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

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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

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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.

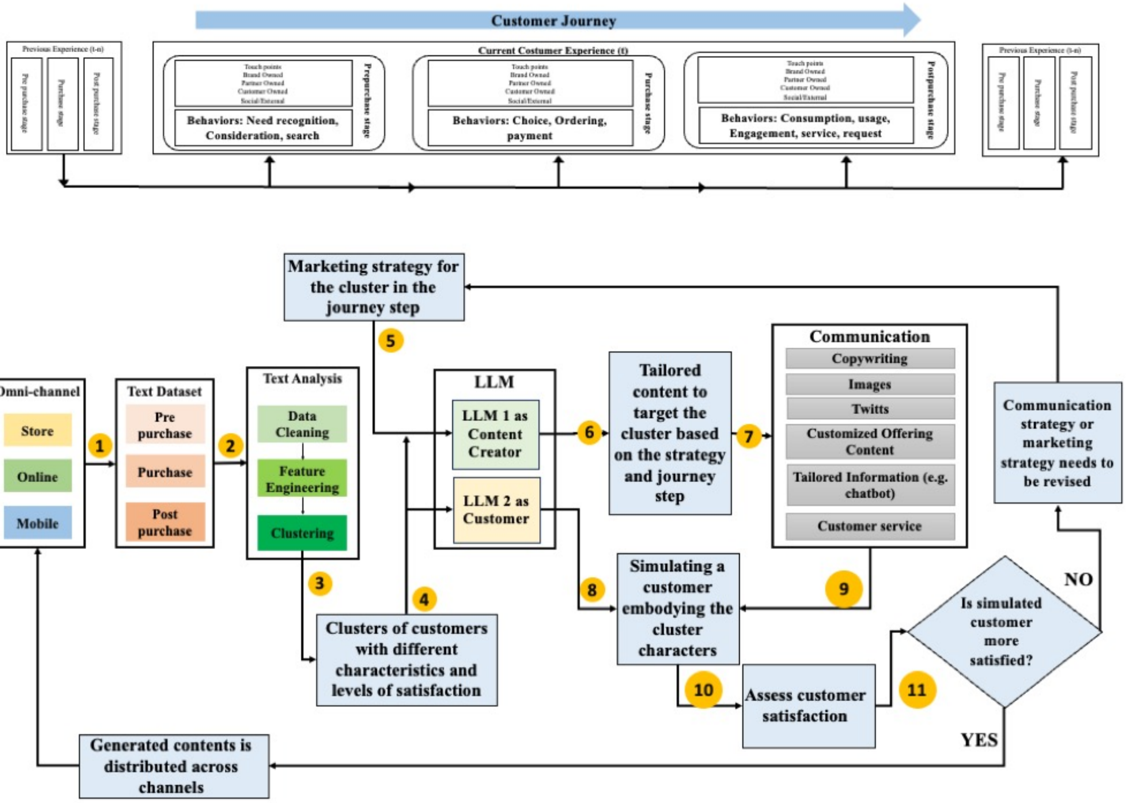

Figure 1: The proposed framework in which a large language model communicates with the customer across channels in different stages of the customer journey.

- *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 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 post-purchase stage of the customer journey, as we only collect reviews from verified purchasers. Our analysis began with the "Nike Men's Air Max 2017" product, where we excluded reviews containing only a few characters or emoji symbols. Additionally, we only considered reviews in English for our analysis. After these steps, we were left with 91 customer reviews for clustering. We used the SpaCy package to preprocess the reviews by converting them to lowercase, lemmatizing, and removing stopwords. We also created an additional feature without lowercasing and dropping stopwords for sentiment analysis. Finally, a new feature containing the number of words was added to the pandas dataframe.

Scikit-learn CountVectorizer is used to create a bag of words consisting of unigrams, bigrams, and trigrams in order to cluster reviews. Additionally, Gensim packages enable us to transform customer reviews into a numerical vector space using word embeddings. This technique makes it easier for cluster algorithms to find similar reviews. However, bag of words and vectorization create many features or dimensions, which can make clustering difficult. To solve the problem, dimension reduction techniques such as Principal Component Analysis (PCA) and Singular Value Decomposition (SVD) can be applied to create a more balanced features-to-rows. 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 2 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 subjectivity score, along with the ratings customers submit, 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 in Figures **??** and 4. The information loss is detrimental when reviews are aggregated into less than three groups. On the other hand, creating four or more clusters results in groups with too few reviews. The latter method has two criteria by which the appropriate clusters can be identified. The elbow plot shows how the total within the sum of squares varies as we add more centroids. The plot suggests that having more than 4 clusters does not significantly reduce distortion compared to having less than that. On the other hand, the average Silhouette score measures whether each data point belongs to the right cluster. Based on this score, it seems that having 3 clusters would be the best option. Eventually, we continue with 4 clusters.

