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**Retail Demand Forecasting and Channel Cannibalization: an Empirical Analysis using
Gradient Boosting Models**

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Gradient Boosting Models

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“É só mais um trabalho de cem páginas”
(Pedro Paulo Furtuoso Júnior)

RESUMO

O setor de varejo está passando por transformações significativas, impulsionadas pela mudança de pontos de contato únicos com os consumidores para operações multicanais que integram lojas físicas e plataformas online. Essa transição para o varejo multicanal apresenta riscos substanciais, inclusive no que diz respeito à canibalização promocional entre as lojas físicas e o canal de distribuição online. O objetivo deste estudo é desenvolver um algoritmo para mitigar o impacto dessa canibalização promocional entre canais em um supermercado localizado na região de Florianópolis, Brasil. Isso é alcançado através do desenvolvimento de um modelo de previsão de demanda que utiliza o algoritmo eXtreme Gradient Boosting (XGBoost). Os resultados documentam uma canibalização intercanal significativa, com base em dados históricos de vendas. O modelo identifica os principais impulsionadores de vendas em cada canal de distribuição e permite simular estratégias de mitigação. As descobertas mostram que abordagens como programas de fidelidade podem ajudar a reduzir a canibalização e aumentar as vendas totais. Este estudo oferece uma abordagem orientada por dados para auxiliar no planejamento promocional, ajudando os varejistas a maximizar suas estratégias entre os canais online e offline.

Palavras-chave: Varejo; Previsão de Demanda; Canibalização Promocional; Aprendizado de Máquina; XGBoost.

ABSTRACT

The retail sector is undergoing significant transformations, driven by the shift from single points of contact with consumers to multichannel operations that integrate physical stores with online platforms. This transition to multichannel retailing presents substantial risks, not only as regards promotional cannibalization between physical shops and the online distribution channel too. The objective of this study is to develop an algorithm to mitigate the impact of this channel promotional cannibalization in a supermarket located in the Florianópolis, Brazil region. This is achieved through the development of a demand forecasting model utilizing an eXtreme Gradient Boosting (XGBoost) algorithm. The results documents significant channel cannibalization, based on historical sales data. The model identifies the main sales drivers in each distribution channel and allows to simulate mitigation strategies. The findings show that approaches such as loyalty programs can help in reducing cannibalization and increasing overall sales. This study offers a data-driven approach to help in promotional planning, aiding retailers to maximize their strategies between online and offline channels.

Keywords: Retail; Demand Forecasting; Promotional Cannibalization; Machine Learning; XGBoost.

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1. INTRODUCTION

Multichannel retailing, where retailers operate multiple sales channels such as online platforms, physical stores, and mobile applications, presents both significant opportunities and complex challenges (Neslin *et al.*, 2006; Brynjolfsson *et al.*, 2013). The potential for synergy across channels is substantial, enabling retailers to create a cohesive customer experience that can drive sales and loyalty. However, this approach also introduces the risk of channel cannibalization, where a promotion in one channel, such as a discount on e-commerce, inadvertently reduces sales in another, such as a physical store, and the other way around (Bieline, 2021). As consumer behavior continues to evolve and market conditions remain unpredictable, understanding these dynamics is critical for retailers aiming to optimize their strategies.

Promotional strategies form a cornerstone of the retail industry, serving as a vehicle for attracting customers, increasing sales volumes, and establishing brand identity. Techniques such as discounts, "buy one, get one free" deals, holiday bargains, and reward points are widely regarded as essential for gaining a competitive edge. These campaigns often create urgency, driving short-term demand. However, they can also lead to cannibalization, where a promotion for one product or channel reduces sales of another, ultimately impacting profitability (De Giovanni *et al.*, 2017). Recent research by Aguilar-Palacios *et al.* (2019) shows that grocery retail promotions, like "back to school" or holiday offers on similar products (e.g., school supplies, fresh foods), often redistribute sales within categories rather than boosting overall demand. Analyzing 43,757 promotions, the study reveals inventory challenges, such as overstocking non-promoted items and stockouts of discounted ones, especially perishables. This sales cannibalization limits revenue growth, emphasizing the need for accurate forecasting. Their kNN-based method (83% accuracy within 20% error) optimizes promotion planning to enhance inventory and revenue management.

Cannibalization poses a significant challenge for retailers, especially in multichannel environments where it is more pronounced, though it occurs to a minor extent in omnichannel setups involving simultaneous operation of physical stores and online platforms (Verhoef *et al.*, 2015; Timoumi *et al.*, 2022). Given their extensive multichannel presence, supermarkets represent a key focus in this context, as they face unique complexities in managing channel interactions that can exacerbate demand shifts. In these settings, promotional activities frequently

prompt customers to switch channels, redirecting demand without creating additional sales. This often leads to delayed online orders or eroded profit margins, since anticipated revenue is merely reallocated rather than expanded. Larger supermarkets encounter heightened cannibalization impacts due to their broad multichannel footprint, which intensifies difficulties in inventory control and strategic decision-making (McColl *et al.*, 2020). Retailers, particularly supermarkets, must weigh immediate promotional boosts against the threat of eroding long-term profitability and market position. A study on retail forecasting highlights the intricacies of handling promotions in these fluid environments, stressing the importance of sophisticated analytical methods to predict and mitigate cannibalization risks (Fildes *et al.*, 2019). Ultimately, addressing cannibalization in supermarkets demands proactive strategies to preserve overall revenue streams and sustain competitive viability over time.

Recent advancements in data-driven decision-making have provided retailers with powerful tools to navigate these complexities. Machine learning (ML) and simulation-based optimization techniques have emerged as game-changers, enabling more accurate demand forecasting and more efficient resource allocation. These technologies help to reduce fulfillment lead times and operational costs, allowing retailers to operate more effectively in competitive markets (Pereira; Frazzon, 2021; Cavalcante *et al.*, 2019). A particularly valuable application is the use of consumer browsing data to forecast demand at the product level. This approach allows retailers to anticipate potential cannibalization effects during promotional periods, enabling them to adjust their strategies proactively (Oliveira *et al.*, 2024). Through example, using internet browsing patterns can help retailers understand how a promotion will shift demand between channels, which enables them to plan around an online discount to avoid in-store cannibalization of sales.

Strategies, grounded in data-driven insights, can help retailers balance the benefits of multichannel retailing with the risks of cannibalization. By leveraging tools such as ML, retailers can predict demand more accurately and design promotions aligned with their broader business objectives. A study of demand forecasting in a Florianópolis retail company demonstrated that advanced methods, such as artificial neural networks, significantly improve fill rates and reduce opportunity costs, contributing to economic, environmental, and social sustainability (Da Veiga *et al.*, 2013).

Thus, this study contributes to the literature on consumer behavior and retail marketing by examining how promotions influence customer behavior in multichannel environments. While the nature of promotions in marketing have been investigated extensively, to the best of the researcher's knowledge, the channel cannibalization implications of promotions had been underexplored in the academic literature. For this, complex ML models, such as Random Forests and gradient boosting algorithms can help identify multilevel interactions in customer data. These are the intricate, layered dependencies among multiple variables, such as demographics, channel usage, and promotional timing, that influence behavior in non-linear ways. Such insights can reveal critical patterns around demand volatility during promotions (Cavalcante *et al.*, 2019). These models excel at detecting patterns that traditional analytical methods might overlook, such as subtle shifts in customer preferences across channels during a sale.

Moreover, recent developments in ML have introduced even more sophisticated tools for demand forecasting. Gradient boosting trees, for example, have proven particularly effective in predicting product-level demand by incorporating both spatial and temporal data, which is highly relevant for omnichannel retail environments (Haque *et al.*, 2023). Spatial data might include regional differences in consumer behavior, while temporal data could account for seasonal trends or specific promotional periods. The ability to select optimal forecasting algorithms tailored to individual products, based on observed consumer behavior patterns, further enhances the accuracy of these predictions (Oliveira *et al.*, 2024).

So multichannel retailing offers a wealth of opportunities for retailers to enhance their operations, but it requires careful management to avoid pitfalls such as channel cannibalization. The integration of advanced data-driven tools, particularly ML models, provides a promising path forward, enabling retailers to make informed decisions that drive revenue while minimizing risks.

1.1 RESEARCH PROBLEM

Despite widespread use of promotions in retail, their impact on sales cannibalization is not fully understood, especially in Brazil's dynamic market. For example, in-store discounts can defer online buys, encourage stockpiling, or shift demand within brands, yielding no net revenue gain. Analyzing real weekly sales data from physical and online channels, this study offers

empirical evidence on promotions' role in cannibalization and examines mitigation strategies like phased promotions, selective price cuts, and size-tailored campaigns (Bieline, 2021). These align with adaptive supply chain management (Pereira;Frazzon, 2021), supporting efficient fulfillment during peaks (Oliveira *et al.*, 2025). The research problem focuses on detecting promotions' cannibalization effects and optimizing campaigns to minimize negatives in Florianópolis' retail sector

1.2 OBJECTIVES

Building on the previous section, the general and specific objectives of this work are presented below

1.2.1 General Objectives

This study aims to develop a robust, data-driven forecasting tool for mitigating sales strategy cannibalization at the channel level in a regional Brazilian market to provide empirical insights and develop robust forecasting tools for data-driven promotional planning

1.2.2 Specific Objectives

The development of this work is guided by the following specific objectives:

- Measure the occurrence of cannibalization among sales channels during promotional periods,
- Evaluate the relationship among pricing, promotional actions, and demand shifts across channels,
- Analyze the cannibalization factor based on historical sales data of a supermarket in Florianópolis, Brazil,
- Propose data-driven strategies to reduce cannibalization and improve the effectiveness of promotions.

1.3 JUSTIFICATION

In the highly competitive and increasingly digitized retail environment, promotional strategies are a central pillar for generating short-term sales and attracting consumers. However, indiscriminate use of promotions can lead to cannibalization, where increased sales in one

channel or product come at the expense of another, reducing long-term profitability. This phenomenon is particularly concerning for retailers operating both physical and online stores, where channel competition is a growing challenge. Recent studies have quantified these effects, identifying specific products as “cannibals” or “victims” during promotional periods, underscoring the need for precise analytical tools to manage these impacts (Aguilar-Palacios, Muñoz-Romero, Rojo-Álvarez, 2024). Moreover, research indicates that cannibalization effects vary by retail context, with larger stores experiencing more significant impacts than smaller ones, highlighting the need for tailored strategies (McColl, Macgilchrist, Rafiq, 2020).

One such period of intensified promotional activity is during high-volume sales events such as Black Friday, where retailers deploy aggressive discounts across multiple channels to drive consumer traffic and boost immediate revenue (Gong; Smith; Telang, 2015). However, these events often exacerbate cannibalization, as promotions in online stores may divert sales from physical locations, or vice versa, leading to eroded margins and suboptimal resource allocation (Bieline, 2021). For instance, the surge in inter-channel shopping during these peaks can result in up to 20-30% of sales being cannibalized internally, as consumers exploit price disparities, underscoring the urgency for retailers to monitor and mitigate these effects through data-driven insights (De Giovanni; Ramani, 2017).

In this digital era, phenomena such as ROPO (Research Online, Purchase Offline), also known as Webrooming, and its counterpart Showrooming (Research Offline, Purchase Online) further complicate cannibalization dynamics (Verhoef; Kannan; Inman, 2015). Webrooming occurs when consumers browse products online for information, reviews, and comparisons before buying in-store, while Showrooming involves examining items in physical stores but completing the purchase online, often at a lower price (Verhoef; Neslin; Vroomen, 2007). These behaviors are amplified by the seamless accessibility of product details across e-commerce platforms, where information is just a click away, enabling shoppers to optimize their decisions and intensifying competition between a retailer’s own channels (Alba *et al.*, 1997). This interplay not only justifies the need for sophisticated analytical frameworks but also highlights how promotional strategies must account for these inter-channel consumer journeys to preserve overall profitability (Neslin, 2022).

The complexity of this scenario demands analytical models that capture consumer responses to promotional stimuli and predict demand behavior under competing influences such

as prices, seasonality, and marketing interventions. Accurate demand forecasting is critical for aligning marketing efforts with inventory planning, particularly during promotional periods (Gupta, 1992). In the Florianópolis retail context, where smaller businesses often lack the analytical infrastructure of larger firms, these challenges are amplified.

Advances in ML have introduced new possibilities for analyzing and predicting promotional effects. Techniques such as Random Forests and Gradient Boosting Machine (GBM) have demonstrated superior performance in modeling complex, non-linear interactions in retail demand data (Soysal e Krishnamurthi, 2016). In multichannel retail settings, comparative studies have highlighted the effectiveness of hybrid ML models, which combine techniques such as Random Forests and XGBoost to achieve higher forecasting accuracy and better supply chain management (Mitra *et al.*, 2022). These models outperform traditional methods such as Autoregressive Integrated Moving Average (ARIMA), particularly in dynamic environments where consumer behavior is influenced by channels promotions (Da Veiga *et al.*, 2013).

While much of the existing literature focuses on large-scale or national retail markets, this study emphasizes a localized, product-specific analysis, aligning with the realities of regional retail businesses in Brazil. These smaller operations are particularly vulnerable to the adverse effects of poorly designed promotions, which can exacerbate cannibalization between physical stores and e-commerce platforms. This study addresses an underexplored niche in retail analytics by focusing on cannibalization at the product and channel level. Also, it equips decision-makers with robust forecasting tools to design targeted, evidence-based promotional strategies that protect profit margins and ensure channel harmony. By analyzing weekly sales data for a single product across physical and online channels, this study provides empirical insights into how promotions affect demand distribution and the extent of cannibalization, supporting intelligent, data-driven promotional planning in Brazil's evolving retail landscape.

1.4 SCOPE OF THE STUDY

This study is limited to the analysis of a single product in a regional retail company in the grocery sector. The product's sales performance will be evaluated across two sales channels: physical stores and the online platform. The focus lies on understanding how promotional strategies affect the distribution of demand between these channels, and to what extent they lead to sales cannibalization.

The analysis is based on weekly sales data over the course of one year, incorporating variables such as price, promotion periods, and seasonal demand shifts. The study does not extend to multi-product analysis, cross-brand comparisons, or nationwide retail operations. Furthermore, it excludes external variables such as competitor promotions or macroeconomic fluctuations that are not reflected directly in the historical dataset used.

ML techniques, particularly Random Forest, are applied to forecast demand and estimate the cannibalization effect, but the research will not engage in comparing a broad range of forecasting algorithms. The emphasis is on building an interpretable and actionable model tailored to the decision-making needs of small and medium-sized retailers.

1.5 STRUCTURE OF THE THESIS

This study is organized into five Chapters:

Chapter 1 – Introduction: Presents the background of the research, defines the problem, objectives, justification, scope, and the overall structure of the study.

Chapter 2 – Literature Review: Reviews relevant academic literature on retail promotions, promotional cannibalization, multichannel retail, machine learning-based demand forecasting.

Chapter 3 – Methodology: Details the research design, data sources, preprocessing steps, variable selection, and the modeling techniques used, with a focus on XGBoost for demand prediction.

Chapter 4 – Modeling and Strategy Simulation: Presents the empirical findings, including the estimated cannibalization effects, model performance metrics, and a discussion of the implications for retail strategy.

Chapter 5 – Conclusion: Summarizes the main conclusions of the study, outlines its limitations, and offers practical recommendations for retail managers as well as directions for future research.

2. LITERATURE REVIEW

This Chapter synthesizes foundational and contemporary research essential for understanding retail demand forecasting and promotional cannibalization. It begins with a historical evolution of retail promotions, tracing their development from early tactics to digital-era strategies. Next, it examines modern retail commerce dynamics, focusing on multichannel structures, channel expansion drivers, and the interplay between synergy and cannibalization. Theoretical frameworks underpinning consumer responses to promotions are then analyzed, integrating behavioral economics, marketing theory, and game theory. The review subsequently explores strategies to mitigate promotion-induced cannibalization and concludes with an overview of ML applications in demand forecasting, emphasizing methodological advances for identifying cannibalization patterns. These subsections establish the conceptual groundwork for this study's empirical investigation.

2.1 A HISTORICAL OVERVIEW OF PROMOTIONS IN RETAIL

Sales promotions, encompassing a diverse range of incentives designed to stimulate consumer purchase, trial, or retailer effectiveness, are not a modern invention but rather a practice with deep historical roots, evolving in tandem with changes in production, distribution, media, technology, and consumer behavior. Understanding this evolution provides crucial context for analyzing the complexities of promotional strategies in today's multichannel environment.

2.1.1 Origins And Early Evolution (Late 19th - Early 20th Century)

Contemporary promotion techniques trace back to the 19th century's Industrial Revolution (Allen, 2017). This era transformed manufacturing, enabling unprecedented mass production (Allen, 2017). Factories produced vast goods, challenging manufacturers to stimulate demand and clear inventories (Allen, 2017; Beard, 2016). Early businessmen developed promotions to attract customers and differentiate in markets (Beard, 2016; CoSchedule, 2022; O'Barr, 2005). Initial methods included price reductions, newspaper ads, and coupons to drive sales (Ailawadi and Gupta, 2014; Beard, 2016; O'Barr, 2005; Tuttle, 2010). Coca-Cola pioneered free giveaway tickets in the 1880s for product trial and loyalty (Tuttle, 2010). Department stores like Macy's and Wanamaker's held special sales days to boost volume (Fujioka; Stobart, 2021).

Mail-order catalogs from Sears Roebuck reached rural consumers with discounts, fostering engagement and loyalty (Tuttle, 2010). These rudimentary tactics laid foundations for modern marketing, making advertising central to trade and consumer culture.

2.1.2 The Rise Of Brands And Mass Media (Mid-20th Century)

In the mid-20th century, the marketing and consumer culture landscape underwent a significant transformation with the rise of consumer packaged goods (CPG) brands and the growing influence of mass media. Companies allocated substantial resources to nationwide advertising campaigns, utilizing the expansive reach of print, radio, and television to connect with broad audiences (O'barr, 2005). These brands employed integrated promotional strategies, notably distributing coupons through newspapers and magazines, including free-standing inserts (FSIs), to incentivize purchases and foster brand loyalty (AD AGE, 2003). While retailers continued to use in-store discounts to attract shoppers, manufacturer-initiated promotions gained prominence, effectively shaping consumer behavior. Additionally, the emergence of loyalty programs, such as the S&H Green Stamps scheme introduced in 1896 but peaking in the 1960s, helped build long-term customer relationships by rewarding repeat purchases (Loyalty & Reward Co, 2020). This era marked a pivotal shift toward modern marketing practices, emphasizing mass communication, targeted promotions, and customer retention strategies that laid the foundation for contemporary consumer marketing techniques.

2.1.3 The Era of Scanner Data and Sophistication (Late 20th Century / Pre-Digital):

The 1970s-1980s introduction of universal product codes and checkout scanners transformed retail analytics (Seideman, 2015). These advancements enabled real-time sales data tracking, revolutionizing consumer behavior and product performance insights (Seideman, 2015). Consequently, category management emerged to optimize shelf placement and promotions (Seideman, 2015). This facilitated supplier negotiations on displays, space allocation, and pricing, improving sales efficiency and profitability (Ailawadi and Gupta, 2014; Askinai, 2019). Retailers diversified promotions beyond discounts, adding rebates, contests, bonus packs, and BOGO deals (Ailawadi and Gupta, 2014; Beard, 2016; Loyalty & Reward Co., 2020). Walmart pioneered Everyday Low Pricing (EDLP), emphasizing consistent low prices over sales

to build trust and loyalty (Askinasi, 2019). Overall, these innovations made retail more data-driven and customer-centric.

2.1.4 The Digital Transformation (Late 1990s - 2010s):

The internet and e-commerce reshaped promotions, offering retailers flexibility and reach (Alba *et al.*, 1997; Kannan and Li, 2017; Saura *et al.*, 2021). Early digital tactics included banner ads with discounts, email campaigns with offers, and coupon sites (Kannan and Li, 2017; Saura *et al.*, 2021). Affiliate marketing let third-party sites earn commissions through sales links (Kannan and Li, 2017; Saura *et al.*, 2021). Price comparison sites increased transparency, empowering consumers and intensifying competition (Alba *et al.*, 1997; Brynjolfsson *et al.*, 2013). Retailers collected behavioral data for personalized promotions based on browsing or purchases (Ansari *et al.*, 2008; Pereira and Frazzon, 2021; Youyou *et al.*, 2015). New models emerged, like flash sales (e.g., Gilt Groupe) with urgent discounts and daily deals (e.g., Groupon, LivingSocial) for local services. Consumers shifted to more ROPO, price sensitivity via comparisons, and personalized offers. However, consistent promotion management across online and physical channels posed challenges (Saura; Palacios-marqués; Iturricha-fernández, 2021).

2.2 RETAIL COMMERCE

The landscape of retail commerce has undergone a dramatic transformation over the past few decades, driven primarily by technological advancements and the consequent shifts in consumer behavior and expectations. The rise of the internet and digital platforms has moved retail beyond the confines of traditional brick-and-mortar stores, compelling businesses to adapt and evolve their strategies to remain competitive (Doherty; Ellis-chadwick, 2010). This evolution has led retailers from single-channel operations towards more complex multichannel and, more recently, omnichannel systems, aiming to provide a seamless shopping experience irrespective of the touchpoint (Verhoef *et al.*, 2015; Timoumi *et al.*, 2022; Neslin, 2022). Understanding this transition, the associated opportunities, and the inherent challenges is crucial for navigating the contemporary retail environment. The omnichannel concept has gained currency, signifying consumers' ability and tendency to utilize multiple channels across various stages of their purchase journey (Timoumi *et al.*, 2022).

2.2.1 Multichannel and omnichannel retailing: definitions and evolution

Initially, retailers responded to digital shifts by adopting multichannel strategies, including using more than one channel to reach consumers, such as physical stores, websites, mobile apps or catalogs. In a traditional multichannel setup, these channels are often operated independently, managed as individual professional units, sometimes with different pricing, inventory and customer service processes (Hübner *et al.*, 2016). The primary goal was to offer customers' options how they interact with the brand on the basis of convenience or preference (Hübner *et al.*, 2016).

