The Path Towards Omnichannel Retailing: How Large Language Models Can Integrate Marketing Communications ⋆,⋆⋆

Iman Mousavi [a,*], Behzad Najafi[b] and Sasan Barak[c]

[c] *Department of Decision Analytics and Risk, University of Southampton, UK*

ARTICLE INFO

Keywords:
Omnichannel retailing
Integrated marketing communications
Generative AI
Large language models
Natural language processing

ABSTRACT

Retailing has evolved significantly to cater to customers with diverse needs and shopping behaviors. Customers can access retailers' products through various channels, including traditional physical stores, websites, and mobile applications. The latest strategy, known as omnichannel retailing, emphasizes a seamless customer journey across these channels. This article reviews the characteristics of omnichannel retailing, with a specific focus on marketing communications. We explore the potential contributions of Large Language Models (LLMs) in achieving greater consistency and integration across channels, thereby enhancing the customer experience. We propose that placing an LLM at the core of content generation can ensure consistent communication with customers across all channels. Furthermore, we simulated customer types extracted from clustering Amazon product reviews and evaluated LLM-generated content effectiveness after receiving them. We found that LLMs can generate personalized messages based on customers' behavior consistently and at a lower cost, contributing to the necessary channel integration in an omnichannel strategy.

1. Introduction

The concept of omnichannel retailing has been prevalent for some time. However, recent technological advancements and emerging tools have led to its wider adoption by retailers. Over a decade ago, the term "omnichannel" emerged as a method of interaction with customers, aiming to provide them with a consistent experience across all channels (Rigby, 2011; Bhatnagar and Ghose, 2004). The primary goal is to treat channels as interconnected touch points, enabling consumers to enjoy a seamless experience within an ecosystem (Shen et al., 2018). Omnichannel management is another related concept that must be considered. The definition Verhoef et al. (2015) has suggested is accepted by many scholars; it is the synergetic management of the numerous available channels and customer touch points in such a way that the customer experience across channels and the performance over channels are optimized.

A channel is any point of contact or medium through which customers and firms can interact (Neslin et al., 2006a). Omnichannel retailing is distinct from multichannel retailing due to the lack of synergy and even cross-channel retailing, which does not meet the required level of integration among channels (Li et al., 2018; Hajdas et al., 2022). However, the transition from single-channel or multichannel to omnichannel is fraught with challenges. Some of these challenges may be effectively resolved or at least mitigated with new developments that have not been thoroughly studied (Saghiri et al., 2017). One challenge we focus on is the isolated conversations with customers at each channel that undermine the main purpose of omnichannel retailing.

The advent of Large Language Models (LLMs), a subset of generative artificial intelligence, has caused significant disruptions in recent years, with more changes anticipated. Businesses, particularly marketing departments, can greatly benefit from artificial intelligence (AI) due to its wide range of applications. However, 64% of marketers lack sufficient knowledge, indicating that there is still a long way to go in fully utilizing AI in marketing (Zwegers, 2023). In this article, we aim to illuminate the capabilities of LLMs, particularly in omnichannel retailing, as a step towards bridging this knowledge gap. Unlike chatbots and automated email marketing, LLMs generate human-like content, making conversations with customers more realistic and engaging. We propose that placing LLMs at the core of marketing communications significantly contributes to the desired level of channel integration. This is because it can serve customers throughout their purchase journey regardless of the channel they use. Furthermore, given sufficient

*Corresponding author
imanmousavi02@gmail.com (I.M.)
ORCID(s):

descriptions, LLMs can simulate human responses, allowing for the evaluation of the content before sending it to the actual customer.

First, we provide a concise literature review to clarify the aspects of omnichannel retailing and marketing. Next, we highlight the importance of Integrated Marketing Communications (IMC) in an omnichannel strategy. Subsequently, we illustrate how LLMs can contribute to consistent and integrated communications with shoppers, presenting the results of testing our proposed framework on product reviews on Amazon. Finally, we conclude by discussing the benefits of our proposed framework and its relationship with other relevant studies.

2. Literature Review

Retailing has evolved significantly from the past to the present, with each new format offering a unique customer experience through its customized channels. By considering the purchasing process, we can explore the distinctive features of each format and identify their inherent strengths and weaknesses. Lemon and Verhoef (2016) conceptualized the customer experience as a journey in three general steps: prepurchase, purchase, and postpurchase, each encompassing several behaviors. A simplified yet insightful framework involves four primary behaviors that customers typically engage in: information search, purchase, acquisition, and returns (Gauri et al., 2021). In traditional retail formats, the entire customer journey used to take place through a single physical channel. However, customers can now opt for a combination of channels to fulfill their information search, product purchase, acquisition, or even product return (Kim and Lee, 2008). For example, some customers prefer to search offline and buy online, a practice widely known as showrooming (Ailawadi and Farris, 2017), or choose products to buy online and collect them at specific locations, known as click-and-collect (Weltevreden, 2008). Even more complex, a customer can place an order in one channel (e.g., on a smartphone), receive the order via another channel (e.g., home delivery), and return it in case of an error through a third channel (e.g., a physical store) (Kembro et al., 2018). Each channel has its own merits, and retailers would benefit from harnessing the advantages and mitigating the disadvantages of each by combining them, accounting for their bidirectional impacts. The more the boundaries between channels are blurred, the more satisfying the customer experience becomes, which is the ultimate goal of omnichannel retailing.

Customers and retailers have been attracted to omnichannel retailing (Hajdas et al., 2022) along with researchers as the number of papers covering the topic has risen sharply (Cai and Lo, 2020). Researchers attempt to explain the numerous strategic decisions that departments should make and the processes that need to be revised and coordinated when transitioning from a multichannel or cross-channel approach to omnichannel retailing (Cao, 2014). In this article, our focus is on those aspects that directly affect customers' perceptions. The concept of omnichannel marketing introduces new elements, such as service consistency, which directly impacts customer experience and loyalty (Quach et al., 2022). Importantly, marketing communications should be strategically adjusted to blur the channels' boundaries, creating a consistent and integrated customer journey that enhances the overall retail experience.

2.1. Omnichannel Marketing and the Vital Role of Customer Experience

The Marketing Science Institute placed a major emphasis on omnichannel retailing as an agenda for marketing research back in 2018 (MSI, 2018). Multichannel marketing is a strategy that allows companies to establish enduring relationships with their customers. It does this by providing customers and potential customers with information, products, services, and support through two or more channels that are synchronized (Neslin et al., 2006b). The ongoing digital expansion has led customers to interact with businesses through various channels, prompting a shift towards "omnichannel" marketing that prioritizes a unified customer experience over mere transaction facilitation (Cui et al., 2020). If the primary goal is to maximize the effectiveness of each individual channel, then the company is employing a multichannel marketing strategy. However, if the focus shifts to maximizing customer profitability across all channels, then the company is utilizing an omnichannel marketing strategy (Verhoef et al., 2015).

