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Between Heritage and Innovation: How Luxury Reinvents Itself Through Technology and Data

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To science, to the curious and to innovation.

Contents

INTRODUCTION

This thesis was developed within an industrial PhD program carried out in collaboration with an Italian company operating in the luxury sector. The underlying interest stems from a shared need, between academia and industry, to understand how the concept of luxury is changing and how technology and data analysis can support strategic decision-making in an increasingly complex environment. From this perspective, the work seeks to combine direct empirical observation of the market with theoretical discussion, aiming to provide an updated view of management models and value-creation logics in contemporary luxury.

To fully grasp the meaning and relevance of this analysis, it is necessary to begin from the context in which it is situated: a sector that, while remaining anchored to its traditional values of exclusivity and craftsmanship, is undergoing a profound transformation. Today, luxury stands as one of the pillars of the global economy, exceeding €1.5 trillion in 2024 and showing stable growth prospects (5-7% annually through 2030) (D'Arpizio et al., 2024). This growth, however, is not only the result of the intrinsic strength of luxury brands, but also of a series of transformations that have redefined demand, technologies, and distribution models.

First and foremost, consumer demand is progressively shifting toward digital channels. Specialized platforms such as Farfetch and Mytheresa have reached new customer segments by offering convenience, a wide assortment, ease of use, and greater product knowledge. These factors, together with the enjoyment of the online experience, have expanded the customer base without necessarily undermining the exclusivity that defines the luxury sector (Hübscher, 2022; Liu et al., 2013; Majeed et al., 2024). Driving this change is a younger and more knowledgeable consumer, particularly Millennials and Generation Z, who seeks personalization, sustainability, and engagement consistent with brand identity and across different touchpoints. This form of demand goes beyond the product itself, being oriented toward meaning, authenticity, and relationship (Pantano et al., 2022; Ameen et al., 2021).

At the same time, the evolution of demand has encouraged the emergence and diffusion of new technologies that enhance the customer experience while also introducing new managerial complexities. Luxury brands have begun adopting an increasingly sophisticated technological portfolio that spans both the front stage and the backstage: from artificial intelligence for advanced personalization, to augmented and virtual reality for immersive experiences, and to blockchain and the Internet of Things for authentication, traceability, and connected environments (Chung et al., 2020). When properly integrated, these solutions can increase perceived value, operational transparency, and data quality (Chen et al., 2024; Huang & Rust, 2021).

Driven by these new consumer needs and by the opportunities offered by technology, luxury companies have undertaken a profound rethinking of their distribution systems. The goal is to move from siloed models toward more fluid forms of integration: first cross-channel, then omnichannel, which combines data, processes, and experiences into a unified structure. In the luxury sector, this evolution takes on distinctly phygital characteristics, where physical and digital contact merge to reinforce the perception of exclusivity and brand coherence (Verhoef et al., 2021).

Within this scenario, luxury companies now operate along three key directions. The first is the democratization of luxury, referring to the expansion of audiences without, ideally, weakening the symbolic aura that distinguishes the brand (Rosendo-Rios & Shukla, 2023; Kapferer & Laurent, 2016). The second concerns the need to preserve symbolic value in a hyper-accessible and digitalized environment, where the so-called "luxury paradox" acts as a constant constraint in strategic design (Bastien & Kapferer, 2013). The third is an increasingly complex omnichannel governance, which requires integrated management of pricing, promotions, assortment, and services (Verhoef et al., 2015). Elements long considered "taboo" in the world of luxury, such as price or promotional policies, are gaining growing importance in the distribution environment, demanding clear rules to maintain coherence with brand identity and values (Dhaliwal et al., 2020).

The directions just described represent not only managerial challenges but also theoretical issues that remain partly unresolved. Despite growing academic attention, research on this topic is still fragmented: many studies have focused on specific aspects, such as the impact of digital technologies, changes in consumer behavior, or the evolution of distribution models, but these elements have rarely been examined together. In other words, there is still a lack of an integrated perspective capable of connecting the technological dimension, channel strategies, and value-creation dynamics that define competition in the luxury industry today.

This thesis lies precisely at the intersection of these two needs. The academic need to fill a knowledge gap and the practical need to provide useful tools for companies to understand and manage the ongoing transformation. Based on a systematic review of the literature and continuous dialogue with managers and industry professionals, several key research questions have emerged: How are new technologies redefining luxury distribution strategies and the roles of different channels? How are consumer behaviors evolving in the shift from exclusivity to accessibility? And, most importantly, under what conditions does omnichannel integration generate synergies rather than conflicts or cannibalization? These questions form the common thread of this work, which is structured around three complementary studies. Each chapter addresses a different level of analysis, theoretical, behavioral, and systemic, to offer a coherent and multilayered understanding of how luxury is evolving in the digital era.

The first chapter, “From Multi-Channel to Phygital: A Systematic Review of Emerging Technologies in Luxury Distribution”, forms the theoretical foundation of this work. Through a systematic literature review and a bibliometric analysis of international literature, the chapter provides an integrated overview of how the topic of channel integration and emerging technologies has been addressed so far in luxury studies. The analysis highlights the fragmented nature of the field and proposes a conceptual synthesis that combines the Theory-Context-Method and Antecedents-Decisions-Outcomes frameworks, clarifying the main technological antecedents, related managerial decisions, and their effects on firm performance. The contribution of this chapter is twofold: on one hand, it offers an updated map of the academic debate and its existing gaps; on the other, it outlines the key principles that should guide technological integration in luxury distribution system while respecting the logic and symbolic codes that define luxury.

The second chapter, “From Prestige to Promotions: Understanding Consumer Dynamics in the Luxury Fashion Industry”, addresses the topic from the perspective of consumer behavior and pricing dynamics in digital channels. Based on a large dataset of transactions from an e-commerce platform, the study analyzes how customers’ entry points, whether through full-price or promotional purchases, affect their subsequent purchasing trajectories. The goal is to understand if and how promotional policies influence brand relationships, distinguishing between consumer segments that are more price-sensitive and those driven by symbolic value. In doing so, the chapter provides an empirical interpretation of the tensions between exclusivity and accessibility, contributing to the debate on the “democratization of luxury” with concrete evidence useful for marketing and pricing decisions.

The third chapter, “When Channels Complement (and When They Don’t) in Luxury Retail”, broadens the analysis to the level of the overall distribution system. Using weekly sales data from a luxury brand, the chapter investigates the dynamic interdependencies among the main direct channels, e-commerce, boutiques, and outlets, to understand when and to what extent effects of complementarity or cannibalization arise. The econometric approach, based on a VARX model, makes it possible to observe how demand shocks in one channel propagate to others and to identify which configurations foster overall value creation. On a theoretical level, the chapter integrates Service-Dominant Logic and Market System Dynamics, offering an interpretation of luxury as a governed ecosystem in which channels act as interdependent nodes, each playing a specific role in the transmission and appropriation of value.

CHAPTER 1

From Multi-Channel to Phygital: A Systematic Review of Emerging Technologies in Luxury Distribution

Abstract

The luxury sector is undergoing profound transformation as emerging technologies reshape distribution strategies once defined by exclusivity, ritual, and heritage. While multi-channel, cross-channel, and omni-channel frameworks have been widely studied in mainstream retailing, their application in luxury contexts remains fragmented and underexplored. This chapter addresses this gap through a PRISMA-guided systematic literature review combined with bibliometric analysis of 244 records, resulting in a core synthesis of 93 conceptual and empirical studies. The review adopts a dual lens: the Theory-Context-Method (TCM) framework to map theoretical foundations, contextual boundaries, and methodological patterns, and the Antecedents-Decisions-Outcomes (ADO) framework to trace causal mechanisms linking technological affordances and market pressures to strategic choices and outcomes. The synthesis highlights that effective luxury channel strategies hinge on selective, brand-coded integration that prioritizes trust and continuity before emotion and spectacle. By consolidating a fragmented field, this study clarifies the trade-offs between access and exclusivity, speed and symbolism, automation and ritual, offering a cumulative knowledge base that advances scholarly understanding and provides decision-oriented insights for luxury managers dealing with the emerging challenges of omnichannel distribution.

1. INTRODUCTION

The luxury industry, valued at more than €1.5 trillion worldwide in 2024 and expected to continue growing steadily in the coming years, represents one of the most distinctive expressions of contemporary consumer culture (D'Arpizio et al., 2024; Bastien & Kapferer, 2013). Yet, this traditional model is now being transformed by technological innovation and by the evolution of consumer expectations. New generations of customers, particularly Millennials and Generation Z, are digitally native, socially connected, and increasingly attentive to personalization, sustainability, and immediacy (Pantano et al., 2022; Ameen et al., 2021). Their habits and values are redefining what luxury means and how it is accessed.

Over the last decade, retailing has experienced a deep structural change. Distribution strategies that were once based on separate multichannel systems, where boutiques, e-commerce, and mobile applications operated independently, have gradually evolved into cross-channel configurations, which allow customers to move from one channel to another, for example by researching online and purchasing in store (Verhoef et al., 2021; Beck & Rygl, 2015). Today, the dominant paradigm is omnichannel, in which all touchpoints are integrated to offer a consistent, seamless, and data-driven experience (Brynjolfsson et al., 2013; Piotrowicz & Cuthbertson, 2014). Within luxury, this evolution often takes the form of phygital experiences, where physical and digital dimensions merge in real time to create personalized and emotionally rich encounters that remain coherent with the brand's identity (Banik, 2021).

This transformation, however, is far from simple. Luxury brands have traditionally adopted a cautious approach toward technology, fearing that excessive accessibility could erode the aura of exclusivity that sustains their value (Dubois et al., 2001; Beverland, 2006). At the same time, the rapid diffusion of digital channels has made innovation not only desirable but necessary. Artificial Intelligence now supports hyper-personalized recommendations (Cenizo, 2025) Augmented and Virtual Reality enhance the sensory experience, blockchain guarantees authenticity and traceability, and the Internet of Things connects stores and logistics in real time (Chung et al., 2020; Grewal et al., 2017; Huang & Rust, 2021; Chen et al., 2024). Together, these technologies are redefining how value is created and perceived. On the front stage, they enrich the customer experience, increasing perceived value, trust, and emotional engagement (Hoang et al., 2023). On the backstage, they improve efficiency, coordination, and data transparency across supply chains and internal processes (Hilken et al., 2017; Kshetri, 2018; Saberi et al., 2019). However, these same tools also introduce new tensions: when technology dominates the relationship, authenticity can be weakened, privacy compromised, and the sense of ritual that defines luxury may fade (Shen et al., 2022; Mukherjee, 2021).

Despite growing academic interest, research on technology and luxury distribution remains fragmented. Many studies focus on individual tools without considering how these innovations interact within a broader channel architecture (Pantano et al., 2018; Hollebeek et al., 2019). This approach leads to isolated insights and makes it difficult to understand the mechanisms that connect technology adoption to strategic and experiential outcomes. Moreover, existing works rarely address the tensions specific to luxury: how to expand digital access without eroding scarcity, how to increase speed and convenience without losing symbolic depth, and how to use automation without diminishing the human touch (Arrigo, 2018; Holmqvist et al., 2020; Bastien & Kapferer, 2013). As a result, our understanding of causal mechanisms, contextual boundaries, and long-term implications remains incomplete, offering limited guidance for both scholars and practitioners (Verhoef et al., 2015; Lemon & Verhoef, 2016; Ko et al., 2019).

To address these gaps, this chapter presents a systematic literature review following the PRISMA protocol (Page et al., 2021; Tranfield et al., 2003). The review is complemented by bibliometric analysis to map the field's evolution and by a dual framework combining Antecedents–Decisions–Outcomes (ADO) and Theory–Context–Method (TCM)perspectives (Paul & Criado, 2020; Hulland & Houston, 2020; Paul et al., 2021). Through this approach, the study identifies the key drivers that have guided luxury brands in adopting and integrating emerging technologies, the strategic decisions that have shaped new forms of distribution, and the outcomes observed at customer, firm, and market levels. The research question guiding this work is:

RQ: How have emerging technologies shaped multichannel, cross-channel, and omnichannel strategies in the luxury sector?

This study contributes to the existing literature in two main ways. First, it offers a comprehensive synthesis that links emerging technologies to luxury channel strategy, clarifying the trade-offs between access and exclusivity, speed and symbolism, and automation and human ritual (Ko et al., 2019; Lemon & Verhoef, 2016). Second, by combining the ADO and TCM frameworks, it provides a clear causal logic and transparent scope conditions that connect antecedents, managerial decisions, and outcomes, generating actionable insights for both scholars and managers (Paul & Criado, 2020; Palmatier et al., 2018).

The chapter is organized as follows. Section 2 describes the review protocol and data collection. Section 3 presents the bibliometric overview. Section 4 synthesizes the findings using the TCM framework, while Section 5 discusses the ADO-based causal model. Section 6 concludes by outlining theoretical implications and future research directions.