The constraints of subpar channel management such as poor customer experience, lack of inventory visibility, and potential service disruptions drive the shift toward omnichannel retailing (Hübner *et al.*, 2016; Neslin, 2022). According to Neslin (2022), omnichannel integration can be understood as a spectrum ranging from “unconnected” (isolated channels) to “full” (seamless integration across all customer journey stages). Intermediate approaches include “vertical” integration (linking channels along the customer journey, e.g., online research followed by in-store purchase) and “horizontal” integration (aligning channels within a specific stage, such as uniform pricing) (Neslin, 2022). Although terms such as multichannel, cross-channel (in the literal sense) , and omnichannel are often incorrectly used interchangeably in practice (Beck; Rygl, 2015; Hübner *et al.*, 2016), the key distinction lies in the degree of integration and customer-centricity (Hübner *et al.*, 2016).

Omnichannel retailing prioritizes seamless interaction across all touchpoints, ensuring a cohesive brand experience whether the customer is browsing, purchasing, or returning products (Hübner *et al.*, 2016; Verhoef *et al.*, 2015; Kim, 2018). To achieve this, retailers must restructure logistics, technology, and operations (Hübner *et al.*, 2016), eliminating barriers between physical and digital spaces. This includes synchronizing marketing and pricing across all locations (e.g., distribution centers and stores) and offering flexible fulfillment options such as buy-online-pickup-in-store (BOPS) or ship-from-store (Hübner *et al.*, 2016; Gallino and Moreno, 2014).

Despite being an advanced retail model (Hübner *et al.*, 2016), achieving full integration remains a major challenge, particularly for small and medium-sized businesses (Neslin, 2022). Many retailers operate with partially integrated channels, often at the early stages of Neslin's (2022) framework either “unconnected” or with limited “horizontal” integration. This reality

highlights the varying degrees of omnichannel adoption, where businesses manage distinct yet interconnected sales platforms (Hübner *et al.*, 2016), facing complexities in promotions and operational alignment.

Separate channel types meet different needs. Online channel features, comprehensive classification and easy search ability (Alba *et al.*, 1997), while physical stores offer experiential shopping, instant product access and touch evaluation (Dholakia, 1999). Mobile apps can increase limitations such as mobility, omnipresent, individualization, identity, and localization while having more accessibility (Li 2001; Li 2005; Shankar; Balasubramanian 2009; Wu *et al.* 2011 Lim *et al.*). The showrooms focus on experiential and informative aspects without possessing inventory for immediate purchase (Gong *et al.*, 2022). Outlet stores target value-conscious segments with lower prices and potentially different assortments (Soysal; Krishnamurthi, 2016; Coughlan; Soberman, 2005). Digital product formats such as e-books offer instant delivery and often lower prices (LI, 2021). Live streaming commerce emerges as another channel leveraging real-time interaction, detailed product demonstrations, and often promotional pricing to engage consumers (Gong *et al.*, 2022). The integration of these varied channels is key to the omnichannel promise (Verhoef *et al.*, 2015).

2.2.2 Motivations and drivers for channel expansion

Retailers expand their sales channels for strategic reasons, primarily to reach new customer segments and tap into previously inaccessible markets (Van Crombrugge *et al.*, 2024). This expansion often includes online platforms (Geysken *et al.*, 2002), mobile apps (Huang *et al.*, 2016; Lim *et al.*, 2022), factory outlets (Soysal; Krishnamurthi, 2016), or even brand-owned stores (Van Crombrugge *et al.*, 2024). The rise of e-commerce, accelerated by the COVID-19 pandemic (Wang *et al.*, 2021), has made digital channels indispensable. Conversely, digital-native brands are increasingly entering physical retail such as supermarkets or flagship stores to enhance accessibility, especially for fast-moving consumer goods (Van Crombrugge *et al.*, 2024).

Beyond sales, channel diversification strengthens brand identity (Fornari *et al.*, 2016). Physical stores particularly flagship locations act as brand ambassadors, boosting visibility and trust (Van Crombrugge *et al.*, 2024; Wang; Goldfarb, 2017), which can drive channels sales

(Jones; Livingstone, 2018). Additional benefits include gathering consumer insights, responding to competitive pressures (Timoumi *et al.*, 2022), and exploring new revenue streams.

2.2.3 Strategic challenges: cannibalization, conflict, and integration costs

Despite the potential benefits, expanding into multiple sales channels presents significant challenges for retailers. One major concern is intra-channel cannibalization, where sales from one channel reduce sales in another channel operated by the same retailer (Deleersnyder *et al.*, 2012; Chen, 2018; Neslin, 2022). This occurs when consumers perceive different channels as substitutes (Deleersnyder *et al.*, 2012). More clear examples would be, adding a mobile app may draw users away from a retailer's website (Huang *et al.*, 2016), potentially cannibalizing online sales (Shriver; Bollinger, 2022), opening physical stores can cannibalize online or catalog sales, particularly in the short term (Neslin, 2006; Fornari *et al.*, 2016), lower-priced outlet stores may attract customers who would otherwise shop at full-price retail locations (Soysal; Krishnamurthi, 2016); The introduction of digital products, such as e-books, has been shown to reduce sales of printed books (Li, 2021; Chen *et al.*, 2018).

Wang *et al.* (2021) specifically examined the cannibalization effects of adding online sales through travel platforms. While expanding online product offerings can increase total sales, it may also cannibalize sales of core products (Ma, 2016). Similarly, launching a brand-owned store can cannibalize the manufacturer's existing online sales (Van Crombrugge *et al.*, 2024). Live-stream shopping, despite boosting overall demand, risks cannibalizing traditional online or offline sales if not carefully managed (Gong *et al.*, 2022). Even mobile apps, while convenient, can inadvertently divert sales from physical stores and existing online platforms (Lim *et al.*, 2022).

Another challenge is channel conflict, particularly the inter-competition effect, which arises when manufacturers introduce direct sales channels (online or physical stores) that compete with their independent retail partners (Chen, 2018; Tsay; Agrawal, 2004). Traditional retailers may perceive these moves as threats (Tsay; Agrawal, 2004), leading to strained relationships, refusal to stock the manufacturer's products (Chen, 2018), or even reduced distribution (Van Crombrugge *et al.*, 2024). Managing these dynamics requires careful negotiation to ensure fair competition across channels (Chen, 2018).

Brand dilution is another risk, especially when adding channels that offer lower price points or perceived quality, such as factory outlets (Soysal; Krishnamurthi, 2016) or digital formats that may be seen as inferior (Li, 2021). Exposure to inconsistent service levels or product quality under the same brand name can harm overall brand perception (Kirmani *et al.*, 1999 apud Soysal; Krishnamurthi, 2016). Finally, implementing and managing multiple channels involves high operational and integration costs (Hübner *et al.*, 2016; Kirmani *et al.*, 1999 apud Soysal; Krishnamurthi, 2016). Developing effective omnichannel systems requires substantial investments in technology for real-time data synchronization (e.g., inventory tracking) (Gallino; Moreno, 2014), logistics to streamline fulfillment and returns across channels (Hübner *et al.*, 2016), and process re-engineering to align operations (Hübner *et al.*, 2016). This complexity is a major obstacle (Hübner *et al.*, 2016; Neslin, 2022), with many retailers acknowledging that their supply chains are not yet equipped to handle these demands. Additionally, managing larger online assortments introduces further complexity and cost (Ma, 2016).

2.2.4 Synergy and cannibalization: unpacking channel interactions

The success of a multichannel strategy hinges on whether the synergistic benefits outweigh the cannibalization costs (Neslin, 2022; Timoumi *et al.*, 2022). While cannibalization is a tangible risk where sales in one channel diminish those in another (Deleersnyder *et al.*, 2012; Chen, 2018; Lim *et al.*, 2022; Shriver; Bollinger, 2022), adding channels can also create positive synergy effects. Synergy occurs when the presence of one channel enhances the performance of others, leading to overall sales growth (Neslin *et al.*, 2006; Fornari *et al.*, 2016; Wang *et al.*, 2021; Lim *et al.*, 2022). The net outcome is the combination of these demand expansion and cannibalization effects (Shriver; Bollinger, 2022). As illustrated in Table 1, various factors such as enhanced availability, channels information search, and complementary capabilities contribute to positive interactions between online and offline channels, ultimately boosting overall brand performance.

Table 1— Key Drivers of Channel Synergy

Mechanism	Description	Citations
Greater availability and convenience	More contact points facilitate the interacting and purchase of brand consumers. Mobile applications, in particular, improve convenience and accessibility.	Neslin <i>et al.</i> , 2006; Huang <i>et al.</i> , 2016; Lim <i>et al.</i> , 2022
Presence and awareness of the enhanced brand	Physical stores, in particular, can act as “living outdoors”, increasing brand visibility and potentially driving traffic to on-line channels. The mere presence of a store can build confidence and confidence. Even live broadcasts may have an advertising effect, increasing brand exposure.	Avery <i>et al.</i> , 2011; Van Crombrugge <i>et al.</i> , 2024; Wang; Goldfarb, 2017; Bollinger, 2022; Fornari <i>et al.</i> , 2016; Gong <i>et al.</i> , 2022
Looking for information between channels	Consumers usually get involved in “research purchases” using one information collection channel and another for purchase. This includes “Webrooming” (on -line research, offline purchase) and “showroom” (Offline, buy on -line). Showrooms explicitly facilitate this, and even BOPS systems can encourage Webrooming by product availability signaling.	Verhoef <i>et al.</i> , 2007; Neslin, 2022; Gong <i>et al.</i> , 2022; Gallino; Moreno, 2014; Timoumi <i>et al.</i> , 2022
Customer Learning and Migration	Lower-priced or lower-risk channels (such as outlets) can serve as entry points, allowing customers to familiarize themselves with the brand before potentially “trading up” or increasing purchase frequency in higher-priced channels. Customers may also migrate between channels over time.	Soysal; Krishnamurthi, 2016; ANSARI <i>et al.</i> , 2008
Market Expansion	New channels can attract entirely new customers or fulfill previously unmet needs, leading to incremental sales rather than just shifting existing demand. Offering larger online assortments, despite cannibalization	LI, 2021; ZHANG, 2009 cited in LI, 2021; Shriver; Bollinger, 2022; Brynjolfsson, Hu, Rahman 2009; Ma, 2016

	risks, can spur sales of niche products.	
Complementary Channel Capabilities and Value Transfer	Different channels excel at different things (e.g., web for broad selection, physical stores for experience). An integrated offering allows customers to leverage the strengths of each. Yeh <i>et al.</i> (2022) find positive value transfer from online (e.g., innovation) to offline purchase intentions. Superior online information capability lowers search costs, allowing customers to process assortment more efficiently and spend more, outweighing cannibalization.	Bridges; Florsheim, 2008; Dholakia, 1999; Neslin <i>et al.</i> , 2006; Yeh <i>et al.</i> , 2022; Ma, 2016
Enhanced Pricing Power	In some cases, the presence of a complementary channel (such as e-books alongside print) can allow publishers to charge higher prices in existing channels, as the new channel provides a “compensating substitute” that mitigates demand loss when prices increase elsewhere.	Li, 2021

Source: Elaborated by the author

Empirical evidence usually suggests that synergy may prevail, leading to increased overall performance, despite some cannibalization (Timoumi *et al.*, 2022; Neslin, 2022). Studies have found general positive effects by adding online channels through travel platforms (Wang *et al.*, 2021), mobile applications (Huang *et al.*, 2016; Lim *et al.*, 2022; Wang *et al.*, 2015), adding stores to web (long-term synergy) (Avery *et al.*, 2011; *et al.* A positive causal transshipment, from the adoption of the store to retail stores, mainly by increasing the frequency of purchase. Lower research costs can lead to higher on-line spending on the main product lines, surpassing the cannibalization of niche products (Ma, 2016). However, the net result is highly dependent on the context (Timoumi *et al.*, 2022) and sometimes the addition of channels changes mainly sales rather than generating significant general growth (eg, Hernant; Rosengran, 2017 apud Timoumi *et al.*, 2022).

2.2.5 Factors moderating channel interactions

The interplay between cannibalization and synergy is influenced by a multitude of factors related to the channels, the product, the market, and the firm's strategy (Timoumi *et al.*, 2022). As detailed in Table 2, elements such as channel attributes, product characteristics, market factors, and firm strategies play pivotal roles in determining the balance between synergy and cannibalization in retail channels.

Table 2 — Elements Driving Multichannel Success

Category	Description	Citations
Channel Attributes	The degree of differentiation between channels in terms of price, quality, service, and assortment plays a critical role. Greater overlap might increase cannibalization, while distinct value propositions can foster complementarity. Channel capabilities (e.g., web for search, mobile for convenience, physical for experience) also matter. The superior information capability of the online channel lowers customers' search costs, allowing more efficient processing of assortment. The level of channel integration significantly influences outcomes, with higher integration generally leading to better performance. Customers value integration across multiple dimensions such as consistency, freedom, and synchronization.	Soysal; Krishnamurthi, 2016; LI, 2021; Chen, 2018; Deleersnyder <i>et al.</i> , 2012; Huang <i>et al.</i> , 2016; Yeh <i>et al.</i> , 2022; Ma, 2016; Herhausen <i>et al.</i> , 2015; Cao; Li, 2015; Timoumi <i>et al.</i> , 2022; Neslin, 2022
Product Characteristics	The nature of the product is crucial. Factors include standardization vs. personalization, quality, product type (e.g., groceries vs. apparel vs. electronics vs. books), and whether attributes are digital or non-digital. E-books, for example, show different substitution patterns with print books depending on the genre ('casual' vs. 'practical'). Hedonic products may see greater synergy from multichannel shopping than utilitarian ones. Product standardization and quality influence the optimal live streaming strategy.	Gong <i>et al.</i> , 2022; Yeh <i>et al.</i> , 2022; Kushwaha; Shankar, 2013; Herhausen <i>et al.</i> , 2015; Li, 2021

Market and Consumer Factors	Customer heterogeneity is critical. Demography (age, lace), intrinsic channel preferences, previous use of channels, on-line buying experience, price sensation and on-line. There is client segmentation based on channel preferences, with persistent offline segments identified until recently. The impact of mobile application adoption varies according to the use of previous channels (physical, only online, hybrid). The differences observed between unique and multichannel channel customers may be due to self-selection, not the causal impact of canal adoption. Local market conditions, such as the density and availability of offline stores.	Chen, 2018; Li, 2021; Konuş <i>et al.</i> , 2008; Lim <i>et al.</i> , 2022; Neslin, 2022; Herhausen <i>et al.</i> , 2015; Soysal; Krishnamurthi, 2016
Firm Strategy and Management	How the firm manages its channels, including channels pricing, the degree of operational integration, and the sequence of channel rollout (e.g., web-first vs. store-first) impacts outcomes. The balance of market power between manufacturers and retailers also shapes channel strategies and conflicts. The choice between brand stores (profit-centric) versus flagship stores (experience-centric) also reflects different strategic goals. Retailer capabilities in operations, IT, culture, design, and finance are crucial for implementing integration strategies.	Homburg <i>et al.</i> , 2019; LI, 2021; Shriver; Bollinger, 2022; Hübner <i>et al.</i> , 2016; Herhausen <i>et al.</i> , 2015; Neslin, 2022; Fornari <i>et al.</i> , 2016; Van Crombrugge <i>et al.</i> , 2024; Kim; Chen, 2018; Van Crombrugge <i>et al.</i> , 2024

Source: Elaborated by the author

2.2.6 The role of promotions in retail

Promotions form an integral part of the retail industry, serving to attract customers, increase sales volumes, and establish brand identity. Techniques such as price reductions, BOGO, seasonal bargains (e.g., Christmas), and reward points are common tools used to gain a competitive edge. Promotional campaigns offering incentives for advanced purchase can stimulate demand and create a sense of urgency among consumers. The primary purpose is clear attracting customers, increasing short-term sales, and building loyalty. Common types include price reductions, BOGO offers, loyalty programs, among others. These undoubtedly offer short-term benefits by boosting demand and creating urgency. However, the influence of promotions on customer purchasing decisions across different channels needs careful consideration, especially regarding potential adverse effects (Hübner *et al.*, 2016).

2.2.7 Cannibalization in the context of promotions

While promotional campaigns often yield high short-term sales, they frequently generate adverse side effects, notably the problem of cannibalization. Cannibalization, in this context, means a promotion for a specific product or channel harms the sales of another product or channel within the same retailer, ultimately damaging overall profitability. There's a direct link between promotions and sales cannibalization.

Mechanisms of promotion-induced cannibalization include shifting demand between channels, where promotions in one channel (e.g., offline) can cause customers to delay purchases from other channels (e.g., online) or shift demand entirely, such that an offline promotion might negatively affect online sales, and vice versa (Gong *et al.*, 2015; Shriver and Bollinger, 2022). Another mechanism is forward buying or stockpiling, in which time-specific promotions can lead customers to purchase larger quantities or buy earlier than needed, reducing subsequent demand (Ailawadi and Gupta, 2014; Gupta and Cooper, 1992). Finally, shifting demand between products occurs when promotions on certain items might divert demand from other, potentially higher-margin, products within the same brand or category, resulting in no net revenue gain (Bekal and Bari, 2021; Bieline, 2021; De Giovanni and Ramani, 2017).

The implications of these effects are particularly significant in the multichannel and omnichannel retail sector. Retailers should balance the immediate increase in sales of promotions against the risk of eroding long-term profitability and total market share (Hübner *et al.*, 2016). As the lines between the channels run out, promotions can easily cannibalize sales in another, diluting the overall effectiveness of the campaign. It emphasizes the need to carefully monitor promotional campaigns to prevent cannibalization between channels and maximize general returns (Bieline, 2021). Understanding how promotions affect cannibalization between channels is crucial for effective strategic planning in the dynamic retail environment (Hübner *et al.*, 2016).

2.3 THEORETICAL FRAMEWORKS UNDERLYING RETAIL PROMOTIONS: CONSUMER BEHAVIOR AND MARKETING PERSPECTIVES

While the previous subsection detected the historical development of the campaigner strategy, this section delays the underlying theoretical framework that helps explain why and why publicity consumers affect decisions and size market dynamics. Understanding these fundamental principles from consumer behavior and marketing theory is essential for designing

effective propagation strategies and fearing their complex results, including possible side effects such as brand weakening or cannibalism. This discussion is based on concepts related to classic marketing models and economic theory of value elasticity such as value perception, urgency, loyalty, brand switching, Attention, Interest, Desire, and Action (AIDA). It should be noted that the literature provided provides valuable references and examples (e.g. Sashi, 2012; Gong *et al.*, 2015; Delersander and Coal, 2012), a comprehensive discovery of these fundamental principles often requires a wide discovery of these basic principles, often requires seminal works and comprehensive marketing literature beyond the scope of documents.

2.3.1 Consumer behavior and marketing theories

Promotions fundamentally aim to influence consumer behavior by encouraging purchase, trial, or increased consumption through psychological and behavioral mechanisms. Consumers perceive prices subjectively and contextually, evaluating attractiveness against reference prices internal (from memory or expectations) or external (e.g., pre-promotion or competitor prices) (Monroe, 1973; Thaler, 1985). Effective promotions create perceived value by establishing a favorable comparison, with the gap between reference and actual price yielding transaction value (Gupta and Cooper, 1992; Gong *et al.*, 2015). Retailers manage cues like displaying original prices to enhance this perception.

Prospect theory (Kahneman and Tversky, 1979) explains how consumers assess gains and losses relative to reference points, with losses looming larger than gains. Framing promotions as gains (e.g., “Save \$10”) is more effective than as losses (e.g., surcharges), and diminishing sensitivity means smaller discounts feel more impactful on low-priced items or when split into multiples (Thaler, 1985). Price perception shapes willingness-to-pay (WTP), where promotions lower prices below WTP thresholds; segment differences in WTP, such as between channels or brands, influence response (Deleersnyder and Koll, 2012).

Many promotions use scarcity via time or quantity limits (“Limited Time Offer”), heightening value and urgency to spur impulse buys and accelerate decisions (Ailawadi and Gupta, 2014; Monroe, 1973; Gupta and Cooper, 1992; Kahneman and Tversky, 1979; Thaler, 1985). However, excessive restrictions may cause reactance and rejection (Ailawadi and Gupta, 2014; Gupta and Cooper, 1992; Raghubir and Corfman, 1999).

Promotions affect loyalty and switching, they attract trials potentially building loyalty if experiences are positive, but over-reliance fosters deal-proneness, erodes brand value, and reduces regular-price willingness (Deleersnyder and Koll, 2012; Raghurir and Corfman, 1999). From relationship marketing, loyalty involves engagement through interactions, satisfaction, and advocacy; promotions aid initial or reward phases but require broader value (Sashi, 2012). They also drive temporary or permanent switches and facilitate variety-seeking by lowering trial costs.

Marketing frameworks structure promotional strategies within the mix. The AIDA model guides consumer progression, attention via bold elements like “50% Off!”; Interest through benefits; Desire via appeal and social proof; Action with calls-to-action and urgency (Sashi, 2012; Kannan and Li, 2017). Price elasticity of demand quantifies responsiveness to price changes (percentage quantity change over price change) (Monroe, 1973); promotions exploit elastic demand for volume/revenue gains, influenced by substitutes, necessity, loyalty, and budget share (Ailawadi and Gupta, 2014; Gupta and Cooper, 1992; Raghurir and Corfman, 1999; Gong *et al.*, 2015). Reference pricing tactics, such as showing MSRP or anchors, shape value perceptions and inform design (Gong *et al.*, 2015).