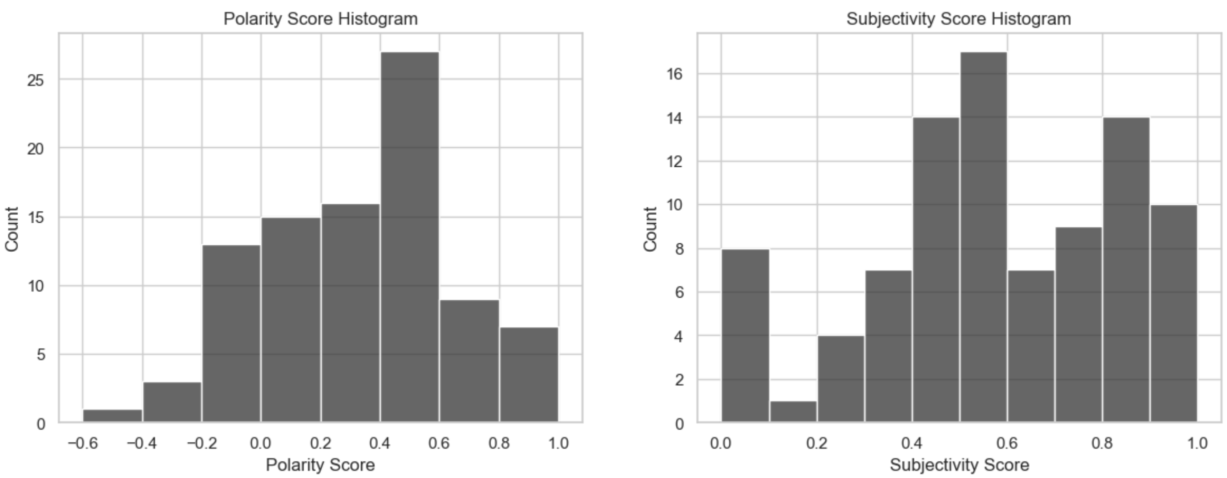

Figure 2: Sentiment Analysis of Amazon Customer Reviews for Nike's Air Max 2017

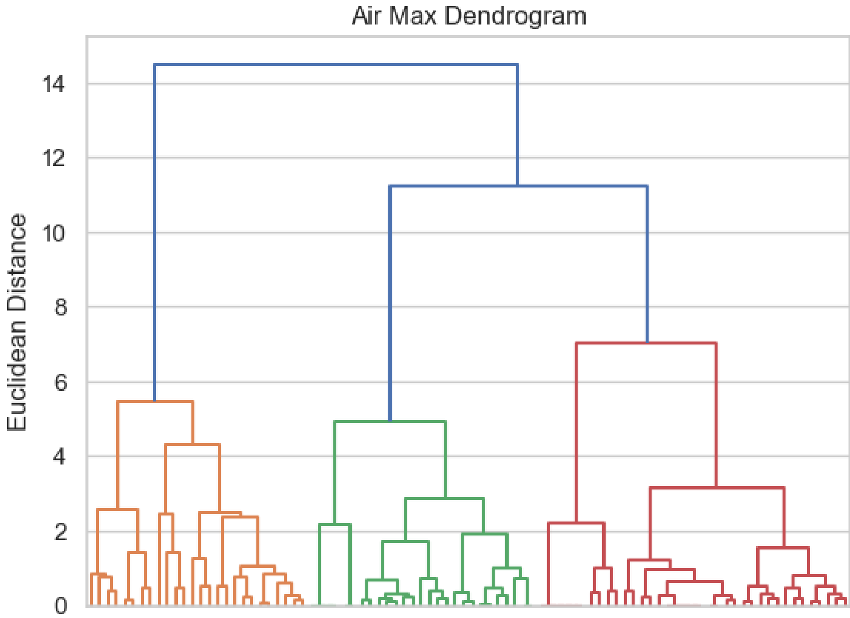

Figure 3: Dendrogram shows how different each group is from one another and suggests the right number of clusters.

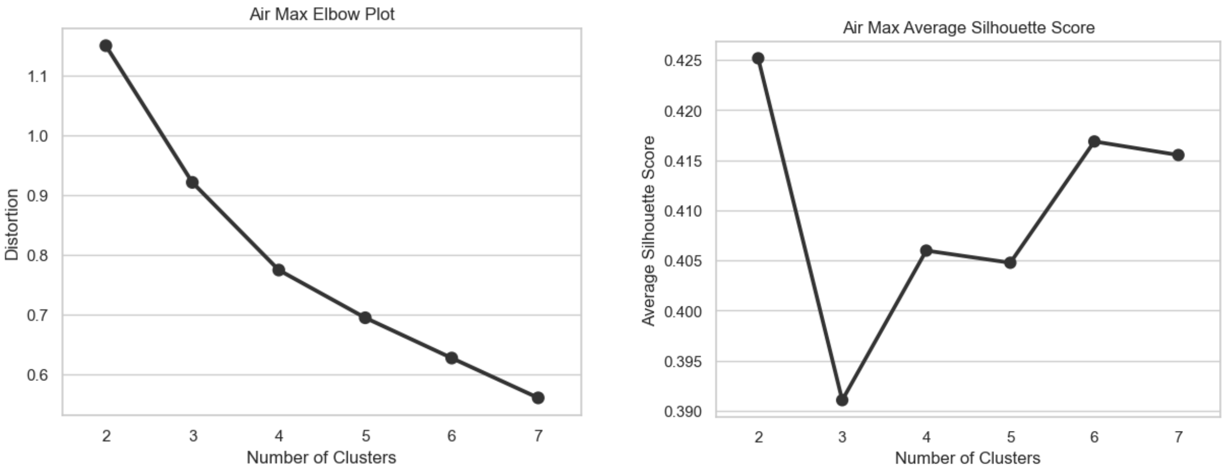

Figure 4: KMeans Clustering Evaluation with Distortions and Average Silhouette Score