2. METHODOLOGY

2.1 Organizing framework

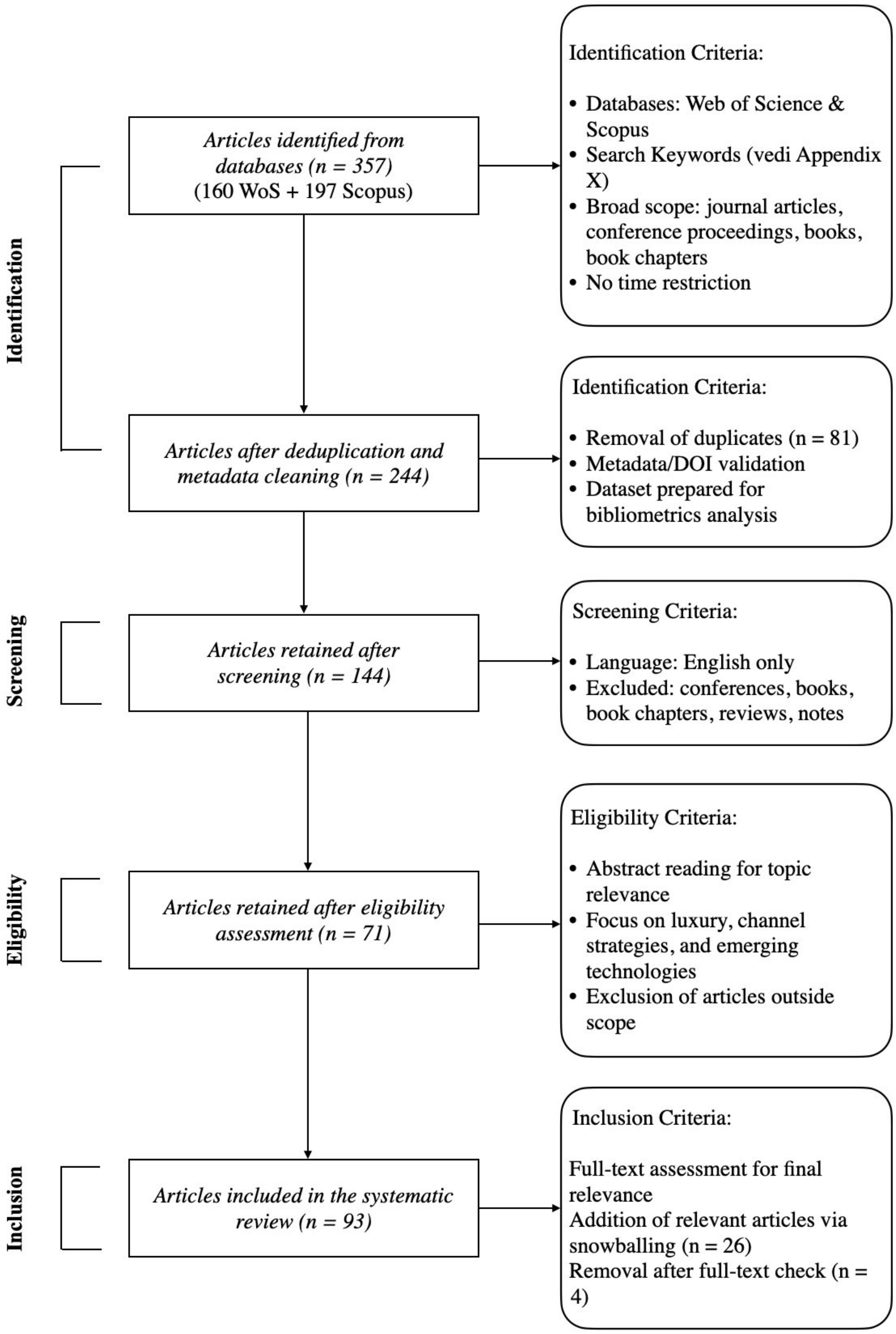
A systematic review is a scientific form of secondary research that uses explicit, replicable procedures to identify, evaluate, and synthesize prior studies for a focused research agenda (Paul & Criado, 2020). Such reviews advance knowledge by bringing together dispersed findings, identifying inconsistencies that may limit generalizability, and mapping theoretical, contextual, and methodological directions for future research (Paul & Criado, 2020). This helps explain their growing presence in outlets focused on cumulative knowledge and theory building in management and marketing (Hulland & Houston, 2020; Palmatier et al., 2018). Reviews can be domain-, theory-, method-, or meta-analysis-based, each serving distinct roles in knowledge accumulation (Paul et al., 2021). Given our objective, to explain how emerging technologies reshape multi-, cross-, and omni-channel strategies in luxury, we adopt a domain-based, framework-driven approach that organizes relationships rather than merely listing themes (Paul & Benito, 2018; Paul & Criado, 2020). This choice responds to a field where technology, channel integration, and luxury branding have evolved on parallel tracks, producing fragmentation around customer journeys, touchpoint orchestration, and exclusivity-accessibility tensions (Verhoef et al., 2015; Lemon & Verhoef, 2016; Ko et al., 2019). Procedurally, PRISMA supplies the identification-screening-eligibility-inclusion spine (Page et al., 2021); analytically, we integrate ADO with TCM so the synthesis simultaneously traces the phenomenon-specific causal chain and documents the evidentiary foundations (Paul & Criado, 2020). In this dual logic, the ADO framework structures prior research by mapping the antecedents that explain why luxury firms have had to rethink their distribution strategies, the managerial decisions taken in response to these drivers, and the resulting outcomes at the customer, firm, and societal levels (Paul & Benito, 2018; Palmatier et al., 2018; Lemon & Verhoef, 2016). Complementarily, TCM structures how the knowledge base is constituted by cataloging theoretical lenses, focal contexts, and methods that bear on internal and external validity across qualitative, quantitative, experimental, and mixed designs (Paul et al., 2021; Siddaway et al., 2019). Because

ADO alone offers limited guidance on theoretical, contextual, and methodological imbalances, and TCM alone is less suited to assembling a causal chain among constructs, their integration couples causal organization with evidentiary transparency, in line with recommendations for rigorous, reproducible reviews (Paul & Benito, 2018; Paul & Rosado-Serrano, 2019; Hulland & Houston, 2020). Operationally, we code each included study on an ADO-TCM template, recording antecedents, decisions, and outcomes alongside stated theories, contexts, and methodological choices (Paul & Rosado-Serrano, 2019; Palmatier et al., 2018). To reinforce coverage and transparency at the identification stage, we pair this framework-driven review with a bibliometric scoping of the field, well-suited to mapping intellectual structures, temporal dynamics, and topical clusters, reducing idiosyncratic sampling, and highlighting high-leverage substreams, via a descriptive overview of publication trajectories and keyword signals (Donthu et al., 2021).

2.2 Procedure

We followed the PRISMA protocol to ensure a transparent, auditable, and replicable workflow for curating and synthesizing the literature on how emerging technologies shape multi-, cross-, and omni-channel strategies in the luxury sector (Page et al., 2021). PRISMA structures the review into four sequential stages, identification, screening, eligibility, and inclusion, which collectively provide a clear procedural spine for study discovery, appraisal, and selection without presupposing substantive results (Ter Huurne et al., 2017; Page et al., 2021). The PRISMA flow diagram corresponding to these stages is reported and each step is detailed in the next paragraph (2.2.1-2.2.4) to document decisions and guard against selection bias.

Figure 1. Flow diagram of article collection using PRISMA protocol



2.2.1 Identification

The first identification stage was designed to maximize recall with pre-specified, replicable searches while postponing restrictive decisions to later stages to limit selection bias (Moher et al., 2009; Page et al., 2021). We relied on Web of Science Core Collection (WoS) and Scopus as complementary multidisciplinary indexes whose combined coverage improves retrieval breadth and reduces database-specific omissions in management and marketing research (Mongeon & Paul-Hus, 2016; Gusenbauer & Haddaway, 2020). Given the field's interdisciplinary nature at the intersection of luxury, retail channels, and emerging technologies, we did not restrict by outlet or document type at this stage to ensure a comprehensive sampling frame (Siddaway et al., 2019; Paul & Criado, 2020).

Search fields and strings. Searches were executed in WoS using the Topic field (TS: title, abstract, author keywords, Keywords Plus) and in Scopus using TITLE-ABS-KEY, with syntax adapted to each index (Page et al., 2021). The WoS query was:

TS=(luxur OR "luxury goods" OR "high-end") AND TS=("cross-channel" OR "omni-channel" OR "multi-channel" OR "channel integration" OR "sales channel" OR omnichannel OR multichannel OR "customer journey" OR "customer experience" OR "retail format*" OR phygital OR "e-commerce" OR ecommerce OR "brick and mortar") AND TS=(tech* OR technolog* OR "digital transformation" OR "digital innovation" OR digitalization OR digital* OR "artificial intelligence" OR "big data")*

The Scopus query was:

(TITLE-ABS-KEY (luxur OR "luxury goods" OR "high-end") AND TITLE-ABS-KEY ("cross-channel" OR "omni-channel" OR "multi-channel" OR "channel integration" OR "channel management" OR "sales channel" OR omnichannel OR multichannel OR "cross channel" OR "multi channel" OR "omni channel" OR "customer journey" OR "customer experience" OR "retail format*" OR phygital OR "e-commerce" OR ecommerce OR "brick and mortar") AND TITLE-ABS-KEY (tech* OR technolog* OR "digital transformation" OR "digital innovation" OR "technology adoption" OR "digitalization" OR "innovation management" OR digital* OR "artificial intelligence" OR "AI" OR "machine learning" OR "big data" OR "data analytics" OR "cloud computing" OR "IoT" OR "internet of things" OR "blockchain" OR "emerging technologies" OR "technology trends" OR "technological advancements" OR "smart technologies")) AND (SUBJAREA (BUSI) OR SUBJAREA (SOCI) OR SUBJAREA (ECON) OR SUBJAREA (DECI)) AND (LANGUAGE ("English"))*

Following established SLR guidance, we constructed a three-block query spanning (1) luxury, (2) channel configuration and customer experience, and (3) technology; we searched title/abstract/keywords to balance precision and recall and tailored field operators to each database's syntax (Paul & Criado, 2020; Page et al., 2021). The luxury block used "luxur*," "luxury goods," and “high-end,” aligning with contemporary definitions of luxury consumption and branding (Ko et al., 2019). The channel block included multi-/cross-/omni-channel: “channel integration”, “sales channel”, “customer journey”, “customer experience”, “retail format*”, “phygital”, “e-commerce/ecommerce”, and “brick and mortar”, reflecting the evolution from multi- to omni-channel retailing and associated experiential constructs. The technology block captured “tech*”, “technolog*”, “digital transformation”, “digital innovation”, “digitalization/digital*”, “artificial intelligence/AI/ML”, “big data/analytics”, “IoT” and “blockchain” consistent with core enablers of channel integration and phygital experiences (Grewal et al., 2017; Bonetti et al., 2018). To improve recall across indexing variations, we employed truncation (e.g., luxur*, tech*), spelling variants (e.g., e-commerce/ecommerce), and hyphenation variants (e.g., cross-channel/cross channel), in line with search-engine best practices for systematic reviews (Gusenbauer & Haddaway, 2020).

We adopted database-specific search configurations to balance recall and precision given known differences in coverage and indexing between WoS and Scopus. In WoS, we applied no ex-ante limits on document type or language to maximize recall of interdisciplinary records whose subject tagging can be conservative or uneven, particularly for adjacent areas such as information systems and human-computer interaction, thereby mitigating under-representation at the search stage (Mongeon & Paul-Hus, 2016; Gusenbauer & Haddaway, 2020). In Scopus, whose wider inclusion of conference proceedings, trade outlets, and non-English sources can inflate off-scope noise, we restricted the query to Business, Social Sciences, Economics, and Decision Sciences and to English to align with the review’s disciplinary scope and ensure metadata consistency across records retrieved at scale (Mongeon & Paul-Hus, 2016; Harzing & Alakangas, 2016; Gusenbauer & Haddaway, 2020). Across both databases, we then harmonized results during screening, deduplicating and applying identical inclusion criteria, so that any asymmetries introduced at query time served only to manage the recall-precision trade-off and not to bias eligibility decisions, in line with best-practice guidance for transparent, reproducible reviews (Siddaway et al., 2019; Page et al., 2021).

The search yielded 160 records from Web of Science and 197 from Scopus; after merging and de-duplicating via DOI, title, author, and year heuristics, 276 unique records remained. We then standardized metadata and validated DOIs, removing entries with incomplete fields to ensure accurate citation matching and network construction, which produced a bibliometric-ready corpus of 244 records (Zupic & Čater, 2015; Donthu et al., 2021). This corpus was used for a pre-screening bibliometric scoping to map publication trends, outlets, and topical signals, thereby reducing topical blind spots and informing the subsequent qualitative assessment (Donthu et al., 2021). All steps, parameters, and counts are documented in the PRISMA flow (Figure 1) for transparency and replicability (Page et al., 2021; Paul & Criado, 2020).

2.2.2 Screening

Consistent with PRISMA, the screening phase applied transparent, a priori criteria to refine the initial pool to records suitable for subsequent eligibility assessment while minimizing selection bias and preserving reproducibility (Page et al., 2021). We implemented a two-step screening protocol: first, we restricted records to English-language, peer-reviewed journal articles with persistent identifiers (DOIs), excluding conference proceedings, books, book chapters, notes, editorials, and review articles; second, we removed cross-database duplicates using DOI matching and fuzzy title checks with manual verification where necessary (Snyder, 2019; Bramer et al., 2016). Limiting to peer-reviewed journal articles focuses the corpus on studies that have undergone rigorous independent scrutiny, which is standard practice in management and marketing SLRs; excluding secondary research and non-article formats avoids double-counting synthesized evidence and reduces heterogeneity attributable to disparate review aims or editorial content; and requiring DOIs secures traceability for full-text retrieval and accurate record linkage, which is essential for both bibliometric profiling and subsequent synthesis (Tranfield et al., 2003; Snyder, 2019).

Applied to the Web of Science set, screening removed six non-English records, 35 conference papers, and four records without DOIs, yielding 116 records retained for eligibility (Page et al., 2021; Bramer et al., 2016). Applied to the Scopus set, screening removed 39 conference papers; 59 non-article items (books, book chapters, notes, and review articles); and five records without DOIs, yielding 95 records retained for eligibility (Page et al., 2021; Snyder, 2019). We then merged the screened WoS and Scopus sets and eliminated 67 cross-database duplicates via DOI and title matching, resulting in 144 unique journal articles entering the eligibility stage for abstract assessment (Bramer et al., 2016; Mongeon & Paul-Hus, 2016). Importantly, no exclusions at screening were made on the basis of theory, context, or method to avoid constraining the ADO-TCM mapping ex ante; topical fit and evidentiary quality were instead evaluated during eligibility and inclusion, as recommended by PRISMA and SLR best practices in marketing (Page et al., 2021; Paul & Criado, 2020; Siddaway et al., 2019).

