus, online consumer ~~review~~reviewing is an ever growing source of product information (Chen and Xie, 2008).

Here, ~~it is worth mentioning~~we need to mention that consumers might perceive ~~a less reliable~~the link between the information that is available and their experience of consumption. as less reliable. Thus, the core and sensory information ~~that~~ they have gathered on their own and via WOM are likely to ~~be~~carry more reliable inferences than ~~are~~ those based on exposure to claims obtained through other sources. ~~The semantic core~~It is essential to understand the semantic core, as Jones et al. (2000) hypothesize that higher levels of core-service satisfaction are associated with higher repurchase intentions. ~~As a result~~Consequently, one ~~might~~can expect ~~that~~ consumer opinions ~~should~~to be ~~rather~~quite varied (Weaver and Hamby, 2019~~), nonetheless~~). Nonetheless, little is known about the diversity of these opinions and to what extent they are associated with customers' satisfaction.

According to Harrison-Walker (2001), the effect of firms' service quality on WOM is "industry dependent". WOM as a form of customer engagement behavior can be interpreted as ~~an~~ oral, every-day, and person-to-person conversation between two or more individuals regarding ~~firm services offering~~firms' service offerings (van Doorn et al., 2010). The problem is that sometimes the process of moving ~~out~~ from unstructured data to structured data, and then to information and knowledge, is not as evident as it might seem (Zins, 2007).

This study uses data publicly available ~~from~~on a Colombian platform of fast food delivery services. The users of this platform are required to create an account if they want to order their favorite meals ~~to~~from a rather varied set of fast food providers. Food providers are categorized according to the type of meals they prepare (e.g., Asian food, pizzas, burgers, etc.) and the users order their meals ~~accordingly~~ through several ~~channel~~channels, such as ~~smartphone, app~~smartphones, apps, a computer with Internet access, and ~~else~~the likes. After deciding on the ~~ordering~~order, customers should confirm the physical address where they want to receive their meals and choose a payment method ~~for it~~ (e.g., cash, debit or credit card) ~~in order to send~~ for the request to go through to the nearest chosen provider. Once the order ~~is~~has been received and approved by the restaurant, the platform shows an expected delivery time. When customers finally receive their orders, they are allowed to post their opinions about the meals they received. The opinions can ~~be accompanied by a~~coincide with rating ~~for~~ the restaurant on a scale of one (bad) to five (excellent~~) scale.~~).

3.2 *Data extraction*

~~A~~We collected a total of ~~6,311~~6311 e-WOM, messages, and ratings in six different product categories~~ were collected~~. By employing ad hoc web scrapers with "Agenty", the cascading style sheet (CSS) tags were used to extract the relevant data. ~~In the first place~~First, we ~~noticed~~noted the CSS tag for the commercial name of each provider. ~~Secondly~~Second, we ~~also~~ retrieved the food category ~~that applies~~applicable to each provider (i.e., ~~Alcoholic~~alcoholic beverages, Asian food, ~~Burgers, Chicken, Meat~~burgers, chicken, meat, and ~~Pizzas~~pizzas). Third, we collected a minimum set of customers' comments per category (ranging from 625 comments for ~~Alcoholic~~alcoholic beverages to ~~1,167~~1167 for chicken ~~restaurants), and finally~~food items). Finally, we retrieved the numeric rating that each customer assigned to the service. This rating reflects the overall customer experience (i.e., delivery time, food variety~~ and~~, taste, ~~as well as~~and price), and it is publicly visible so that others can use it as supporting information ~~that motivates the decision for selecting~~in motivating their selection of a specific provider inside the platform.

The raw data set contains ~~the following~~ variables we organized in six columns. The first column contains an ascending consecutive number that allowed us to identify each customer comment. The second column contains the category of the food provider, the third column contains the commercial name of the provider, the fourth column contains the customer's written comment, and in the fifth and sixth columns we ~~include~~give the rating provided by the customer, and the total number of comments that each food provider received ~~by~~at the moment ~~we collected the~~of data collection.