As part of our research, we asked Bing AI (ChatGPT-4) to summarize each group of reviews and their attitudes toward Nike's products. 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. They appreciate the shoe's comfort, fit, and design, and many have multiple pairs in different colors. Some even use them for specific needs, such as gym workouts or alleviating physical discomfort. ChatGPT named the first person embodying cluster number 1 Max. He seems to be a fitness enthusiast who values comfort and style in his footwear. He has been a long-time fan of Nike, especially the Air Max line. The 2017 model is his favorite, and he owns several pairs in different colors. He uses them for various activities, from gym workouts to casual wear, and appreciates their perfect fit and arch support. Despite the high price, Max believes the shoes are worth the investment for their quality and comfort. While there are some complaints among reviews regarding airbags and price, ChatGPT guessed their level of satisfaction is around 9 out of 10.

Table 1
Inpirational Content for Each Customer Generated by ChatGPT-4

Customer	Message
Max	Max, your passion for the Air Max 2017 is truly inspiring! Why not take your love for fitness to the next level? With each new pair of Air Max, you could set a new personal fitness goal. Whether it's running a marathon or setting a new personal best in the gym, let every step in your Air Max take you closer to your goal!
Alex	Alex, we understand that your experience with the Air Max 2017 wasn't perfect. But don't let that discourage you! Nike is constantly innovating and improving. Our upcoming Air Max models promise better fit and durability. Give us another chance and let the new Air Max inspire you to reach new heights in your fitness journey!.
Chris	Chris, we're sorry to hear about your experience. But remember, every setback is a setup for a comeback. We invite you to try our latest Air Max model. We've made improvements based on valuable feedback from customers like you. Let the new Air Max be a part of your comeback story!.
Jordan	Jordan, we're thrilled that you're enjoying your Air Max 2017! Why not challenge yourself with each new pair? Set a new fitness goal, join a local sports club, or plan a hiking adventure. Let your Air Max 2017 be a symbol of your commitment to an active lifestyle!

Based on the GPT analysis, the reviews in cluster 2 have a mixed experience with Air Max 2017. They generally like the shoes and find them comfortable, but there are some issues with fit and durability. Alex is the name of a typical consumer. He finds the shoes comfortable and likes the feeling of "walking on air." However, he initially had some issues with the fit, finding them a bit tight. He also experienced some squeaking, which stopped after washing the shoes. Alex had a major issue with the shoes' durability, with the air pockets rupturing and the toe peeling back after just a few months of use. His satisfaction score would be around 6 out of 10.

People who have purchased Air Max in cluster 3 have negative experiences. Chris is the name of a consumer in cluster 3. Chris is a customer who was initially excited about his Nike Air Max 2017 purchase, expecting a high-quality product. However, his experience has been marred by quality issues. The shoes started showing signs of wear and tear much sooner than expected, with the air pockets popping and the material wearing out. He also had issues with the fit, finding them too tight. Chris is disappointed and feels that the shoes are not worth the high price tag. His level of satisfaction is 3 out of 10.

Finally, Air Max 2017 shoppers in cluster 4 have the most positive experience. They find the shoes comfortable, stylish, and true to size. Many use them for gym workouts and daily wear and appreciate the fast shipping and excellent customer service. Jordan is the name of the customer in this cluster. Jordan is a fitness enthusiast who values comfort, style, and quality in his footwear. He recently bought the Nike Air Max 2017 and is extremely satisfied with it. He finds the shoes comfortable and stylish, and they fit him perfectly. Jordan uses them for his gym workouts and loves how they feel. He was also impressed with the fast shipping and excellent customer service. His level of satisfaction is 10 out of 10.

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 1 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 5 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.

Figure 5: Creative images generated by OpenAI DALL-E that can make textual content more engaging.

ChatGPT-4 mentioned that personalized messages and images were sent to all four customers, taking into account their unique experiences. The images conveyed a dynamic and energetic vibe, while the messages were focused on inspiring and motivating the customers rather than just offering deals. Additionally, the messages emphasized Nike's commitment to innovation and improvement, which could potentially address Alex's dissatisfaction. For Chris, the message acknowledged his negative experience and used a motivational tone to remind him that every setback is an opportunity for a comeback. ChatGPT-4 cannot guarantee how the customers' satisfaction levels will change but believes that the positive steps taken through these messages can help rebuild trust for unsatisfied customers while strengthening the relationship between satisfied customers and the brand.

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.

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Appendix

Appendix A