2.2.3 Eligibility

At the eligibility stage, we applied pre-specified content criteria aligned with our ADO-TCM framing and PRISMA guidance (Figure 1) to determine which records were substantively pertinent to the research question while maintaining transparency and replicability (Page et al., 2021; Paul & Criado, 2020). Studies were eligible only if they simultaneously satisfied three conditions: first, an explicit focus on the luxury sector, operationalized as research on luxury brands, categories, or markets as understood in the marketing literature, so that contextual inferences are grounded in luxury's distinctive logics of scarcity, symbolic value, and experiential control (Ko, et al., 2019; Bastien & Kapferer, 2013); second, clear engagement with digital transformation or technological innovation, including, but not limited to, AI/ML, AR/VR, RFID/IoT, clienteling and CRM platforms, data analytics, and related digitalization processes as antecedents or enablers of channel-related change (Verhoef et al., 2021; Grewal et al., 2017); and third, an explicit treatment of distribution/channel strategy in multi-, cross-, or omni-channel contexts. Consistent with review best practices, we retained conceptual and empirical peer-reviewed journal articles and excluded any residual editorials, commentaries, and secondary reviews that may have passed initial screening to avoid double-counting synthesized evidence and to focus on primary contributions (Snyder, 2019; Palmatier et al., 2018). We manually assessed the abstracts of all 144 screened records against these inclusion criteria, records that were ambiguous on any single criterion were flagged for full-text verification in the subsequent inclusion phase to minimize erroneous exclusions (Page et al., 2021). Applying these rules reduced the pool from 144 to 71 (See Figure 1) articles whose abstracts unambiguously met all three criteria, with the most common reasons for exclusion being a non-luxury focal context, a focus on digital marketing communications rather than distribution/channel strategy, or technological innovation unrelated to channel integration (Page et al., 2021; Verhoef et al., 2015).

2.2.4 Inclusion

In the inclusion phase, we conducted full-text assessments of the 71 articles retained at eligibility against the pre-specified criteria (luxury sector focus, engagement with digital transformation or technological innovation, and explicit treatment of multi-, cross-, or omni-channel distribution strategies) to confirm substantive fit with the review question in a PRISMA-consistent procedure that prioritizes transparency and reproducibility (Page et al., 2021).

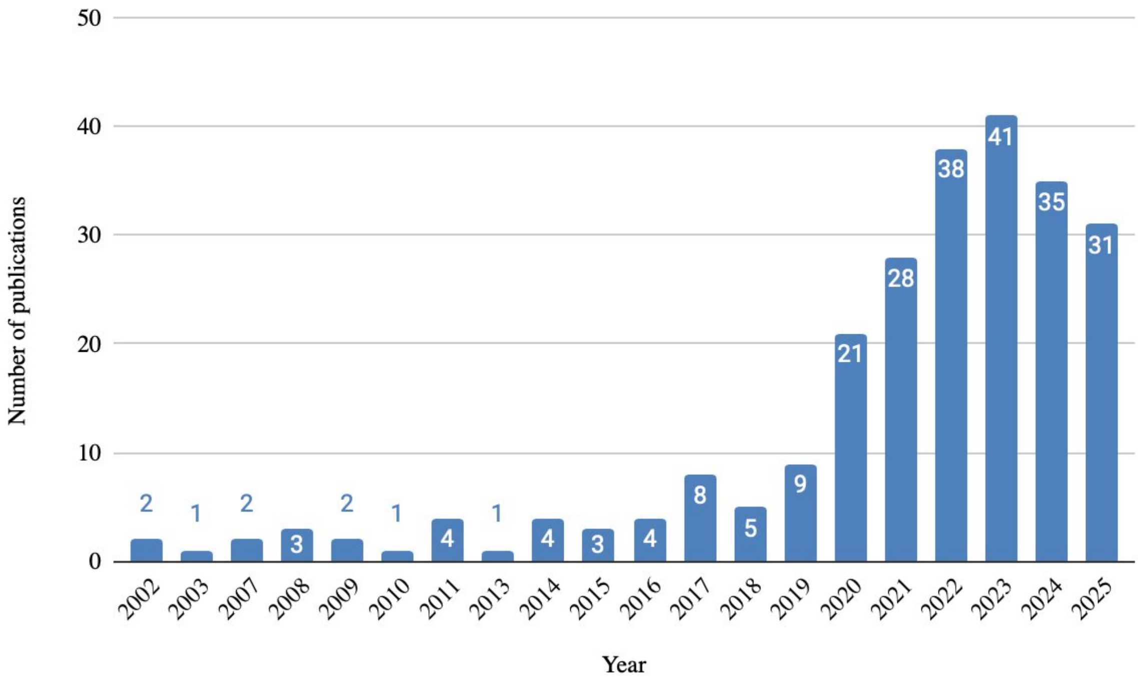
Four records were excluded at full text due to misalignment identified only upon detailed reading reducing the set to 67 studies for synthesis. To enhance completeness and mitigate indexing bias, we then executed backward and forward snowballing from the reference lists and citation trails of the eligible seed set using WoS, Scopus, and Google Scholar, applying the same inclusion criteria and deduplication rules, which yielded 26 additional eligible journal articles and aligns with established protocols for expanding coverage in complex, interdisciplinary evidence bases (Wohlin, 2014; Greenhalgh & Peacock, 2005; Bramer et al., 2016). Snowballing proceeded iteratively until a stop rule was reached, two successive iterations with no new eligible records, after which we performed a final manual sweep of "in-press" sections of leading marketing, retailing, and information systems journals to offset database indexing lags; no further eligible records were identified at that time, supporting the comprehensiveness of the corpus (Gusenbauer & Haddaway, 2020; Mongeon & Paul-Hus, 2016). The final dataset (Figure 1) for synthesis comprised 93 conceptual and empirical journal articles, which were then subjected to a content analysis guided by the ADO and TCM frameworks to extract and organize information on antecedents, channel decisions, outcomes, and the theories, contexts, and methods underlying each study (Paul & Benito, 2018; Paul et al., 2021).

3. BIBLIOMETRIC CHARACTERISTICS OF THE STUDY

Our corpus comprises 244 records: 142 journal articles, 54 books/chapters, 42 conference papers, and 5 reviews. Across these documents, we observe contributions spread over 188 distinct journals, authored by 641 unique scholars, with an average of 2.80 authors per document.

The temporal distribution confirms a classic "emergence-surge" pattern. Publications appear sporadically until the late 2010s, followed by a sharp acceleration from 2020 onward, peaking in 2023 and remaining elevated through 2025 (Figure 2). Such S-shaped growth is typical when a research niche reaches critical mass in terms of methods, data, and managerial salience (Donthu et al., 2021).

Figure 2. Number of publications over years



Regarding outlets, contributions are widely dispersed, but several journals exhibit higher concentration (Table 1). The Journal of Retailing and Consumer Services leads with 7 publications, followed by the Journal of Business Research (6), and a set of outlets with 3-4 items each, including International Journal of Consumer Studies, Sustainability, Electronic Commerce Research, International Journal of Advertising, International Journal of Retail & Distribution Management, Journal of Global Fashion Marketing, and Journal of Global Scholars of Marketing Science; the Asia Pacific Journal of Marketing and Logistics accounts for 2. This dispersion indicates a field that is methodologically and thematically plural, with no single dominant home outlet (Donthu et al., 2021).

Table 1. Distribution of Publications by Journal Outlet

Journal	No. of publications
Journal of Retailing and Consumer Services	7
Journal Of Business Research	6
International Journal of Consumer Studies	4
Sustainability	4
Electronic Commerce Research	3
International Journal of Advertising	3

International Journal of Retail & Distribution Management	3
Journal Of Global Fashion Marketing	3
Journal Of Global Scholars of Marketing Science	3
Asia Pacific Journal of Marketing and Logistics	2

Citation indicators show a mean of 16.14 citations per record, with a maximum of 182 for "Social media and luxury brand management: The case of Burberry," underscoring the early centrality of social media as a technological driver for luxury branding (Phan et al., 2011). Aggregated by citing venue (Table 2), citations are concentrated in the Journal of Business Research (293), Journal of Global Fashion Marketing (254), Journal of Brand Management (194), Computers in Human Behavior (151), and the International Journal of Hospitality Management (147), reflecting both marketing and adjacent consumer/technology communities engaging with this topic (Donthu et al., 2021).

Table 2. Distribution of Citations Across Journal Outlets

Journal	**No. of citations**
Journal of business research	293
Journal of global fashion marketing	254
Journal of brand management	194
Computers in human behavior	151
International journal of hospitality management	147

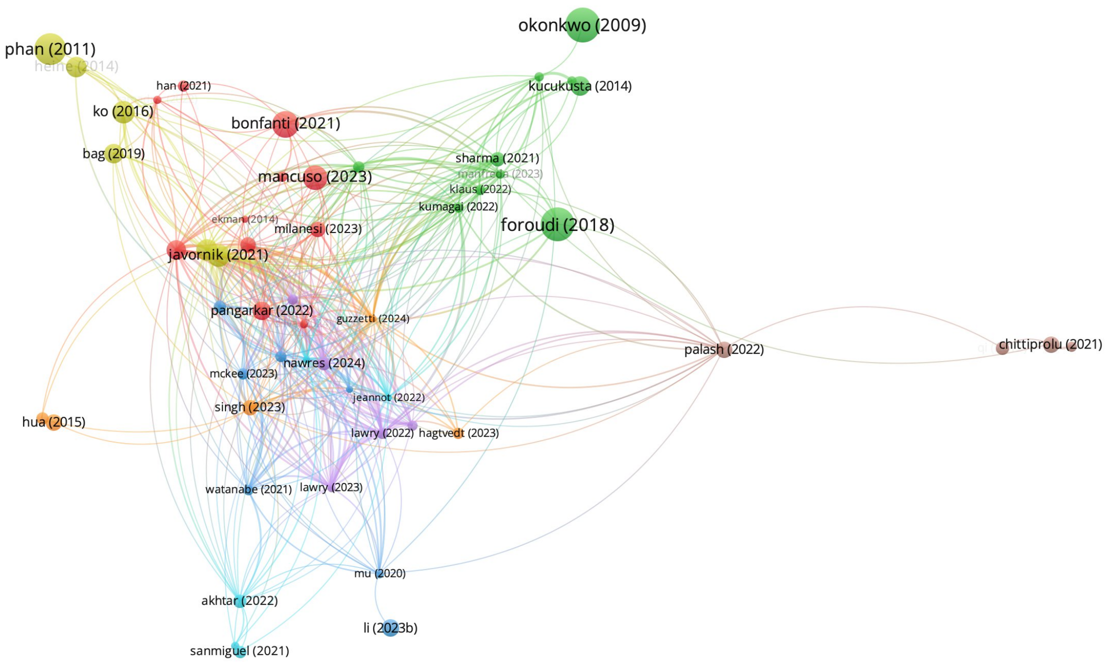
Methodologically, we can interpret citation counts as indicators of intellectual influence while acknowledging that citations are an imperfect but widely accepted proxy for scholarly impact and knowledge flows (Appio et al., 2014; Pieters & Baumgartner, 2002; Stremersch et al., 2007). To probe the field's intellectual structure, we conducted a co-citation analysis over the reference lists of all 244 records. Despite the breadth of the dataset, only eight references were co-cited by at least two documents, pointing to limited theoretical convergence and a still-fragmented knowledge base, features commonly observed in emergent and interdisciplinary domains (Hjørland, 2013; Rossetto et al., 2018; Liu et al., 2015). In line with co-citation logic, this signals that foundational "shared anchors" are not yet consolidated and that multiple theoretical lineages currently coexist (Donthu et al., 2021).

3.1 Bibliographic coupling

Bibliographic coupling links documents that share references, based on the assumption that a common bibliography signals topical relatedness. Unlike co-citation, which privileges seminal and highly cited contributions, coupling highlights the current configuration of research fronts (Kessler, 1963; Weinberg, 1974; Zupic & Čater, 2015; Donthu et al., 2021). This makes it particularly useful in emerging domains such as luxury channel strategies, where knowledge consolidation is still ongoing.

We implemented the analysis with VOSviewer, using a dataset constructed directly from DOIs. VOSviewer allows inputting a plain list of DOIs (one per line) and automatically retrieves the bibliographic metadata needed for constructing citation-based maps; the inclusion of "cited references" enables the creation of bibliographic coupling and co-citation networks (van Eck & Waltman, 2010; van Eck & Waltman, 2019). To ensure interpretability, we applied a minimum threshold of 10 citations per document. Out of 244 records, 63 met the threshold, of which 54 formed connections (i.e., shared at least one bibliographic link), resulting in a network that is present but still relatively sparse (Zupic & Čater, 2015; Donthu et al., 2021).

Figure 3. Bibliographic coupling graph



Bibliographic coupling yielded eight macro-thematic clusters (Figure 3), computed in VOSviewer by constructing a document-by-document coupling network from shared references, normalizing link weights using association strength, and detecting communities with the VOS clustering algorithm (Kessler, 1963; Van Eck & Waltman, 2010; Waltman & van Eck, 2013). Cluster 1 captures research on strategic phygital and omnichannel transformation in luxury, focusing on innovation paths, human-technology complementarities, and market-specific adoption. Contributions in this stream highlight the balance between radical and incremental rollouts, the integration of salesperson-mediated rapport into digital journeys, and tailoring orchestration to generational cohorts or geographic markets such as China (Bonfanti, 2021; Liu, 2019; Mancuso et al., 2024; Milanesi, 2023; Pangarkar, 2022; Pantano, 2022; Ramadan & Nsouli, 2022; Silva et al., 2024).

Cluster 2 consolidates consumer- and service-experience lenses for luxury channels, addressing shopping orientations, online luxury experience (OLX) segments, self-service technology acceptance, well-being effects of channel formats, and early luxury strategy syntheses. This cluster provides the behavioral scaffolding for omnichannel design in high-touch contexts (Foroudi et al., 2018; Kim & Lee, 2011; Klaus, 2020; Klaus and Tynan, 2022; Kumagai & Nagasawa, 2022; Okonkwo, 2009).

Cluster 3 centers on channel architecture, examining direct-to-consumer (DTC) logics, supra-omnichannel platform evolution, blockchain-based authentication, international integration patterns, and e-service capability gaps (Guercini et al., 2020; Hoang, 2023; Li et al., 2023; McKee et al., 2023; Mu et al., 2020; Watanabe et al., 2021).