3.3 *Data preparation*

Processing and extracting knowledge from ~~consumer'~~consumers' feedback, e-WOM, and reviews ~~is possible with the use of~~can be done using applied computer science techniques, such as web scraping (Munzert, Rubba, Meißner, and Nyhuis, 2014), text mining (Silge and Robinson, 2016), and ~~the application of~~ core/periphery network analysis (Borgatti and Everett, 2000) applied to the words co-occurrence network (Schouten, van der Weijde, Frasincar, and Dekker, 2018). ~~The combination of~~Combining these techniques allows one to understand the impact ~~of~~ consumers' e-WOM and reviews have on purchase decisions. ~~When it comes to understanding~~To understand customers' written opinions, ~~the use of~~using topic identification ~~might~~could be particularly convenient ~~for~~in deriving meaningful information (Micu et al., 2017; Zhang et al., 2012). In the case of omni-channel food delivery services, these techniques focus on ~~the extraction~~extracting and ~~analysis of~~analyzing customers' comments and ratings ~~as~~because they are publicly available on websites. The procedure to obtain this information ~~in an automatic way~~automatically, is known as “web scraping” (Landers et al., 2016). Web scraping is possible because the computer language underlying the display of modern web pages, called Hypertext Markup Language (HTML), is hierarchically structured around the meaning of the text. This is commonly known as a “semantic web” (Feigenbaum, Herman, Hongsermeier, Neumann ~~&~~, and Stephens, 2007). In practical terms, this refers to the raw code used to create HTML documents in the form of nested virtual objects. As ~~can be seen~~we will show, these computational techniques are useful for observing what customers experience, ~~expressed~~express, or ~~wrote~~write when they ~~used~~use food delivery services. ~~The analysis of~~Analyzing customers’ written feedback is finally possible with the aid of text mining techniques ~~that are~~ conceived as a means ~~to extract~~of extracting useful information from textual data (Feinerer, Hornik, and Meyer, 2008; Silge and Robinson, 2016).

Following standard guidelines on text mining analysis (Silge and Robinson, 2016), ~~the preparation of~~we prepared the data ~~consisted of~~by generating a document-term matrix. In this matrix, customers’ comments are arranged as rows, while words are arranged as columns, and each cell contains the number one if the *i*th word is present on the *j*th comment or zero if otherwise. ~~The deployment of this~~This matrix can be ~~coerced~~deployed into a standard data frame that can be used as ~~an~~ input for the core-periphery analysis. In creating this document-term matrix, we removed numbers, Spanish stop words, and punctuation symbols (Benoit, Watanabe, Wang, Nulty, Obeng, Müller, Matsuo, 2018). Next, we analyzed the co-occurrence of words to derive a topic modeling of the underlying themes (Alghamdi and Alfalqi, 2015). Based on established practice in informetric studies (Teichert, Shehu, 2010), we proceeded with ~~the~~a core-periphery analysis ~~for the identification of~~to identify core attributes, and finally we conducted a factor analysis for differentiating the dimensions of actual and augmented products.

3.4 Core-periphery analysis for identifying OFD´s core attributes

~~One~~Based on the conceptual model of ~~the key uses of network~~SMD, we expect a shared core in consumers’ review. Network theory ~~is~~provides the ~~identification of summary statistics for large networks in order to develop a~~methodological framework for analyzing and comparing such complex structures~~; and the~~. The most popular quantitative method for investigating core-periphery structure was proposed by Borgatti and Everett in the late 1990s (Rombach et al., 2014). A core~~/~~-periphery network structure is characterized by a cohesive subgroup of core actors and a set of peripheral actors that are loosely connected to the core (Borgatti and Everett, 2000, p. 375). According to Cattani and Ferriani (2008~~)~~), the coreness of a node can be understood as “the degree of closeness of each node to a core of densely connected nodes observable in the network” (p. 832). Here, core nodes should also be reasonably well connected to peripheral nodes, but the latter are not well connected to core or to each other (Rombach et al., 2014).