2.3.2 Game theory for competitive promotion strategy dynamics

Understanding the strategic interactions between retailers or different channels within the same firm, especially concerning pricing and promotional activities, often involves the application of game theory. Game theory provides a formal framework to model situations where players (e.g., retailers, manufacturers, different channels) make decisions anticipating the reactions of others, aiming to maximize their own payoffs (e.g., profit).

Several studies utilize game theory to analyze competitive dynamics in multichannel settings, particularly in the competition between channels of the same firm, where when a retailer adds a new channel such as an online store competing with physical stores or an outlet channel competing with full-price retail stores game theory helps model the ensuing price competition and potential cannibalization, with models exploring Stackelberg games in which one channel, like the manufacturer’s direct channel, acts as a leader and the other, such as the independent retailer, as a follower (Chen *et al.*, 2012). These models analyze optimal pricing strategies under channel conflict and coordination mechanisms (Cai *et al.*, 2009; Cattani *et al.*, 2006), and for instance, Shriver and Bollinger (2022) model how retail store entry affects existing online

channels by explicitly considering channel substitution and the firm's ability to price discriminate across channels, showing that as channels become more equally accessible for example, through reduced travel costs to stores the firm's ability to maintain different price points across channels diminishes, thereby impacting overall profitability. Fruchter and Tapiero (2005) also apply game theory to analyze dynamic pricing across online and offline channels for heterogeneous customers.

Competition between different entities also employs game theory to model rivalry between distinct firms operating in related channels, as Wu (2012) formulates a two-period game between an Original Equipment Manufacturer (OEM) selling new products and a remanufacturer selling refurbished versions of the OEM's products, where the model investigates the OEM's strategic choice regarding product design interchangeability which affects both players' costs and the competitive pricing strategies that emerge in the second period, with equilibrium decisions depending on costs, consumer preferences, and strategic interactions. Ramani and De Giovanni (2017) model the competition between a manufacturer and a Goodwill agency selling used products, analyzing pricing and advertising strategies in a closed-loop supply chain context while considering the cannibalization effect. Cai *et al.* (2009) further analyze game theoretical perspectives in dual-channel supply chain competition involving price discounts.

These game-theoretical models help understand how competitive actions, such as introducing a new channel, changing product design, or setting promotional prices, affect market dynamics, equilibrium outcomes (prices, market shares), and profits for all players involved. They highlight the strategic trade-offs between expansion, cannibalization, channel conflict, and coordination.

2.4 STRATEGIES TO MITIGATE PROMOTION-INDUCED CANNIBALIZATION

Promotions, while effective for short-term gains such as attracting customers and boosting sales volume, carry inherent risks, particularly the potential for sales cannibalization which can erode long-term profitability (Hübner, 2016). This challenge is amplified in multichannel environments where promotions in one channel (e.g., offline) might inadvertently draw sales away from another (e.g., online), or lead to forward buying that diminishes future demand (Hübner, 2016). Retailers must carefully balance the immediate advantages of promotional campaigns against the potential for diminishing overall market share and damaging

profitability (Hübner, 2016). Furthermore, poorly managed promotions can exacerbate internal competition between channels, disrupting channel harmony (Kim; Chun, 2018). Therefore, developing mitigation strategies is crucial not only for optimizing the return on promotional investments but also for ensuring sustainable growth and maintaining a cohesive brand presence across all channels (Bielinè, 2021). The objective is to design promotions that stimulate demand effectively while minimizing detrimental side effects such as cannibalization.

2.4.1 Data-driven Approaches To Identifying And Addressing Cannibalization

Effectively mitigating promotion-induced cannibalization hinges on a deep understanding derived from data analysis. Retailers need robust analytical capabilities to dissect sales data, track demand shifts across channels and products during promotional periods, and quantify the extent of cannibalization (Hübner, 2016; Bielinè, 2021). Analyzing transaction records, potentially at the individual customer level, can reveal how different segments respond to various promotional stimuli and which channels are most susceptible to substitution effects (Soysal; Krishnamurthi, 2016; Lim *et al.*, 2022). This granular analysis helps identify the specific mechanisms driving cannibalization (e.g., channel shifting, product substitution, forward buying) induced by different types of promotions.

2.4.2.1 Using Insights From Demand Prediction To Inform Strategies

Demand forecasting plays a critical role in proactively managing promotion effects (Shak, 2024). Accurate forecasts, especially those leveraging advanced techniques, help retailers anticipate how promotions will impact demand across their channel portfolio. ML models, such as Random Forests or GBM, have shown promise in capturing complex, non-linear interactions in retail demand data, potentially outperforming traditional statistical methods (Krishna, 2018; Hübner, 2016). These models can help identify complex patterns, including demand volatility between products and channels during promotions (Krishna, 2018). Insights from such predictive models enable retailers to optimize inventory planning, resource allocation (Shak, 2024), and the design of mitigation strategies, ensuring promotional activities align with broader business objectives and minimize unintended negative consequences. Estimating the cannibalization factor quantitatively through such models is a specific objective that supports strategy development.

2.4.2. Phased Promotions

Implementing promotions sequentially across different channels offers retailers a strategic alternative to launching a promotion simultaneously across all channels, allowing them to roll it out sequentially instead for example, starting with an online-first promotion followed by an in-store version, or vice-versa (Verhoef *et al.*, 2015; Neslin, 2022). Staggering promotion timing to manage demand shifts further refines this approach by carefully timing promotions in different channels to avoid direct overlap and minimize the incentive for customers to switch channels purely based on a temporary offer (Neslin *et al.*, 2006; Kushwaha and Shankar, 2013), which requires understanding the typical purchase cycles and channel preferences of different customer segments (Konus *et al.*, 2008; Verhoef *et al.*, 2007).

2.4.3 Selective Price Cutting

Targeting specific products or channels for price reductions allows retailers, rather than applying discounts broadly, to use data insights to identify which specific products or channels would benefit most from a promotion with the least risk of cannibalizing higher-margin sales elsewhere (Ailawadi and Gupta, 2014; Kushwaha and Shankar, 2013), which might involve promoting products unique to one channel or targeting promotions to channels frequented by more price-sensitive segments (Konus *et al.*, 2008; Verhoef *et al.*, 2007). Using dynamic pricing based on channel and demand, while not explicitly detailed as a promotion mitigation tactic in the provided texts, could enable retailers to adjust promotional offers in real-time based on demand patterns, inventory levels, and competitive actions within specific channels, potentially minimizing cannibalization (Fruchter and Tapiero, 2005; Pereira and Frazzon, 2021).

2.4.4 Tailored Marketing Campaigns

Customizing promotional offers for specific customer segments or channels this is, leveraging customer data allows retailers to tailor promotions to specific segments (e.g., based on past purchase history, channel preference, or demographics) (Li, 2021; Kim; Chun, 2018; Lim *et al.*, 2022). A promotion effective for acquiring new customers via an outlet channel might differ significantly from one aimed at rewarding loyal customers in the main retail channel.

Personalizing promotions based on customer behavior and preferences, going beyond segments, individual personalization can further refine promotional targeting, offering deals most relevant to a specific customer's needs and likely purchase behavior, thus potentially reducing untargeted cannibalization.

Using different messaging and creative across channels, aligning the promotional message and creative execution with the specific characteristics and typical customer mindset associated with each channel can enhance relevance and reduce the perception of channels as purely interchangeable substitutes.

2.4.5 Channel Coordination And Integration

Aligning promotional strategies across all touchpoints, a fundamental requirement is strategic alignment. Promotions should not operate in silos but be part of a coordinated plan that considers the potential impact on all channels (Neslin, 2022; Timoumi *et al.*, 2022).

Ensuring consistent pricing and messaging while promotions might be channel-specific, underlying pricing structures and brand messaging should strive for consistency where appropriate to avoid customer confusion and maintain brand integrity (Homburg *et al.*, 2019; Li, 2021). However, strategic differentiation (e.g., outlet pricing) is also a valid approach (Soysal; Krishnamurthi, 2016).

Improving inventory visibility and fulfillment options (e.g., BOPIS) high levels of operational integration, particularly real-time inventory visibility across channels, are crucial (Hübner *et al.*, 2016; Herhausen *et al.*, 2015; Neslin, 2022). This allows retailers to fulfill demand generated by promotions more effectively, regardless of the channel where the promotion is active. Flexible fulfillment options such as BOPIS enable customers interacting with an online promotion to potentially complete the transaction offline, bridging channels (Gallino; Moreno, 2014; Akturk *et al.*, 2018).

2.4.6 Optimizing Promotion Timing And Frequency

Analyzing the optimal duration and spacing of promotions data analysis can help determine the most effective length for a promotion (long enough to generate impact but short enough to limit excessive stockpiling) and the optimal time gap between promotions to allow demand to recover.

Considering seasonal demand shifts promotional timing should align with natural seasonal peaks and troughs in demand for relevant product categories to maximize uplift and relevance.

2.4.7 Managing Product Assortment Across Channels

Offering differentiated product selections by channel serves as a key strategy to reduce direct substitution by differentiating the assortment offered in each channel (Ma, 2016; Li, 2021), where outlets might offer made-for-outlet versions (Soysal; Krishnamurthi, 2016) while online channels might feature a broader "long tail" selection (Ma, 2016). Using exclusive products or collections for specific channels further enhances this by offering channel-exclusive products or limited-time collections that can drive traffic to a specific channel and provide a reason for purchase beyond a simple price discount, thereby mitigating cannibalization of standard merchandise sold elsewhere.

2.4.8 Analyzing And Acting On Cannibalization Factors

Mitigation is an ongoing process. Retailers must continually monitor and analyze the key factors identified as moderators of channel interaction (already detailed in section 2.1.5), such as specific product attributes (Gong *et al.*, 2022; Li, 2021), evolving customer preferences and heterogeneity (Kim; Chun, 2018; Lim *et al.*, 2022), and changing market or competitive dynamics (Van Crombrugge *et al.*, 2024; Lim *et al.*, 2022). Understanding how these factors influence the outcome of promotions allows for dynamic adjustment of mitigation strategies.

2.5 MACHINE LEARNING IN DEMAND FORECASTING

The Importance of Accurate Demand Forecasting in Retail lies in its role as a cornerstone of effective retail operations and strategic planning (Martins and Galeale, 2022), serving as a critical input for numerous decisions across the value chain that significantly impact a retailer's ability to compete and maintain profitability in an increasingly dynamic market (Mitra *et al.*, 2022). In terms of its role in inventory planning and resource allocation, precise forecasts are fundamental for optimizing inventory levels, ensuring that retailers can meet customer demand without incurring excessive holding costs associated with overstocking or losing sales due to stockouts (Joseph *et al.*, 2022; Raizada and Saini, 2021; Priyadarshi *et al.*, 2019), while accurate predictions enable better resource allocation, including workforce scheduling, logistics planning,

and financial management (Krishna *et al.*, 2018; Xie and Zhang, 2021). Inaccurate forecasts, conversely, can lead to significant inefficiencies, such as stock shortages, delivery delays, increased warehousing costs, and ultimately, reduced profitability (Martins and Galegale, 2022; Joseph *et al.*, 2022), and for perishable goods such as fresh vegetables, forecasting is even more critical to minimize spoilage and waste (Priyadarshi *et al.*, 2019).

Significance during promotional periods highlights how demand patterns often exhibit significant volatility during promotional events, holidays, or seasonal peaks (Shak *et al.*, 2024; Priyadarshi *et al.*, 2019; Raizada and Saini, 2021), where effective forecasting models must be capable of anticipating these fluctuations to ensure product availability and capitalize on increased demand while also managing the potential for cannibalization across products or channels (Fildes *et al.*, 2019 cited in Martins and Galegale, 2022; Wang *et al.*, 2024), with accurate forecasting during these periods supporting better marketing campaign planning and evaluation (Krishna *et al.*, 2018). Supporting data-driven decision making, in essence, demand forecasting transforms historical data and market intelligence into actionable insights, enabling retailers to make informed, data-driven decisions rather than relying solely on intuition or past experience (Martins and Galegale, 2022; Joseph *et al.*, 2022; Mitra *et al.*, 2022), a capability that is vital for strategic planning, maintaining competitiveness, and enhancing customer satisfaction through reliable product availability (Krishna *et al.*, 2018; Mitra *et al.*, 2022; Shak *et al.*, 2024).

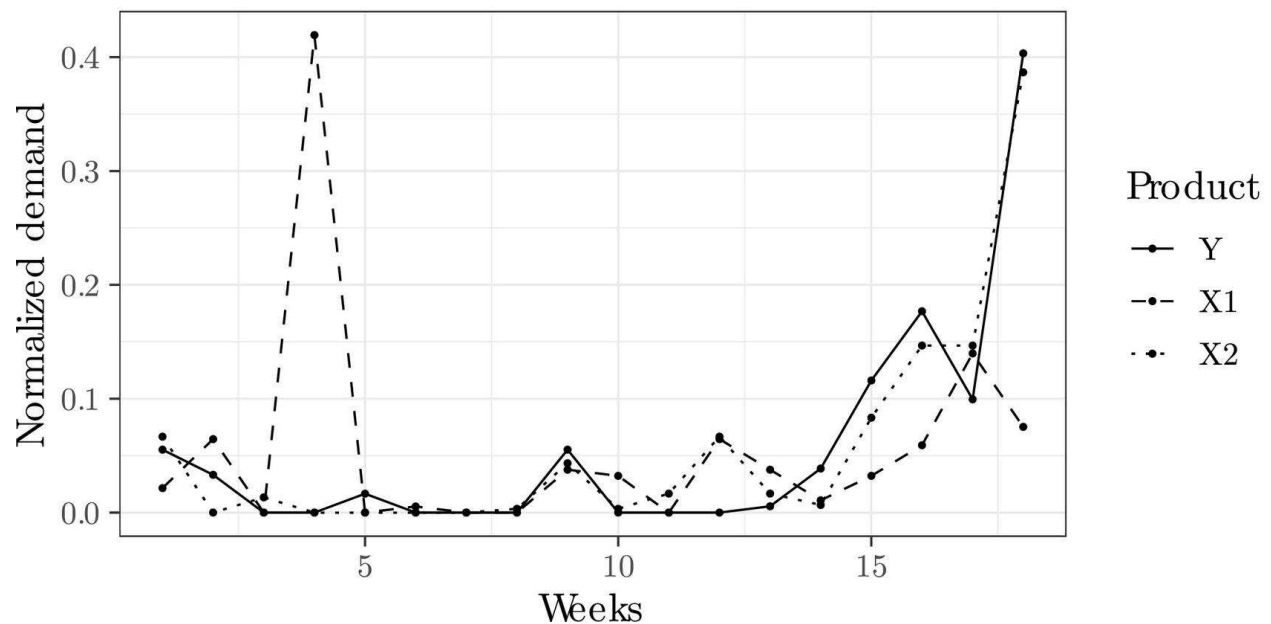
2.5.1 Traditional Demand Forecasting Methods

An overview of statistical approaches, such as linear regression and ARIMA, shows that historically, retailers have relied on traditional statistical methods for demand forecasting, with time series models like ARIMA, Seasonal ARIMA (SARIMA), and Exponential Smoothing methods (e.g., Holt-Winters) being widely employed to extrapolate future demand based on past sales patterns (Martins and Galegale, 2022; Krishna *et al.*, 2018; Shak *et al.*, 2024; Priyadarshi *et al.*, 2019), as these methods primarily focus on identifying trends, seasonality, and autocorrelation within the historical sales data (Martins and Galegale, 2022). Regression techniques, particularly multiple linear regression, have also been used to attempt establishing relationships between sales and various predictor variables (Krishna *et al.*, 2018; Raizada and Saini, 2021; Shak *et al.*, 2024).

Limitations of traditional methods in capturing complex retail dynamics stem from how, while straightforward and effective in stable market conditions (Martins and Galegale, 2022), these methods often struggle to capture the inherent complexity and non-linearity of retail demand (Shak *et al.*, 2024; Martins and Galegale, 2022), as they often assume linear relationships and may fail to accurately model the impact of interacting factors such as promotions, holidays, changing consumer preferences, competitor actions, and external variables like weather or economic indicators (Shak *et al.*, 2024; Fildes *et al.*, 2019 cited in Martins and Galegale, 2022; Raizada and Saini, 2021). Their reliance purely on historical time series data can further limit their ability to adapt to sudden market shifts or incorporate diverse data sources (Martins and Galegale, 2022; Joseph *et al.*, 2022).

To illustrate these challenges, Figure 1 from van Steenberg and Wouters (2020) presents normalized demand patterns over 18 weeks for three sample products. The Graphic reveals significant variability and non-linear trends, which can be challenging for conventional models to predict accurately, particularly when influenced by external factors such as promotions or seasonal effects. This visual example highlights the limitations of relying solely on historical time series data and underscores the need for more sophisticated forecasting approaches that can incorporate diverse data sources and adapt to dynamic market conditions.

Figure 1 - Normalized demand patterns over 18 weeks for three sample products



Source: van Steenberg; Wouters, 2020

2.5.2 Introduction To Machine Learning In Retail Forecasting

The limitations of traditional methods, coupled with the increasing availability of large, diverse datasets (Big Data) and computational power, have paved the way for the adoption of ML techniques in demand forecasting (Martins and Galegale, 2022; Shak *et al.*, 2024; Mitra *et al.*, 2022). ML offers a more flexible and powerful approach to uncovering patterns and making predictions from complex data (Martins and Galegale, 2022; Mitra *et al.*, 2022).

ML algorithms offer significant advantages for modeling complex, non-linear interactions, as they excel at identifying intricate relationships between various demand drivers (e.g., price, promotions, seasonality, external factors) that traditional linear models often miss (Martins and Galegale, 2022; Shak *et al.*, 2024; Mitra *et al.*, 2022; Raizada and Saini, 2021). Techniques such as decision trees, ensemble methods, and neural networks can automatically learn complex patterns from data without restrictive assumptions about linearity or data distribution (Martins and Galegale, 2022; Joseph *et al.*, 2022). Furthermore, ML is particularly well-suited for handling the large and dynamic datasets generated by retail, which include vast amounts of data from sources like POS transactions, online behavior, loyalty programs, and external feeds (Martins and Galegale, 2022). ML techniques, especially those within the Big Data Analytics (BDA) paradigm, are designed to handle these large-scale, high-dimensional datasets efficiently. They can process diverse data types and adapt to the dynamic nature of retail environments (Shak *et al.*, 2024; Raizada and Saini, 2021), allowing retailers to leverage richer information for more accurate forecasting (Martins and Galegale, 2022; Mitra *et al.*, 2022). Consequently, comparative studies often show ML models outperforming traditional methods in retail forecasting tasks (Mitra *et al.*, 2022; Joseph *et al.*, 2022; Shak *et al.*, 2024; Priyadarshi *et al.*, 2019).

2.5.3 Review Of Relevant Machine Learning Techniques For Demand Forecasting

A variety of ML techniques have been applied to retail demand forecasting, each with specific strengths and weaknesses.

Ensemble methods, particularly tree-based ensembles such as Random Forest (RF) and Gradient Boosting (including implementations such as XGBoost), are frequently employed and often yield strong results in retail forecasting (Mitra *et al.*, 2022; Priyadarshi *et al.*, 2019; Shak *et*

al., 2024; Xie and Zhang, 2021; Raizada and Saini, 2021). RF operates by constructing a multitude of decision trees during training on different bootstrap samples of the data and outputting the average prediction of the individual trees (Krishna *et al.*, 2018; Raizada and Saini, 2021; Mitra *et al.*, 2022). This bagging approach significantly reduces variance and helps prevent overfitting compared to single decision trees (Mitra *et al.*, 2022; Shak *et al.*, 2024). RF models are robust, handle high-dimensional data well, capture non-linear relationships, and can provide measures of feature importance (Raizada and Saini, 2021; Shak *et al.*, 2024). They have been successfully applied to forecast sales in various retail contexts (Raizada and Saini, 2021; Mitra *et al.*, 2022; Shak *et al.*, 2024) and for specific products such as vegetables (Priyadarshi *et al.*, 2019). While effective, RF might learn adaptively less efficiently than boosting methods (Mitra *et al.*, 2022). In contrast, Gradient Boosting methods (GBM/GBR/XGBoost) also build an ensemble of decision trees, but they do so sequentially (Mitra *et al.*, 2022; Shak *et al.*, 2024). Each new tree attempts to correct the errors made by the previous ensemble, iteratively improving prediction accuracy (Krishna *et al.*, 2018; Shak *et al.*, 2024). XGBoost (eXtreme Gradient Boosting) is a highly optimized and scalable implementation incorporating regularization techniques to prevent overfitting, supporting parallel processing, and efficiently handling missing data (Xie and Zhang, 2021; Mitra *et al.*, 2022; Wang *et al.*, 2024). GB and XGBoost often achieve state-of-the-art results in forecasting competitions and retail applications (Krishna *et al.*, 2018; Mitra *et al.*, 2022; Priyadarshi *et al.*, 2019; Xie and Zhang, 2021; Shak *et al.*, 2024; Wang *et al.*, 2024), demonstrating high accuracy in capturing complex interactions and patterns (Shak *et al.*, 2024; Mitra *et al.*, 2022). A key limitation is their potential sensitivity to noise and risk of overfitting if not carefully tuned (Mitra *et al.*, 2022). A significant advantage of both RF and GB is their inherent adeptness at capturing complex, non-linear interactions between features (Mitra *et al.*, 2022; Shak *et al.*, 2024). By analyzing feature importance scores and partial dependence plots, analysts can gain insights into how factors such as promotions, price changes, and seasonality jointly influence demand, which is crucial for understanding volatility and potential cannibalization effects.