As mentioned earlier, each channel offers distinct benefits for both customers and sellers. Quick delivery, a more extensive assortment, competitive prices, and purchase convenience are the primary reasons online retailers attract customers (Jindal et al., 2021). Offline stores also have features that add value to overall business goals. Breugelmans et al. (2023) suggested five major benefits for customers to visit physical stores: discovery, convenience, customization, community, and shoppertainment (shopping and entertainment). Thus, customers are likely to interact with multiple channels throughout their purchasing journey. For instance, customers typically progress through various stages, starting with need recognition, followed by information search, purchase, and finally, after-sales service, using separate channels or combinations of them (Neslin et al., 2006a). Adding a new channel, whether online or offline,

contributes to the bottom line, as demonstrated by an empirical study (Wang and Goldfarb, 2017). Wang and Goldfarb (2017) highlights the complementary effect of online and offline channels despite their potential substitution effect in distribution. It emphasizes that opening a physical store for the first online retailer or vice versa becomes a strategic initiative in a competitive market. Retailers initially establishing brick-and-mortar stores (e.g., Walmart, Target, and Kroger) aim to protect their market shares by launching and integrating their online channels (Jindal et al., 2021). The complementary effect also increases the willingness-to-pay of customers looking for expressive, durable goods (goods that, unlike functional goods, cannot be assessed and compared before purchase and have higher uncertainties) in an omnichannel retailer compared to a pure online retailer (Chatterjee and Kumar, 2017). One study introduced the term "supercharging" to describe the valuable effects of customer-experience-focused offline brand stores with no inventory or instant fulfillment on customers' purchasing behavior. These effects relate to one channel's complimentary impacts on another channel, creating a delightful customer experience. Supercharged customers who have visited the store and had a positive brand experience spend up to 60% more on average, make purchases more frequently, and have fewer returns (Bell et al., 2020).

On that basis, customer experience is a core marketing concept in omnichannel strategy that deserves attention in both research and practice. Customer experience can be defined as a multidimensional construct that encompasses customers' cognitive, emotional, behavioral, sensorial, and social responses to what a business offers at every touch point in the purchasing process (Lemon and Verhoef, 2016). The quality of the overall experience is a key factor influencing customers' intent to shop and is crucial in determining the success of an omnichannel business (Saghiri et al., 2017). Nowadays, customers interact more frequently and through myriad touch points with a firm, complicating the customer journey (Lemon and Verhoef, 2016). Følstad and Kvale (2018) defines customer journey as the usual way that a customer follows to reach or utilize a company's product or service. The customer journey is the real process that shapes the customer experience and helps to comprehend how customer objectives, anticipations, and actions change over time (Olson et al., 2019). Nonetheless, service integration, which consists of service consistency and transparency, is found to have a direct relationship with several aspects of customer experience (such as flow, referring to involvement in a specific activity without realizing the time, and perceived privacy risk), resulting in repeat purchasing (Quach et al., 2022). One aspect of service consistency should happen in the communications retailers usually have with customers throughout their journey. Oh et al. (2012) state that information technology allows retailers to create an integrated communication system where the website not only provides after-sales support for products purchased in physical stores but also offers real-time live chat, giving online customers immediate access to customer service assistants. In addition, informative advertisements by stores generate more sales for the online channel, demonstrating the synergy omnichannel retailing engenders (Wang and Goldfarb, 2017). Indeed, marketing communication is pivotal in crafting a unique customer experience and positively impacting the bottom line. This article's primary contribution is a framework that enables omnichannel retailers to leverage the capabilities of Large Language Models (LLMs) for content generation, thereby facilitating the creation of an omnichannel environment.

2.2. Marketing Communications in Omnichannel Strategy

Retailers have used various channels to communicate with their targeted customers. In the past, the media retailers used to promote and connect with their prospects were press, television, and commercial radio (Fulop, 1988). However, the promotional mix has widened to include paid media, such as Facebook advertisements; earned media, such as traditional or electronic word-of-mouth; and owned media, such as Facebook brand pages or websites (Lu and Miller, 2019). With unprecedented advances in technology, advertisements have become more personalized. For example, retailers now use public personalized advertising (PPA) through digital displays (Hess et al., 2020). This personalization results in a more engaging shopping experience (Shankar et al., 2011). Email marketing is considered a top ROI driver, but it must be delivered with carefully designed elements, such as subject length, email size, purchase links, non-purchase links, and banners (Kumar, 2021).

Over the years, media retailers have transformed their operations. For instance, catalogs were once inflexible, but with the advent of the internet and data mining, retailers can now target specific customer segments more effectively (Villanova et al., 2021). In-store communication has also evolved too. Baxendale et al. (2015) proposed measuring the relative importance of each touch point instead of considering them separately. They found that in-store communications influence brand consideration via frequency and positivity more than other touch points. However, retailers must be mindful of the content they send customers during the purchasing stage. Grewal et al. (2023) focused on inspirational content, which has a different effect from deal-oriented content on spending and activates stronger customer motivations to buy. Klabjan and Pei (2011) studied distributing coupons with smartphones and RFID during

the purchasing stage instead of pre-purchase or post-purchase. Roggeveen et al. (2016) conducted field experiments to measure the effect of digital displays on sales and found that this medium increases sales, spending time, and the number of purchased products in hypermarkets but does not change the variables in supercenters or even has detrimental effects in smaller-sized stores. The study also emphasizes the message content, which must highlight the price.

Mobile and social media channels usage are replacing more traditional channels such as brick-and-mortar and online stores (Sands et al., 2016). A customer's cellphone, with access to the internet, is another medium with which retail marketers can send promotional content to their targeted segment at low cost (Funk, 2005). One technology used in the infancy of one-to-one in-store communication is Near Field Communication (NFC). This technology allows retailers to send a website link with promotional material to those who are in the purchase stage (Klabjan and Pei, 2011). Customers can also download the application retailers developed to search for the right product during the purchase stage. For example, the H&M application suggests pants, shoes, and jackets if the user picks a polo shirt (Grewal et al., 2023). Retailers can boost customer engagement in mobile devices both in an online format as well as multichannel format and increase the likelihood of customer reviews (Thakur, 2018).

Social media has become a new interactive way for marketers to obtain valuable consumer insights. Consumers use social media platforms to research products they would like to buy during the pre-purchase stage, as retailers do not entirely control them. Therefore, an objective for the marketing team is to shape discussions on social media platforms (Lindsey-Mullikin and Borin, 2017). Empirical evidence suggests that marketing content engages a fashion retailer's customer the most on Facebook (Escobar-Rodríguez and Bonsón-Fernández, 2017). It can influence consumer behavior, including awareness, information acquisition, opinions, attitudes, purchase behavior, and post-purchase communication and evaluation (Mangold and Faulds, 2009). Brands are capable of disseminating information that customers are looking for and curating content and messages to influence conversations (Watanabe et al., 2021). Customer service requests and building a relationship with the brand are also happening on social media platforms (Felix et al., 2017). Data shows a positive relationship between social media informative posts (with topics of health, environment, and price) and green product sales on loyalty reward programs (Lu and Miller, 2019).

Retailers face a wide range of technologies and terminology, including iBeacons, mobile POS, Near Field Communications, and the Internet of Things (Inman and Nikolova, 2017). Trust issues in online shopping can be mitigated by information richness, as suggested by Chesney et al. (2017). They also found that human-like features in service technology reduce customer dissatisfaction (Fan et al., 2016). Customers' shopping behavior is more exposed to new technologies, and retailers need to provide them with new experiences and more trustworthy customer-to-employee relationships (Pantano and Gandini, 2017). Retailers are now attempting to send personalized promotions during the shopping trip in real-time or suggestions based on Customer Relationship Management (CRM) data even in physical stores (Inman and Nikolova, 2017). Augmented Reality (AR) is another new promotional tool for product presentation that might be superior to traditional web-based presentations in effect on media novelty, immersion, media enjoyment, usefulness, attitude toward the medium, and purchase intention (Yim et al., 2017).