The core~~/~~-periphery structure is ubiquitous in network studies~~;~~, and the discrete version of the concept is that individuals in a group belong to either the core, which has a high density of ties, or to the periphery, which has a low density of ties (Boyd *et al.*, 2006). By computing a network’s core-periphery structure, one can determine which nodes are part of a densely connected core and which are part of a sparsely connected periphery (Rombach et al., 2014). The periphery is populated by lighter-colored nodes that are tied to the core by looser linkages and are scarcely connected to each other~~ and these~~. These nodes reside in the boundaries of the networks and thus are not as visible or as socially engaged as those in the core (Wright and Russell, 2012).

3.5 Factor analysis for revealing actual and augmented products’ dimensions

Complementary to the core~~/~~-periphery analysis, singular value decomposition as a dimensionality reduction technique allows us to differentiate between the secondary dimensions of actual and of augmented products. For this part of the work, we applied principal component analysis to differentiate sets of words that constitute the periphery of the network (Cao, Duan, and Gan, 2011). The terms that belong to the periphery are arranged as columns, while all the customers’ words (including those that belong to the core) are arranged as rows. When ~~applying~~we apply singular value decomposition as a dimensional reduction technique, there are multiple possibilities for identifying the content dimensions of actual and augmented products. As the rule of retaining factors with eigenvalues greater than 1 has been identified as the worst method for these purposes (e.g., Hayton, Allen and Scarpello, 2004), we opted ~~in~~ for an ad-hoc solution ~~consisting~~ of analyzing the occurrence of the words in context as a means ~~for~~of topic identification. We identified four possible semantic contexts for the appearance of all words, and then we set the number of components to keep in the solution with varimax rotation and Kaiser normalization and 25 iterations for the estimates in SPSS. ~~The~~In all, the four factors explain ~~in total~~ 62% of total variance.

4 Findings

4.1 The semantic core of SMDs

The semantic core of the ~~service mixed decision~~SMD consisted of a set of 11 words that, according to their statistical importance within the word co-occurrence network, proved to be the terms that emerged from the set of 194 unique words in customers' comments. Table 1 depicts the content-based peripheral dimensions of SMDs. The following words belonged to this semantic core: food, delay, delivery, wait, cold, hour, arrive, bad, minute, service, time. The ~~resulting~~ words in this core point out the aspects of service that consumers value the most, and that refer to the core benefits of the food beyond the extrinsic benefits.

The meaning of this core reflects the service ~~used by~~that the consumers ~~to wait~~used for the delivery of meals at their home or office. We call this the "semantic core" of SMDs as it ~~was~~is composed of the 11 most frequently used words. Most words are related to speed, while ~~other~~ items related to food quality are also linked to the delivery, e.g. the attribute "cold". Thus, we can conclude that consumers´ core evaluation of food deliveries is truly about "fast" food.

Table1: The semantic core of fast food delivery evaluations

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4.2 Factors within the periphery

In the core/-periphery analysis, a second step consists of understanding the set of words that constituted the periphery of the ~~network~~ co-occurrence network, from a semantic viewpoint. In Table 2, we ~~summarized~~summarize the content-based peripheral dimensions of fast food services, resulting from their empirical correlation with the latent components estimated via singular value decomposition (Cao, Duan, and Gan, 2011). The estimated factors account for an explained variance of 62%, showing that in the context of SMD customers' ~~word of mouth~~

~~reveals the existence of~~WOM contributions reveal four other factors that support the idea ~~that~~of fast food ~~is~~being not only about ~~speed~~speedy delivery or "eating fast." Instead, fast food is also associated with two additional ~~yet~~ important tiers, namely, the actual product (i.e., product issues and brand satisfaction) and an augmented product (payment process and service handling) that, in combination, posit exciting implications for both research and managerial purposes.