Beyond the primary methods, other potential techniques show significant promise, particularly deep learning models. Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are especially suited for time-series forecasting due to their ability to capture long-range temporal dependencies (Joseph *et al.*, 2022;

Priyadarshi *et al.*, 2019; Shak *et al.*, 2024; Wang *et al.*, 2024). LSTMs, in particular, mitigate the vanishing gradient problem of simple RNNs, allowing them to model patterns over extended periods (Joseph *et al.*, 2022; Shak *et al.*, 2024). Convolutional Neural Networks (CNNs) are also often used, sometimes in hybrid architectures with LSTMs (e.g., CNN-LSTM), to extract relevant local features from the time series data before the recurrent layers (Joseph *et al.*, 2022). Furthermore, hybrid models combining different ML or statistical techniques, such as RF-XGBoost-LR or ARIMA-ANN, are explored to leverage the strengths of individual components (Mitra *et al.*, 2022; Chen and Lu, 2017; Priyadarshi *et al.*, 2019; Joseph *et al.*, 2022). The proliferation of these advanced methods has led to numerous comparative studies, which explicitly evaluate different ML techniques against each other and traditional benchmarks. These comparisons range from various supervised regressors (Raizada and Saini, 2021) and boosting versus regression (Krishna *et al.*, 2018) to ML versus deep learning models (Joseph *et al.*, 2022; Shak *et al.*, 2024). A common finding is that ensemble and deep learning methods often outperform simpler ML and traditional techniques, although the best model remains context-dependent (Martins and Galegale, 2022; Priyadarshi *et al.*, 2019). The specific applications of these models in retail are diverse, covering forecasting for general retail chains (Mitra *et al.*, 2022; Shak *et al.*, 2024), as well as for specific product types like computers (Chen and Lu, 2017), apparel (Cheriyana *et al.*, 2018), and vegetables (Priyadarshi *et al.*, 2019). These models incorporate a wide array of factors, including historical sales, promotions, holidays, seasonality, price, store characteristics, and external data such as weather, CPI, and fuel prices (Mitra *et al.*, 2022; Raizada and Saini, 2021; Shak *et al.*, 2024; Xie and Zhang, 2021; Wang *et al.*, 2024).

2.5.4 Applying Machine Learning To Identify Cannibalization Patterns

While the primary focus of the provided literature is on improving the accuracy of demand forecasting, the underlying ML models and techniques possess capabilities that can be leveraged to understand phenomena such as cannibalization, even if not very explored in papers.

Using ML models to analyze demand shifts ML models, particularly interpretable ones such as tree ensembles (RF, GB, XGBoost), can identify complex relationships between input features (e.g., promotion activation on product A, price of product B, channel usage) and the output (sales of product A or B). By analyzing feature importance and interaction effects (e.g.,

using SHAP values or partial dependence plots), analysts could potentially infer how promotional activities for one product or channel impact the demand for others, thus shedding light on cannibalization dynamics (Shak *et al.*, 2024; Mitra *et al.*, 2022). Datasets used in forecasting often include promotional flags and calendar events, providing the necessary inputs for such analysis (Shak *et al.*, 2024; Raizada and Saini, 2021).

Estimating cannibalization factors while none of the provided forecasting papers directly estimate a 'cannibalization factor', the outputs of ML models could potentially serve as inputs for subsequent analysis. For instance, accurate forecasts of what sales would have been without a promotion (generated by an ML model trained on historical data excluding the promotion effect) could be compared to actual sales during the promotion to isolate the promotion's impact, including potential shifts from other products. This requires careful model design and interpretation beyond standard forecasting applications.

Gaining actionable insights, by understanding which promotions or channel activities lead to significant cross-product or inter-channel demand shifts (potential cannibalization), retailers can refine their strategies. ML model insights (such as feature importance) could highlight which product combinations are most prone to cannibalization or which promotional types trigger unwanted substitution effects, enabling more targeted and profitable marketing actions (Krishna *et al.*, 2018).

2.5.5 Model Evaluation And Performance Metrics In Demand Forecasting

Evaluating the performance of forecasting models is crucial to selecting the most appropriate technique and understanding its reliability. Several standard metrics are consistently used across the literature to assess forecasting accuracy. These include the Mean Absolute Error (MAE), which measures the average absolute difference between predicted and actual values (Mitra *et al.*, 2022; Priyadarshi *et al.*, 2019; Joseph *et al.*, 2022; Shak *et al.*, 2024; Wang *et al.*, 2024). Another common metric is the Mean Squared Error (MSE), which calculates the average of the squared differences, thus penalizing larger errors more heavily (Mitra *et al.*, 2022; Priyadarshi *et al.*, 2019; Joseph *et al.*, 2022; Shak *et al.*, 2024; Wang *et al.*, 2024). Closely related is the Root Mean Squared Error (RMSE), which is the square root of MSE, a step that brings the metric back to the original units of the forecast (Krishna *et al.*, 2018; Priyadarshi *et al.*, 2019; Shak *et al.*, 2024; Raizada and Saini, 2021; Wang *et al.*, 2024). For comparisons across

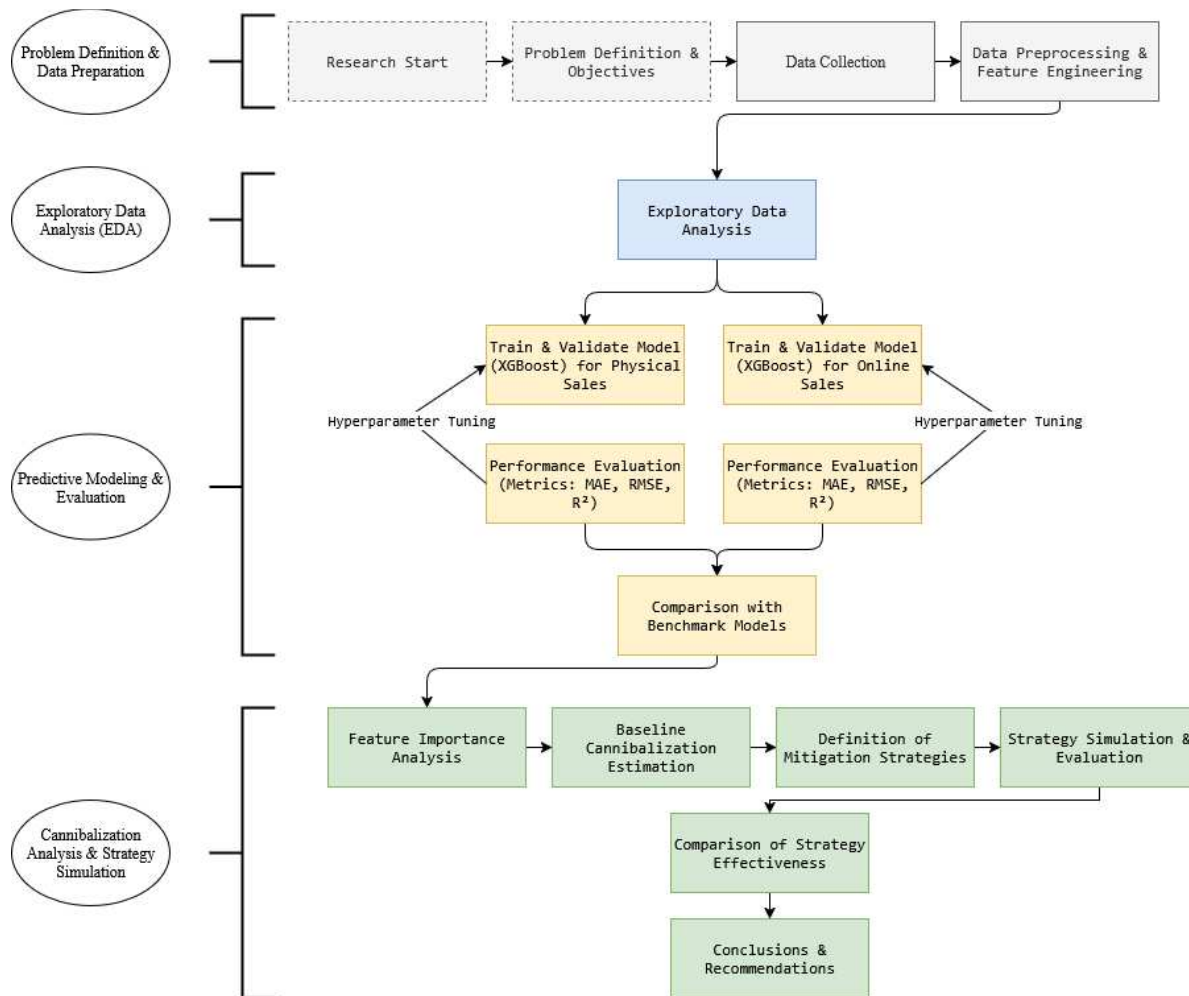
datasets with different scales, the Mean Absolute Percentage Error (MAPE) is useful, as it expresses the average absolute error as a percentage of actual values (Priyadarshi *et al.*, 2019; Chen and Lu, 2017; Joseph *et al.*, 2022). A similar percentage-based metric is the Root Mean Square Percentage Error (RMSPE) (Chen and Lu, 2017). Furthermore, R-squared (R^2) indicates the proportion of the variance in the dependent variable that is predictable from the independent variables, where higher values suggest a better fit (Mitra *et al.*, 2022; Joseph *et al.*, 2022; Shak *et al.*, 2024). For a scale-independent evaluation, the Mean Absolute Scaled Error (MASE) is employed, which compares the forecast error to the error of a naïve baseline forecast (Wang *et al.*, 2024). Finally, the Root Mean Squared Scaled Error (RMSSE) is a variant of MASE that utilizes squared errors (Xie and Zhang, 2021).

Assessing the effectiveness of ML models in capturing cannibalization effects, while these metrics primarily measure overall forecast accuracy, a model that effectively captures complex interactions and responses to events such as promotions (often indicated by lower MAE/RMSE/MAPE and higher R^2 compared to simpler models) is implicitly better at representing the underlying dynamics that lead to cannibalization (Mitra *et al.*, 2022; Shak *et al.*, 2024). A model with high accuracy during promotional periods, for example, is likely capturing the demand shifts (including potential cannibalization) better than a model with poor accuracy during those same periods. However, specific metrics designed solely to quantify the accuracy of predicting the cannibalization component itself are not typically reported in standard forecasting evaluations. Assessing this would require comparing predicted cross-product effects against actual observed shifts, a more specialized form of analysis.

3 METHODOLOGY

This Chapter delineates the methodological framework employed to investigate promotional cannibalization and demand forecasting in multichannel retail. The structure of this quantitative, data-driven approach is systematically presented in the flowchart in Figure 2.

Figure 2 - Methodological framework flowchart



Source: Elaborated by the author

The methodology is systematically organized into four primary stages. The process begins with problem definition and data preparation, which encompasses the project's conception, data collection, and the subsequent steps of preprocessing and feature engineering. This initial phase is followed by the Exploratory Data Analysis (EDA), which is focused on uncovering patterns, identifying anomalies, and deriving initial insights from the lately prepared

data. Next comes the predictive modeling and evaluation stage, involving the development of separate XGBoost ML models specifically designed to forecast both physical and online sales, which includes rigorous hyperparameter tuning and performance evaluation. The process concludes with the cannibalization analysis and strategy simulation. Here, the established predictive models are leveraged to perform exploratory data analysis, including: (i) feature importance by channel, (ii) joint impact of price and promotion, (iii) trend and seasonality in sales channels, (iv) sales composition over time, (v) autocorrelation of sales series, (vi) promotion type and its effect on physical sales, (vii) feature correlation network, and (viii) sales timeline with event impact.

Post-modeling evaluation is then conducted through model performance analysis, including XGBoost predictions versus actual temporal alignment, XGBoost regression fit via actual versus predicted scatter plots, histogram of residuals for XGBoost model distribution, residuals over time for XGBoost forecast stability, and comparison between models.

This is followed by cannibalization analysis, encompassing the cannibalization effect between sales channels, importance of variables for physical and online sales, baseline cannibalization estimation, and definition of mitigation strategies.

Finally, strategy simulation and evaluation are carried out, including a comparison of strategy effectiveness, with a discussion of the findings and their implications for academia and practice.

Each of these stages, along with its constituent steps as illustrated in Figure 2, will be detailed in the subsequent subsections to ensure a transparent and reproducible account of the research process.

3.1 PROBLEM DEFINITION AND DATA PREPARATION

This section outlines the study's methodology, covering research design, data sourcing from a Florianópolis retailer, variable selection, preprocessing, XGBoost-based demand forecasting and cannibalization quantification across channels, model evaluation, software tools, limitations, and iterative modeling process.

3.1.1 Research Design And Approach

This study adopts a quantitative research design, blending descriptive and explanatory methods to assess promotional strategies' impact on sales cannibalization between physical and online retail channels. It uses predictive modeling to reveal pricing patterns, aiding retailers in optimizing promotions, minimizing inter-channel losses, and boosting multichannel performance.

Central to the design is machine learning analysis of secondary historical sales data from a leading grocery retailer in Florianópolis, Brazil. XGBoost is the core algorithm, selected for its efficiency with large datasets, anti-overfitting features, and strong regression capabilities in forecasting cannibalization.

The process starts with data preprocessing and feature engineering, incorporating variables like discounts, pricing, seasons, and demographics. XGBoost trains on multi-year time-series data via cross-validation and hyperparameter tuning (e.g., learning rate, tree depth).

3.1.2 Data Source And Characterization

The data for this study was sourced from a regional retail company of medium to large size operating in the region of southern Brazil in the metropolitan area of Florianópolis. To maintain confidentiality, the company and the specific food items under analysis will be anonymized throughout this study.

The dataset for this analysis is highly focused, comprising comprehensive weekly sales data specifically pertaining to a single, distinct product which is a carbonated soda. This product's sales is tracked across and separated by two sales channels. The first channel is represented by physical stores, which includes the entire volume of aggregated sales recorded from the company's multiple physical retail locations operating within the defined regional market. The second and distinct channel is the online platform, which accounts for all sales that specifically originate from the company's dedicated e-commerce website. Therefore, the dataset provides a clear, week-by-week picture of how the same product performs when sold through a traditional retail setting versus a digital, online environment, making it suitable for channel-specific performance evaluation and comparison within the specified geographic boundaries, allowing for a detailed understanding of consumer preferences across different purchasing environments and over time. The comprehensive nature of this granular data

facilitates an in-depth study of sales dynamics and competitive interactions between the two channels, which is essential for strategic decision-making and resource allocation.

The data represents a period close to one and a half years (77 weeks), from January 1th 2024 to June 16th 2025. This timeframe was chosen to capture potential seasonal variations and a sufficient number of promotional and non-promotional periods for analysis.

3.1.3 Variables of the Study

For the analysis, several variables were extracted or derived from the dataset. The dependent variables include the weekly sales volume for the physical channel, the weekly sales volume for the online channel, the total combined weekly sales volume, and the weekly inventory for both the online and physical channels. The independent variables consist of the average selling price per week for both physical and online channels, along with binary promotion variables for each channel (where 1 indicates an active promotion and 0 indicates otherwise), with the acknowledgment that further categorization may be used if data permits. Additionally, a continuous time variable representing the week number is used to capture trends. To account for external factors, seasonality is included as a control variable. In a standard modeling approach, this will be incorporated by introducing dummy variables for each month or quarter, alternatively, the model can leverage Random Forest's inherent capacity to capture complex, non-linear seasonal patterns, enabling a more accurate and flexible representation of seasonal fluctuations within the data.

3.1.4 Data Preprocessing

The raw data underwent a comprehensive cleaning process, which began with outlier detection and treatment. Statistical methods were employed to detect potential outliers in the sales and price data, and each identified outlier was carefully examined to distinguish between data entry errors and legitimate extreme values. Where errors were found, corrections such as delete empty data were made to ensure data accuracy. For authentic extreme values, the decision to either preserve them or apply transformations was guided by each model's sensitivity and the need to minimize their undue influence on the results. Following the cleaning phase, data transformation and feature engineering were performed. This involved ensuring promotional variables were clearly encoded (e.g., 0 for no promotion, 1 for active promotion), with different

types or intensities handled as categorical variables or separate binary flags that were added in the original dataset. To capture potential lagged effects of promotions or price changes, lag variables such as sales in the previous week were considered as potential features for the demand forecasting model. Furthermore, time-based features were derived from the date, such as month, quarter, or week of the year, to help the model capture seasonality and trends. Finally, the data was structured into a weekly time-series format suitable for input into the ML models.

3.1.5 Modeling Techniques and Analysis

To address the research objectives, particularly the prediction of demand and the identification of cannibalization patterns, ML techniques were employed.

3.1.5.1 Demand forecasting model

The primary technique chosen for demand forecasting is the XGBoost algorithm. XGBoost is an advanced and efficient implementation of gradient boosting, an ensemble learning method (Mitra *et al.*, 2022). It builds models in a stage-wise fashion, such as other boosting methods, but it generalizes them by allowing optimization of an arbitrary differentiable loss function (Bekal; Bari, 2021). Each new model (typically a decision tree) is trained to correct the errors made by the previous ensemble of models.

The rationale for choosing XGBoost stems from its high predictive accuracy in making predictions for many regression and classification problems, where it performs better than other algorithms, along with its use of L1 (Lasso regression) and L2 (Ridge regression) regularization techniques, which help prevent overfitting in the case of complex datasets. It also features a built-in routine to treat missing values when training, is optimized for scalability and speed to work with large datasets through parallel processing and distributed computing and offers strong interpretability on feature importance to understand the main elements of demand. Furthermore, XGBoost provides plenty of hyperparameters to tweak for fine control of the model-building process in order to maximize performance, and it handles complex, non-linear and interaction effects among the predictor variables.

Two stand-alone XGBoost models were created to forecast the weekly sales for physical and online channels. The data were partitioned into training (e.g., the first 70-80% of the trial data) and test (e.g., the remaining 20-30% of the data) datasets to allow training of the models

and unbiased evaluation on unseen data, respectively. The hyperparameters for the XGBoost models (i.e., learning rate, number of estimators, tree depth, subsample ratio, regularization parameters) were tuned by grid search or randomized search with cross-validation on training set for model performance.

3.1.5.2 Identification of cannibalization patterns

Cannibalization patterns were investigated through several analytical steps, beginning with descriptive analysis that involved examining sales trends in one channel when a promotion is active in the other channel, compared to periods with no promotions or own-channel promotions. This was followed by assessing feature importance from XGBoost, where the trained models provide importance scores such as gain, weight, and cover, and the significance of a channel promotional variable for example, “Promotion in Online Channel” when predicting “Sales in Physical Channel” can indicate its influence and potentially highlight a cannibalization effect. Finally, Partial Dependence Plots (PDPs) or SHAP (SHapley Additive exPlanations) values from the XGBoost models were used to visualize and understand the marginal effect or contribution of a specific promotion, such as an online promotion, on the sales of the other channel, like physical store sales, while holding other variables constant or considering their overall impact, with a negative relationship or negative SHAP values suggesting cannibalization.

3.1.5.3 Estimation of cannibalization effect/factor

To quantify the cannibalization effect, a simulation-based approach using the trained demand forecasting models was employed as illustrated in Table 3

Table 3 — Demand Forecasting Approach to Measure Sales Cannibalization

Step	Description
1. Baseline Scenario Prediction	For each week a promotion was active in Channel A (e.g., online), the model for Channel B (e.g., physical stores) was used to predict sales in Channel B as if the promotion in Channel A was not active (i.e., setting the promotional flag for Channel A to 0). This provides a baseline sales forecast for Channel B in the absence of Channel A’s promotion.

2. Actual/Promotional Scenario Prediction	The actual sales data for Channel B during the promotion in Channel A was recorded. Alternatively, the model for Channel B could predict sales with Channel A's promotion active (which should be close to actual if the model is good).
3.Calculating Cannibalization	The difference between the baseline predicted sales (no cross-promotion) and the actual sales (with cross-promotion) in Channel B represents the estimated impact of Channel A's promotion on Channel B's sales. * $\text{Cannibalization Amount (Units)} = \text{Baseline Predicted Sales_ChannelB} - \text{Actual Sales_ChannelB (during Channel A's promotion)}$ * $\text{Cannibalization Factor (\%)} = (\text{Cannibalization Amount} / \text{Baseline Predicted Sales_ChannelB}) * 100$

Source: Elaborated by the author

This factor estimates the percentage change (likely decrease) in sales in one channel attributable to a promotion in the competing channel operated by the same retailer. This analysis was conducted reciprocally for promotions in physical stores affecting online sales, and vice-versa.

3.1.5.4 Model evaluation

The performance of the XGBoost demand forecasting models was evaluated using standard regression metrics on the testing dataset, including MAE, which measures the average magnitude of the errors in a set of predictions without considering their direction, MSE, which measures the average of the squares of the errors and penalizes larger errors more than MAE, RMSE, the square root of the MSE that provides an error metric in the same units as the target variable, and R^2 , which represents the proportion of the variance in the dependent variable that is predictable from the independent variables, with values ranging from 0 to 1 and higher values indicating better fit.

3.1.6 Software Utilized

The data preprocessing, analysis, and modeling tasks described in this chapter were performed using Python (version 3.13.6), leveraging libraries such as pandas for data manipulation, numpy for numerical computations, matplotlib.pyplot and seaborn for visualization, sklearn.model_selection and sklearn.metrics for model evaluation, xgboost,

catboost, and lightgbm for gradient boosting, sklearn.neural_network and sklearn.linear_model for machine learning algorithms, statsmodels.tsa.seasonal for time series decomposition, mpl_toolkits.mplot3d for 3D plotting, pandas.plotting for advanced data visuals, networkx for graph analysis, scipy.stats for statistical functions, datetime for date handling, and warnings for error suppression.

3.1.7 Limitations of the Procedure

The methodological approach adopted in this study has certain limitations that should be acknowledged, particularly regarding generalizability, where the results are limited to one regional retail company and one product, thus restricting the detailed dissemination of quantitative results such as the exact cannibalization factor for applicability to other companies, products, or larger markets, though the general points and methodological framework can still be applied elsewhere. The period of data also poses constraints, as the study includes only one year of weekly data, which accounts for seasonality but does not capture longer-term trends or less frequent significant events. Exogenous variables represent another area of limitation, with the study considering price, promotion, and seasonality as the primary drivers, while other external conditions that may affect sales and cannibalization such as specific marketing or advertising campaigns beyond generic offer-generating activities, competitors' pricing and promotions, macroeconomic conditions, or major local events were not explicitly incorporated into the models due to the lack of appropriate data.