With all these media at their disposal, content consistency has been identified as one of the prerequisites to integrating channels and creating an omnichannel environment. Hossain et al. (2020) developed a framework in which three fundamental aspects of channel integration quality (INQ) are identified, and one of them is content consistency, including information consistency as a subdimension. Shen et al. (2018) also emphasized the importance of content consistency in determining channel integration quality. As a result, the marketing team should pay serious attention to the concept of integrated marketing communication (Kumar, 2021). The primary goal of Integrated Marketing Communications (IMC) is to send clear, consistent, and compelling brand and company messages through integrated and coordinated communication channels (Kotler and Armstrong, 2011). In an omnichannel world, IMC underpins the entire strategy, as service consistency is at the heart of channel unification. The messages that customers receive at each step of their journey must be crafted in alignment with the retailer's value proposition. This business capability enables a company to convert its communication resources and brand assets into market-driven results or returns on these assets (Sandra Luxton and Mavondo, 2015).

2.3. Large Language Models

3. Integrated Communication with Large Language Models

Large language models have emerged as a technology disruption, especially in business and marketing. Nonetheless, in customer journey literature, technological disruption has not been explored enough (Tueanrat et al., 2021). Our proposition contributes to identifying LLM applications in the customer journey. We aim to customize customer

interactions at specific touch points with the retailer through the power of content generation of LLMs. Improving these touch points has a direct impact on marketing outcomes. For instance, customer satisfaction depends on fulfilling interactions (Halvorsrud et al., 2016), while customer dissatisfaction and higher churn rates result from confusing and frustrating interactions (Ieva and Ziliani, 2018). Thus, our proposition is expected to impact customer satisfaction directly.

In the framework we designed, the customers' attitudes towards the product, which are in the form of texts, are collected. It is imperative to take into account which step of the customer journey such information belongs to. We focus on the same three stages in the customer journey suggested by Lemon and Verhoef (2016): Prepurchase, Purchase, and Postpurchase. Next, Neslin et al. (2006b) noted the importance of customer segmentation in designing a multichannel strategy. As a result, customer segmentation is used to obtain different characteristics and feelings towards a product, which helps in designing the message for each type of shopper. After receiving instructions from the marketing team and analyzing the dominant characteristics and attitudes of a particular customer segment, ChatGPT-4 generates appropriate messages. Recently, Brand et al. (2023) and Horton (2023) showed that a large language model can act similarly to an economic agent and be used in market research studies. To evaluate the effectiveness of these messages, we use a new chat that mimics a customer with similar attributes and satisfaction levels. Then, we test the generated message on it. Finally, we ask LLM to determine the level of satisfaction and compare it to the previous state. The following section will provide a more detailed explanation of the framework.

3.1. Proposed Framework

In this section, we introduce a structured framework delineating the role and application of Generative AI, specifically emphasizing Large Language Models (LLMs) aimed at enhancing and integrating communication across channels. In the initial segment, we collect and analyze text data produced during each customer journey stage to elucidate different attitudes and satisfaction regarding a specific product. Subsequently, the LLM facilitates relationships between the customer and the retailer, leveraging insights derived from marketing communication strategy and the analysis conducted in the first segment. 1 illustrates the detailed depiction of the proposed framework, expounded upon in the subsequent sections.

An omnichannel retailer can have different channels, such as a physical store, a website, and a mobile application. Collecting textual data must be related to one of the customer journey stages, which includes prepurchase, purchase, and postpurchase. Customers can express their opinions during any of these stages. Therefore, we can apply this framework throughout the entire customer journey if our dataset and customer segmentation encompass all phases. To furnish LLM with valid data, we introduce a text analysis section. The primary objective of this section is to discern customer personality types and their satisfaction levels achieved through clustering. Data cleaning and feature engineering constitute crucial data pre-processing steps undertaken to enhance the performance of clustering algorithms. Data cleaning involves tokenization, lemmatization, lowercasing, and dropping stopwords. However, for sentiment analysis, some standard steps must be ignored. Feature engineering is the cornerstone of this section because clustering analysis depends largely on the input features. We devised a variety of features, such as the bag-of-words matrix, word embeddings, and polarity score, to obtain the best possible results.

An essential facet underscored in this framework is incorporating human expert opinions to oversee and regulate the outcomes generated by the LLM. In this context, the marketing team delineates crucial points that the LLM must adhere to based on the team's strategy and tactics. Another input for the LLM comprises the attitudes or sentiments identified in the text analysis section, attempting to create positive feelings with personalized communications. Thus, The application of the LLM in this proposed framework revolves around two fundamental axes: content creator and customer simulator. LLM1 is designed to generate content for each cluster by leveraging marketing strategy and customer sentiment. The content produced by LLM1 offers four key advantages:

- *Personalized content production:* LLM1 creates tailored content to align with distinct personality types within each cluster, ensuring a personalized approach.
- *Production of content based on organizational strategies:* The personalized content generated by LLM1 adheres to conditions and rules set by the expert team, incorporating marketing strategies and constraints.
- *Diverse content production:* A broad spectrum of outputs is achievable by enhancing LLM capabilities and deploying applications. This includes creating communication items such as copywriting, images, tweets, customized offering content, tailored information (e.g., chatbot responses), and customer service materials.