Table 2. Peripheral dimensions of fast food delivery evaluations

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The visual structure of the full network of word co-occurrences (including core) is depicted via multidimensional scaling in Figure 2. By examining the grouping of words, as summarized in Table 2, and the structural positions of the words in the co-occurrence network, we ~~identified~~gained interesting insights regarding customers' e-WOM. These will be outlined in the following sections for each revealed factor.

Figure 2. Tiers of ~~Service Mix Decisions: Consumers'~~SMDs: consumers' assessments of fastfood delivery

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Factor 1 (Service Handling~~, marked in yellow in Figure 2~~): As an augmented product, this factor highlights customers' concerns regarding service handling management through restaurant-~~diners~~diners' communication. This refers to consumers' experiences when ~~interacting~~they interact with both the electronic platform and its corresponding physical delivery services. The most important words in this factor (words marked in yellow in Figure 2) are those related to the communication channels that customers use to confirm problems of physical ~~addresses~~address, incomplete ~~orders~~order, or failure of electronic and physical means. The topics of this conversation type and associated words ~~might~~could encompass a brand, a product, a service, or an organization (Chen and Xie, 2008; Raassens and Haans, 2017) leading to switching intention (Wangenheim 2016). It is ~~evident how~~ striking that customers ~~pinpoint~~raise notions of respect and personal support to ~~clients'~~their orders, revealing that not only food quality ~~matters,~~ but also ~~the~~ customer service is ~~another~~a vital element.

Factor 2 (Product Issues~~, marked in green in Figure 2~~): The second factor reflects the actual product that inherently shows the ~~lexically diverse~~lexical diversity captured in the number of unique words. Depicted in Table 2, (words marked in green), these words are related to product issues~~ as it captures~~, and articulate customers' sensitive opinions in terms of food ~~items~~item variety, food presentation, and ~~meals~~meal delivery conditions. For example, the most important words in this factor are those related to meat, chicken, and potato~~ that~~, which shows ~~that~~what consumers are considering as a dimension of product issues or quality level.

Factor 3 (Brand Satisfaction~~, marked in light blue in Figure 2~~): Mirroring the actual product, the third factor relates to customers' words of satisfaction ~~towards~~regarding food and service brands. (words marked in light blue in Figure 2). This dimension relates to a set of comments ~~targeting~~verbalizing the importance of food temperature and flavor as critical conditions that managers and restaurant owners should consider when ~~delivering~~they deliver their products. For example, this dimension includes words such as delicious, perfect, thanks, excellent, rich, good, quick, hot, super, love, and recommend. Arguably, satisfied customers will be those whose expectations (with the brands) will be met, either because the service delivery will be on time or ~~because it will occur~~ before it was expected; dissatisfied customers will be those whose expectations won't be met because of a delivery delay and/or because what they receive ~~an unrequested order~~is not what they ordered.

Factor 4 (Payment Process~~, marked in dark blue in Figure 2~~): The fourth factor relates to the augmented product as it encompasses terms which are commonly present in most customers' comments about the payment process. (words marked in dark blue in Figure 2). In online stores, consumers are deprived of actual touch prior to making a purchase~~ and~~: they need to make their purchase decisions based on the visual attributes of products, and/or according to other product-extrinsic features, ~~including~~such as price, brand, ~~and~~ store image, and payment process. For example, this aspect of service includes the words cash, card, pay, money, data-phone, change, and ticket ~~in~~showing the issues about which consumers care the most.

5 Discussion and implications

Online food ordering services constitute a major trend in the food industry (Seitz et al., 2017). Like other service providers, restaurants and food retailers can use an omni-channel strategy to remain competitive in the changing business environment. Nevertheless, ~~its usage encounters~~using this strategy entails several challenges that managers need to overcome. For example, Lan, Ya, and Shuhua (2016) reported that in countries like China, the commercial operations of online food delivery services is also associated with sanitary problems (e.g., food quality and manipulation).