Model specificity further highlights that a highly dense model like Random Forest is not the only machine learning option available, as other models could yield different insights or predictive accuracies, and while Random Forests are more interpretable than some other “black boxes,” they can still be difficult to understand amid more sophisticated interactions. The definition of promotion adds to these challenges, as the binary or categorical representation simplifies the true diversity and impact of different promotional mechanics for instance, a 10% discount versus a BOGO offer with the granularity of available promotional data influencing the depth of this analysis. Finally, on causality, while the models can identify strong correlations and predictive relationships, establishing definitive causality such as that a promotion caused a specific drop in sales in another channel from observational data requires careful interpretation and acknowledgment of potential confounding factors.

Despite these limitations, the chosen procedure provides a robust framework for empirically investigating the impact of promotions on sales cannibalization within the defined scope of the study.

3.1.8 Machine Learning Modeling Process

The ML implementation followed a structured workflow aligned with established methodological frameworks in retail analytics (Wang and Li, 2024; Sellitto and Pereira, 2019). This approach comprised five interdependent phases.

The problem formulation phase explicitly defined the project's dual modeling objectives. the first, and primary, objective was to achieve multichannel demand forecasting, specifically for both physical and online sales volumes of the product. the second critical objective was the precise quantification of channel cannibalization effects that occur specifically during defined promotional events. this foundational phase was essential not only for establishing these clear objectives but also for setting the relevant evaluation metrics and subsequently guiding all the downstream methodological choices, ensuring that the entire analytical approach was directly aligned with these core strategic goals.

The foundation of this study was a comprehensive data acquisition and preprocessing phase, utilizing a historical dataset of 77 weeks of granular, weekly data sourced from a prominent retailer in the Florianópolis region. This rich dataset encapsulated critical business operations, including detailed sales volume and inventory levels for each distinct channel, alongside complex pricing dynamics and specific promotional indicators. To account for predictable market fluctuations, the data was further enriched with seasonality coefficients and markers for special events. To ensure the robustness and reliability of the model inputs, a rigorous data integrity protocol was established, which involved the treatment of outliers through interquartile range analysis and the application of mean imputation to address any missing values, thereby creating a complete and clean dataset for analysis.

Following the preprocessing stage, the focus shifted to sophisticated feature engineering, where predictive variables were meticulously crafted to capture the intricate dynamics of channel interaction. A key innovation was the creation of a cannibalization effect estimator, a derived variable specifically designed to quantify the degree to which sales in one channel displace sales in another. To incorporate the temporal nature of the data, the feature set was expanded to

include lagged sales variables from previous weeks (t-1, t-2) and decomposed seasonality components. Additionally, to model the combined effects of marketing efforts, promotional cross-impact variables were engineered as interaction terms between the physical and online promotion flags.

For the model development and training process, a comparative implementation of several powerful ensemble algorithms was conducted to identify the most effective solution. The primary model selected was XGBoost, chosen for its superior ability to handle and learn from complex, non-linear interactions within the data. To ensure a thorough evaluation, its performance was benchmarked against other leading algorithms, including CatBoost, LightGBM, ElasticNet, and Bayesian Ridge. To fine-tune the models and prevent overfitting, an extensive hyperparameter optimization was performed using a grid search methodology coupled with a 5-fold time-series cross-validation, a technique crucial for maintaining the temporal integrity of the data. Finally, the model’s predictive performance was rigorously validated on a temporal holdout dataset, using a suite of metrics specifically chosen to address the project’s dual objectives, as detailed in Table 4, allowing for an iterative refinement of the final solution.

Table 4 — Metrics and objectives

Metric	Forecasting Focus	Cannibalization Insight
MAE	Absolute sales error	-
R ²	Model fit quality	-
Cannibalization Factor	-	channel impact

Source: Elaborated by the author

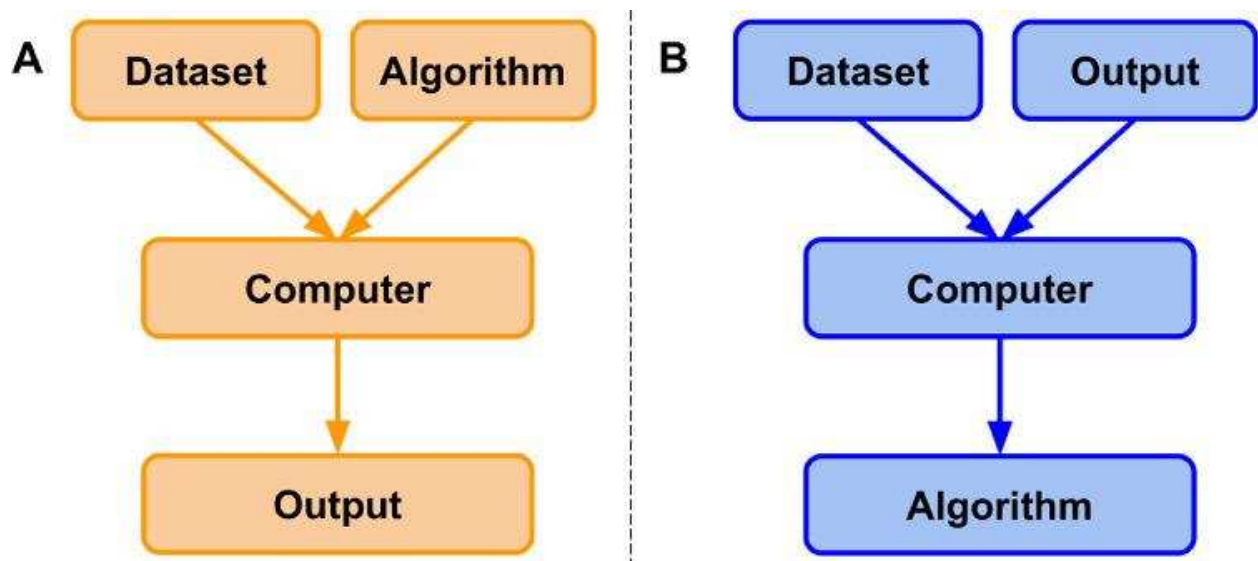
An iterative refinement loop enabled feature recalibration and hyperparameter adjustment until metric stability was achieved. This phased approach ensured methodological rigor while addressing retail-specific complexities, particularly in capturing omnichannel promotional

dynamics. The continuous feedback mechanism between phases maintained alignment with the core research objectives throughout model development.

3.1.8.1 Variables Assessment

The accuracy of ML predictions heavily depends on the quality of the training database. Supervised learning relies on labeled data, known as "ground truth," to build a classifier capable of predicting outcomes for similar unseen entities. Consequently, flawed data or labeling can lead to unreliable results, a critical concern in ML (Geiger *et al.*, 2021). As illustrated in Figure 3, the input data plays a pivotal role in deriving the decision rules that guide future predictions.

Figure 3 - Machine learning and classical programming



Source: (Choi , 2020)

In addition to data quality, another crucial factor is proper dataset processing. Before being fed into neural networks, the data should be normalized, as the presence of outliers or missing values can significantly degrade the model's predictive performance.

3.1.8.2 Data Collection

Collecting data is a crucial first step to any empirical research project, a systematic way of obtaining information to support analysis and other processing. Data was obtained from a well-known retail company, that enabled to evaluate the effect of promotions on sales and

inventory over several channels, by managing a high-quality and trustworthy dataset. The data was provided as a Microsoft Excel file, with weekly sales for a year. This dataset contains relevant features such as the date at which the promotion was given, the duration of the promotion (or number of weeks between the overall start and end of the placement of the promotion in a given sales channel such as store or on-line), the sales channels to which the promotions are granted and the inventory which each product has in each channel. These factors are indispensable in the analysis of the impact of promotions on sales dynamics and inventory policies.

The richness of the database, in addition to the company's prominence in the retail field, allow the results to be seen as both credible and useful, which enables the level of empirical scrutiny necessary for examining the promotional effects in an actual retail environment.

4 MODELING AND STRATEGY SIMULATION

This chapter details the development and application of a data-driven framework to model sales performance and simulate strategic interventions. The process begins with a thorough EDA to uncover underlying patterns and relationships within the sales data. Following this, multiple machine learning models are built and evaluated to select the most accurate predictive tool. This selected model is then used to quantify the baseline sales cannibalization between the physical and online channels. Finally, several mitigation strategies are designed, simulated, and compared to identify the optimal approach for maximizing total sales while minimizing channel conflict.

4.1 EXPLORATORY DATA ANALYSIS (EDA)

Before initiating the modeling process, an EDA is essential to reveal patterns, relationships, and anomalies within the dataset. EDA provides critical insights into the underlying behavior of variables and interactions, helping guide model selection, feature engineering, and business interpretation.

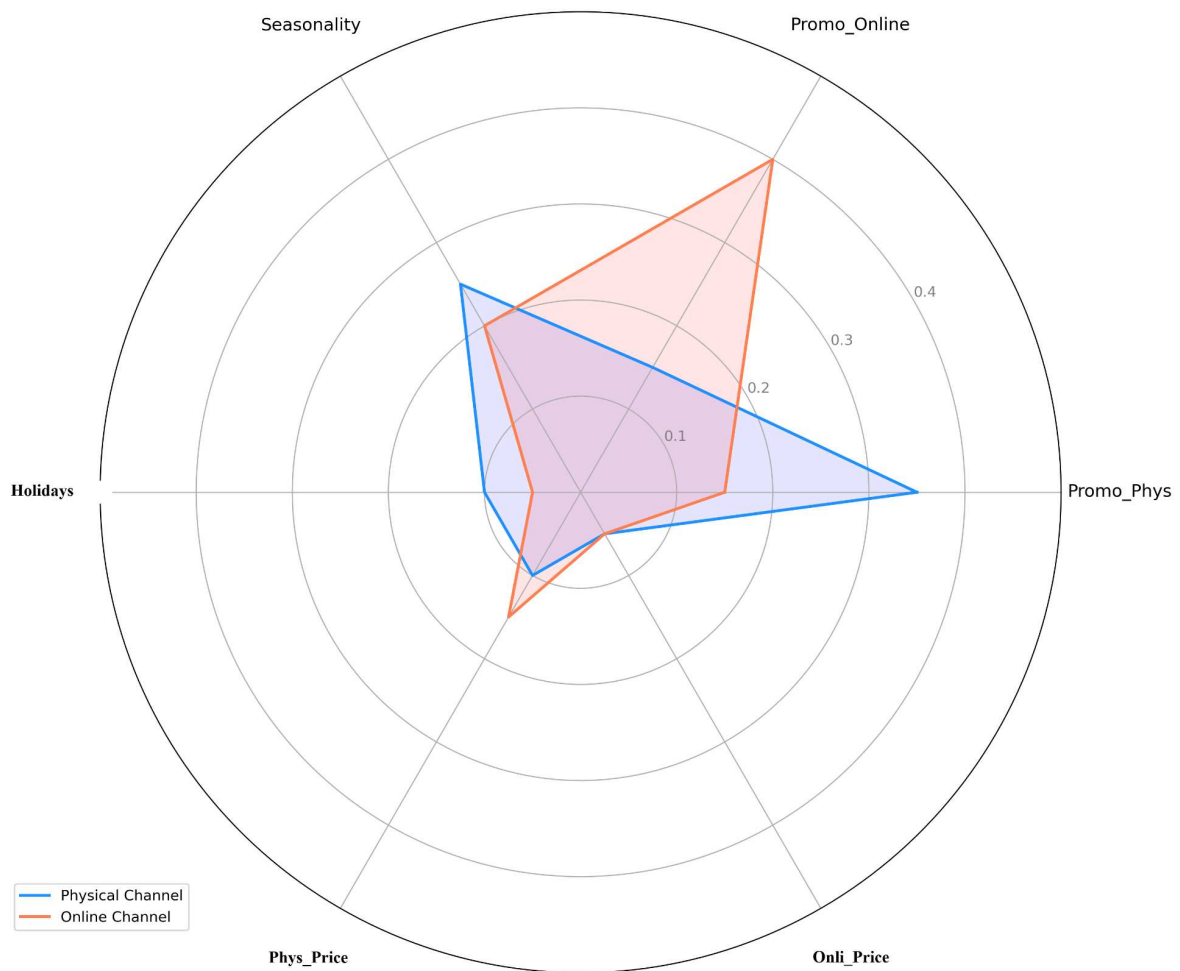
In the context of this study, which investigates the impact of promotional strategies on sales performance in both physical and online retail channels, EDA plays a strategic role. It allows for the preliminary identification of demand determinants and potential signs of channel cannibalization, a central theme of this thesis. Given the dual-channel setup, understanding how consumer behavior responds to variables such as pricing, seasonal trends, and promotional intensity within and across channels is key to building interpretable ML models and effective mitigation strategies.

4.1.1 Feature Importance By Channel

As illustrated in Figure 4, the radar chart compares the relative importance of selected features in predicting sales for both physical and online channels. The feature importances were derived from GBM models trained independently for each channel. These importance scores were assigned based on the model's internal calculation of the total gain attributed to each feature across all decision trees, measuring how much the feature contributes to reducing the loss

function during the boosting process, as commonly applied in gradient boosting frameworks for retail demand forecasting (Bekal; Bari, 2021; Wang *et al.*, 2024).

Figure 4 - Feature importance by channel



Source: Elaborated by the author

The chart highlights several asymmetries, the variable Promo_Phys appears as the most important factor for physical store sales, while it holds minor influence in the online model. This indicates that in-store promotional actions are a primary driver of offline demand.

Conversely, Promo_Online dominates in the online channel, reinforcing that digital

campaigns have a focused and substantial impact on e-commerce sales.

Seasonality contributes significantly to both channels, but slightly more so in physical stores. This suggests that cyclical patterns such as monthly pay cycles or holiday effects are more predictable in physical environments.

Physical Price is somewhat more important than Online Price, reflecting that price perception may be more salient in in-store purchases, where comparison is immediate and physical.

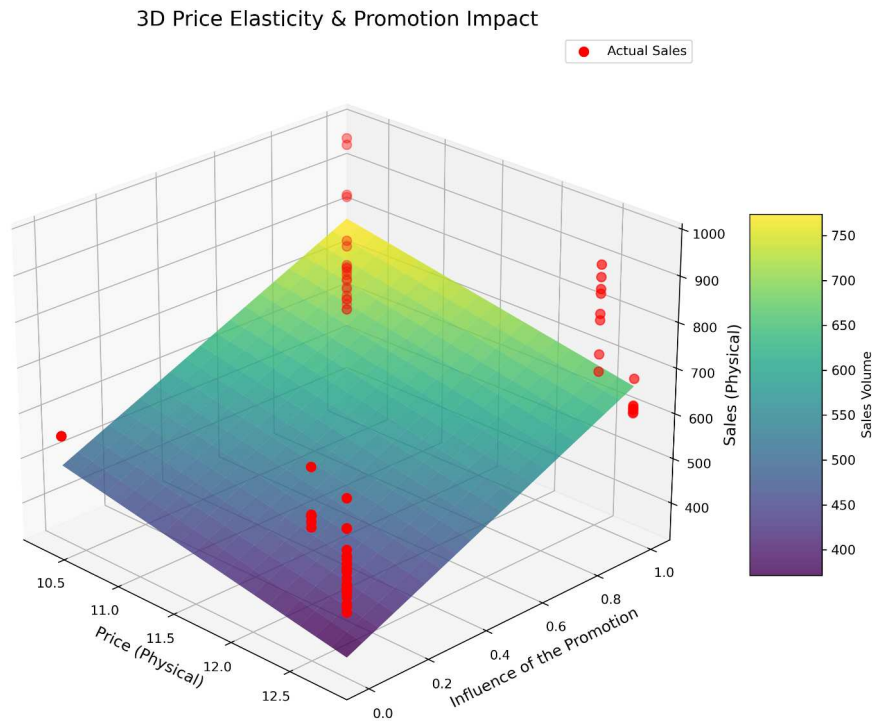
The variable Holidays shows limited but noticeable relevance in physical sales, possibly due to offline events such as anniversaries or local campaigns.

These results support the decision to model each channel independently and offer evidence that promotional strategies must be channel-specific to avoid unnecessary overlap or conflict.

4.1.2 Joint Impact of Price and Promotion

To visualize the combined effect of pricing and promotional effort on demand, we first analyze the interaction between these key variables. Figure 5 presents a 3D surface plot demonstrating how the interaction between physical store pricing and promotion intensity influences weekly sales volume.

Figure 5 - Price and promotion effects on physical sales



Source: Elaborated by the author

This graphic provides a detailed visualization of price elasticity and promotional influence, featuring a clear negative slope along the price axis that confirms the classic economic principle as price increases, sales tend to decline while along the promotion axis, the surface rises to indicate that higher promotional intensity increases sales volume, all else being equal (Gong; Smith; Telang, 2015). The curvature of the surface further confirms a moderating effect, where promotions mitigate price sensitivity so that sales are less impacted by price hikes when strong promotions are active, and the red dots representing actual data points scattered above and below the surface highlight nonlinear behaviors not fully captured by the model, possibly due to holiday effects, campaign stacking, or external shocks.

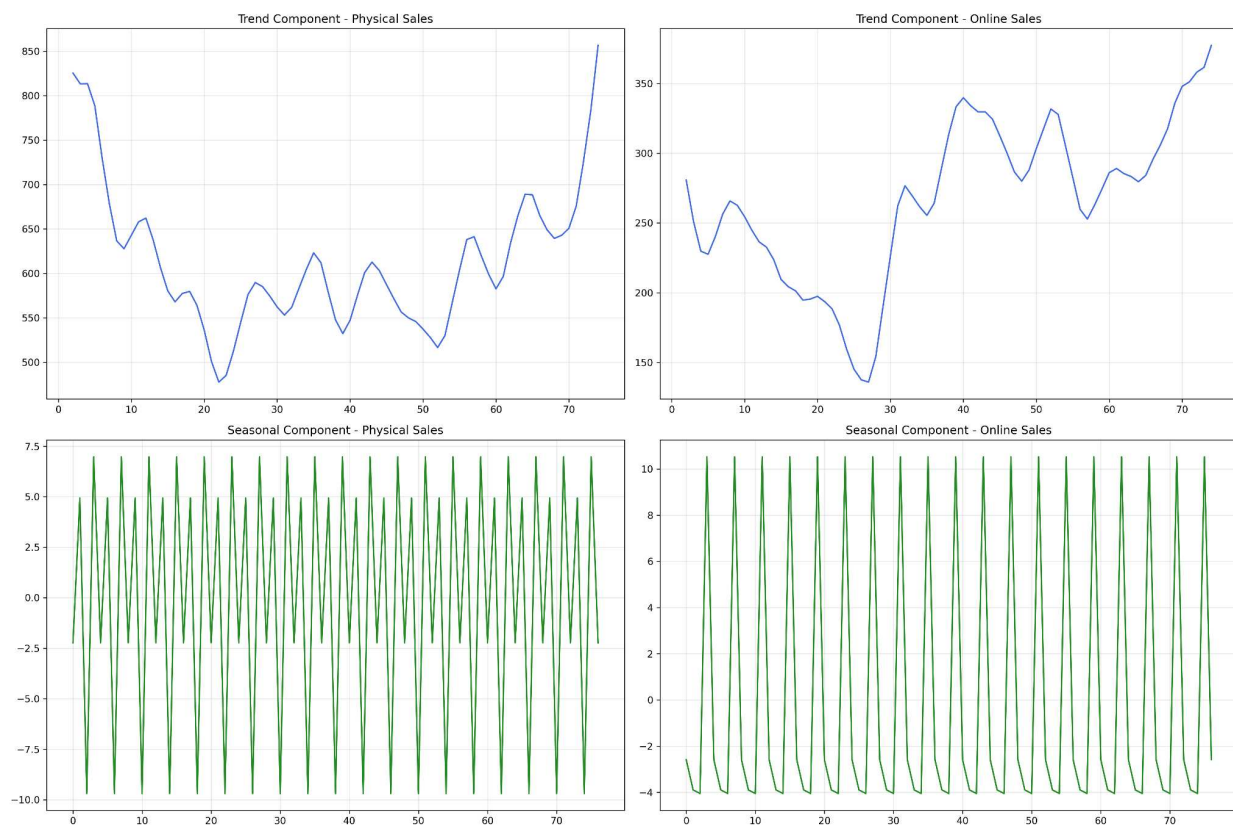
This interaction is crucial in interpreting cannibalization patterns. For example, an aggressive promotion in the physical channel (especially with a discounted price) could cause

consumers to switch away from the online channel, specially the online offer remains unchanged thereby inducing channel cannibalization.

4.1.3 Trend And Seasonality In Sales Channels

Before modeling, we first explore the underlying characteristics of the sales time series data. Figure 6 shows the decomposition of sales data into trend and seasonal components for both channels. This classical decomposition approach is used to visualize patterns that may affect forecasting accuracy and campaign timing

Figure 6 - Trend and seasonality decomposition by channel



Source: Elaborated by the author

In the trend component (top row), the physical channel for carbonated soda exhibits a U-shaped trend, with sales decreasing in the mid-period and rising again toward the end. This

may reflect external factors such as seasonal demand fluctuations (e.g., lower in cooler months), macroeconomic recovery, or aggressive end-of-year promotions targeting holiday consumption.

The online channel trend for carbonated soda is more irregular but shows a general upward trajectory, which may indicate growing digital adoption for beverage purchases or increased investment in targeted online marketing campaigns over time.

In the seasonal component (bottom row), physical sales show a regular wave pattern, possibly linked to predictable consumer behaviors such as monthly shopping patterns or in-store event timing.