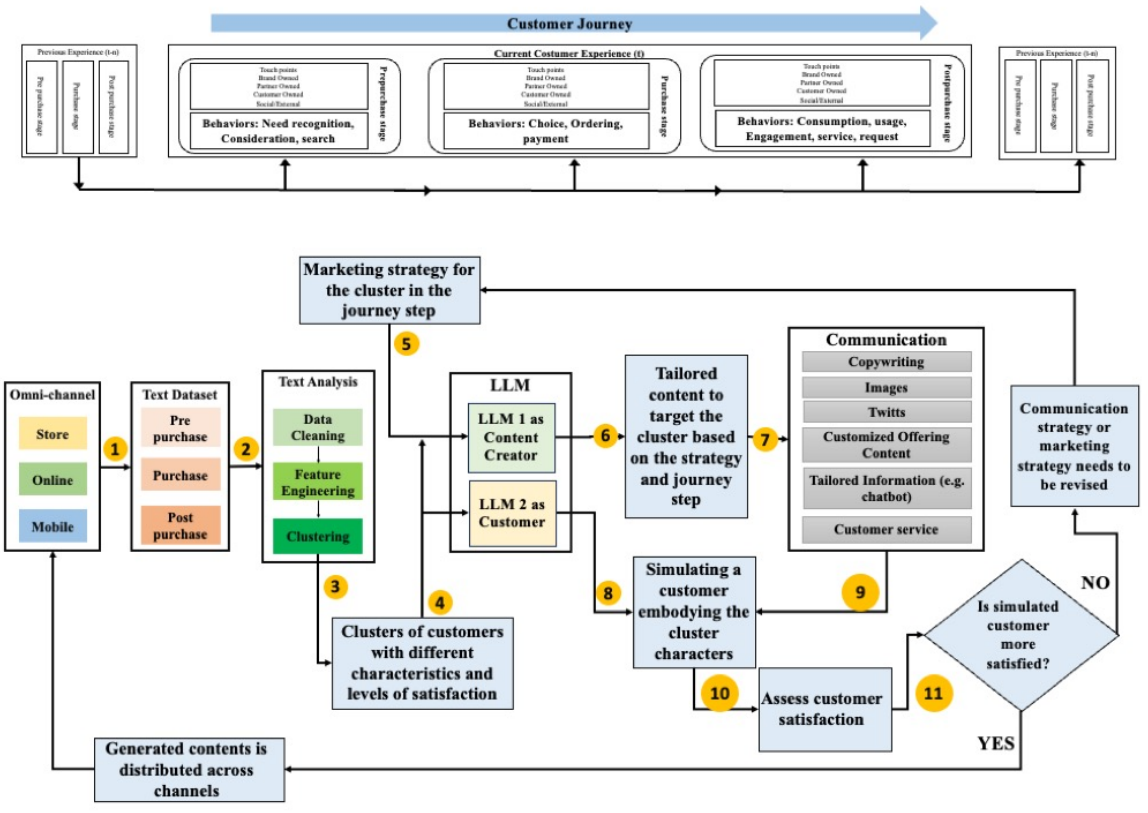

Figure 1: The proposed framework in which a large language model communicates with the customer across channels in different stages of the customer journey.

- *Cost reduction:* Using LLM in marketing communication can significantly reduce costs and increase efficiency by reducing the content marketing team without losing efficacy.

The content generated by LLM1 needs evaluation through customer feedback. However, this process encounters limitations related to customer access and high costs. To address these challenges, we introduce LLM2 as the customer alternative contributor. The primary advantage of LLM2 lies in its utilization of PTI. This feature enables us to simulate diverse customer types at a minimal cost and in the shortest time. By conditioning LLM2 based on personality types, we employ it as a customer with various personality types derived from real customer data within the proposed framework.

LLM2 is given the characteristics and level of satisfaction in order to simulate the customer representing customers within the cluster. The content generated by LLM1 serves as input for LLM2, which subsequently provides opinions and satisfaction levels based on the personality type. If the content is satisfactory from the simulated customer's point of view, the message will be sent to the channel the actual customer is interacting with. If LLM2 expresses dissatisfaction with the content produced by LLM1, we recommend transferring these results to the retailer's marketing team. Following their evaluation and resolution of identified issues, the framework iterates. This iterative process establishes a continuous improvement cycle, focusing on the PDCA (Plan-Do-Check-Act) cycle, enhancing the framework's performance and ensuring the production of acceptable results.

The framework's main strength lies in its ability to use LLM as the central thinking core, working with human experts to enable decision-making and provide a seamless customer experience across various channels. LLMs help to integrate channels and ensure consistent customer experience regardless of the channel and journey stage. The decisions made by LLMs are based on real data from the pre-purchase, purchase, and post-purchase stages, which are

Table 1
Accuracy and F1 Scores of each model classifying product reviews based on their sentiment.

Product	Model	Accuracy Score	F1 Score
Nike Men's Airmax 2017	BERT	0.805	0.792
	RoBERTa	0.671	0.731
	DistilBERT	0.659	0.647
Adidas Men's Lite Racer Adapt 5.0	BERT 4	0.672	0.658
	RoBERTa	0.597	0.618
	DistilBERT	0.582	0.553
Apple Watch SE	BERT	0.783	0.789
	RoBERTa	0.731	0.749
	DistilBERT	0.634	0.641
Under Armour Men's Tech 2.0	BERT	0.707	0.713
	RoBERTa	0.668	0.674
	DistilBERT	0.615	0.592

further verified and approved by the marketing team. This ensures that the customized information aligns with the retailer's policy and marketing strategy.

4. Results

We applied our conceptual framework to analyze customer reviews of various products available on Amazon. Our analysis focuses on the postpurchase stage of the customer journey, as we only collect reviews from verified purchasers. Product reviews of Nike Men's Arimax 2017 and Adidas Men's Lite Racer Adapt 5.0 are collected, manipulated, and cleaned. At this stage, reviews must be clustered into several groups that share common attitudes about the product they have bought. To do so, we can employ feature engineering to obtain the optimal clustering based on standard criteria, such as elbow plot and dendrogram. One way to determine customer types is through sentiment analysis, which measures customer feelings based on reviews.

There are several open-source Language Model Models (LLMs) available on HuggingFace that are used for sentiment analysis. We have chosen to use the models that have been downloaded the most. The models that we have selected are bert-base multilingual uncased model that has been finetuned on product reviews in six languages, distilbert-base-multilingual cased sentiments, and RoBERTa-base model trained on millions of tweets. Huggingface provides its Python API through the "transformers" package. Additionally, the "evaluate" package includes metrics that developers and researchers use to assess their LLM output. We have applied all three models to four products in one category and evaluated the output using accuracy and f-score, which is a harmonic average of recall and precision metrics. In order to compare LLM sentiment classification with the real classification, ratings are divided into three groups. Reviewers who submit ratings of 1 or 2 are considered "negative", those who submit 3 are considered "neutral", and those with ratings of 4 or 5 are considered "positive". The results in Table 1 emphasize that fine-tuning llm weights on product reviews makes more accurate sentiment classification. Therefore, we continue with the sentiment predictions of BERT-based model finetuned on product reviews.

Both hierarchical and KMeans methods are used to determine the optimal number of clusters. The results of hierarchical clustering are shown through a dendrogram, while the quality of the KMeans method is evaluated using elbow and average silhouette scores. Finally, the already trained SpaCy English model (en_core_web_md) can assess the polarity and subjectivity of each review in a numerical range. The most positive review would be 1, and the most negative one would be -1. Similarly, the subjectivity score can be as low as 0, and the highest possible score can be 1. Figure **??** demonstrates how these two scores vary across Amazon reviews for Nike's Air Max 2017.

Both hierarchical and Kmeans clustering suggested that sentimental features like polarity and predicted rating scores result in more distinguished groups. In order to evaluate the results of our clustering analysis, we plotted the Hierarchical dendrogram, Kmeans distortions, and silhouette average. Dendrogram showed that information loss is detrimental when reviews are aggregated into less than 3 groups. Creating 4 or more clusters leads to groups with insufficient reviews. By using an elbow plot in K-means method, we can determine the optimal number of clusters. The plot shows the variation in the total within the sum of squares as we add more centroids. The plot implies that having more than 5 clusters does not significantly decrease distortion compared to having less than that. The average

Silhouette score measures whether each review belongs to the right or wrong cluster. Based on this score, it seems that having 3, 5, and 6 clusters would be the best options. Eventually, we continue with 3 clusters because of having sufficient reviews in each cluster and the meaningful separation.

As part of our research, we asked Bing AI (ChatGPT-4) to summarize each group of reviews and their attitudes toward Nike's products. Also, we asked ChatGPT to create three persona representing each cluster and then estimate its Net Promoter Score (NPS), which is an approximation of their satisfaction level. The exact prompts and responses can be found in Appendix A. The first cluster consists of shoppers who are satisfied with their running shoes and are typically loyal to Nike. Customers seem to be very satisfied with their purchase of the Nike Men's Airmax 2017, praising its comfort, fit, and style. However, some customers raised concerns about the durability of the air bubble and the shoe's grip. Max is a fitness enthusiast who loves the Nike Men's Airmax 2017 for their comfort, fit, and style. He appreciates the lightweight design and breathable fabric, which make the shoes comfortable for extended wear. He finds the shoes versatile, suitable for running, calisthenics, and jobs requiring a lot of physical activity. However, he has minor concerns about the durability of the air bubble and the shoe's grip. Despite these issues, he's satisfied with his purchase and plans to buy more pairs. Given his overall positive experience, Max would likely give a Net Promoter Score (NPS) of 9.