Cluster 4 highlights digital touchpoints for luxury brand storytelling and experiential value, exploring social media communities, executive playbooks for owned/earned/paid assets, multi-actor service encounters, and AR strategies that amplify aura and personalization (Heine & Berghaus, 2014; Holmqvist et al., 2020; Javornik et al., 2021; Ko et al., 2019; Phan et al., 2011).

Cluster 5 foregrounds phygital experiential design and adoption drivers, clarifying the hedonic, status, and social mechanisms underpinning consumer acceptance of AR and virtual goods. Studies in this group examine affect-trust-behavior pathways, motivations for self-gifting and NFTs, and the preservation of exclusivity in hybrid spaces (Khelladi et al., 2024; Lawry, 2023; Nawres et al., 2024; Pangarkar & Shukla, 2023).

Cluster 6 examines sensory substitution and AI/haptic innovation in high-touch luxury services, including digital gastronomy staging, the current limitations and promises of haptic technologies for "touch," and AI-based virtual try-ons, which reveal trade-offs between perceived quality and aesthetics (Jeannot et al., 2022; Ornati & Kalbaska, 2022; Sanmiguel et al., 2021; Song & Bonanni, 2024).

Cluster 7 focuses on high-tech/high-touch orchestration in physical luxury spaces, analyzing technology portfolios in luxury hospitality and in-store phygital solutions. These studies show how brands balance efficiency, immersion, and exclusivity to reduce consumer resistance and enhance engagement (Bharwani & Mathews, 2021; Guzzetti et al., 2024; Hagtvedt & Chandukala, 2023; Singh & Basu, 2023).

Finally, Cluster 8 groups operations- and analytics-oriented perspectives on online-to-offline retailing and "new retail" precursors, which provide early insights into digital channel optimization and capability building for luxury omnichannel, although with more limited theorization specifically tied to luxury (Chittiprolu et al., 2021; Palash et al., 2022; Chen & Qi, 2013).

3.2 Keyword analysis

Co-word analysis examines the co-occurrence of keywords to infer thematic relationships, thereby capturing the content structure of a field and complementing citation-based maps; it is particularly useful to enrich clusters and surface emerging trends (Donthu et al., 2021). We implemented the analysis in VOSviewer, building a keyword co-occurrence network from the 244-record corpus and applying a minimum co-occurrence threshold of 4; out of 798 keywords, 38 met the threshold and were included in the map. Network weights were normalized using association strength, and clusters were identified via the VOS modularity-based algorithm (Van Eck & Waltman, 2010; Waltman & van Eck, 2013; Zupic & Čater, 2015).

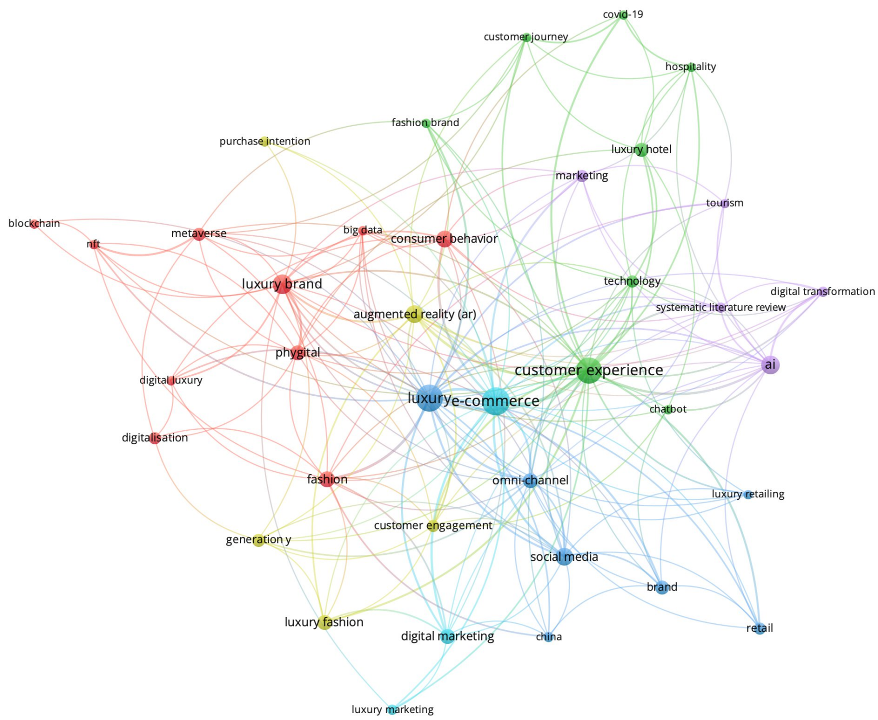
Table 3. Most Frequent Keywords in the Co-Word Analysis

Keyword	Frequency
E-Commerce	34
Luxury	31
Customer experience	29
Luxury brands	17
AI	15
AR	13
Social media	13

Consumer behavior	12
Digital marketing	9
Fashion	11
Phygital	10

The keyword frequency (Table 3) shows domain anchors and technology vectors: e-commerce (34), luxury (31), customer experience (29), luxury brands (17), AI (15), AR (13), social media (13), consumer behavior (12), fashion (11), and phygital (10), signaling concurrent emphases on channel integration, experiential value, and immersive/algorithmic technologies.

Figure 4. Keyword analysis clusters



VOSviewer's clustering yielded six thematic groups with concise topical signatures (Figure 4). Cluster 1 spans technology-infused luxury ecosystems, big data, blockchain, metaverse, NFT, phygital, bridging digitalization and fashion/luxury brand strategy with consumer behavior. Cluster 2 concentrates on customer experience engineering, chatbot, customer journey, technology, with contextual ties to hospitality, luxury hotel, and COVID-19 adaptations. Cluster 3 foregrounds market/platform contexts, brand, social media, retail, omni-channel, with a geographic focus on

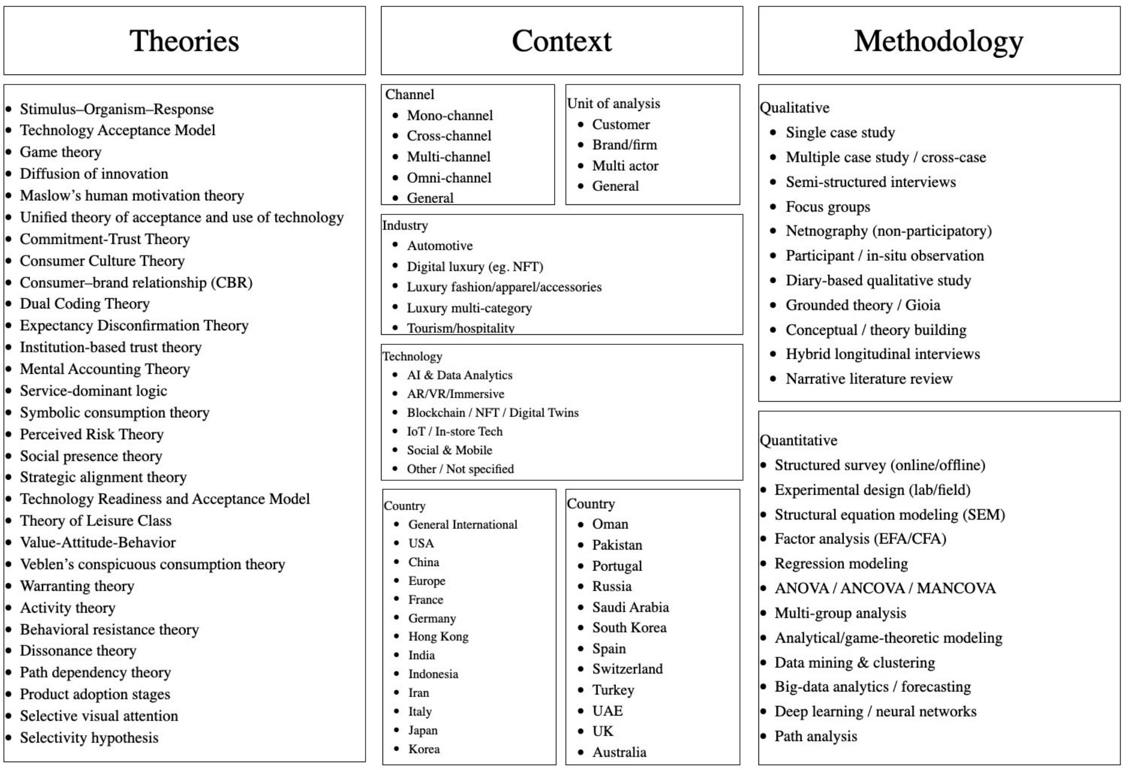
China and a distribution lens via luxury retailing. Cluster 4 is AR/engagement-centric, augmented reality (AR), customer engagement, purchase intention, situated in luxury fashion and Generation Y adoption. Cluster 5 groups AI and transformation, AI, digital transformation, marketing, and methodological consolidation via systematic literature review, with applications in tourism. Cluster 6 aligns digital marketing and commerce, digital marketing, e-commerce, luxury marketing, capturing the operational/managerial layer of luxury's online presence.

4. TCM FRAMEWORK-BASED REVIEW OF THE STUDIES

This work adopts the TCM lens, Theory, Context, Method, to turn a heterogeneous literature into a comparable map (Figure 5). We arrived at TCM after screening the corpus and finding that studies vary as much in their conceptual lenses as in the settings and techniques used to produce evidence. TCM disciplines this variation by asking three simple questions: which theories are mobilized, where and with whom they operate, and how claims are generated and tested (Paul et al., 2021). The approach clarifies mechanisms, boundary conditions, and the weight of evidence without forcing artificial uniformity.

The section is structured accordingly. Section 4.1 maps the theory space and visualizes its dominant clusters (Table 4). Section 4.2 codifies the contextual boundaries, channel configuration, unit of analysis, technology, industry, and geography, reported in Table 5 and summarized descriptively. Section 4.3 audits the methodological landscape across qualitative, quantitative, and mixed designs, detailing typical purposes and techniques (Table 6).

Figure 5. TCM map



4.1 Theories

As shown in Table 4, the theoretical ground is rather uneven. Most studies (61) don't rely on a specific theory, while the rest draw on more than 30 different frameworks. This variety has led to some fragmentation but also opens interesting possibilities for connecting ideas. Within the TCM framework, these perspectives can be seen as three main groups: those focusing on how experiences shape emotions, those explaining how people decide to adopt new technologies, and those exploring how governance and signaling help manage risk. Together, they offer different angles to understand how technology is changing luxury channel strategies (Zeng et al., 2025; Kim et al., 2025; Jang and Kang, 2025).

The first, grounded in S-O-R and social presence theories, explores how augmented reality, multisensory cues, and digital companions shape emotions, perceived value, and engagement across phygital brand journeys (Zeng et al., 2025; Rahman et al., 2023; Nawres et al., 2024; Guzzetti et al., 2024; Javornik et al., 2021; Pelet et al., 2021).

The second pillar, focused on technology adoption, extends classical models such as TAM, TRAM, and UTAUT by adding affective and symbolic dimensions. Factors like emotional appeal, social presence, and engagement help explain the specific motivations behind technology use in luxury contexts (Kim et al., 2025; Khamoushi Sahne and Kalantari Daronkola, 2025; Erdogmus et al., 2021; Oe and Yamaoka, 2023).

The third pillar, centered on governance, risk, and signaling, combines theories of warranting and institution-based trust with mental accounting and game-theoretic perspectives. These approaches shed light on how brands manage authentication, traceability, and platform choices, especially in blockchain-enabled and resale markets (Jang and Kang, 2025; Youn et al., 2025; Varshney et al., 2024; Chen et al., 2024; Li et al., 2023; Choi, 2019).

Other relational and cultural perspectives, such as Commitment-Trust Theory, Customer-Brand Relationship Theory, Consumer Culture Theory, and Service-Dominant Logic, reinterpret technology as a backstage enabler of human rituals, co-creation, and intimacy in luxury experiences (Pangarkar et al., 2022; Bartoli et al., 2023; Cenizo, 2025; Holmqvist et al., 2020).

Finally, a set of micro-theories connects media and cognition to channel outcomes, from dual coding in rich email formats to disconfirmation in online communities and gender-related differences in e-service quality (Scheinbaum et al., 2017; Basile et al., 2024; Kim, 2020).

Table 4. Theory

Theory	N articles	Theory	N articles
Stimulus–Organism–Response (S-O-R)	7	Perceived Risk Theory	1
Technology Acceptance Model (TAM)	5	Social presence theory	1
Game theory	3	Strategic alignment theory	1
Diffusion of innovation	3	Technology Readiness and Acceptance Model (TRAM)	1
Maslow's human motivation theory	2	Theory of Leisure Class	1
Unified theory of acceptance and use of technology (UTAUT)	2	Value-Attitude-Behavior	1
Commitment-Trust Theory	1	Veblen's conspicuous consumption theory	1
Consumer Culture Theory	1	Warranting theory	1
Consumer–brand relationship (CBR)	1	Activity theory (ACT)	1
Dual Coding Theory	1	Behavioral resistance theory	1
Expectancy Disconfirmation Theory	1	Dissonance theory	1
Institution-based trust theory	1	Path dependency theory	1
Mental Accounting Theory	1	Product adoption stages	1
Service-dominant logic	1	Selective visual attention	1
Symbolic consumption theory	1	Selectivity hypothesis	1

4.2 Context

To render the corpus comparable and make contextual boundaries explicit, we coded each study along five complementary axes: channel configuration, unit of analysis, focal technology, industry vertical, and country (Table 5). Channel configuration distinguishes mono-channel, multi-channel, cross-channel, and omni-channel designs, with a "general" bucket for work not tied to a specific configuration. Units of analysis include customer, brand/firm, and multi-actor ecosystem, plus a general category. Technologies are grouped into AI & data analytics; AR/VR/immersive; blockchain/NFT/digital twins; IoT/in-store technologies; social & mobile; and other/not specified. Industries comprise automotive, digital luxury, luxury fashion/apparel/accessories, luxury multi-category, and tourism/hospitality. Countries register the geographical locus of evidence; because studies may span multiple nations or report cross-national samples, and may examine more than one technology, counts on the technology and country axes exceed the number of unique articles, whereas channel, unit, and industry are single-coded per study to avoid double-counting.