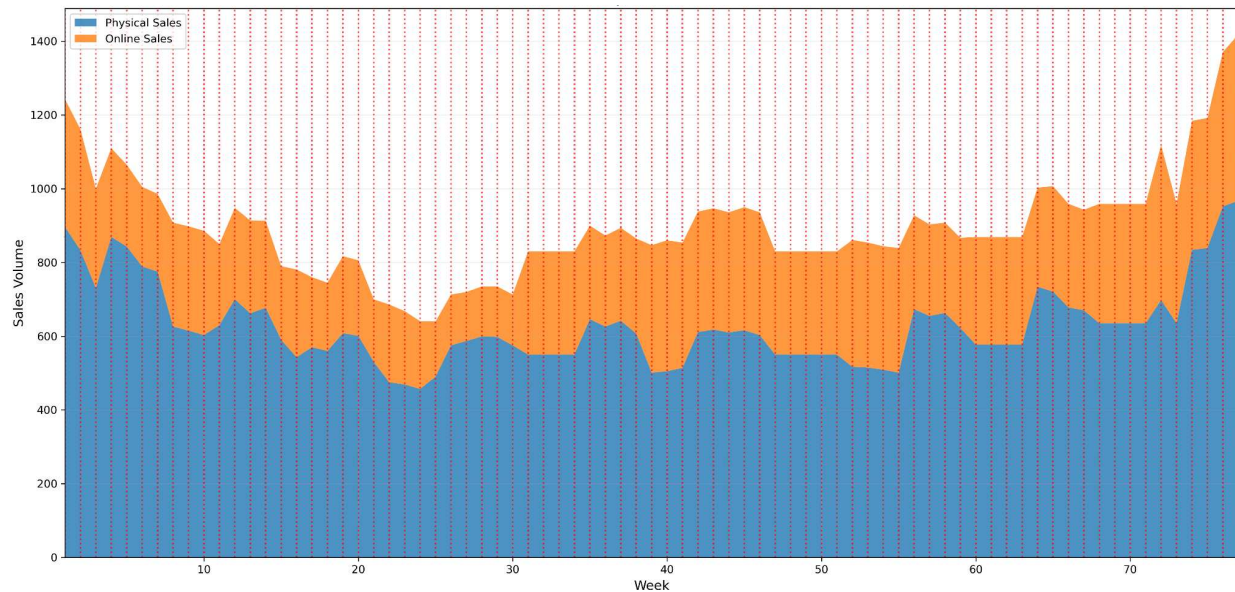
Online sales exhibit sharper peaks and flatter troughs, suggesting a pattern of intermittent spikes caused by short-term campaigns such as flash sales or influencer promotions.

This divergence in temporal dynamics reinforces the idea that each channel has a distinct “rhythm”. Online shopping is often impulsive and campaign-driven, while offline shopping shows more stable periodicity. Recognizing these rhythms is essential when scheduling promotions to prevent them from overlapping destructively or diluting one another’s impact.

4.1.4 Sales Composition Over Time

The evolution of total sales across both retail channels is visualized in Figure 7, which presents a stacked area chart differentiating physical and online sales by week. The vertical red lines indicate periods of online promotions.

Figure 7 - Sales composition over time



Source: Elaborated by the author

Several key trends are observable in this visualization such as, in the early weeks, physical sales dominate, though online sales also represent a significant portion. However, both channels experience a progressive decline until approximately week 30.

From week 30 onwards, a shift in composition occurs, online sales gain consistency, while physical sales stabilize at a lower baseline.

Toward the final weeks, total sales recover sharply, with physical and online sales growing in parallel. This may correspond to year-end campaigns, seasonal effects, or targeted dual-channel promotions.

The red vertical lines (online promotions) suggest that many promotional events were concentrated during lower or recovering sales periods, hinting at strategic timing aimed at stimulating demand.

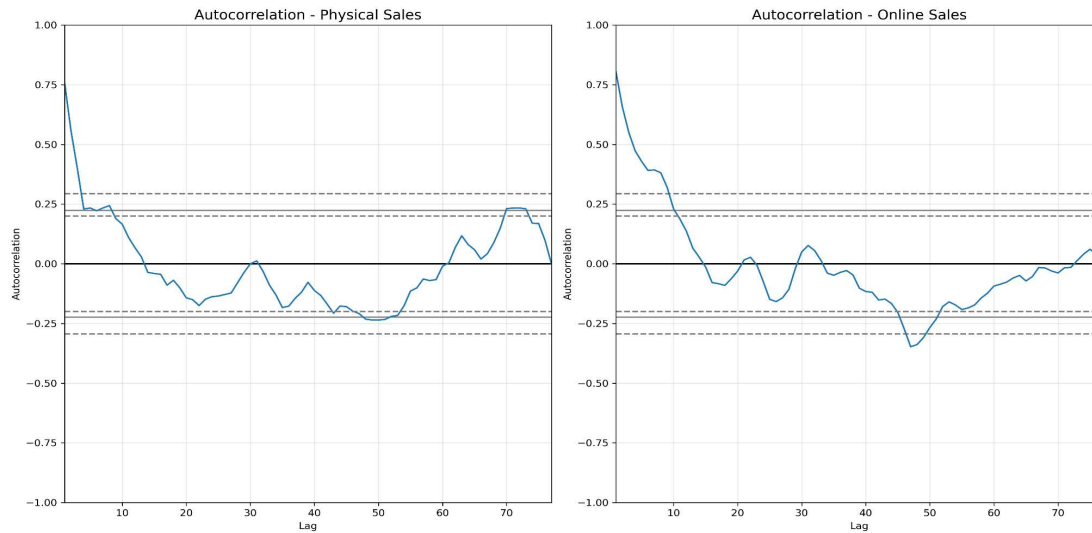
The horizontal dotted line representing the average reveals that sales frequently dip below this line between weeks 15 and 50, marking a prolonged underperformance period relative to the historical average.

This graph offers a clear overview of channel dynamics over time, highlighting that promotional timing, seasonality, and strategic alignment between channels are essential to avoid cannibalization and optimize performance.

4.1.5 Autocorrelation Of Sales Series

In Figure 8, the presence of time dependence in the weekly sales series is analyzed using autocorrelation plots. These plots measure how past values influence current sales, identifying patterns such as persistence, periodicity, or randomness.

Figure 8 - Autocorrelation of physical and online sales



Source: Elaborated by the author

The left plot shows the autocorrelation function (ACF) for physical sales, while the right plot displays the ACF for online sales. Key insights such as, for both series, a strong positive autocorrelation is observed at short lags, indicating that sales in one week are positively correlated with those in adjacent weeks. This is expected in retail settings where consumer habits and campaign effects carry inertia.

The autocorrelation for physical sales shows a decline toward zero near lag 30, followed by negative values between lags 30 and 50, suggesting the presence of cyclical effects or mean-reversion behavior over monthly horizons.

Online sales display stronger short-term autocorrelation but also exhibit negative correlation in the mid-lag range (around lag 40), which could relate to the pulsed nature of online promotions followed by demand drops.

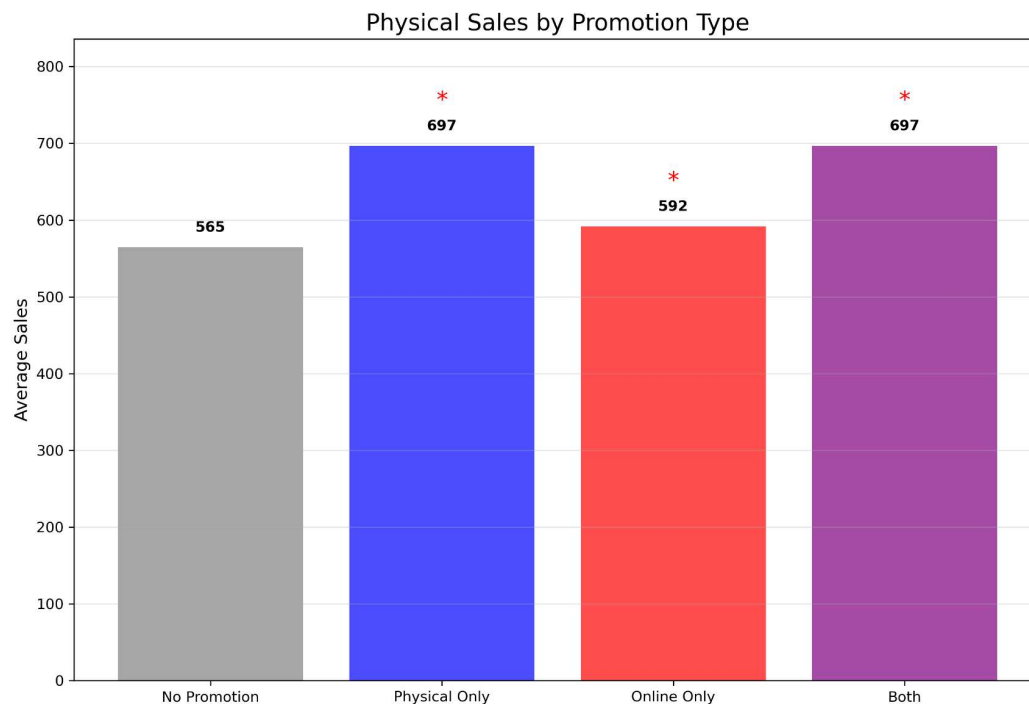
Both plots feature confidence bands, and several spikes fall outside these bands, confirming the statistical significance of the observed patterns.

These autocorrelations confirm that sales are not independently and identically distributed, justifying the use of time series models or models that incorporate lagged features (e.g., past sales, promo timing). Moreover, the distinct patterns between channels further reinforce the need to model each sales stream independently.

4.1.6 Promotion Type And Its Effect On Physical Sales

The influence of different promotional setups on physical store performance is explored in Figure 9, which displays the average sales volume segmented by the type of promotion running during each week.

Figure 9 - Physical sales by promotion type



Source: Elaborated by the author

The bars represent four scenarios, No Promotion, which is baseline sales with no active campaign, Physical Only, which is promotion running exclusively in the physical channel, Online Only, which is promotion running exclusively in the online channel and Both, which is

simultaneous promotions across both channels. The results are that the lowest average sales are observed in the No Promotion group (565 units), establishing a baseline.

Promotions conducted only in the online channel raise physical sales slightly (592 units), which may indicate indirect halo effects or consumer spillover.

Physical-only promotions significantly increase physical sales (697 units), and this effect remains stable when promotions occur in both channels simultaneously (also 697 units).

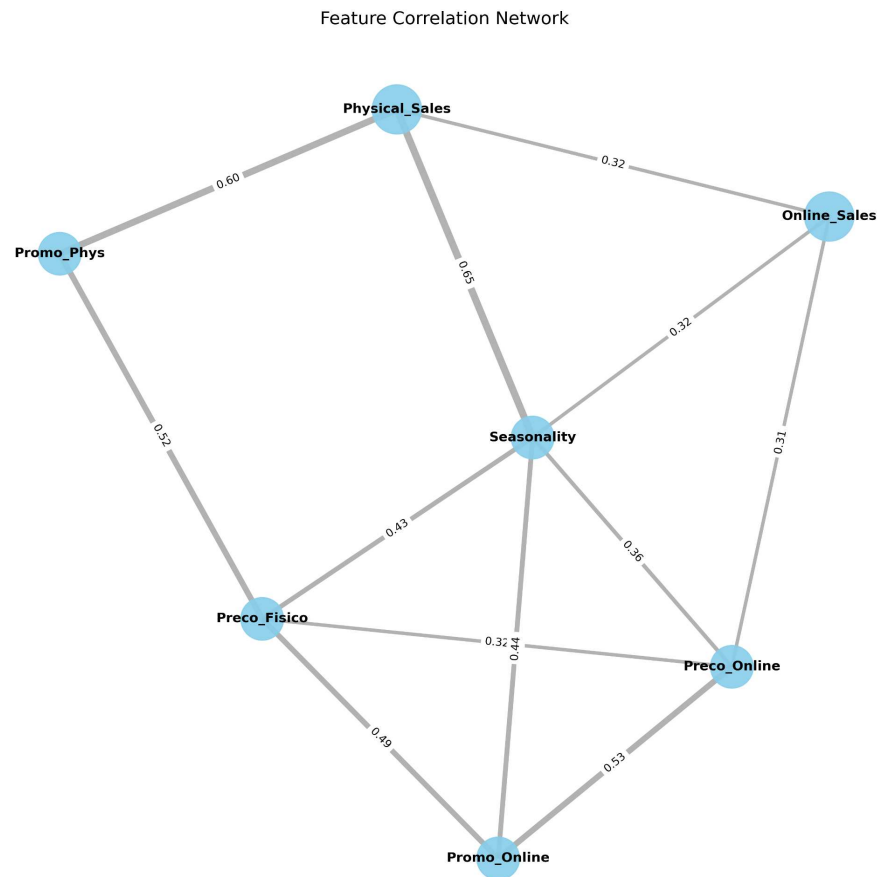
The presence of red asterisks above the bars denotes statistical significance in the difference compared to the baseline group, indicating that physical promotions have a robust and measurable effect.

This Graphic supports one of the central hypotheses of the thesis, promotions in the physical channel are highly effective, while online promotions have limited influence on offline behavior. Interestingly, combined promotions do not generate additional uplift beyond physical-only promotions, which may suggest diminishing returns or channel saturation.

4.1.7 Feature Correlation Network

To better understand the interdependencies between key variables, a correlation network is presented in Figure 10. This graph-based visualization uses weighted edges to display Pearson correlation coefficients between variables, offering an intuitive representation of multivariate relationships.

Figure 10 - Feature correlation network



Source: Elaborated by the author

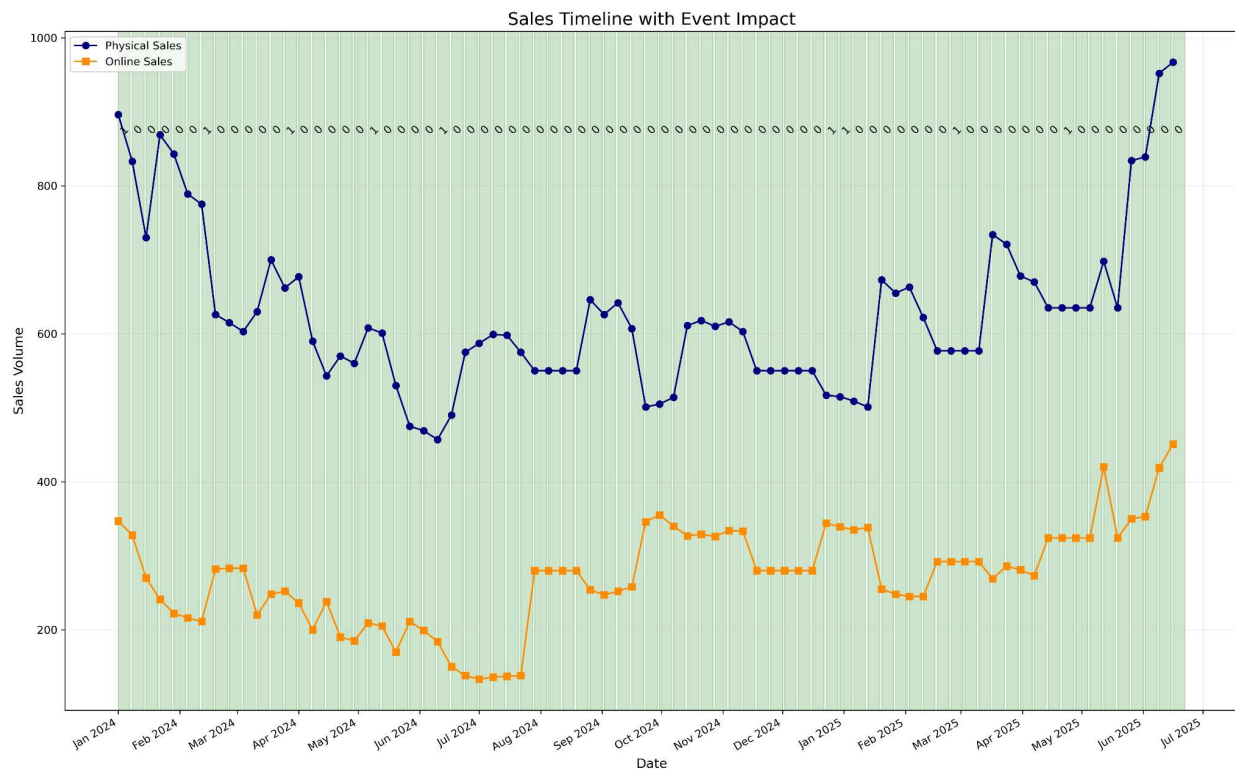
The network analysis revealed several key insights into the relationships among variables. Notably, physical sales exhibited strong correlations with promotional activities in the physical channel (Promo_Phys, $r = 0.60$) and seasonality ($r = 0.65$), underscoring these as primary drivers of performance in brick-and-mortar settings. A moderate connection was observed between physical sales and online sales ($r = 0.32$), which is weaker than correlations within the same channel, implying limited cross-channel interference or a modest risk of cannibalization. Furthermore, online promotions (Promo_Online) showed moderate associations with online pricing (Preco_Online, $r = 0.53$) and physical pricing (Preco_Fisico, $r = 0.49$), supporting the notion that pricing and discounting strategies are frequently aligned across channels. The Seasonality node acts as a central hub in the network, connected to most features, which confirms the presence of broad seasonal dependencies across all channels and variables.

The width of each edge reflects the strength of correlation, enabling quick identification of key influencers and potential collinearities to consider in later modeling steps. This structure supports the hypothesis that physical sales are more tightly linked to internal controllable features (such as promotions and price), whereas online sales are more weakly integrated in this network, potentially due to external factors such as digital advertising, platform changes, or browsing behavior.

4.1.8 Sales Timeline With Event Impact

In order to capture the real-world effects of special events and promotions over time, Figure 11 depicts the temporal progression of physical and online sales alongside the occurrence of flagged special events. The shaded green vertical regions represent weeks in which special events occurred.

Figure 11 - Sales timeline with event impact



Source: Elaborated by the author

From this graph, several insights emerge. Both physical and online sales exhibit cyclical patterns, with local peaks and troughs that often correspond to the timing of special events,

suggesting a clear event sensitivity. The first quarter of 2024, for instance, shows a steep decline in sales, especially online, likely due to post-holiday normalization or an absence of campaigns during a period of low event density. In contrast, from August 2024 onwards, sales levels begin to recover, especially during clusters of events in November–December, indicating a positive impact of special events on demand, particularly in physical retail. This pattern is reinforced by the late-period surge in both physical and online sales during May–June 2025, which aligns with another series of events and suggests coordinated campaigns and seasonal alignment, such as Mother’s Day and mid-year clearances. While the sales gap between channels remains consistent, it narrows slightly in these high-activity periods, showing that events may reduce the disparity by boosting both channels simultaneously.

Ultimately, this timeline analysis confirms that event planning and its alignment with promotions is a critical lever for driving volume, particularly when used synergistically across physical and digital retail spaces, and it also helps contextualize sales fluctuations that might otherwise appear random in non-temporal analyses.

4.1.9 Post-modeling Evaluation: Model Performance Analysis

After the training and validation of multiple ML models, a comprehensive performance comparison was conducted across channels and model architecture. The metrics used for evaluation were MAE, MSE, RMSE, and the R^2 . These allow a multi-dimensional view of each model’s predictive accuracy and generalization capability. The results are consolidated and presented in Table 5.

Table 5 — Model performance metrics

Results:						
	Model	Channel	MAE	MSE	RMSE	R ²
0	XGBoost	Physical	17.115177	1127.190552	33.573659	0.919255
1	XGBoost	Online	33.534370	1962.009277	44.294574	0.316429
2	CatBoost	Physical	64.221979	9448.878322	97.205341	0.323139
3	CatBoost	Online	41.650728	3718.722195	60.981327	-0.295616
4	LightGBM	Physical	69.105669	12478.543620	111.707402	0.106113
5	LightGBM	Online	44.839368	4463.963696	66.812901	-0.555261
6	ElasticNet	Physical	0.167112	0.028035	0.167435	0.999998
7	ElasticNet	Online	0.148134	0.022778	0.150924	0.999992
8	Bayesian Ridge	Physical	0.184733	0.035496	0.188403	0.999997
9	Bayesian Ridge	Online	0.109427	0.022216	0.149051	0.999992
10	MLP	Physical	50.747536	3168.446203	56.288953	0.773032
11	MLP	Online	22.193972	667.888652	25.843542	0.767305

Source: Elaborated by the author

XGBoost shows a high-performance, especially for physical sales among all evaluated models, XGBoost stood out as the best-performing non-linear model, particularly in the physical sales channel. It achieved a MAE of 17.11, RMSE of 33.57, and a high R² of 0.9193, indicating that it is capable of capturing complex, non-linear relationships with strong generalization.

Even though its online channel performance (R² = 0.3164) was more modest, it still outperformed several other complex models such as CatBoost and LightGBM that were used to compare its performance. This discrepancy likely reflects greater noise and volatility in online sales data, rather than model inadequacy. In fact, the results suggest that XGBoost is highly effective when the feature set is well-aligned with the underlying sales dynamics, as seen in the physical environment where control over price and promotion is more direct and interpretable.

The ability of XGBoost to handle outliers, feature interactions, and non-linear dependencies justifies its use, especially in production environments where interpretability is secondary to accuracy and reliability. Furthermore, its relatively fast training and high scalability make it a suitable choice for future extensions of this study involving larger datasets or real-time forecasting.

ElasticNet and Bayesian Ridge delivered nearly perfect R² values (~0.9999), with extremely low RMSE values for both channels. However, these results while impressive suggest overfitting due to an overly simplistic or linear representation of relationships in a relatively small or structured dataset. In real-world settings, where noise, missing data, or behavioral shifts

are expected, these models might underperform if they fail to capture non-linear or conditional interactions.