In the second cluster, while many customers are satisfied with the comfort, style, and fit of the Nike Men's Airmax 2017, there are concerns about the durability of the air bubble, the sizing of the shoes, and the color and appearance of the shoes. Despite these issues, many customers have bought multiple pairs and plan to buy more, indicating high satisfaction with the product. However, the high price, quality control issues (such as receiving defected or dirty shoes or shoes with unusual tags), and the shoes not looking as expected are areas of dissatisfaction among some customers. Alex is a long-time user of Air Max shoes. He likes the shoes for their support, especially for bad ankles and after surgeries. However, he's disappointed with the durability of the air bubble, which popped after a few months of normal wear. He also had issues with the sizing of the shoes and the color being different than expected. Despite these issues, he still plans to buy more pairs. However, due to the issues he faced, Alex would likely give a Net Promoter Score (NPS) of 7.

Finally, in the third cluster, while a few customers found the Nike Men's Airmax 2017 to be comfortable initially, there are significant concerns about the durability of the shoes, particularly the air pockets. The high price, poor customer service, and quality control issues (such as receiving worn or used shoes) are major areas of dissatisfaction among customers in this cluster. Some customers even advised others not to buy these shoes. Despite these issues, a few customers still found the shoes to be comfortable and stylish. However, the overwhelming majority of reviews in this cluster are negative. Chris bought the Nike Men's Airmax 2017 expecting high-quality shoes. However, he's disappointed with his purchase. The air pockets in his shoes deflated after a few weeks of use, and he received a pair that looked worn upon arrival. He also found the shoes to be too tight and not true to size. He's dissatisfied with the customer service, stating that the seller did not respond to his complaints or help with warranty issues. Given his negative experience, Chris would likely give a Net Promoter Score (NPS) of 3.

Once we had identified the attitudes of the typical customers in each cluster, we requested ChatGPT to generate content that could motivate them to consider Air Max during their next shopping trip. Instead of a message focused only on deals, the marketing team could ask for more inspirational content that would stimulate stronger motivations and encourage even dissatisfied customers to revisit future product releases. Table 2 shows the message ChatGPT-4 generated in order to send them to the customer through the channel the customer is interacting with after purchasing Air Max. In addition, large language models have the capability to generate images based on the textual input from the user. The marketing team can send an image with the text message to engage even more. Figure 2 is an image created by Open-AI ChatGPT and DALL-E models.

We evaluated the generated content by using a new ChatGPT topic and simulating each customer with our LLM. We then sent them the text and the image. LLMs can respond in a way that is similar to a real customer, making the feedback reliable. If the feedback is positive and the content raises the level of satisfaction, then we can send the content to the real customer. However, if it fails to engage the simulated customer and does not satisfy them, the marketing team should adjust based on the feedback.

The new GPT-4, which does not remember anything from the past, now takes into account the customer's attitudes and experience, in addition to the message previously generated by LLM and sent to the customer from Amazon. Based on its judgment, the message from Amazon is well-crafted and addresses Max's concerns about the Nike Men's Airmax 2017. It acknowledges the positive aspects that Max appreciates, such as comfort, fit, and style. The message addresses Max's concerns about the durability of the air bubble and the grip of the shoe. It indicates that the company

Table 2
Inpirational Content for Each Customer Generated by ChatGPT-4

Customer	Message
Max	Hi Max, we're thrilled to hear that you're enjoying the comfort, fit, and style of our Nike Men's Airmax 2017. These shoes are perfect for your morning runs or gym workouts. They're designed with lightweight and durable materials, making them ideal for rigorous training. We understand your concerns about the durability of the air bubble and shoe's grip. We're constantly working on improving our products, and your feedback is invaluable in that process. After your workouts, remember to clean your shoes regularly to maintain their appearance and longevity. Thank you for being a loyal customer!
Alex	Hello Alex, thank you for being a long-time user of our Air Max shoes. We're sorry to hear about the issues you've experienced with the air bubble and sizing. We're committed to improving our products based on customer feedback like yours. We also offer a variety of styles and sizes to ensure the perfect fit. Whether you're running, doing calisthenics, or working a job that requires a lot of physical activity, our Air Max shoes are designed to support you. After wearing your Airmax, it's a good idea to let them air out to keep them fresh. We hope you'll continue to find value in our products.
Chris	Dear Chris, we're sorry to hear about your disappointing experience with our Nike Men's Airmax 2017. We take your feedback seriously and are committed to improving the durability of our shoes. We also understand the importance of receiving new and unworn shoes when making a purchase. We're working diligently to ensure all our products meet the high standards our customers expect. After purchasing your Airmax, remember to break them in gradually to ensure maximum comfort. Whether you're hitting the gym, going for a run, or just walking around town, our Air Max shoes are designed to provide comfort and support. We hope you'll give us another chance in the future.

Figure 2: Creative images generated by OpenAI DALL-E that can make textual content more engaging.

values customer feedback and is working to make improvements. The advice on maintaining the shoes could be seen as helpful. This personalized and thoughtful response shows that Amazon values Max's feedback and is committed to enhancing their products. As a result, it could potentially increase Max's satisfaction and loyalty towards Amazon. Whether Max's Net Promoter Score (NPS) remains the same or increases slightly depends on his personal interpretation of the message and his subsequent experiences with the product.

Based on the information provided, it seems that Amazon has responded to Alex in a thoughtful and considerate manner that addresses his concerns. They express gratitude for his loyalty, acknowledge the issues he faced with the air bubble and sizing, and reassure him of their commitment to improving their products. Additionally, they offer advice on how to maintain the shoes, which could be helpful. However, Amazon did not address the issue of the color being different from what Alex expected, which could be a source of dissatisfaction for him. As a result, it is possible that Alex's Net Promoter Score (NPS) will remain the same or increase slightly due to the acknowledgment of his concerns and the assurance of improvements. However, the exact score will depend on Alex's personal interpretation of the message and his subsequent experiences with the product. It is also important to note that addressing all of Alex's concerns in future communications could potentially lead to a higher NPS.

Based on the information provided, Amazon's response to Chris has addressed some but not all of his concerns. They apologized for the disappointing experience and expressed their commitment to improving the durability of their shoes. They also acknowledged the importance of receiving new and unworn shoes, which is one of Chris's complaints. However, they did not address Chris's issues with the shoes being too tight and not true to size. Furthermore, they did not respond to his dissatisfaction with the customer service, particularly concerning the lack of response to his complaints and help with warranty issues. These unaddressed issues could be significant points of dissatisfaction for Chris. Therefore, it is possible that Chris's Net Promoter Score (NPS) may remain the same or even decrease after receiving this message since not all of his concerns were addressed. The exact score would depend on Chris's personal interpretation of the message and his subsequent experiences with the product and customer service. It is also important to note that addressing all of Chris's concerns in future communications could potentially lead to a higher NPS.