Table 5. Context

Context	*N* Articles	Context	*N* Articles
Channel		Country	
Mono-channel	20	General International	33
Cross-channel	12	USA	11
Multi-channel	11	China	10
Omni-channel	27	Europe	2
General	23	France	7
Unit of analysis		Germany	2
Customer	43	Hong Kong	1
Brand/firm	32	India	5
Multi actor	7	Indonesia	1
General	11	Iran	1
Technology		Italy	11
AI & Data Analytics	20	Japan	1
AR/VR/Immersive	22	Korea	2
Blockchain / NFT / Digital Twins	11	Oman	1
IoT / In-store Tech	12	Pakistan	1
Social & Mobile	35	Portugal	2
Other / Not specified	18	Russia	1
Industry		Saudi Arabia	1
Automotive	1	South Korea	2
Digital luxury (eg. NFT)	2	Spain	1
Luxury fashion/apparel/accessories	40	Switzerland	3
Luxury multi-category	43	Turkey	2
Tourism/hospitality	7	UAE	1
		UK	8
		Australia	1

Omnichannel accounts for 27 of 93 articles (29.0%), followed by mono-channel (20; 21.5%) and general, non-specific channel discussions (23; 24.7%), with multi-channel (11; 11.8%) and cross-channel (12; 12.9%) less represented, signaling a tilt toward end-to-end integration debates over transitional configurations. The modal unit of analysis is the customer (43; 46.2%), then brand/firm (32; 34.4%), with comparatively few ecosystem-level analyses (7; 7.5%), indicating a consumer-centric lens with limited multi-actor theorization. On technology, social & mobile dominates (35 of 118 tags; 29.7%), followed by AR/VR/immersive (22; 18.6%) and AI & data analytics (20; 16.9%), whereas IoT/in-store (12; 10.2%) and blockchain/NFT/digital twins (11; 9.3%) are less prevalent, suggesting a front-stage experiential emphasis over back-stage operational integration or tokenized asset logics. Industry coverage concentrates in luxury multi-category (43 of 93; 46.2%) and fashion/apparel/accessories (40; 43.0%), with tourism/hospitality (7; 7.5%) and automotive (1; 1.1%) comparatively sparse, reflecting where luxury channel transformations are most visible in practice. Geographically, "General International" contexts are common (33 of 111 tags; 29.7%), while single-country studies cluster in the USA (11; 9.9%), Italy (11; 9.9%), China (10; 9.0%), the UK (8; 7.2%), and France (7; 6.3%), with other markets appearing sporadically, an imbalance that both mirrors luxury market concentration and indicates opportunities for broader cross-cultural and emerging-market evidence.

4.3 Methodological landscape

The analysis of the 93 core studies reveals a methodologically diverse research landscape, important for capturing the multifaceted nature of digital transformation in the luxury sector (Table 6). The field is led by qualitative approaches (35 studies), followed by quantitative (37 studies) and mixed methods designs (21 studies). This distribution, detailed in Table 6, focus on a scholarly preference for deep contextual understanding, complemented by a robust effort to measure and model emergent phenomena.

Table 6. Summary of methodological approach

Methodological Approach	E.g. Methods Employed	Primary Research Focus & Purpose	Illustrative Examples
Qualitative (35 studies)	Case Studies (Single & Multiple); Semi-structured & In-depth Interviews; Netnography / Content Analysis; Grounded Theory Conceptual/Theoretical Development	In-depth exploration of complex, context-rich phenomena: Understanding the "how" and "why" of strategic decisions and consumer experiences. Theory building and proposition development.	Pantano et al., 2022; Cedrola & Hu, 2022; Pangarkar et al., 2022; Basile et al., 2024; Klaus, 2020; Lawry, 2023
Quantitative (37 studies)	Surveys & Questionnaires; Experimental Designs Analytical & Game-Theoretic Modeling; Structural Equation Modeling (SEM); Data Mining & Secondary Data Analysis	Testing hypotheses and examining causal relationships; Modeling market dynamics, competition, and profitability; Identifying and measuring generalizable patterns in consumer behavior.	Kumagai & Nagasawa, 2022; Cowan & Kostyk, 2024; Varshney et al., 2024; Chung et al., 2020; Chen et al., 2025
Mixed Methods (21 studies)	SLR / Bibliometric Analysis + Content/Case Analysis; Survey + fsQCA / Interviews; Case Study + Quantitative Metrics; Co-design Workshops + Experiments	Triangulating findings for a comprehensive and multi-layered understanding; Validating qualitative insights with quantitative data (or vice versa); Synthesizing existing literature.	Rahman et al., 2023; Xue et al., 2023; Brun et al., 2017; Tam & Lung, 2025; Phan et al., 2011

Qualitative methodologies are instrumental in exploring the "how" and "why" behind strategic shifts and consumer experiences. The case study is the most prominent qualitative method, employed to conduct fine-grained investigations into firms' omnichannel implementation (Silva et al., 2024), the adoption of smart technologies (Pantano et al., 2018; Passavanti et al., 2020), and strategic responses to market-specific dynamics, such as post-COVID digital adoption in China (Cedrola and Hu, 2022; Liu et al., 2019). These studies are typically enriched by semi-structured interviews with senior executives and consumers to explore complex topics like the role of phygital environments in building rapport (Pangarkar et al., 2022) or the challenges of integrating haptic technologies (Ornati and Kalbaska, 2022). Beyond the case study, scholars utilize other powerful qualitative techniques, including netnography to analyze value co-creation in online brand communities (Basile et al., 2024), grounded theory to build models of the online luxury experience (Klaus, 2020), and conceptual development to frame theoretical propositions on phygital luxury (Lawry,2023).

This rich qualitative tradition is balanced by a substantial body of quantitative research focused on hypothesis testing, measurement, and modeling. Survey methodologies are widely used to examine for example consumer behavior, linking channel usage to hedonic value and well-being (Kumagai and Nagasawa, 2022), assessing purchase intentions among Gen Z (Kim-Vick and Yu, 2023), and evaluating the impact of AI-driven marketing (Cunha et al., 2024) or chatbot interactions (Chung et al., 2020). Experimental designs provide causal insights, for example by manipulating brand personality to test consumer reactions to digital engagement (Cowan and Kostyk, 2024) or by comparing the efficacy of different marketing communication formats (Scheinbaum et al., 2017). A particularly sophisticated stream of quantitative work employs analytical and game-theoretic modeling to dissect complex strategic decisions, such as optimizing blockchain-based traceability in supply chains (Chen et al., 2024; Choi, 2019) or navigating the impact of second-hand markets on brand profitability (Varshney et al., 2024; Li et al., 2023).

Finally, 21 studies leverage mixed-methods to achieve triangulation and a more holistic understanding. These studies elegantly combine qualitative and quantitative paradigms, for instance by integrating survey data (PLS-SEM) with fuzzy-set qualitative comparative analysis (fsQCA) (Rahman et al., 2023), or by combining co-design workshops with experimental testing based on the Technology Acceptance Model (Xue et al., 2023).

5. ADO FRAMEWORK-BASED REVIEW OF THE STUDIES

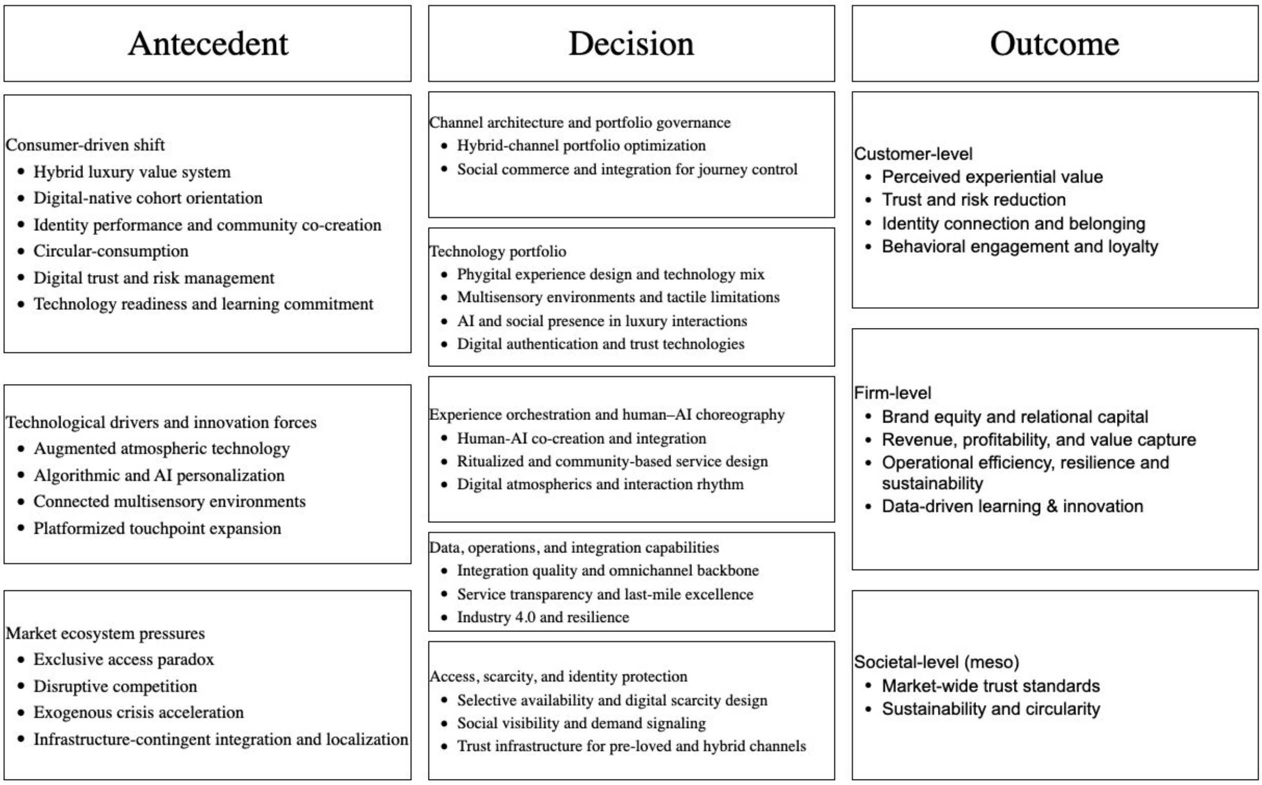
To answer the research question, how emerging technologies have shaped multichannel, cross-channel, omnichannel, and phygital strategies in the luxury sector, this section organizes the evidence using the Antecedents-Decisions-Outcomes (ADO) framework. The framework is particularly suited to this context because it helps to connect technological drivers with the managerial decisions that luxury brands take, and with the outcomes these choices generate at different levels (Paul & Criado, 2020).

In this perspective (Figure 6), the antecedents represent the underlying forces that drive change. From the analysis emerged three broad categories: shifts in consumer behavior and demand, the opportunities and constraints created by new technologies, and the structural pressures coming from markets, platforms, and broader ecosystems. Together, these factors define the environment in which luxury firms decide whether and how to integrate digital and physical channels.

The decisions refer to the concrete choices companies make. These include how to design the channel architecture, which technologies to adopt, how to orchestrate customer experiences, how to align data and operations, and how to protect access and identity. Each decision requires balancing efficiency and emotion, automation and human presence, to preserve continuity, trust, and symbolic value across the luxury journey (Verhoef et al., 2015; Matić & Bajs, 2022).

Finally, the outcomes capture what these decisions produce in practice. They are observed at three levels, customer, firm, and market or society, and include effects such as higher engagement, stronger brand equity, improved performance, and broader gains in trust and sustainability (Zeng et al., 2025; Son et al., 2023; Okonkwo, 2009).

Figure 6. ADO framework



This section proceeds as follows. Subsection 5.1 synthesizes antecedents into the three macro-categories noted above. Subsection 5.2 organizes decisions into five interlocking domains that translate antecedents into orchestrated channel portfolios. Subsection 5.3 details outcomes at customer, firm, and societal levels and links them back to antecedents and decisions via empirically supported mechanisms.

5.1 Antecedents

The antecedents represent the foundation of the ADO chain, capturing the underlying shifts in consumer behavior, technological possibilities, and market structures that make new forms of channel integration both necessary and feasible. As shown in Table 7, these antecedents can be grouped into three broad domains: consumer-driven shifts, technological drivers, and market and ecosystem pressures. Each of them will be analyzed in the following part.