Customers' satisfaction with E-commerce platforms plays an important role in explaining why people decide to use these commercial channels (Thakur, 2018). Nisar and Prabhakar (2017) showed that a high level of customer satisfaction is responsible for a high rate of customer retention and for large sums of revenue in E-commerce platforms like Amazon, Apple, eBay, Wal-Mart, Staples, or Sears. While these findings are valid for general E-commerce platforms, little is known about customers' ~~feedbacks~~feedback on food delivery services in the omni-channel retail environment. Practically, to determine consumers' online marketing strategy, a firm needs to deeply understand the link between customer satisfaction and loyalty programs in the omni-channel retail environment according to consumer reviews~~ to establish their online marketing strategy.~~.

From a retailer's perspective, a profitable customer loyalty view is recognized as a key path to profitability. In a B2C retail context, the omni-channel strategy has passed the point of "nice-to-haves". Instead, ~~service mix decisions~~SMDs nowadays prove to be a "must have" for most businesses. Marketing managers should realize that~~ consumers'~~ product loyalty does not necessarily bring customers back for repurchases (Zhang, Li and Chen, 2012~~), and hence, that~~). Hence, a deep understanding of consumer retention begs attention~~ with regard to shopper~~, specifically regarding shoppers' experience with the company at all touchpoints.

This study elaborates the conceptual framework and presents a data-driven approach that allows ~~to scrutinize~~scrutiny of the three tiers of SMDs in online food delivery services. The semantic core benefits (capturing the minimal ~~semantical~~semantic elements of food delivery services as they appeared in customers' comments), the actual product, and the augmented product were ~~found~~identified as three layers that account for customers' experiences in omni-channel environment. These dimensions are deemed ~~as an attempt~~ to ~~analyze~~be important for meaningfully analyzing consumers' experiences regarding food delivery services, although ~~it~~the dimensions can be generalized to another sort of platform.

Findings show that consumers do not only value the speed of fast food delivery. Rather, consumers additionally value service handling, as well as product issues, making it important for delivery companies to align the quality of products and services in SMDs. The payment process was found, on its own, to be an independent service dimension. Hence, food delivery companies should attend to avoiding consumer frustration in the payment process. They might even consider providing positive experiences in the payment process, possibly by cooperating with fintech companies on easy and emotionally appealing payment solutions. Finally, fast food delivery companies should strengthen the emotional bonds to their brand which can lead to brand satisfaction separate from the satisfaction with the delivered fast food product.

In sum, this research offers at least two important contributions. Food delivery services are conceptualized and empirically validated as ~~service mix decisions~~SMDs, so that marketing practitioners can address consumer benefits along the three layers of semantic core, actual product, and augmented product. ~~A~~We described a multi-stage approach ~~is described~~ that allows ~~to automatically analyze customers feedbacks~~an automatic analysis of customers' feedback about online delivery services~~ by combining~~. The analysis relies on a combination of web scraping (Landers et al., 2016) for extracting data from customers' reviews~~, with~~ and text mining (Silge and Robinson, 2016) for processing unstructured data like customers' comments. Findings show that the combination of these techniques contributes to ~~the~~our knowledge ~~about~~of the design of online food delivery services, though the method can ~~be~~ easily be applied to platforms of other business models. In fact, these techniques might offer a contrasting view regarding consumer reviews and elicited judgments of information quality (Nakayama and Wan, 2017).