5. Discussion

Omnichannel retailing has not been achieved to the desired extent yet. Various elements of marketing activities must be applied with an integrated approach. For example, integrated marketing communications are a prerequisite of an omnichannel environment since inconsistent or isolated information leads to customer dissatisfaction. Our conceptual framework suggests that retailers can adopt large language models as a content generator that considers the attitudes a customer might have toward the product and the marketing department's strategy.

Customer experience can be seen as a journey with three main stages: prepurchase, purchase, and postpurchase. The more blurred channel boundaries in each stage, the more omnichannel a retailer is. Due to the capabilities of an LLM, retailers can create any form of content according to the channel a customer is using (e.g. physical store, website, mobile, social media, etc), considering customers' previous experience, the stage of their journey, and the marketing strategy. For instance, we analyzed Amazon product reviews as one information source for customers who purchased the product (postpurchase step). After clustering verified product reviews, several types of customer attitudes toward the product are identified.

Large language models contribute significantly to personalizing advertisements, email marketing, and catalogs, focusing on the prepurchase stage in which customers are looking for product information, peer-review comments, etc. Social media conversations can influence consumer behavior based on a retailer's strategy, which can be shaped by our conceptual framework. LLMs enhance the information richness in online shopping, thereby increasing consumers' trust. In the purchase stage, the quality of digital in-store communications would be enhanced, too. In-store displays' effectiveness has been demonstrated through the impact on brand consideration via both frequency and positivity. The type of content does not have to be deal-oriented. In order to activate stronger customer motivations and increase spending, inspirational content can be sent to customers throughout their journey. One effective way to implement this strategy is by using LLMs, as we did with Amazon reviews. A combination of CRM data (previous purchases) and the LLM produces personalized promotions during the shopping trip. In the postpurchase stage, human-like messages that a large language model generates as a service technology mitigate customer dissatisfaction.

The primary benefit of large language models, however, lies in their capability to send messages in various types of channels. It enables retailers with multiple channels to create a unified and consistent customer experience regardless of the touch points customers interact with. It serves the ultimate goal of integrated marketing communications (IMC), sending clear and consistent messages and signals promoting the retailer's value proposition. Moreover, not only does the optimization of customer experience result in higher revenues, but the cost reduction by utilizing LLMs also reduces marketing costs, leading to more profits. Our contribution to marketing literature is to use LLMs as the core of marketing communications, delivering tailored messages to each customer based on channel format, journey stage, and marketing strategy. This would help to accelerate the transition from multichannel retailing to omnichannel retailing.

Additional empirical studies must be done to support the suggested framework. For example, numerical data, especially CRM data, can be added to the initial analysis for extra content personalization. Retailers that have enough computational resources should train their own LLM since it might generate responses tailored to the targeted customers even better than commercial, well-known LLMs like ChatGPT and Bard that have been trained on irrelevant texts, too.

References

K. L. Ailawadi and P. W. Farris. Managing multi- and omni-channel distribution: Metrics and research directions. *Journal of Retailing*, 93(1): 120–135, mar 2017. doi: 10.1016/j.jretai.2016.12.003. URL https://doi.org/10.1016%2Fj.jretai.2016.12.003.

S. Baxendale, E. K. Macdonald, and H. N. Wilson. The impact of different touchpoints on brand consideration. *Journal of Retailing*, 91(2):235–253, June 2015. ISSN 0022-4359. doi: 10.1016/j.jretai.2014.12.008. URL http://dx.doi.org/10.1016/j.jretai.2014.12.008.

D. R. Bell, S. Gallino, and A. Moreno. Customer supercharging in experience-centric channels. *Management Science*, 66(9):4096–4107, sep 2020. doi: 10.1287/mnsc.2019.3453. URL https://doi.org/10.1287%2Fmnsc.2019.3453.

A. Bhatnagar and S. Ghose. A latent class segmentation analysis of e-shoppers. *Journal of Business Research*, 57(7):758–767, jul 2004. doi: 10.1016/s0148-2963(02)00357-0. URL https://doi.org/10.1016%2Fs0148-2963%2802%2900357-0.

J. Brand, A. Israeli, and D. Ngwe. Using GPT for market research. *SSRN Electronic Journal*, 2023. doi: 10.2139/ssrn.4395751. URL https://doi.org/10.2139%2Fssrn.4395751.

E. Breugelmans, L. Altenburg, F. Lehmkuhle, M. Krafft, L. Lamey, and A. L. Roggeveen. The future of physical stores: Creating reasons for customers to visit. *Journal of Retailing*, November 2023. ISSN 0022-4359. doi: 10.1016/j.jretai.2023.10.005. URL http://dx.doi.org/10.1016/j.jretai.2023.10.005.

Y.-J. Cai and C. K. Lo. Omni-channel management in the new retailing era: A systematic review and future research agenda. *International Journal of Production Economics*, 229:107729, nov 2020. doi: 10.1016/j.ijpe.2020.107729. URL https://doi.org/10.1016%2Fj.ijpe.2020.107729.

L. Cao. Business model transformation in moving to a cross-channel retail strategy: A case study. *International Journal of Electronic Commerce*, 18(4):69–96, jul 2014. doi: 10.2753/jec1086-4415180403. URL https://doi.org/10.2753%2Fjec1086-4415180403.

P. Chatterjee and A. Kumar. Consumer willingness to pay across retail channels. *Journal of Retailing and Consumer Services*, 34:264–270, jan 2017. doi: 10.1016/j.jretconser.2016.01.008. URL https://doi.org/10.1016%2Fj.jretconser.2016.01.008.

T. Chesney, S.-H. Chuah, A. R. Dobele, and R. Hoffmann. Information richness and trust in v-commerce: implications for services marketing. *Journal of Services Marketing*, 31(3):295–307, May 2017. ISSN 0887-6045. doi: 10.1108/jsm-02-2015-0099. URL http://dx.doi.org/10.1108/JSM-02-2015-0099.

T. H. Cui, A. Ghose, H. Halaburda, R. Iyengar, K. Pauwels, S. Sriram, C. Tucker, and S. Venkataraman. Informational challenges in omnichannel marketing: Remedies and future research. *Journal of Marketing*, 2020. doi: 10.1177/0022242920968810.

T. Escobar-Rodríguez and R. Bonsón-Fernández. Facebook practices for business communication among fashion retailers. *Journal of Fashion Marketing and Management: An International Journal*, 21(1):33–50, March 2017. ISSN 1361-2026. doi: 10.1108/jfmm-11-2015-0087. URL http://dx.doi.org/10.1108/JFMM-11-2015-0087.

A. Fan, L. L. Wu, and A. S. Mattila. Does anthropomorphism influence customers' switching intentions in the self-service technology failure context? *Journal of Services Marketing*, 30(7):713–723, October 2016. ISSN 0887-6045. doi: 10.1108/jsm-07-2015-0225. URL http://dx.doi.org/10.1108/JSM-07-2015-0225.

R. Felix, P. A. Rauschnabel, and C. Hinsch. Elements of strategic social media marketing: A holistic framework. *Journal of Business Research*, 70: 118–126, January 2017. ISSN 0148-2963. doi: 10.1016/j.jbusres.2016.05.001. URL http://dx.doi.org/10.1016/j.jbusres.2016.05.001.