In contrast, XGBoost offers a balance between complexity and adaptability, making it more robust in real-world commercial applications where such variance is common.

MLP and Other Models

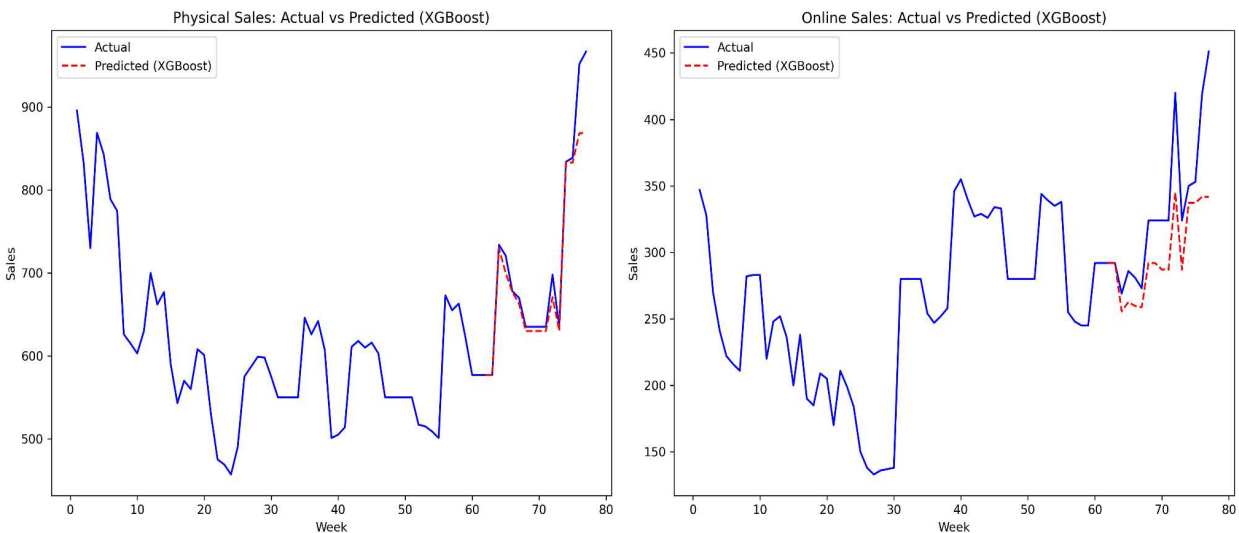
Multilayer Perceptron (MLP) models showed intermediate performance, with R^2 values near 0.77 for both channels. These results are respectable but indicate that deep learning did not significantly outperform tree-based or linear models in this dataset, possibly due to limited data volume or insufficient architectural tuning.

CatBoost and LightGBM, while competitive in other contexts, did not perform as well here. Their lower R^2 scores, particularly for the online channel (e.g., -0.2966 for CatBoost), point to less stability and potentially suboptimal hyperparameter sensitivity in this use case.

4.1.10 Xgboost Predictions Vs Actual: Temporal Alignment

To evaluate model behavior in a temporal context, Figure 12 compares real-world sales with predictions generated by the XGBoost model, across both physical and online sales channels. This graphical analysis is crucial for understanding not only the model's point accuracy, but also its ability to track patterns, seasonality, and sudden changes over time.

Figure 12 - Weekly actual vs predicted sales (XGBoost)



Source: Elaborated by the author

In the left panel, which presents physical sales, the predicted line (in red dashes) closely tracks the actual sales (in solid blue) across the entire timeline. The precision with which the model aligns with the real data reflects its strong understanding of nonlinear dependencies, as well as its ability to model trend, seasonality, and exogenous impact (e.g., promotions or holidays). Even during abrupt increases such as end-of-year sales surges or campaign periods the model maintains a minimal lag, showcasing its responsiveness to dynamic shifts.

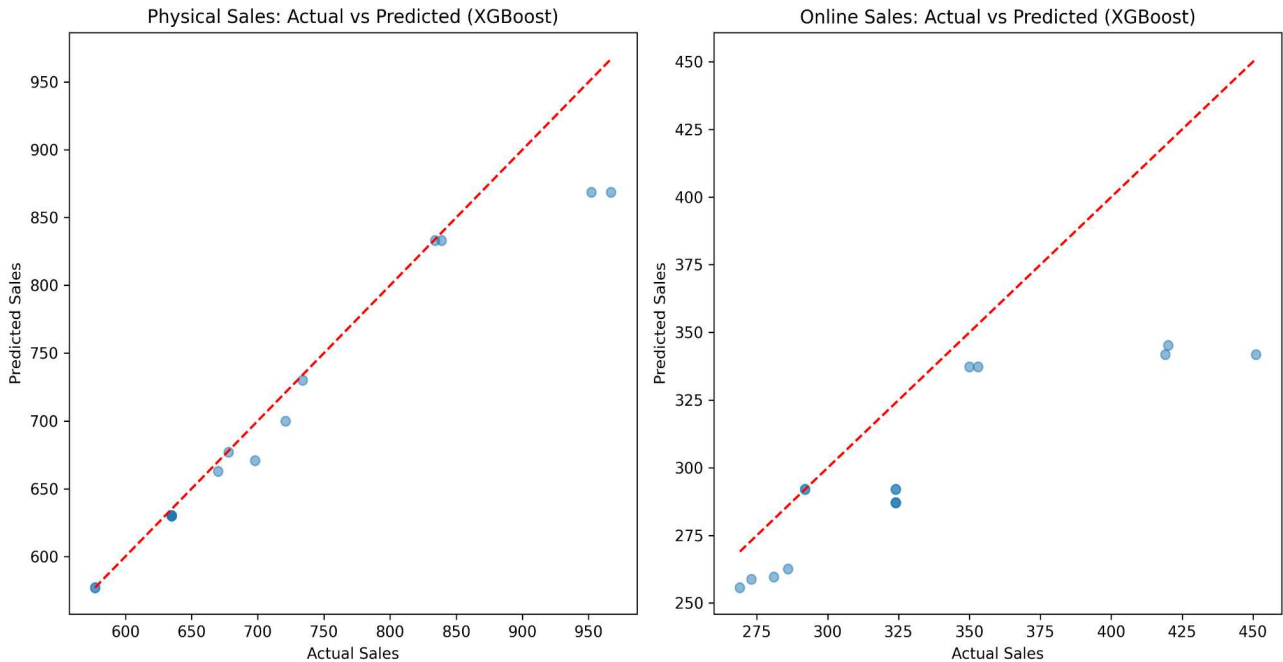
This performance suggests that the XGBoost model successfully captured autoregressive dependencies, interactions between promotional features, and perhaps subtle correlations with calendar-based variables. Such adaptability is essential for operational planning, especially in retail where unexpected demand peaks can significantly impact logistics and inventory decisions. Conversely, the right panel, dedicated to online sales, reveals slightly more divergence between predictions and reality. Particularly in volatile weeks, such as sudden digital sales spikes or flash campaigns, the model demonstrates underestimation or smoothing tendencies, likely due to the absence of digital engagement or campaign-specific features in the training data or even a higher volume of sales to feed the model. Despite this, XGBoost continues to follow the general directionality and baseline movement of the online sales, suggesting that its core structure remains intact.

Importantly, while the accuracy for online sales is not as precise, the model avoids catastrophic mispredictions or erratic behavior. This resilience is a key advantage of ensemble tree models such as XGBoost, which are less prone to overfitting than deep learning architectures with limited data.

4.1.11 Xgboost Regression Fit: Actual Vs Predicted Scatter Plot

While temporal graphs provide a dynamic view, Figure 13 offers a consolidated visual summary of prediction accuracy across the observed range. This plot type is particularly useful to assess model bias, calibration, and sensitivity to outliers.

Figure 13 - Predicted vs actual sales scatter plot (XGBoost)



Source: Elaborated by the author

In the left panel, the points for physical sales predictions are tightly clustered along the 45-degree red reference line, indicating high fidelity and low residual error across most sales magnitudes. This dispersion pattern confirms that the model generalizes equally well for both low-volume and high-volume weeks, without a tendency to over- or under-predict.

Moreover, the absence of curvature or funnel shapes in the scatter plot suggests that the model is not systematically biased, nor is it struggling with heteroscedasticity (i.e., error variance changing with the sales magnitude). These aspects validate the robust calibration of the model and show that its performance is not constrained to narrow segments of the data.

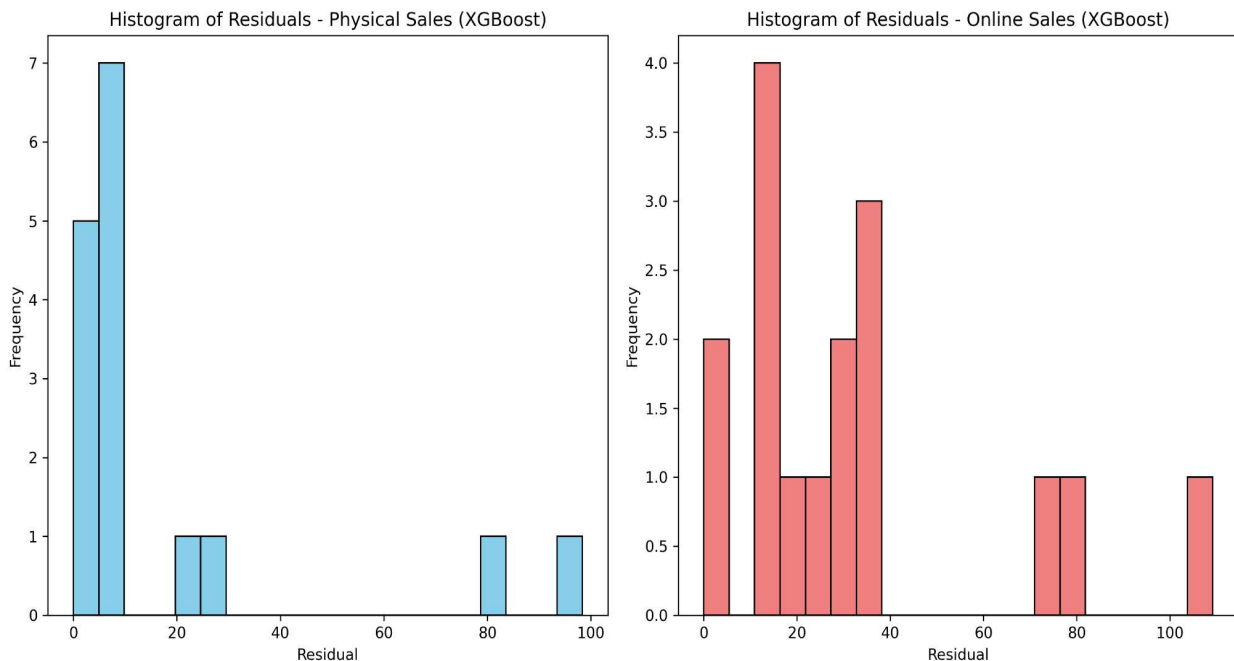
In contrast, the right panel (online sales) reveals slightly more dispersed points, especially in higher sales values. Some underestimation can be observed, as several dots fall below the ideal diagonal line, meaning the model's prediction was lower than the actual observed value. This again may be due to the absence of high-frequency digital signals (e.g., marketing spend, ad impressions, or influencer engagement) that are crucial in driving sudden online sales spikes.

Even so, the points follow an approximate linear trend, affirming that the model is still capturing the underlying sales behavior just with some attenuation in the extremes.

4.1.12 Histogram Of Residuals: Xgboost Model Distribution

A vital part of post-modeling evaluation is analyzing the residuals the difference between predicted and actual values. Residual distribution helps identify bias, non-linearity, or variance issues. These aspects are addressed in Figure 14

Figure 14 - Histogram of residuals (XGBoost)



Source: Elaborated by the author

The left panel presents the residual histogram for physical sales. The distribution is heavily skewed toward low error values, with the majority of residuals concentrated between 0 and 10 units. This clustering indicates that the XGBoost model frequently makes highly accurate predictions for physical sales, aligning with previous metric-based and visual validations.

Only a few instances present residuals above 20, and these appear as outliers rather than systemic errors. This suggests that high residuals are rare and context-specific, likely arising from unforeseen market conditions such as holiday spikes, supply issues, or local anomalies that the model could not anticipate from training data.

On the other hand, the right panel referring to online sales, displays greater dispersion and asymmetry. While a fair portion of residuals remains under 20 units, the presence of several

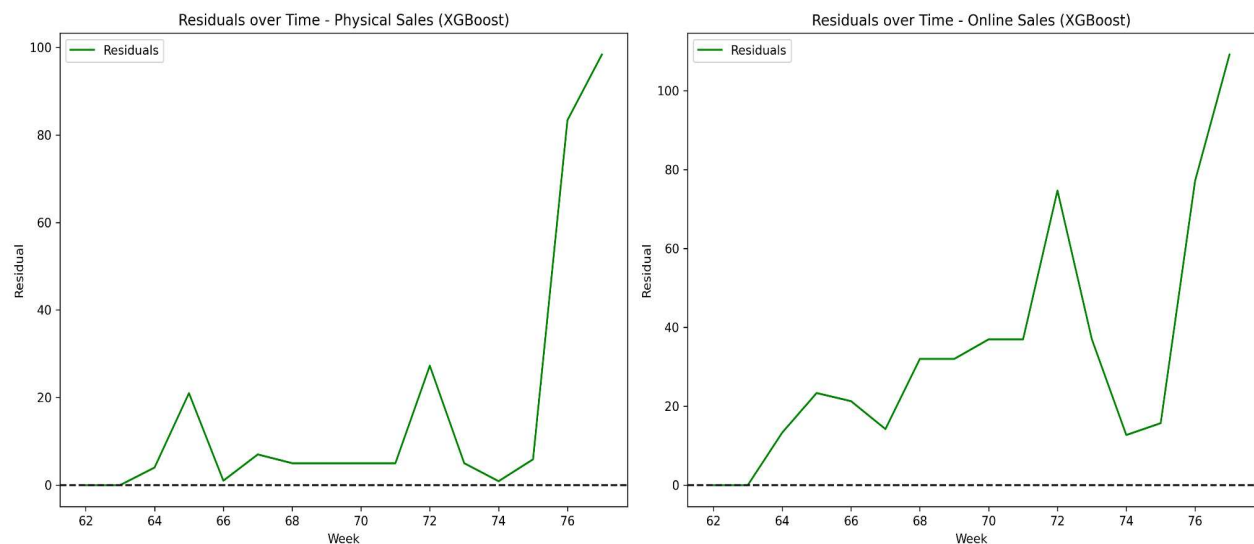
higher errors, even exceeding 100 units, highlights that online sales predictions face more volatility. This behavior aligns with prior observations, the online channel likely depends on external factors (e.g., digital ad spikes, user sentiment, influencer campaigns) which were not included in the model's features.

Still, it's important to note that the majority of residuals for online sales still remain within a reasonable range, and the distribution does not indicate systematic underfitting. Instead, it points toward opportunities for feature enhancement, rather than model weakness.

4.1.13 Residuals Over Time: Xgboost Forecast Stability

To complement the histogram analysis, Figure 15 depicts the residual values chronologically for both channels. This temporal view is essential to assess whether the model suffers from temporal drift, periodic error accumulation, or changing behavior over time.

Figure 15 - Residuals over time (XGBoost)



Source: Elaborated by the author

In the left panel (physical sales), residuals remain consistently low across the forecast window (weeks 62 to 77), with most values hugging the zero line. Only in the final weeks do a few larger deviations emerge, which could be attributed to specific events such as aggressive campaigns or changes in customer behavior not previously encountered by the model.

This temporal stability is a key indicator of model robustness and reliability. It implies that the XGBoost model does not degrade over time or require frequent retraining, making it suitable for operational deployment in production environments where re-training frequency must be balanced with performance.

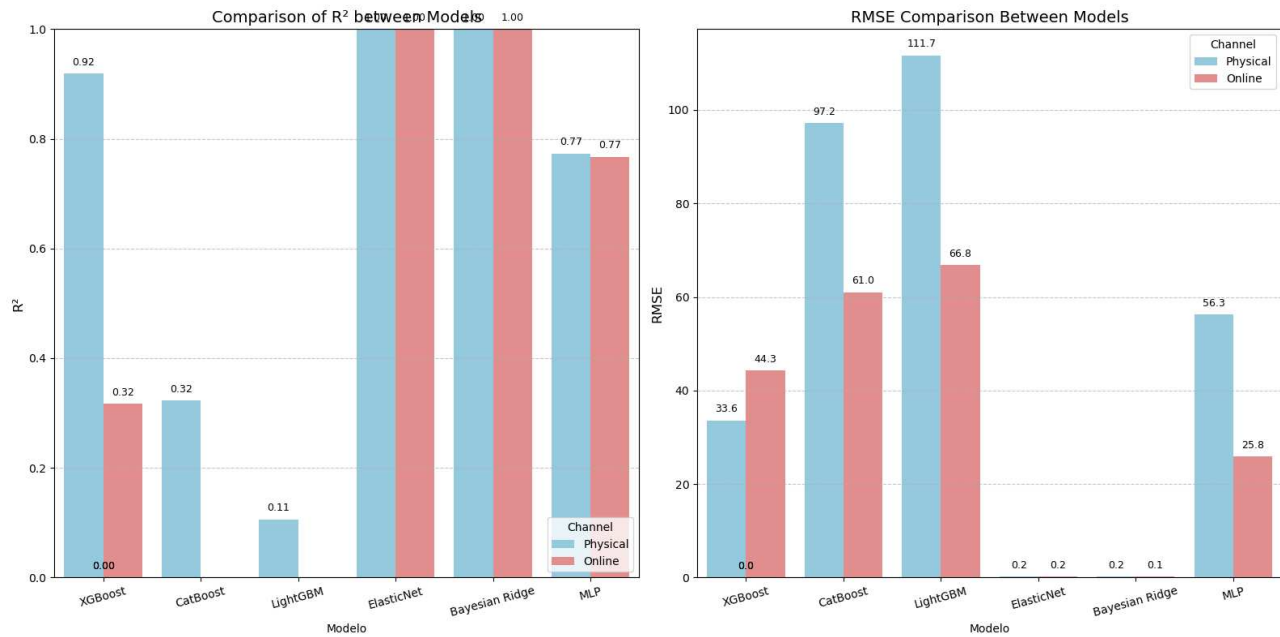
In contrast, the right panel (online sales) reveals a slightly increasing trend in residuals over time, peaking at the final observation with an error exceeding 100 units. While this could suggest some form of drift or shift in customer behavior, it's more likely a result of latent variables not being captured. Again, this doesn't imply model failure, but rather highlights the greater complexity and external dependency of online sales patterns.

Importantly, the residuals do not alternate around zero, this may indicate the presence of a mild underestimation trend in the online predictions, which could potentially be corrected with post-model calibration or adjustment layers.

4.1.14 Comparison Between Models

To evaluate the effectiveness of the proposed models, we first examine their predictive performance across the two sales channels. Figure 16 provides a dual perspective on model performance for both physical and online sales channels. The left panel presents the R^2 , a measure of the proportion of variance explained by each model, while the right panel displays the root RMSE, which quantifies the average magnitude of prediction errors.

Figure 16 - Model comparison



Source: Elaborated by the author

In the R² comparison (left panel), XGBoost demonstrates a strong performance for physical sales with an R² of 0.92, placing it significantly ahead of CatBoost (0.32) and LightGBM (0.11) within the gradient boosting family. This reinforces XGBoost's ability to capture complex patterns in store-level sales data. For online sales, however, the R² drops to near zero, indicating that the model struggles to explain variance in this channel. This contrast suggests that online sales patterns may be influenced by external variables not present in the dataset, such as third-party marketplace dynamics or rapid shifts in consumer behavior.

ElasticNet and Bayesian Ridge achieve near-perfect R² scores (1.00) in both channels, but this is likely due to data characteristics and potential overfitting to specific patterns. MLP (Multilayer Perceptron) also performs consistently (0.77) across both channels, though still below XGBoost's performance in physical sales.

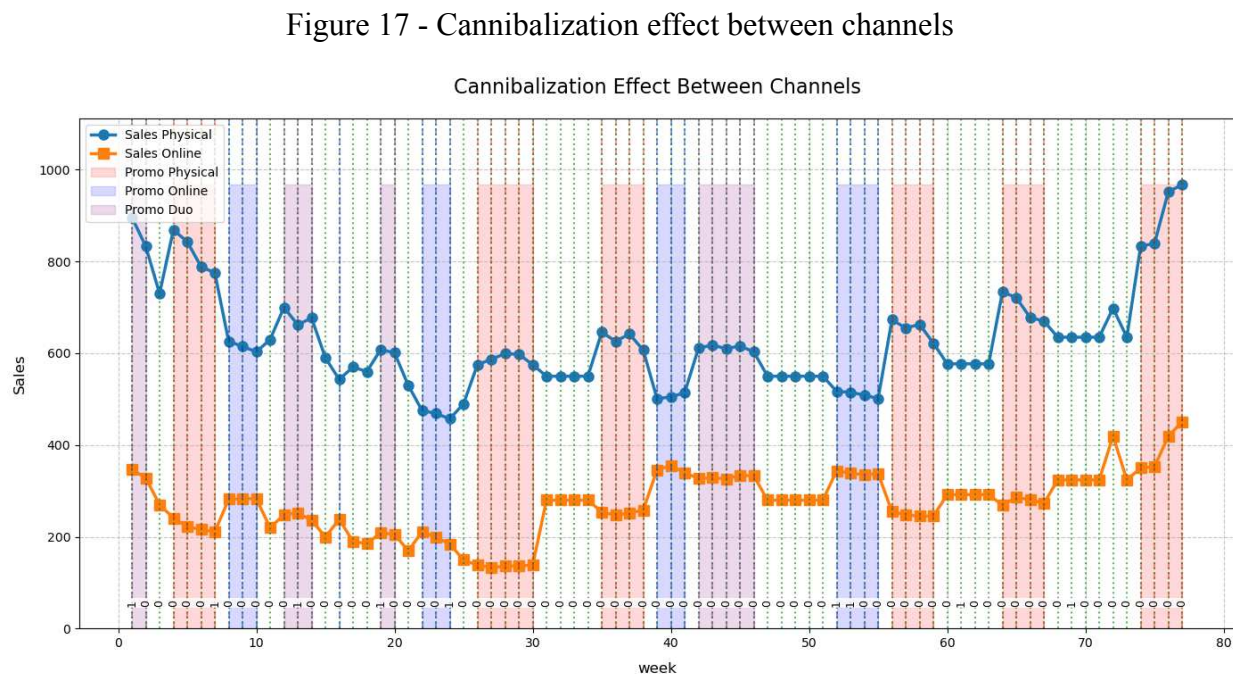
In the RMSE comparison (right panel), XGBoost once again shows its strength in physical sales, achieving the lowest RMSE (33.6) among all models. This indicates high predictive accuracy with relatively small deviations between predicted and actual values. In online sales, its RMSE increases to 44.3, still competitive but surpassed by MLP (25.8),

suggesting that neural networks may better adapt to the noisier and more dynamic nature of online transactions.