Table 7. Antecedents

Antecedents' category	Antecedents	Summary	Key Sources
Consumer-driven shift	Hybrid luxury value system	Coexistence of hedonic, status/social, and functional motives elevates expectations for immersion, personalization, and convenience, increasing demand for integrated touchpoints.	Kim & Lee, 2011; Erdogmus et al., 2021; Jain, 2024; Rahman et al., 2023; Bartoli et al., 2023; Ritz et al., 2024; Cunha et al., 2024; McKee et al., 2023
	Digital-native cohort orientation	Gen Y and Z, driven by digital fluency, convenience, and social connection, make faster decisions influenced by social validation and heavy mobile and social media use.	Kim-Vick & Yu, 2023; Oe & Yamaoka, 2023; Son et al., 2023; Jain, 2024
	Identity performance and community co-creation	Identity performance and co-creation in digital channels increase demand for symbolic touchpoints and coherent signals to sustain brand meaning.	Ramadan &Nsouli, 2022; Bartoli et al., 2023; Jain & Schultz, 2019
	Circular-consumption	Acceptance of rental/resale and heterogeneity by ownership status redefine channel preferences and phygital paths.	Arrigo, 2023; Kim-Vick & Yu, 2023; Cassidy, 2017
	Digital trust and risk management	Uncertainty in e-luxury and second-hand markets increases the need for reliable authentication, product traceability, and trusted review systems.	Youn et al., 2025; Chen et al., 2024; Jang & Kang, 2025; Shin & Darpy, 2020
	Technology readiness and learning commitment	Technology readiness, prior in-store tech experience, and commitment to learn reduce resistance and facilitate participation in smart retail.	Guzzetti et al., 2024; Foroudi et al., 2018; Das et al., 2024
Technological drivers and innovation forces	Augmented atmospheric technology	Emerging AR and tech-enhanced environments create new value opportunities when design successfully combines practical usefulness with emotional and sensory appeal.	Zeng et al., 2025; Xue et al., 2023; Nawres et al., 2024; Javornik et al., 2021
	Algorithmic and AI personalization	The rise of AI assistants, smart recommenders, and multisensory features raises customer expectations for personalized experiences at scale.	Rahman et al., 2023; Kim et al., 2025; Khamoushi Sahne and Kalantari Daronkola, 2025; Arora et al., 2023; Hoang et al., 2025; Cunha et al., 2024
	Connected multisensory environments	IoT, wearables, and connected environments enable congruent multisensory orchestration and operational efficiency in high-touch luxury settings.	Bharwani & Mathews, 2021; Pelet et al., 2021
	Platform touchpoint expansion	New platform ecosystem expands orchestratable touchpoints and prestige signaling.	Liu et al., 2018; Arora et al., 2023; Scheinbaum et al.,

			2017
Market ecosystem pressures	Exclusive access paradox	Structural tension between digital reach and scarcity/heritage necessitates selective digitalization and governance constraints within the digital perimeter.	Okonkwo, 2009; Watanabe et al., 2021; Cassidy, 2017; Matić & Bajs, 2022
	Disruptive competition	Substitution threats, DTC proliferation, and agile start-ups intensify competitive pressure on technology adoption and omni orchestration.	McKee et al., 2023; Ramadan & Nsouli, 2022
	Exogenous crisis acceleration	Exogenous shocks (e.g. COVID-19) normalized remote engagement and accelerated phygital adoption and operational digitalization.	Cedrola & Hu 2022, Ornati & Kalbaska, 2022 Colella & Amatulli, 2022; Hoang et al., 2023
	Infrastructure-contingent integration and localization	Integration depth depends on local retail/digital infrastructures and platform path-dependency (e.g., China's New Retail), with cross-cultural/cohort responses shaping design and governance.	Guercini et al., 2020; Liu et al., 2018; Shi & Chen, 2025; Zeng et al., 2025

5.1.1 Consumer-driven shift

The first antecedent emerged from the analysis refers to a demand-side push and a transformation in the luxury consumer. In particular, luxury consumption today reflects a complex mix of pleasure, social distinction, and functional value. These motives constantly interact, guiding consumers toward experiences that feel personal, effortless, and emotionally engaging. In this context, the notion of quality no longer depends solely on product excellence, but on how connected and seamless the overall journey feels (Kim & Lee, 2011; Rahman et al., 2023; Bartoli et al., 2023). Younger, digital-native generations have further accelerated this transformation: they expect immediacy, mobile-first access, and social validation (Oe & Yamaoka, 2023). As a result, purchase decisions increasingly rely less on traditional brand cues and more on the usability of platforms and the credibility of peer recommendations within online communities (Kim-Vick & Yu, 2023; Son et al., 2023; Jain, 2022). At the same time, the ways in which individuals express their identity and co-create meaning on digital platforms make it essential for brands to design symbolic, shareable, and emotionally resonant experiences across all touchpoints (Jain & Schultz, 2019; Bartoli et al., 2023).

In parallel, the growing diffusion of rental, resale, and circular luxury preference among younger generations is reshaping how firms structure their portfolios and balance brand-owned versus third-party channels. Different ownership mindsets shape which phygital pathways are perceived as legitimate and desirable by each segment (Cassidy, 2017; Kim-Vick & Yu, 2023;

Arrigo, 2023). At the same time, growing awareness of digital risks, especially in e-luxury and second-hand contexts, is elevating the importance of provenance, authentication, and trusted review systems. What once appeared as ancillary features now represents a central condition for online adoption (Shin & Darpy, 2020; Chen et al., 2024; Youn et al., 2025; Jang & Kang, 2025).

5.1.2 Technological drivers and innovation forces

The second antecedent concerns the technological push that is constantly redefining what luxury brands can offer and how they shape the customer experience (Javornik et al., 2021; Matić & Bajs, 2022). New technologies broaden the range of experiences that brands can design, but their value in the luxury context depends on how consistently they support the brand's identity and experiential coherence.

A first group of innovations includes AR applications and smart mirrors, which enrich the buying journey by combining practical utility with emotional engagement. These tools allow customers to visualize products interactively, compare styles, or access additional information while maintaining a sense of immersion and exclusivity (Javornik et al., 2021; Xue et al., 2023; Zeng et al., 2025; Nawres et al., 2024).

In recent years artificial intelligence has emerged as another key driver. Algorithmic engines, virtual assistants, and recommendation systems help brands simulate human presence and deliver more personalized interactions (Cungh et al., 2020). When designed around trust and empathy, these systems can create a feeling of connection and tailor-made attention that reinforces the brand's emotional value (Rahman et al., 2023; Khamoushi Sahne & Kalantari Daronkola, 2025; Kim et al., 2025; Cunha et al., 2024; Hoang et al., 2025).

Additionally, the growing use of connected and multisensory environments, powered by the Internet of Things (IoT) and wearable technologies, allows brands to integrate touch, sight, sound, and scent into coordinated experiences (Bharwani & Mathews, 2021; Pelet et al., 2021). Finally, digital platforms such as WeChat-based CRM systems, shoppable social media, and rich media interfaces have further expanded the perimeter of interaction. Through these platforms, brands can orchestrate communication, commerce, and community in a unified and controlled way (Liu et al., 2018; Scheinbaum et al., 2017).

5.1.3 Market and ecosystem pressures

The third antecedent concerns the structural pressures emerging from the broader market and platform ecosystems in which luxury brands operate. Demand and technological shifts unfold within interconnected market logics, digital platforms, and institutional frameworks that define the boundaries of what luxury brands can realistically pursue (Watanabe et al., 2021). These external forces establish the “rules of the game,” shaping how firms structure their channels, safeguard brand equity, and recalibrate their business models in response to evolving ecosystem constraints.

One of the most distinctive ecosystem challenges is what scholars describe as the “abundant rarity” paradox: luxury brands must balance the democratizing power of digital reach with the need to preserve scarcity, heritage, and symbolic distance. This tension pushes firms toward selective digitalization, curated availability, and tight control over how products circulate across online and offline channels (Cassidy, 2017; Watanabe et al., 2021; Matić & Bajs, 2022).

At the same time, competitive pressures from direct-to-consumer models and adjacent categories are shortening innovation cycles and forcing luxury firms to act with greater agility (Nguyen & Pan, 2023; McKee et al., 2023).

External shocks have also played a crucial role. The COVID-19 pandemic, for example, normalized remote interactions and accelerated the adoption of phygital formats, turning once-optional technologies, such as virtual showrooms, live commerce, and online clienteling, into essential infrastructure for continuity and care (Cedrola & Hu, 2022; Ornati & Kalbaska, 2022; Colella & Amatulli, 2022; Hoang et al., 2023).

Finally, these ecosystem dynamics also vary across geographies: in markets such as China, where WeChat-centered “New Retail” ecosystems dominate, platform infrastructures and cultural logics jointly determine how technologies are adopted and reinterpreted within luxury experience design (Guercini et al., 2020; Liu et al., 2018; Shi & Chen, 2025; Zeng et al., 2025).

5.2 Decisions

Building on the antecedents discussed above, this section synthesizes the main decision areas identified through the ADO framework. These decisions translate structural and contextual antecedents into design choices that shape luxury channel architectures, technologies, and experiences. As summarized in Table 8, and as we will see in the following subsections, five interdependent decision domains emerge from the literature: channel architecture, technology portfolio, experience choreography, data-operations integration, and access and identity protection.

Table 8. Decisions

Decisions category	Decisions	Summary	Key Sources
Channel architecture and portfolio governance	Hybrid-channel portfolio optimization	Balance DTC, wholesale, mono- and multi-brand formats according to brand tier and market infrastructure.	Guercini et al., 2020; Kumagai & Nagasawa, 2022; Klaus, 2020
	Social commerce and integration for journey control	Shift from multi-channel to cross-/omni-channel by embedding social commerce, metaverse, voice, and kiosks to upgrade the service portfolio and re-balance channel power, especially for DTC brands seeking end-to-end journey control.	McKee et al., 2023; Dutot, 2016
Technology portfolio	Phygital experience design and technology mix	Blend digital and physical touchpoints through AR tools that enhance convenience and personalization.	Zeng et al., 2025; Xue et al., 2023; Javornik et al., 2021
	Multisensory environments and tactile limitations	Use visual, audio, and ambient cues to enrich immersion and emotion.	Pelet et al., 2021; Ornati & Kalbaska, 2022; Bharwani & Mathews, 2021
	AI and social presence in luxury interactions	Leverage AI and gamified interfaces to create a sense of exclusivity and social connection. Design assistants that feel human and engaging while remaining accurate and credible.	Milanesi et al., 2023; Scheinbaum et al., 2017; Chung et al., 2020; Kim et al., 2025
	Digital authentication and trust technologies	Adopt blockchain or NFT-based certificates to signal authenticity and provenance. Balance technological transparency with the preservation of prestige and craftsmanship.	Li et al., 2023; Chen et al., 2024; Tandon et al., 2021; Youn et al., 2025; Jang & Kang, 2025; Henkin et al., 2025
Experience orchestration and human-AI choreography	Human-AI co-creation and integration	Combine human and AI tools to deliver personalized, emotionally resonant interactions across channels.	Pangarkar et al., 2022; Ramadan & Nsouli, 2022
	Ritualized and community-based service design	Create structured rituals, exclusive activities, or co-creation experiences that reinforce belonging and symbolic status.	Lawry, 2023; Pangarkar & Shukla, 2023
	Digital atmospherics and interaction rhythm	Craft rich storytelling, multisensory media, and measured pacing to sustain prestige without eroding service warmth.	Okonkwo, 2009; Scheinbaum et al., 2017
Data, operations, and integration capabilities	Integration quality and omnichannel backbone	Ensure consistent data, processes, and service standards across all touchpoints. High integration quality in content, systems, and logistics forms the backbone of reliable omni execution and brand trust.	Yeğin & Ikram, 2022; Silva et al., 2024

	Service transparency and last-mile excellence	Enhance transparency in delivery, returns, and cross-border operations to strengthen reliability and satisfaction. Use real-time tracking and process analytics to optimize order-to-cash flow and on-time performance.	Mu et al., 2020; Ritz et al., 2024
	Industry 4.0 and resilience	Adopt smart manufacturing, automation, and predictive analytics to boost responsiveness and scalability. Align supply-chain intelligence with product and channel strategies to sustain flexibility under disruption.	Nguyen & Pan, 2023; Brun et al., 2017
Access, scarcity and identity protection	Selective availability and digital scarcity design	Limit online access to core collections and engineer scarcity through curated drops or timed releases. Tailor availability to market maturity and brand personality to prevent ubiquity and preserve prestige.	Tam & Lung, 2025; Liu et al., 2019; Cowan & Kostyk, 2024
	Social visibility and demand signaling	Manage pricing and exposure dynamically as social visibility rises. Use omnichannel signaling to satisfy status needs while avoiding overexposure.	Gao et al., 2023; Hamdani et al., 2023
	Trust infrastructure for pre-loved and hybrid channels	Implement blockchain or NFT authentication to ensure provenance and safety in resale and phygital contexts. Translate transparency into trust without eroding luxury cues or cost efficiency.	Jang & Kang, 2025; Youn et al., 2025; Varshney et al., 2024; Li et al., 2023; Choi, 2019; Chen et al., 2024

5.2.1 Channel architecture and portfolio governance

The first group of decisions are related to channel architecture and portfolio governance, which define how luxury brands organize control, data ownership, and experiential consistency across multiple touchpoints (Klaus, 2020; Matić & Bajs, 2022). In recent years, many companies have started to move from traditional multichannel structures toward fully integrated cross and omnichannel systems (Silva et al., 2024). This strategic shift reflects the growing need to oversee the entire customer journey, to unify data flows, and to deliver a coherent experience across every point of contact with the brand.

Within this integrated perspective, luxury firms design hybrid channel portfolios that balance exclusivity with accessibility. The combination of direct-to-consumer (DTC) and wholesale logics, together with mono-brand and multi-brand formats, allows them to adapt distribution strategies to both market infrastructures and brand positioning (Guercini et al., 2020; Klaus, 2020). For high-end firms, physical mono-brand boutiques remain the strategic and symbolic center of the ecosystem. These spaces concentrate hedonic value and emotional engagement, justifying a selective digital presence and a store-led orchestration that protects the aura of rarity and craftsmanship (Klaus, 2020). By contrast, brands positioned in accessible or premium-luxury tiers adopt broader digital participation. They rely on e-retail platforms and marketplaces to reach new audiences and expand demand, while still maintaining control over key brand cues to avoid dilution and preserve well-being perceptions (Kumagai & Nagasawa, 2022; Klaus, 2020).

In this scenario, decisions about how much control to retain or delegate become crucial (Dutot, 2016). Choosing the right balance and power among owned channels, partners, and intermediaries determines not only visibility but also who governs the customer relationship and the data behind it (Kumagai & Nagasawa, 2022, Dutot, 2016).

5.2.2 Technology portfolio

The second group of managerial decisions concerns the technology portfolio, that is, the set of digital tools that luxury brands choose and combine to sustain trust, continuity, and prestige within their overall channel architecture (Okonkwo, 2009; Javornik et al., 2021). These decisions are not purely technical but strategic, as every technological choice influences how customers perceive authenticity, attention, and exclusivity across the brand experience.

Among the most studied technologies, AR technologies have shown strong potential to bridge physical and digital touchpoints. Research indicates that these solutions designed with a focus on utility and simplicity tend to be more effective for in-store adoption than purely hedonic or entertainment-based approaches (Javornik et al., 2021; Xue et al., 2023).

In parallel, the growing use of connected environments powered by the Internet of Things and wearable technologies opens new possibilities for multisensory immersion. Through synchronized visual, audio, and ambient cues, brands can recreate emotional engagement and enhance the feeling of presence even in digital or hybrid spaces (Pelet et al., 2021). However, fully reproducing tactile sensations remains challenging, and most firms currently rely on visual and audiovisual components as the main carriers of experiential richness (Ornati & Kalbaska, 2022).