C. Fulop. The role of advertising in the retail marketing mix. *International Journal of Advertising*, 7(2):99–117, January 1988. ISSN 1759-3948. doi: 10.1080/02650487.1988.11107049. URL http://dx.doi.org/10.1080/02650487.1988.11107049.

J. L. Funk. The future of the mobile phone internet: an analysis of technological trajectories and lead users in the japanese market. *Technology in Society*, 27(1):69–83, January 2005. ISSN 0160-791X. doi: 10.1016/j.techsoc.2004.10.001. URL http://dx.doi.org/10.1016/j.techsoc.2004.10.001.

A. Følstad and K. Kvale. Customer journeys: a systematic literature review. *Journal of Service Theory and Practice*, 28(2):196–227, February 2018. ISSN 2055-6225. doi: 10.1108/jstp-11-2014-0261. URL http://dx.doi.org/10.1108/JSTP-11-2014-0261.

D. K. Gauri, R. P. Jindal, B. Ratchford, E. Fox, A. Bhatnagar, A. Pandey, J. R. Navallo, J. Fogarty, S. Carr, and E. Howerton. Evolution of retail formats: Past, present, and future. *Journal of Retailing*, 97(1):42–61, mar 2021. doi: 10.1016/j.jretai.2020.11.002. URL https://doi.org/10.1016%2Fj.jretai.2020.11.002.

D. Grewal, C.-P. Ahlbom, S. M. Noble, V. Shankar, U. Narang, and J. Nordfält. The impact of in-store inspirational (vs. deal-oriented) communication on spending: The importance of activating consumption goal completion. *Journal of Marketing Research*, 60(6):1071–1094, April 2023. ISSN 1547-7193. doi: 10.1177/00222437221149508. URL http://dx.doi.org/10.1177/00222437221149508.

M. Hajdas, J. Radomska, and S. C. Silva. The omni-channel approach: A utopia for companies? *Journal of Retailing and Consumer Services*, 65: 102131, mar 2022. doi: 10.1016/j.jretconser.2020.102131. URL https://doi.org/10.1016%2Fj.jretconser.2020.102131.

R. Halvorsrud, K. Kvale, and A. Følstad. Improving service quality through customer journey analysis. *Journal of Service Theory and Practice*, 26(6):840–867, November 2016. ISSN 2055-6225. doi: 10.1108/jstp-05-2015-0111. URL http://dx.doi.org/10.1108/JSTP-05-2015-0111.

N. J. Hess, C. M. Kelley, M. L. Scott, M. Mende, and J. H. Schumann. Getting personal in public!? how consumers respond to public personalized advertising in retail stores. *Journal of Retailing*, 96(3):344–361, September 2020. ISSN 0022-4359. doi: 10.1016/j.jretai.2019.11.005. URL http://dx.doi.org/10.1016/j.jretai.2019.11.005.

J. J. Horton. Large language models as simulated economic agents: What can we learn from homo silicus? 2023. URL https://arxiv.org/pdf/2301.07543.pdf.

T. M. T. Hossain, S. Akter, U. Kattiyapornpong, and Y. Dwivedi. Reconceptualizing integration quality dynamics for omnichannel marketing. *Industrial Marketing Management*, 2020. doi: 10.1016/j.indmarman.2019.12.006.

M. Ieva and C. Ziliani. Mapping touchpoint exposure in retailing: Implications for developing an omnichannel customer experience. *International Journal of Retail amp; Distribution Management*, 46(3):304–322, March 2018. ISSN 0959-0552. doi: 10.1108/ijrdm-04-2017-0097. URL http://dx.doi.org/10.1108/IJRDM-04-2017-0097.

J. J. Inman and H. Nikolova. Shopper-facing retail technology: A retailer adoption decision framework incorporating shopper attitudes and privacy concerns. *Journal of Retailing*, 93(1):7–28, March 2017. ISSN 0022-4359. doi: 10.1016/j.jretai.2016.12.006. URL http://dx.doi.org/10.1016/j.jretai.2016.12.006.

R. P. Jindal, D. K. Gauri, W. Li, and Y. Ma. Omnichannel battle between amazon and walmart: Is the focus on delivery the best strategy? *Journal of Business Research*, 122:270–280, jan 2021. doi: 10.1016/j.jbusres.2020.08.053. URL https://doi.org/10.1016%2Fj.jbusres.2020.08.053.

J. H. Kembro, A. Norrman, and E. Eriksson. Adapting warehouse operations and design to omni-channel logistics. *International Journal of Physical Distribution &amp Logistics Management*, 48(9):890–912, aug 2018. doi: 10.1108/ijpdlm-01-2017-0052. URL https://doi.org/10.1108%2Fijpdlm-01-2017-0052.

J. Kim and H.-H. Lee. Consumer product search and purchase behaviour using various retail channels: the role of perceived retail usefulness. *International Journal of Consumer Studies*, 32(6):619–627, oct 2008. doi: 10.1111/j.1470-6431.2008.00689.x. URL https://doi.org/10.1111%2Fj.1470-6431.2008.00689.x.

D. Klabjan and J. Pei. In-store one-to-one marketing. *Journal of Retailing and Consumer Services*, 18(1):64–73, January 2011. ISSN 0969-6989. doi: 10.1016/j.jretconser.2010.09.012. URL http://dx.doi.org/10.1016/j.jretconser.2010.09.012.

P. Kotler and G. Armstrong. *Principles of Marketing*. Prentice Hall, 14th edition, 2011. ISBN 9780132167123.

A. Kumar. An empirical examination of the effects of design elements of email newsletters on consumers' email responses and their purchase. *Journal of Retailing and Consumer Services*, 58:102349, January 2021. ISSN 0969-6989. doi: 10.1016/j.jretconser.2020.102349. URL http://dx.doi.org/10.1016/j.jretconser.2020.102349.

K. N. Lemon and P. C. Verhoef. Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6):69–96, nov 2016. doi: 10.1509/jm.15.0420. URL https://doi.org/10.1509%2Fjm.15.0420.

Y. Li, H. Liu, E. T. Lim, J. M. Goh, F. Yang, and M. K. Lee. Customer's reaction to cross-channel integration in omnichannel retailing: The mediating roles of retailer uncertainty, identity attractiveness, and switching costs. *Decision Support Systems*, 109:50–60, may 2018. doi: 10.1016/j.dss.2017.12.010. URL https://doi.org/10.1016%2Fj.dss.2017.12.010.

J. Lindsey-Mullikin and N. Borin. Why strategy is key for successful social media sales. *Business Horizons*, 60(4):473–482, July 2017. ISSN 0007-6813. doi: 10.1016/j.bushor.2017.03.005. URL http://dx.doi.org/10.1016/j.bushor.2017.03.005.

Q. S. Lu and R. Miller. How social media communications combine with customer loyalty management to boost green retail sales. *Journal of Interactive Marketing*, 46:87–100, May 2019. ISSN 1094-9968. doi: 10.1016/j.intmar.2018.12.005. URL http://dx.doi.org/10.1016/j.intmar.2018.12.005.

W. G. Mangold and D. J. Faulds. Social media: The new hybrid element of the promotion mix. *Business Horizons*, 52(4):357–365, July 2009. ISSN 0007-6813. doi: 10.1016/j.bushor.2009.03.002. URL http://dx.doi.org/10.1016/j.bushor.2009.03.002.