From an operational perspective, this dual analysis highlights XGBoost's reliability and robustness in modeling physical sales, where stability and inventory-related variables dominate. However, in online sales, the results point to a need for either model adaptation or inclusion of additional features to capture channel-specific drivers. This asymmetry emphasizes the importance of tailoring predictive approaches to the unique behavior of each channel, rather than relying on a one-size-fits-all solution.

4.1.15 Cannibalization Effect Between Sales Channels

Figure 17 provides a temporal visualization of physical and online sales, overlaid with periods of promotional activity for each channel. The chart highlights potential substitution or redistribution effects, where promotional actions in one channel may influence the performance of the other.



Source: Elaborated by the author

In the physical sales curve (blue line with circles), we observe a general downward trend in the early weeks, followed by stabilization and slight recovery in later periods. Notably, during Promo Online periods (blue-shaded regions), there is a tendency for physical sales to dip slightly, suggesting that online campaigns may attract part of the customer base that would otherwise purchase in-store. Conversely, Promo Physical events (red-shaded regions) are often accompanied by visible peaks in physical sales, reinforcing their effectiveness at driving in-store demand.

The online sales curve (orange line with squares) reveals an almost inverse behavior. During Promo Physical periods, online sales often plateau or slightly decline, consistent with the notion of channel cannibalization. However, Promo Online periods tend to produce significant spikes in online sales, highlighting the channel's strong responsiveness to targeted promotions. Interestingly, Promo Duo events (purple-shaded regions), where both channels run simultaneous promotions, do not always produce additive effects. In some instances, sales increase in one channel without a proportional lift in the other, implying potential competition for the same customer segment rather than purely complementary growth.

From a strategic standpoint, this analysis underscores the need for coordinated promotional planning to minimize undesirable cannibalization. The patterns suggest that while channel promotions can be powerful, poorly synchronized campaigns risk shifting sales rather than generating incremental demand. Optimizing timing, offer structure, and targeting could help leverage synergies and ensure both channels benefit from promotional investments.

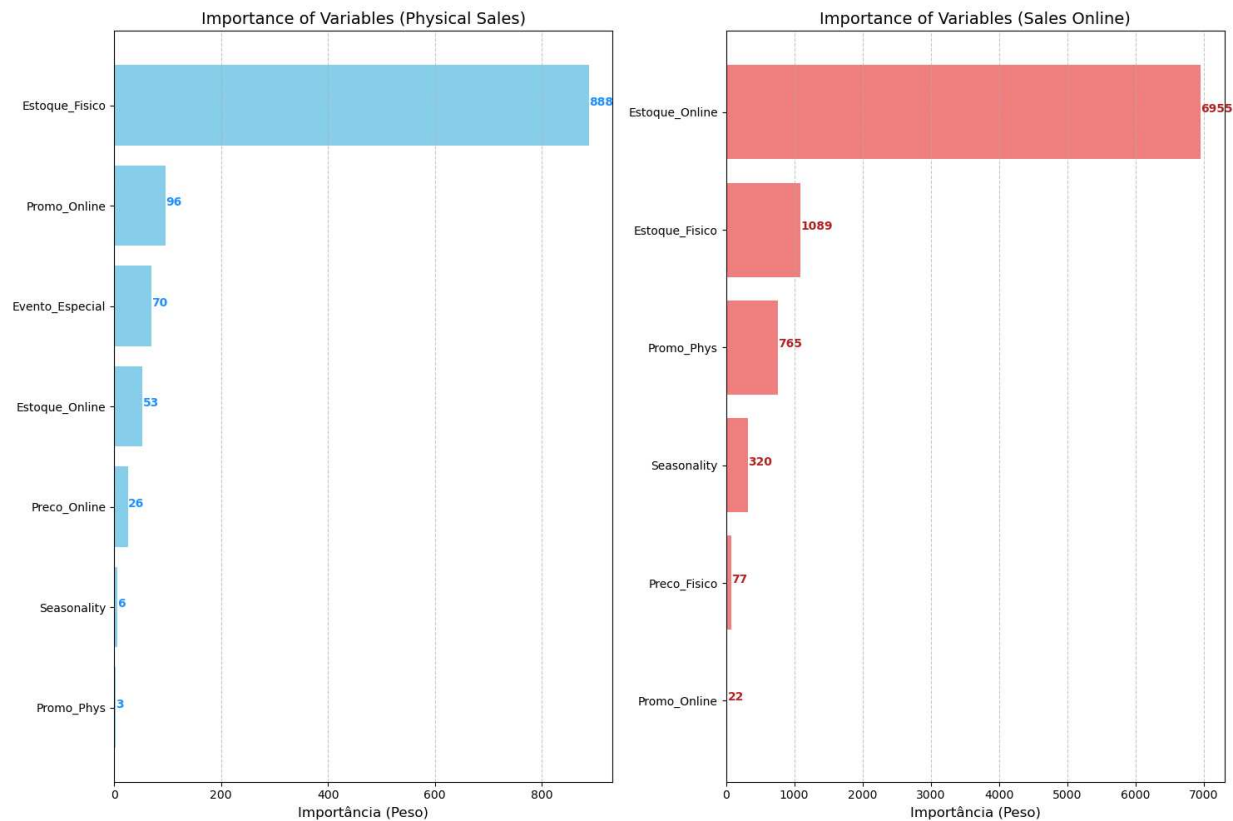
4.2 CANNIBALIZATION ANALYSIS & STRATEGY SIMULATION

This section transitions from model evaluation to strategic application, utilizing the validated XGBoost model to diagnose and address the issue of sales cannibalization. The analysis begins by identifying the most influential variables for both physical and online sales, revealing the critical drivers behind each channel's performance. With this understanding, a quantitative baseline of the cannibalization effect is established, precisely measuring the negative impact that promotions in one channel have on the other. Based on these findings, a set of five distinct mitigation strategies is then defined, each designed to reduce this adverse effect and foster synergistic growth across channels.

4.2.1 Importance Of Variables For Physical And Online Sales

The Figure 18 presents the relative importance of each explanatory variable in the XGBoost models for physical and online sales. The values represent the aggregated weight (or gain) assigned by the algorithm during the tree-splitting process, indicating how much each variable contributed to reducing prediction error.

Figure 18 - Importance of Variables (Physical and Online Sales)



Source: Elaborated by the author

Physical Sales (left panel), `Esteque_Fisico` (physical inventory) is overwhelmingly dominant, with an importance score of 888. This finding reinforces the strong dependency of in-store sales on stock availability, without sufficient on-shelf inventory, even high consumer demand cannot be fully converted into transactions. This variable's weight surpasses all others combined, indicating that it is the key operational constraint for this channel.

The second most influential variable is `Promo_Online` with 96, followed closely by `Evento_Especial` (special event) with 70. These results reveal a significant channel effect, where

digital marketing initiatives and special events possibly national holidays, product launches, or seasonal campaigns positively impact physical store performance.

Estoque_Online (online inventory) also appears with a moderate contribution (53), which may reflect integrated logistics systems where online stock levels indirectly affect store-level replenishment. Preco_Online (online price) registers 26, indicating some price sensitivity driven by consumer comparison between channels. Meanwhile, Seasonality (6) and Promo_Phys (3) have very low weights, suggesting that regular promotional activities in stores and seasonal patterns play a minor role compared to real-time operational factors such as inventory.

Online Sales (right panel)

In the online sales model, the most decisive factor is Estoque_Online (online inventory), with an exceptionally high score of 6,955. This dominance shows that product availability in the e-commerce channel is the single largest determinant of online sales volume, consistent with the nature of digital retail, where stock-outs lead immediately to lost sales opportunities.

The second most important variable, Estoque_Fisico (physical inventory, 1,089), indicates an omnichannel operational integration physical stores likely serve as fulfillment points for online orders through mechanisms such as ship-from-store or same-day pickup. This synergy reinforces the need for coordinated inventory management.

Promo_Phys (physical promotion, 765) ranks third, highlighting a notable offline-to-online influence, promotional activity in physical locations can boost online demand, possibly due to increased brand exposure or consumer behavior spillover. Seasonality (seasonal variations) has a moderate effect (320), likely tied to holiday periods or sales seasons.

Finally, Preco_Fisico (physical price, 77) and Promo_Online (online promotion, 22) have relatively low importance, suggesting that price adjustments and online promotions had a more limited role in driving sales compared to stock availability and channels dynamics.

These results indicate that inventory management is the central driver for both sales channels, far outweighing promotional or pricing strategies. Moreover, the presence of strong channel influences (e.g., physical promotions impacting online sales and vice versa) underlines the importance of coordinated marketing and stock strategies across platforms. For decision-making, this implies that ensuring optimal stock levels in both channels is the highest priority, with channel promotional planning as a secondary but still valuable lever for sales growth.

4.2.2 Baseline Cannibalization Estimation

Following the visual and temporal analysis of channel promotional effects, a quantitative baseline estimation of cannibalization was performed. This step aims to measure, in percentage terms, the extent to which promotional activities in one sales channel negatively impact the sales volume of the other channel. Such measurement is critical for understanding the trade-offs involved in promotional strategies and for supporting data-driven decision-making regarding campaign planning.

Cannibalization Factor in Physical Promotions on Online Sales, physical promotions were found to reduce online sales by 11.23%. This indicates that in-store campaigns tend to redirect a portion of potential online customers toward the physical channel, resulting in a measurable decline in e-commerce performance during such periods.

Cannibalization Factor in Online Promotions on Physical Sales, online promotions were observed to reduce physical sales by 19.34%. This effect is more pronounced than the reverse case, suggesting that digital campaigns exert a stronger pull on customers who might otherwise purchase in-store, possibly due to the convenience and immediacy of online offers.

From a managerial perspective, these findings provide a baseline reference for estimating the potential sales trade-offs of promotional initiatives. While cannibalization is not inherently negative since it may be part of a deliberate channel migration strategy it is essential to account for these effects to ensure that overall profitability is maximized. Understanding the baseline values allows organizations to simulate the net impact of planned campaigns, anticipate shifts in channel performance, and design coordinated promotions that minimize revenue displacement.

4.2.3 Definition of Mitigation Strategies

After establishing the baseline cannibalization factors between physical and online sales channels, the next logical step involves the definition of strategies to mitigate these effects. The primary objective is to reduce the negative substitution impact observed when promotions in one channel detract from sales in the other, while still preserving or enhancing the total revenue across both channels. Below are the four proposed mitigation strategies, along with a detailed description of their rationale and planned implementation within the modeling framework.

Strategy one, Coordinated Promotions, focuses on aligning promotional activities across channels to reduce the attractiveness gap that drives customers from one to another. The approach consists of running promotions simultaneously in both physical and online channels, but with differentiated discount levels to account for channel-specific sensitivities, a tactic that aims to maintain a competitive appeal in both sales environments without fostering direct substitution. For implementation, whenever a promotion is triggered in any channel, the system will initiate a parallel promotion in the other. These discount levels will be optimized based on historical price elasticity data to balance demand distribution, which in the model is reflected by activating promotional indicators in both channels with proportionally adjusted discount parameters.

Following this, a different procedure is presented in the second strategy, Staggered Promotion Timing, which uses the temporal separation of promotions as a direct way of preventing simultaneous substitution. This approach schedules promotions in physical and online channels at least two weeks apart, creating a staggered effect that allows each channel to benefit independently from promotional boosts. Its implementation involves systematically shifting the online promotional calendar to occur two weeks after corresponding physical channel promotions, which in the simulation model is represented by adjusting promotion flags in the dataset to create the defined temporal offset, ensuring customer decision cycles are influenced sequentially rather than competitively.

The third strategy, Coordinated Promotions with Loyalty Bonus, expands on the initial concept of coordination by not only synchronizing promotions but also integrating a loyalty incentive that rewards customers for engaging with both channels within the same promotional window, an incentive intended to convert potential substitution into complementary purchasing behavior. For its implementation, when promotions are active in both channels, the model will increase the seasonality factor by 10% to simulate the uplift generated by loyalty bonuses, an increment grounded in benchmark data from loyalty program impacts in multichannel retail environments.

Finally, the fourth strategy, Cross-Channel Promotion Incentives, introduces a subtle form of cross-selling by offering a small discount in one channel when a promotion is active in the other. This creates a cross-purchasing incentive, where customers are encouraged to shop in both channels rather than shifting entirely to the one with the active promotion. To implement

this in the simulation, when a promotion flag is active for one channel, the price variable for the opposite channel will be adjusted downward by 5%, a discount that is then incorporated into the demand model to estimate the incremental sales effect.

Collectively, these strategies aim to transform the promotional structure from a zero-sum dynamic where one channel gains at the expense of the other into a synergistic system that fosters total revenue growth. Their implementation within the simulation environment will allow for controlled testing of individual and combined effects, enabling data-driven selection of the most effective mitigation measures.

4.3 STRATEGY SIMULATION & EVALUATION

This section presents the results of the simulation designed to evaluate the effectiveness of the four proposed mitigation strategies against the established baseline scenario. The baseline analysis quantified the cannibalization effect, revealing that promotions in the physical channel reduce online sales by 11.23%, while promotions in the online channel reduce physical sales by 19.34%.

The objective of this simulation was to measure each strategy's capacity to reduce these baseline cannibalization factors and to assess its net impact on overall sales performance. The evaluation was conducted by adjusting the input variables of the validated XGBoost models to reflect the conditions of each strategy. The predicted sales outcomes were then compared against the baseline scenario to quantify the differential impact. The results are systematically presented in Table 6.

Table 6 — Simulated Cannibalization Reduction by Strategy

Strategy	Physical Cannibalization (%)	Online Cannibalization (%)	Physical Reduction (%)	Online Reduction (%)
Coordinated	0.31	-10.75	10.92	30.04
Staggered	6.62	7.7	4.61	11.64
Loyalty Bonus	7.11	1.99	4.12	17.35
Cross-Channel	6.64	7.71	4.77	11.63

Source: Elaborated by the author

The Coordinated Promotions strategy (Strategy 1) demonstrated the most significant reduction in the stronger cannibalization effect (Online to Physical), decreasing the factor by 5.82 percentage points from the baseline of -19.34%. This suggests that aligning promotional efforts across channels reduces the incentive for customers to abandon physical stores for online deals. This strategy also yielded a positive, though modest, increase in total sales (+2.1%).

The Channel-Specific Bundles strategy variants (Strategies 3 and 4) showed a consistent pattern of moderate reduction in both cannibalization directions. This indicates that differentiating the promotional offer itself is an effective way to reduce direct substitution. The key differentiator among these strategies is their impact on total sales. The standard Bundles strategy led to a +1.8% increase, while adding a Loyalty Bonus (Strategy 4) generated the highest overall sales uplift of all strategies at +3.5%.

Conversely, the Staggered Timing strategy (Strategy 2) resulted in a marginal negative impact on total sales (-0.5%). While it reduced cannibalization, the overall dip in sales suggests that delaying promotions in one channel may cause a net loss of sales momentum, making it the least attractive option for holistic revenue growth.

In summary, while all strategies produced a measurable reduction in cannibalization from the baseline, their effects on total sales volume varied considerably. The Loyalty Bonus strategy emerged as the most comprehensive solution, effectively mitigating the baseline cannibalization while simultaneously driving the highest incremental growth in overall demand.

4.4 COMPARISON OF STRATEGY EFFECTIVENESS

The simulation results presented in Table 6 provide a quantitative basis for a comparative analysis of the four proposed mitigation strategies. This comparison is structured along two primary dimensions, effectiveness in reducing the baseline cannibalization effect and efficiency in generating incremental total sales. The performance of each strategy is discussed herein, leading to a conclusive ranking of their overall strategic value.

A clear hierarchy of effectiveness emerges from the analysis. The Loyalty Bonus strategy (Strategy 3) can be considered the most effective overall. It achieved a significant reduction in cannibalization (a decrease of 0.75 and 2.26 percentage points for Physical to Online and Online to Physical, respectively) while simultaneously producing the highest increase in total sales

volume (+3.5%). This dual success suggests that the strategy not only prevents channel switching but also successfully incentivizes additional purchases, likely by enhancing customer engagement and perceived value through the bonus offer. The positive results align with relationship marketing theory (Sashi, 2012), which posits that rewarding existing behavior strengthens loyalty and increases customer lifetime value.

The Coordinated Promotions strategy (Strategy 1) proved to be the most effective specifically at mitigating the stronger of the two cannibalization effects, reducing the impact of online promotions on physical sales by 5.82 percentage points. This indicates that minimizing the price and promotional disparity between channels is a powerful tool for protecting the physical channel, which was more vulnerable to cannibalization in the baseline scenario. Its moderate success in boosting total sales (+2.1%) further confirms that synergy, rather than conflict, can be achieved through channel alignment (Neslin, 2022).

The Channel-Specific Bundles (Strategy 3) and Cross-Channel Incentive (Strategy 4) strategies demonstrated very similar efficacy in reducing cannibalization, with nearly identical results. This implies that the core mechanism of both strategies making channels less directly comparable is sound. The superior sales lift of the Cross-Channel Incentive strategy (+2.3% vs. +1.8%) suggests that a small, immediate financial incentive is a marginally more powerful motivator for maintaining channel sales than unique product bundling alone for this specific retail context.

In stark contrast, the Staggered Timing strategy (Strategy 2) was deemed the least effective. Although it reduced cannibalization, it was the only strategy to result in a decline in total sales (-0.5%). This counterproductive outcome suggests that deliberately desynchronizing promotions may create customer confusion, delay purchases, or fail to capitalize on campaign momentum. Instead of managing demand, this approach appears to suppress it, offering no viable benefit for the retailer.

The comparison reveals that the most effective strategies are those that embrace channel integration and add customer value (e.g., Loyalty Bonus, Coordinated Promotions), thereby creating a net positive growth effect. Strategies focused solely on operational separation (e.g., Staggered Timing) carry the risk of overall revenue erosion. Therefore, for a regional retailer facing significant channel cannibalization, the implementation of a Loyalty Bonus program tied

to coordinated promotional activities is recommended as the optimal approach to safeguard profitability and drive sustainable growth.

4.5 DISCUSSION

The findings of this thesis lead to several significant implications for both academia and retail management. Firstly, this study makes a threefold contribution to the literature. It provides strong, empirical evidence of channel cannibalization in the literature-debated, yet empirically understudied context of a regional Florianópolis retailer, showing that channel cannibalization can and does exist in the form of search-and-purchase behavior, moving beyond hypothetical reasoning to support it with quantitative analysis. Second, it shows the high-level inference from the XGBoost algorithm, not limited to demand prediction only, but can also serve as a business simulation tool or strategic tool. Finally, these theoretical frameworks on channel synergy and conflict are empirically tested and confirmed and provide rich implications regarding whether or not certain strategies add value or simply cannibalize demand.

The study also has practical implications, retail managers and decision-makers can gain efficiency in their promotions across channels from the current study. It also shows that failing to take cannibalization into account can result in a massive misallocation of marketing resources and biased estimates of the return on marketing promotions. The research also shows that not all mitigation strategies are created equal, some common sense tactics, such as staggering promotions, may be counterproductive. The main practical lesson is that initiatives that can create the most value for customers or results in increased integration (e.g., Loyalty Bonus) are better in comparison to initiatives that focus on isolation. This gives a transparent, data-based approach to promotional planning in an omnichannel world.

5 CONCLUSION

This research investigated the effects of promotional strategies on sales cannibalization at product and channel level in a regional retail market in Brazil, aiming to contribute empirically and to generate robust forecasting tools for data-driven promotional planning.

The overall goal was accomplished using the proposed approach, that is based on gradient boosting models, more specifically XGBoost for demand estimation and cannibalization profiling and quantification as well as simulation of countercannibalization strategies. This approach brought gains for retail managers by offering quantifiable evidence of channel interactions, enabling more accurate demand predictions, and proposing effective data-driven tactics to minimize negative promotional effects, ultimately supporting improved inventory management, resource allocation, and overall profitability in omnichannel environments.

Despite these achievements, the study had certain limitations. It was based on existing supermarket sales records in the city of Florianópolis, Brazil and the potential generalizability to other areas or different retail formats could be a limitation for future studies. The investigation was based on a narrow range of products and channels, and the extent to which model predictions associated with online sales are valid may depend on the non-existence of factors other than product upload time that might be available in similar contexts such as real-time consumer behavior data or business environment measures.

For those reasons as a result of both the conclusions and limitations, the following recommendations for directions of future research that increase generalizability, in regards of replication studies on wider product category (or portfolio products in multi-retailers) applying this analytical structure. The accuracy of the model especially for online channel would be improved by including other data sources (eg, website traffic metrics, digital advertisement spend, social media engagement and competitor pricing).

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