4 Limitations and future research

Of all omni-channel retailing opportunities and challenges, the impact ~~of~~ shopping experience has on consumers' ~~perception~~perceptions of online food delivery has not been thoroughly addressed. The ~~finding~~findings of this study ~~is~~are limited to B2C service providers~~ and future~~. Future studies should consider B2B ~~review~~reviews and feedback to uncover the core benefits of the services. In addition, future researchers should distinguish between goal-oriented shoppers

~~with~~and experiential shoppers. Goal-oriented shopping reflects task-oriented, efficient, rational, and planned purchases, while experiential shopping reflects ~~the~~ fun, hedonic, compulsive, and impulsive purchases.

As our primary data source was a Latin-American ~~Food Delivery~~food delivery service, an obvious limitation lies in potential regional and cultural idiosyncrasies of our results. The generalizability of findings remains particularly questionable for ~~non-developed~~developing countries where the market size of online transactions is below 10% of consumer transactions, according to the Global Retail E-commerce index. Future research ~~might~~could overcome this limitation by extracting data from platforms ~~of~~used on other continents. Such an effort will be useful to empirically evaluate cultural differences regarding the ~~usage~~use of online food delivery services, a topic that currently remains unexplored in ~~the current~~ research.

The increasing popularity of online food delivery platforms offers opportunities for further research. As customers ~~express~~give their comments regarding the service they received by using these platforms, their ~~stated comments~~statements can easily help us to understand what they value the most and what the least (Thakur, 2018). As ~~customers~~customer comments remain visible ~~by users of~~to E-commerce ~~websites~~website users, they constitute ~~a long-lasting~~an enduring secondary data set which opens the opportunity to employ ~~ever~~ new methods of web scraping and analyzing customers ~~feedbacks~~feedback (Danneman and Heimann, 2014; Landers, Brusso, Cavanaugh, and Collmus, 2016~~), which in~~). In turn, this can help to extend our current research toolbox.

However, as a final caveat it has to be recognized that the text mining methodology of itself has limitations. There are inherent limits to the representativeness of findings due to the self-selection of actively writing respondents. The various steps of coding and data handling still need some researcher intervention that will deter fully automatic and purely objective data treatment. While topic modelling – which has been applied in our study – already constitutes a state-of-the art approach, more complex sentiment analyses are still in an emergent state and in need of further methodological development (Mäntylä, Graziotin, and Kuutila, 2018).

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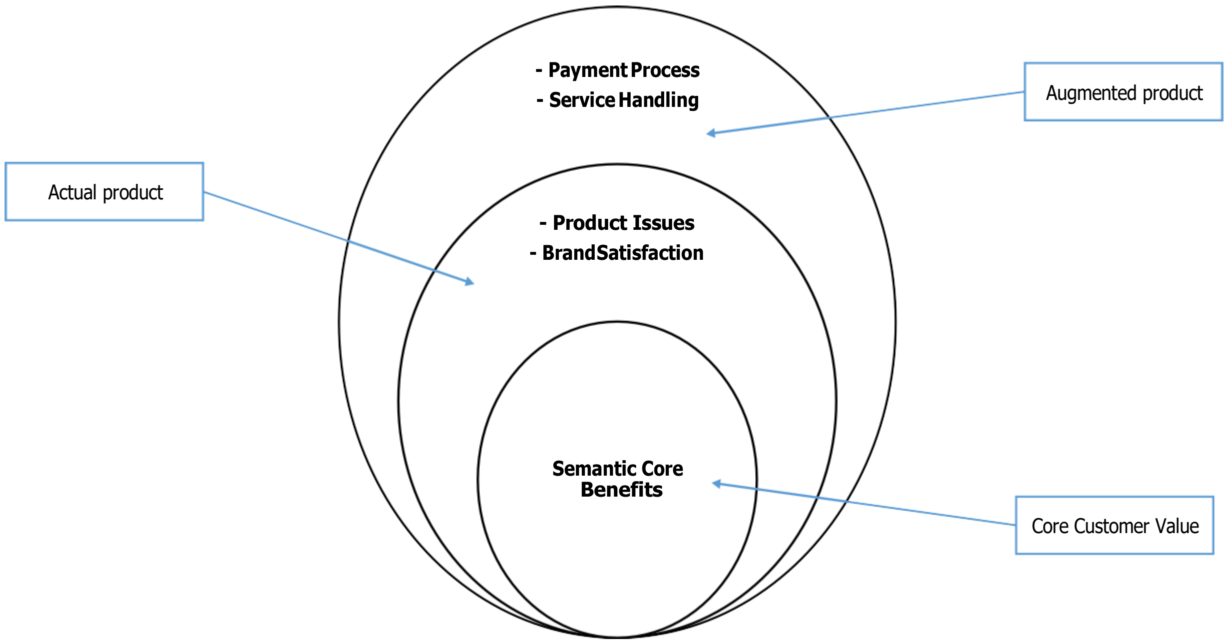
Figure 1: Tiers of Service Mix Decisions ~~(SMD)~~: Conceptual Framework