MSI. 2018-2020 research priorities: Marketers' strategic imperatives, may 2018. URL https://www.msi.org/articles/marketers-top-challenges-2018-2020-research-priorities.

S. A. Neslin, D. Grewal, R. Leghorn, V. Shankar, M. L. Teerling, J. S. Thomas, and P. C. Verhoef. Challenges and opportunities in multichannel customer management. *Journal of Service Research*, 9(2):95–112, nov 2006a. doi: 10.1177/1094670506293559. URL https://doi.org/10.1177%2F1094670506293559.

S. A. Neslin, D. Grewal, R. Leghorn, V. Shankar, M. L. Teerling, J. S. Thomas, and P. C. Verhoef. Challenges and opportunities in multichannel customer management. *Journal of Service Research*, 9(2):95–112, 2006b. doi: 10.1177/1094670506293559. URL https://doi.org/10.1177/1094670506293559.

L. Oh, H. Teo, and V. Sambamurthy. The effects of retail channel integration through the use of information technologies on firm performance. *Journal of Operations Management*, 2012. doi: 10.1016/j.jom.2012.03.001.

E. D. Olson, S. W. Arendt, E. FitzPatrick, S. Hauser, A. J. Rainville, B. Rice, and K. L. Lewis. Marketing mechanisms used for summer food service programs. *Journal of Nonprofit amp; Public Sector Marketing*, 2019. doi: 10.1080/10495142.2019.1589632.

E. Pantano and A. Gandini. Exploring the forms of sociality mediated by innovative technologies in retail settings. *Computers in Human Behavior*, 77:367–373, December 2017. ISSN 0747-5632. doi: 10.1016/j.chb.2017.02.036. URL http://dx.doi.org/10.1016/j.chb.2017.02.036.

S. Quach, M. Barari, D. V. Moudrý, and K. Quach. Service integration in omnichannel retailing and its impact on customer experience. *Journal of Retailing and Consumer Services*, 65:102267, mar 2022. doi: 10.1016/j.jretconser.2020.102267. URL https://doi.org/10.1016%2Fj.jretconser.2020.102267.

D. K. Rigby. The future of shopping, 2011. URL https://www.oresky.eu/wp-content/uploads/2016/09/The-Future-of-Shopping.pdf.

A. L. Roggeveen, J. Nordfält, and D. Grewal. Do digital displays enhance sales? role of retail format and message content. *Journal of Retailing*, 92(1):122–131, March 2016. ISSN 0022-4359. doi: 10.1016/j.jretai.2015.08.001. URL http://dx.doi.org/10.1016/j.jretai.2015.08.001.

S. Saghiri, R. Wilding, C. Mena, and M. Bourlakis. Toward a three-dimensional framework for omni-channel. *Journal of Business Research*, 77:53–67, aug 2017. doi: 10.1016/j.jbusres.2017.03.025. URL https://doi.org/10.1016%2Fj.jbusres.2017.03.025.

M. R. Sandra Luxton and F. Mavondo. Integrated marketing communication capability and brand performance. *Journal of Advertising*, 44(1):37–46, 2015. doi: 10.1080/00913367.2014.934938. URL https://doi.org/10.1080/00913367.2014.934938.

S. Sands, C. Ferraro, C. Campbell, and J. Pallant. Segmenting multichannel consumers across search, purchase and after-sales. *Journal of Retailing and Consumer Services*, 33:62–71, November 2016. ISSN 0969-6989. doi: 10.1016/j.jretconser.2016.08.001. URL http://dx.doi.org/10.1016/j.jretconser.2016.08.001.

V. Shankar, J. J. Inman, M. Mantrala, E. Kelley, and R. Rizley. Innovations in shopper marketing: Current insights and future research issues. *Journal of Retailing*, 87:S29–S42, July 2011. ISSN 0022-4359. doi: 10.1016/j.jretai.2011.04.007. URL http://dx.doi.org/10.1016/j.jretai.2011.04.007.

X.-L. Shen, Y.-J. Li, Y. Sun, and N. Wang. Channel integration quality, perceived fluency and omnichannel service usage: The moderating roles of internal and external usage experience. *Decision Support Systems*, 109:61–73, may 2018. doi: 10.1016/j.dss.2018.01.006. URL https://doi.org/10.1016%2Fj.dss.2018.01.006.

R. Thakur. Customer engagement and online reviews. *Journal of Retailing and Consumer Services*, 41:48–59, March 2018. ISSN 0969-6989. doi: 10.1016/j.jretconser.2017.11.002. URL http://dx.doi.org/10.1016/j.jretconser.2017.11.002.

Y. Tueanrat, S. Papagiannidis, and E. Alamanos. Going on a journey: A review of the customer journey literature. *Journal of Business Research*, 125:336–353, March 2021. ISSN 0148-2963. doi: 10.1016/j.jbusres.2020.12.028. URL http://dx.doi.org/10.1016/j.jbusres.2020.12.028.

P. C. Verhoef, P. Kannan, and J. J. Inman. From multi-channel retailing to omni-channel retailing. *Journal of Retailing*, 91(2):174–181, jun 2015. doi: 10.1016/j.jretai.2015.02.005. URL https://doi.org/10.1016%2Fj.jretai.2015.02.005.

D. Villanova, A. V. Bodapati, N. M. Puccinelli, M. Tsiros, R. C. Goodstein, T. Kushwaha, R. Suri, H. Ho, R. Brandon, and C. Hatfield. Retailer marketing communications in the digital age: Getting the right message to the right shopper at the right time. *Journal of Retailing*, 97(1):116–132, March 2021. ISSN 0022-4359. doi: 10.1016/j.jretai.2021.02.001. URL http://dx.doi.org/10.1016/j.jretai.2021.02.001.

K. Wang and A. Goldfarb. Can offline stores drive online sales? *Journal of Marketing Research*, 54(5):706–719, oct 2017. doi: 10.1509/jmr.14.0518. URL https://doi.org/10.1509%2Fjmr.14.0518.

N. M. Watanabe, J. Kim, and J. Park. Social network analysis and domestic and international retailers: An investigation of social media networks of cosmetic brands. *Journal of Retailing and Consumer Services*, 58:102301, January 2021. ISSN 0969-6989. doi: 10.1016/j.jretconser.2020.102301. URL http://dx.doi.org/10.1016/j.jretconser.2020.102301.

J. W. Weltevreden. B2c e-commerce logistics: the rise of collection-and-delivery points in the netherlands. *International Journal of Retail &amp Distribution Management*, 36(8):638–660, jun 2008. doi: 10.1108/09590550810883487. URL https://doi.org/10.1108%2F09590550810883487.

M. Y.-C. Yim, S.-C. Chu, and P. L. Sauer. Is augmented reality technology an effective tool for e-commerce? an interactivity and vividness perspective. *Journal of Interactive Marketing*, 39:89–103, August 2017. ISSN 1094-9968. doi: 10.1016/j.intmar.2017.04.001. URL http://dx.doi.org/10.1016/j.intmar.2017.04.001.

R. Zwegers. Long road ahead for broad application and understanding of ai in marketing. https://www.ama.org/marketing-news/long-road-ahead-for-broad-application-and-understanding-of-ai-in-marketing/, 2023. Accessed: 2023-11-15.

Appendix

Appendix A