At the interaction level, Artificial Intelligence plays a central role in personalizing relationships and sustaining a sense of exclusivity. Virtual assistants, recommender systems, and gamified applications can simulate human presence and attentiveness, strengthening emotional engagement and perceived prestige when they combine accuracy, empathy, and reliability (Scheinbaum et al., 2017; Chung et al., 2020; Milanesi et al., 2023; Kim et al., 2025).

Finally, decisions about authentication and provenance technologies complete the technology portfolio by addressing the dimension of trust. Tools such as blockchain and NFT-based certificates are increasingly used to verify authenticity and traceability across channels (Tandon et al., 2021; Chen et al., 2024; Youn et al., 2025; Jang & Kang, 2025).

5.2.3 Experience orchestration and human-AI choreography

The third group of managerial decisions concerns experience orchestration, that is, how human and artificial intelligence elements are combined across touchpoints to transform the technology portfolio into coherent and emotionally resonant brand experiences. In luxury contexts, this orchestration is not only about efficiency but about preserving intimacy, meaning, and authenticity in a progressively digital environment (Beverland, 2006).

Recent studies on personalized client interaction emphasize that, despite the rise of automation, the human role remains central in creating value and trust. Sales associates increasingly act as stylists, advisors, and relationship managers, using direct and continuous communication channels such as messaging apps, virtual consultations, or exclusive digital events (Pangarkar et al., 2022). Through these interactions, brands extend the warmth and attention typical of the boutique experience beyond physical spaces, allowing clients to perceive a seamless form of care and personal recognition that bridges online and offline worlds (Pangarkar et al., 2022).

Alongside these practices, the literature highlights the importance of ritualized service gestures, such as small symbolic actions, shared codes, and moments of community, that reinforce emotional resonance and the perception of belonging (Lawry, 2023; Pangarkar & Shukla, 2023). These rituals play a dual role: they satisfy status and pleasure motives while positioning technology as a silent enabler that amplifies, rather than replaces, human presence (Pangarkar & Shukla, 2023). In this sense, the most effective human-AI collaborations are those in which digital tools act as an invisible infrastructure supporting the emphatic human touch.

Finally, research on digital atmospherics and storytelling underlines how rhythm and tone shape the perceived quality of luxury experiences. A slower and more deliberate cadence, in communication, response, and presentation, can elevate the sense of prestige and refinement, making interactions feel more exclusive (Okonkwo, 2009).

5.2.4 Data, operations, and integration capabilities

The fourth group of managerial decisions concerns data, operations, and integration capabilities, which define how different systems and processes are connected to ensure consistency, reliability, and responsiveness across channels. Luxury should decide how tightly to integrate data flows, logistics, and customer interfaces, ensuring that efficiency supports rather than constrains the brand’s experiential promise.

The literature highlights that data synchronization and process alignment are central to this balance, as they determine the speed and accuracy of information shared between physical stores, e-commerce platforms, and customer service centers (Yeğin & Ikram, 2022; Silva et al., 2024). When integration works smoothly, it allows sales associates and digital systems to access the same updated data in real time, enabling continuity in service and pricing consistency across markets.

Operational decisions also extend to the last mile, where logistics and service choices have a visible impact on both performance and perception. Models such as buy-online-pick-up-in-store, cross-border delivery, and returns management illustrate how small operational details can become expressions of the brand’s values (Mu et al., 2020; Ritz et al., 2024). For instance, a flexible return policy or an elegant unboxing experience can reinforce the idea of care and reliability, while delays or inconsistencies risk eroding the perceived refinement of the brand.

A further set of decisions involves investments in Industry 4.0 technologies that allow firms to enhance responsiveness and build supply-chain resilience (Nguyen & Pan, 2023; Brun et al., 2017). These technologies support scalability and precision, making it possible to adapt production and distribution dynamically to shifts in demand while maintaining the level of craftsmanship and quality control expected in luxury (Brun et al., 2017)

5.2.5 Access, scarcity, and identity protection

The fifth and final group of managerial decisions concerns how luxury brands manage access, scarcity, and identity protection, balancing the opportunities of a wider digital reach with the need to preserve aura and exclusivity (Okonkwo, 2009; Liu et al., 2018).

Research shows that selective online availability and digitally limited releases are among the most effective ways to protect brand prestige. Many firms restrict their core collections to controlled channels while using scarce digital drops or capsule releases to create anticipation and maintain desirability (Liu et al., 2018; Tam & Lung, 2025). The level of openness or restriction often reflects both market context and brand personality. Contemporary and fashion-forward brands, which thrive on cultural relevance and fast cycles, are more exposed to the risk of ubiquity; heritage houses, by contrast, preserve their mystique through tighter control and curated diffusion (Cowan & Kostyk, 2024; Matić & Bajs, 2022). In both cases, the key challenge lies in managing exposure without eroding symbolic scarcity. This dynamic can trigger both "snob" effects, where exclusivity drives demand, and "conformist" effects, where social validation becomes a source of appeal (Gao et al., 2023; Hamdani et al., 2023).

Finally, In pre-loved and other hybrid channels, where the boundaries between ownership, authenticity, and sustainability are increasingly fluid, managers face complex decisions on how to govern trust and brand identity (Chen et al., 2024) Determining whether and to what extent to integrate technologies such as blockchain or NFT-based authentication is not merely a technical choice but a strategic one (Li et al., 2023) When implemented thoughtfully and communicated with attention to tone and aesthetics, these tools increase trust and transparency while still preserving the codes of discretion that define luxury (Jang & Kang, 2025).

5.3 Outcomes

As shown in Table 8, the studies reviewed converge on a set of outcomes that capture the effects of technology-enabled channel integration across the luxury sector. These outcomes trace how digital and phygital strategies influence customer experience, firm performance, and market-level dynamics, completing the causal chain initiated by the antecedents and decisions discussed above.

Table 9. Outcome

Outcomes category	Outcomes	Summary	Key Sources
Customer-level	Perceived experiential value	Customers perceive higher value, enjoyment, and flow when experiences are immersive, realistic, and easy to use. These effects are stronger in low-tactility categories, while limited haptic realism constrains satisfaction in high-tactility goods.	Zeng et al., 2025; Nawres et al., 2024; Xue et al., 2023; Ornati & Kalbaska, 2022
	Trust and risk reduction	A stronger sense of authenticity and safety increases confidence in purchase decisions, especially when supported by credible signals and social proof. Trust reduces uncertainty and raises satisfaction and adoption.	Jang & Kang, 2025; Youn et al., 2025; Shin & Darpy, 2020
	Identity connection and belonging	Phygital experiences reinforce self-expression, personal connection, and community belonging, enhancing symbolic and emotional attachment to the brand. However, excessive digital exposure can weaken perceived exclusivity.	Bartoli et al., 2023; Holmqvist et al., 2020; Hamdani et al., 2023; Cowan & Kostyk, 2024; Henkin et al., 2025; Liu et al., 2019; Okonkwo, 2009
	Behavioral engagement and loyalty	Engaged consumers show stronger purchase intentions, e-WOM, and willingness to maintain relationships with the brand, following both hedonic and functional motivations	Rahman et al., 2023; Hoang et al., 2025; Kim-Vick & Yu, 2023; Oe & Yamaoka, 2023
Firm-level	Brand equity and relational capital	Consistent integration of content and processes enhances perceived quality, awareness/associations, loyalty, and advocacy and long-term attachment.	Yeğin & Ikram, 2022; Pangarkar et al., 2022; Bartoli et al., 2023; Hoang et al., 2023
	Revenue, profitability and value capture	They improve conversions, sales, retention, and margins; models such as proprietary resale and rental expand demand with limited cannibalization when well designed.	Cunha et al., 2024; Milanesi et al., 2023; Arrigo, 2023; Li et al., 2023; Varshney et al., 2024; Watanabe et al., 2021; Arora et al., 2023
	Operational efficiency, resilience and sustainability	Compliance and timeliness increase, while costs and emissions decrease; responsiveness to shocks and overall performance improve when supply chains and channels are aligned with the brand–product portfolio.	Ritz et al., 2024; Nguyen & Pan, 2023; Brun et al., 2017; Guercini et al., 2020; Pantano et al., 2018; Silva et al., 2024; Passavanti et al., 2020

	Data-driven learning & innovation	Synchronized data ecosystems accelerate learning, personalization, and innovation; a deeper understanding of digital segments refines targeting and offer development.	Watanabe et al., 2021; Volkova & Karpushkin, 2025; Chen et al., 2025; Heine & Berghaus, 2014; Castagna et al., 2020; McKee et al., 2023
Societal-level	Market-wide trust standards	The diffusion of blockchain and NFT-based standards strengthens market trust and platform credibility. Welfare effects depend on cost, quality, and convenience, with hybrid systems and policy coordination needed for sector-wide maturity.	Jang & Kang, 2025; Youn et al., 2025; Li et al., 2023; Choi, 2019; Tandon et al., 2021
	Sustainability and circularity	Circular and authenticated resale models broaden access and sustainability; process improvements lower emissions, while welfare outcomes depend on authentication costs and market balance.	Arrigo, 2023; Ritz et al., 2024; Kim et al., 2024; Li et al., 2023; Choi, 2019

5.3.1 Customer-level outcomes

At the customer level, four main types of outcomes emerge from the analysis (Table 9): perceived experiential value, trust and risk reduction, identity connection and belonging, and behavioral engagement and loyalty.

First, phygital technologies enhance perceived experiential value by making interactions immersive, simple, and consistent with the brand's identity. Tools such as augmented reality make experiences more realistic and intuitive, increasing emotion, flow, and value perception, with value emerging as the main driver of engagement (Zeng et al., 2025).

Second, trust and risk reduction arise from the perception of safety and authenticity. Digital authentication systems strengthen confidence in product provenance and increase the assurance of authenticity, especially in second-hand luxury markets or among price-conscious consumers (Jang & Kang, 2025; Youn et al., 2025). Similarly, online ratings and reviews act as social proof, reducing uncertainty during decision-making and reinforcing perceived credibility (Shin & Darpy, 2020).

Third, phygital experiences affect consumers' identity connection and sense of belonging. Hybrid digital environments support self-expression, psychological ownership, and community affiliation, reinforcing emotional ties with the brand (Bartoli et al., 2023; Holmqvist et al., 2020). However, excessive digital exposure can dilute perceived exclusivity, particularly for more modern or accessible brands. The replication of products through NFTs or digital twins may even reduce the perceived luxuriousness of physical items if not aligned with the brand's symbolic universe (Hamdani et al., 2023; Cowan & Kostyk, 2024; Henkin et al., 2025).

Finally, behavioral engagement and loyalty are reinforced through seamless and coherent experiences. Customers who navigate fluid omnichannel journeys show stronger purchase intentions, higher electronic word-of-mouth and a greater willingness to maintain relationships with the brand (Rahman et al., 2023; Hoang et al., 2025).

5.3.2 Firm-level outcomes

At the firm level, from the literature emerge four main types of outcomes (Table 8): brand equity and relational capital, revenue and value capture, operational efficiency and resilience, and data-driven learning and innovation. First, consistent integration of content and processes across channels strengthens the foundations of brand equity (Yeğin & Ikram, 2022). When customers perceive continuity and coherence in their interactions, they attribute higher quality, stronger brand associations, and greater trust and loyalty to the firm (Yeğin & Ikram, 2022). Phygital environments that preserve brand identity and enable personalized clienteling nurture emotional attachment and long-term advocacy, turning engagement into durable relational capital (Pangarkar et al., 2022; Bartoli et al., 2023; Hoang et al., 2023).

Second, integration delivers measurable financial effects (Milanesi et al., 2023). The use of AI-based personalization, targeted remarketing, and community engagement mechanisms improves conversion rates, sales growth, and retention (Cunha et al., 2024; Milanesi et al., 2023). Expanding into rental or resale models helps reach new customer segments with minimal cannibalization when aligned with luxury positioning (Arrigo, 2023). At the same time, tighter control of recommerce and authentication systems allows better value capture and safeguards profitability under competitive pressure (Li et al., 2023; Varshney et al., 2024; Watanabe et al., 2021; Arora et al., 2023).

Third, firms achieve higher operational efficiency and resilience when digital integration extends to supply chains and production processes (Ritz et al., 2024). Technologies such as process mining, predictive analytics, and Industry 4.0 applications improve conformance, on-time delivery, and cost control, while also reducing carbon emissions and increasing responsiveness to disruptions (Ritz et al., 2024; Nguyen & Pan, 2023; Brun et al., 2017; Pantano et al., 2018; Silva et al., 2024; Passavanti et al., 2020). Aligning production and logistics with brand–channel portfolios enhance performance, though many luxury companies still show uneven maturity between back-end capabilities and seamless front-stage execution (Guercini et al., 2020).

Finally, integrated ecosystems of data and partners enable faster learning, personalization, and innovation (Watanabe et al., 2021). When data flows are synchronized across digital stores, CRM systems, and on-demand manufacturing, firms accelerate experimentation and uncover heterogeneous digital customer segments that inform more precise targeting and product development (Volkova & Karpushkin, 2025; Chen et al., 2025; Heine & Berghaus, 2014). These effects depend, however, on the firm's data maturity and capability to translate insights into innovation (Castagna et al., 2020; McKee et al., 2023).

5.3.3 Societal-level outcomes.

At the broad societal level, two main types of outcomes emerge from the literature (Table 9): market-wide trust standards and sustainability and circularity.

First, the diffusion of authentication and transparency standards strengthens sector-wide trust and institutional assurance (Jang & Kang, 2025). When these standards become widely adopted, they raise product warranting value and platform credibility, extending benefits beyond individual brands to the entire market (Youn et al., 2025). However, the welfare impact depends on factors such as cost differentials, defect rates, and convenience-authenticity trade-offs. In many cases, hybrid solutions combining technological and institutional safeguards deliver the best balance between reliability and accessibility, while uneven sectoral maturity calls for policy coordination and standard-setting efforts (Li et al., 2023; Choi, 2019; Tandon et al., 2021).