Adopted from Kotler and Armstrong (2014)

Figure 2. Tiers of Service Mix Decisions: Consumers´ assessments of fast food delivery

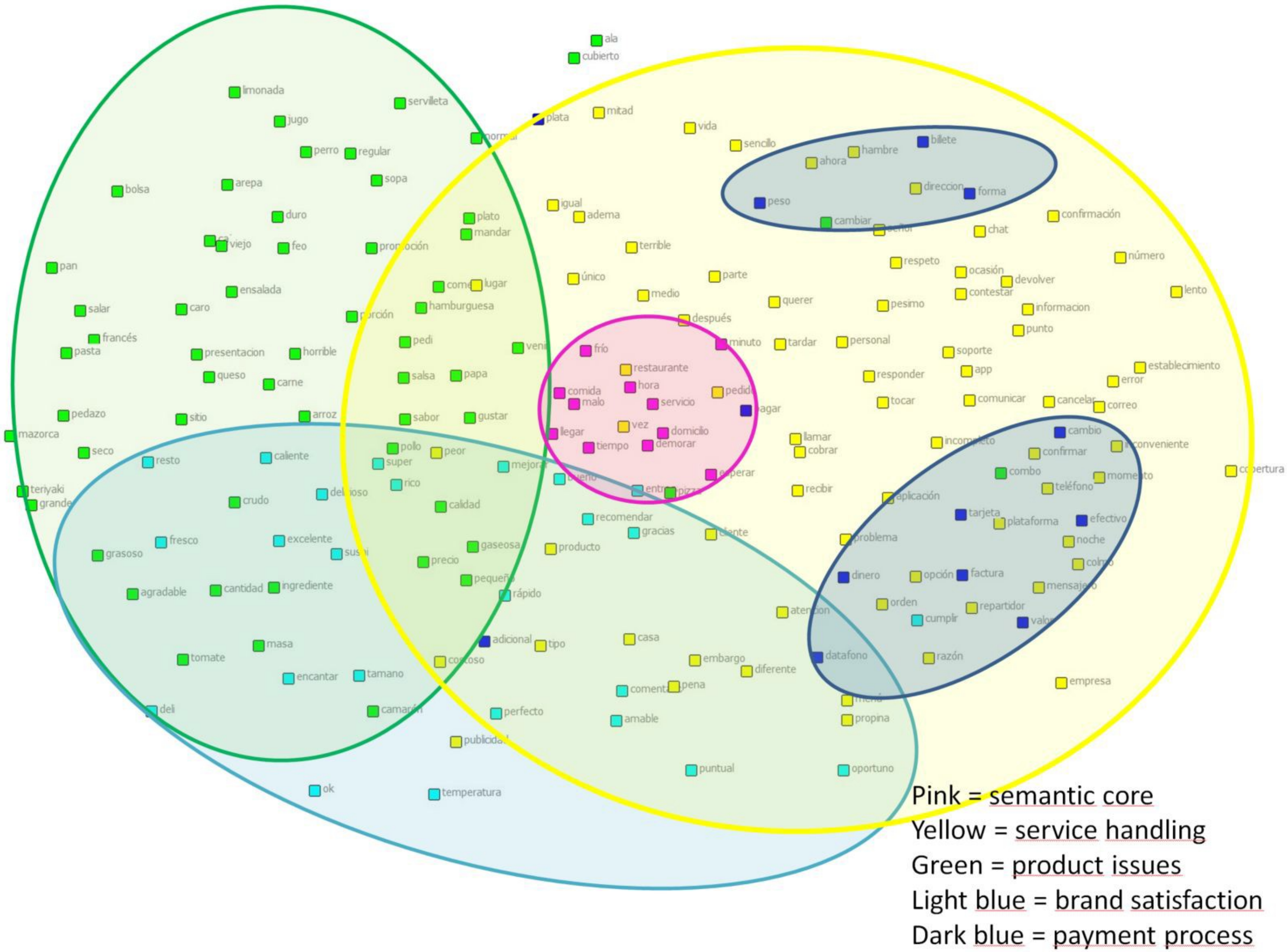


Table 1: The semantic core of fast food delivery evaluations

	bad	delay	delivery	cold	food	wait	hour	arrive	minute	service	time
bad	570	91	125	92	123	63	141	265	44	179	47
delay	91	528	84	86	95	37	174	190	81	72	59
delivery	125	84	554	50	119	73	137	256	60	118	71
cold	92	86	50	404	132	16	93	309	33	46	31
food	123	95	119	132	733	54	95	273	45	116	139
wait	63	37	73	16	54	275	109	156	53	60	69
hour	141	174	137	93	95	109	528	335	106	114	55
arrive	265	190	256	309	273	156	335	1730	166	212	265
minute	44	81	60	33	45	53	106	166	259	44	58
service	179	72	118	46	116	60	114	212	44	688	73
time	47	59	71	31	139	69	55	265	58	73	672

Table 2. Peripheral dimensions of fast food delivery evaluations

F #	Retrieved Factor	Keywords	Product Dimension
1	Service Handling (84 words) 46.8% explained variance	to call, reply, communicate, answer, support, to receive, order, confirm, information, phone, chat, cancel, establishment, restaurant, personal, platform, app, problem, after, number, confirmation, time, mail, touch, point, want, application, error, night, medium, address, coverage, terrible, chance, order, inconvenient, client, belate (overdue), give back, appalling (awful), moment, slow, worst, part, reason, now, height, home, respect, attention, hungry, incomplete, message, experience, day, there was, request, lack, same, drink, thing, full, charge, Sir, place, same, besides, delivery courier, only, tip, delivery man, pain, menu, kind, simple, different, lifetime, product, embargo, company, option, expensive, half, advertising,	Augmented product
2	Product Issues (60 words) 8.6% explained variance	meat, chicken, potato, old, ugly, hard, horrible, raw, taste, fatty, asked, sauce, rice, to Salt, salad, cheese, expensive, quality, hamburger, eat, come, quantity, ingredient, send, bread, pasta, site, portion, like, plate, cob, arepa, s~~S~~oup, price, dry, small, nice, napkin, normal, regular, juice, box, piece, soda, presentation, p~~P~~izza, bag, f~~F~~rench, covered, dog, change, wing, promotion, combo, dough, big, teriyaki, shrimp, lemonade, tomato,	Actual product
3	Brand Satisfaction (25 words) 4.0% explained variance	delicious, perfect, thanks, excellent, rich, good, quick, hot, super, love, recommend, sushi, timely, cool, deliver, punctual, comply, delicious, temperature, friendly, improve, size, commet, rest, okay	Actual product
4	Payment Process (13 words) 2.6% expl. variance	cash, card, pay, money, card-reader, change, ticket, p~~P~~eso, bill, value, additional, shape, silver	Augmented product

Note: *Number of words*