Second, advances in circular and sustainable business models create social and environmental spillovers that complement firm-level efficiencies. Rental and authenticated resale models expand access to luxury goods while supporting circular consumption and resource efficiency (Arrigo, 2023). Operational improvements enabled by process mining and smart manufacturing contribute to lower emissions and greater transparency across value chains (Ritz et al., 2024). In adjacent sectors, awareness of AI-enabled sustainability practices can foster broader sustainability intentions and responsible consumption (Kim et al., 2024).

6. CONCLUSION

This systematic literature review examines how emerging technologies are reshaping the configuration and coordination of distribution channels in the luxury sector. Drawing on a PRISMA-guided search combined with the ADO-TCM framework and bibliometric analysis, it integrates dispersed findings into a map of knowledge that connects technological affordances, managerial decisions, and observed outcomes (Page et al., 2021; Paul & Criado, 2020).

The synthesis shows that new technologies have not merely expanded the number of channels but have transformed the way they interact and create value within luxury ecosystems. These transformations occur through two main mechanisms. First, they raise experiential intensity, for example, AR and social presence increase realism, flow, and perceived value across phygital journeys, which supports smoother moves between online and offline (Zeng et al., 2025; Javornik et al., 2021; Rahman et al., 2023). Second, they build informational assurance, authentication, reviews, and clear policies reduce risk, especially online and in resale, making deeper integration acceptable without eroding trust (Jang & Kang, 2025; Youn et al., 2025).

These effects are not uniform. They depend on what is sold, who the brand is, and where and to whom it sells. Brands with modernist codes can open more digital touchpoints; heritage-heavy brands benefit from tighter selectivity to protect aura (Okonkwo, 2009; Cowan & Kostyk, 2024; Matić & Bajs, 2022). Cohorts and platform ecologies also matter: Gen Y/Z and super-app environments pull toward faster, mobile-led integration, while other markets show different thresholds (Liu et al., 2018; Guercini et al., 2020; Son et al., 2023). These boundary conditions explain why the same tool can support omni-channel in one setting but only cross-channel in another.

The evidence also points to a governance sequence. Channel architecture comes first because it sets control rights and feasible depth of integration, the technology portfolio is then chosen to fit that architecture and back-end integration quality (data and processes) connects these choices to brand equity (Klaus, 2020; Verhoef et al., 2015; Javornik et al., 2021; Chen et al., 2024; Yeğin & Ikram, 2022). Within this sequence, human-technology choreography acts as the mediator: AI keeps continuity and speed between touchpoints, while people carry the ritual and high-stakes moments that define luxury (Pangarkar et al., 2022; Holmqvist et al., 2020; Son et al., 2023).

The theoretical insights derived from this study also offer direct guidance for practice. The mechanisms and boundary conditions identified in the analysis can be read as actionable principles for managers seeking to translate theory into strategic decisions. From a managerial perspective, the review highlights four key principles that can guide luxury brands in navigating digital transformation. First, integration should be selective and brand coded. In luxury contexts, technology should not be adopted everywhere but aligned with the brand's identity, level of exclusivity, and product category. Selective integration allows brands to expand access while protecting their aura. Second, the results show a sequence of value creation, where trust and continuity come before emotion and spectacle. Technologies create real value when they first strengthen reliability, through authentication, transparency, and data integration, and only then enhance the sensory and emotional dimensions of the experience with tools such as AR or AI. Third, the human-AI choreography acts as a safeguard for symbolic value. Digital tools should extend, not replace, human touch. AI supports efficiency and consistency, while human interaction preserves the sense of ritual, care, and exclusivity that defines luxury experiences. Finally, channel architecture is a strategic boundary condition that shapes all subsequent decisions. Clearly defining the degree of direct control, the mix between physical and digital channels, and the rule of access allows brands to align technology, clienteling, and scarcity management in a coherent system.

Building on these theoretical and managerial insights, some limitations of this study should be acknowledged. First, the review focused on English-language, peer-reviewed journal articles indexed in Web of Science and Scopus. This ensured methodological rigor and comparability across studies but may have excluded relevant contributions published in other languages or outlets, particularly in regions where luxury distribution is evolving rapidly (Page et al., 2021; Mongeon & Paul-Hus, 2016). Second, the synthesis through the ADO-TCM framework required a process of manual coding and interpretation. Although coding procedures were systematically applied and cross-checked, some degree of subjectivity remains in mapping antecedents, managerial decisions, and outcomes, as well as in assigning theories, contexts, and methods (Paul & Criado, 2020; Hulland & Houston, 2020). Finally, the evidence base is uneven across categories and geographies. Most studies focus on fashion and multi-category luxury and adopt a consumer-level perspective, with limited attention to ecosystem-level dynamics or to high-touch categories such as jewelry, hospitality, or automotive. This restricts the generalizability of findings and calls for broader empirical validation across markets and product types (Ko et al., 2019; Liu et al., 2019).

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CHAPTER 2

From prestige to promotions: understanding consumer dynamics in the luxury fashion industry

Abstract

The luxury fashion industry stands apart for its emphasis on symbolic value and exclusivity, where price often reinforces rather than diminishes desirability. Despite the growing adoption of price promotions in digital luxury retail, little is known about how such initiatives relate to customers' purchasing patterns over time. Drawing on four years of transaction-level data from a European luxury brand's online platform, this research applies Sequential Pattern Analysis and ANOVA to examine how entry through full-price or promotional purchases corresponds to distinct purchase trajectories. The results offer empirical evidence of behavioral segmentation within the luxury market, revealing that promotional exposure and full-price purchasing evolve along different paths within the same digital environment. Overall, the study contributes to a deeper understanding of pricing dynamics in digital luxury, offering an evidence-based foundation for scholars and managers seeking to preserve brand exclusivity while strategically broadening access.

1. INTRODUCTION

Over the past decade, the global luxury market has consistently grown, reaching $362 billion in 2023, primarily driven by the shift towards online purchasing channels (D'Arpizio et al., 2024). Platforms such as Mytheresa and Farfetch exemplify this trend, achieving significant success with net sales and revenue increases of 36.2% and 35%, respectively, in 2021 (Danziger, 2024; Hübscher, 2022). This transition to online luxury shopping is propelled by factors including convenience, product availability, and evolving consumer preferences (Jebarajakirthy et al., 2020; Liu et al., 2013). The enhanced online accessibility of luxury goods, contrary to initial concerns, has not diminished their perceived scarcity or brand desirability (Kluge & Fassnacht, 2015). Instead, digital channels have facilitated luxury purchases and expanded market reach through competitive pricing and promotional strategies (Hübscher, 2022).

Concurrently, the concept of luxury democratization has emerged, highlighting the necessity for luxury firms to adapt their strategies to cater to middle-class demands by making previously inaccessible and highly exclusive products available to a broader population, including millennials and new affluent consumers (Rosendo-Rios & Shukla, 2023; Kapferer & Laurent, 2016; Cristini et al., 2016). This phenomenon challenges the traditional notion of luxury based on exclusivity, introducing a tension known as the "luxury paradox" (Kapferer & Laurent, 2016). In this context, luxury firms face the challenge of balancing the traditional concept of exclusive, inaccessible luxury with the need to expand their market (Kapferer & Valette-Florence, 2016; Chandon et al., 2016) even through digital channels and targeted promotions.

However, it is essential to consider that online luxury shopping possesses unique characteristics, with consumers in this segment influenced by different factors compared to traditional in-store settings. Online luxury shoppers prioritize ease of purchase, cost, and the availability of products (Liu et al., 2013), while also being significantly influenced by product knowledge, perceived enjoyment, ease of use, and brand awareness (Majeed et al., 2024). Research has identified distinct segments of online luxury consumers, each exhibiting unique motivations and behaviors (Klaus, 2020; Burnasheva et al., 2018). Despite the sensitivity of online luxury consumers to convenience and price promotions (Liu et al., 2013), these variables have historically received limited attention in luxury sector research. This oversight stems from the longstanding belief, as articulated by Kapferer & Bastien (2009, 2012), that price should not be a defining product characteristic or particularly significant to luxury consumers. Nevertheless, the relationship between price and purchasing behavior in the luxury context remains unclear (Dhaliwal et al., 2020). Furthermore, research on price promotions within the luxury sector, especially in online channels, is scarce and fragmented, predominantly limited to non-fashion industries (Zhi & Ha, 2023; Jang & Moutinho, 2019).

To address these gaps, this study contributes to a deeper theoretical understanding of price promotion as a tool in the luxury fashion industry, examining its consequences for both consumers and firms. This research employs a two-level empirical analysis using four years of customer-level purchase data from a luxury fashion company's e-commerce website. This dataset comprises all transactions made by individual customers on the company's online platform and will be analyzed using sequential pattern analysis (SPA) to identify promotion-related patterns. Subsequently, ANOVA analysis will be conducted to assess differences associated with promotions on consumer purchase metrics, including purchase frequency and inter-purchase intervals.

The chapter is structured as follows: first, it provides a comprehensive review of the existing literature on pricing strategies and price promotions in the luxury context, establishing the theoretical foundation of the research. Second, it details the methodology employed, including the analysis of four years of transactional data from a luxury brand's e-commerce platform using SPA to identify purchase sequences and ANOVA to assess the impact of promotions. Third, the key findings are presented, revealing that promotions attract specific customer segments and that, in the presence of promotions, customers typically drawn to full-price products tend to extend their repurchase intervals. Finally, we discuss the theoretical and managerial implications, acknowledges limitations, and proposes directions for future research.

2. CONCEPTUAL BACKGROUND

The pricing strategies in the luxury industry involve complex dynamics that distinguish these products from non-luxury items. Luxury goods, known for their high price, quality, and exclusivity, serve as status indicators and fulfill socio-psychological needs (Jin & Cedrola, 2017; Heine, 2010). Unlike non-luxury products focused on functionality, luxury items appeal through experiential and symbolic values (Shukla et al., 2009). Despite their higher prices, luxury brands often experience stable or increased demand, following unique marketing principles (Bastien & Kapferer, 2013). However, the use of price promotions in this sector is controversial, balancing short-term sales boosts with potential long-term brand image erosion (Dhaliwal et al., 2020). This section aims to explore deeply into the existing literature on the role of price and price promotions in the luxury sector, providing a comprehensive analysis of their impacts on consumer behavior.

2.1 Price in luxury

The role of the price variable in the luxury industry is complex and multifaceted, influenced by various intangible factors that set luxury brands apart from other market segments. In the context of luxury marketing, price is often intertwined with the brand's history, legend, and prestige, making it a less explored area in traditional marketing literature (Jin & Cedrola, 2017; Kapferer, Klippert, & Leproux, 2014). The primary objective for luxury brand managers is to cultivate a customer base that becomes insensitive to price, nurturing "price-insensitive fans" who perceive the value of luxury products beyond their economic cost (Bastien & Kapferer, 2012, 2009). This perception is reinforced by the fact that luxury products are frequently purchased as gifts without disclosing their price, emphasizing the symbolic rather than the financial value of these goods (Bastien & Kapferer, 2012, 2009). The literature suggests that luxury pricing strategies should avoid explicit price displays in advertisements or stores, maintaining an aura of exclusivity and prestige (Truong, 2009; Truong et al., 2008). Despite its critical role, the impact of price on consumer behavior in the luxury sector has been predominantly theoretical, with few empirical studies investigating this dynamic (Kapferer et al., 2014; Fassnacht et al., 2012). High prices in the luxury market serve as indicators of quality and brand strength, with premium pricing seen as a reward for long-term brand stability (Ailawadi et al., 2003). Furthermore, the high cost of luxury items allows consumers to signal their social or economic status, enhancing self-esteem and expressing identity (Keim & Wagner, 2018; Woodside, 2013; Latter et al., 2010;). Recent studies, such as Yao et al. (2021), highlight the dual nature of price effects, where positive price-prestige effects can be counterbalanced by negative substitution effects, varying across consumer segments. Salem and Chaichi (2018) underline the importance of self-identity and social influences in consumers' willingness to pay premium prices, suggesting that attitudes and subjective norms play crucial roles in luxury consumption. Kapferer and Laurent (2016) reveal that price expectations for luxury products are highly variable, indicating that expensiveness and luxury are relative concepts dependent on consumer perceptions and product categories. Ultimately, the price of luxury goods is inextricably linked to their exclusivity and the perceived status they confer upon consumers, rendering them signals of wealth and power (Dubois, 2021; Fok et al., 2006; Bolton, 1989).

2.2 Price promotion

Strategic price management covers a variety of promotional techniques, such as discounts, vouchers, reward programs, product samples, and exclusive displays. These tactics are intended to influence consumer behavior, often by temporarily altering the perceived value of a product to achieve short-term goals (Broderick & Pickton, 2001). Price promotions serve as key components in marketing strategies, offering incentives to accelerate purchasing decisions, encourage repeat sales, or clear out outdated inventory, particularly in contexts where immediate results are prioritized (Kotler, 2003). The effect of price promotion in the luxury industry has been a topic of considerable debate, with various studies yielding mixed results. Price as a determinant of luxury purchases has produced conflicting findings, highlighting both positive and negative impacts on consumer behavior (Dhaliwal et al., 2020). Price promotions, such as lowering the price or offering more products for the same price, are often used as short-term sales incentives to boost purchase behavior (Raghubir and Corfman, 1999). Several studies have found positive effects of these promotions (Table 1). Lin (2012) reported that promotional activities generally have positive effects on purchasing behavior. Chandon et al. (2000) and De Run and Jee (2009) suggested that sales promotions, including price discounts, can enhance consumer purchase satisfaction and behavioral intention. Jing et al. (2022) found higher purchase intentions for high-priced luxury products with price promotions, where consumers perceive higher quality and social status. According to Jang and Moutinho (2019), the effectiveness of price promotions is influenced by perceived social status, which tends to rise as the price of accessible luxury products increases (Truong et al., 2009).

Table 1. Positive effects of price and price promotions

Author's	**Key findings**
Lin, 2012	Promotional activities generally have positive effects on purchasing behavior.
Chandon et al., 2000; De Run & Jee, 2009	Sales promotions, including price discounts, can enhance consumer purchase satisfaction and behavioral intention.
Jing et al., 2022	Higher purchase intentions for high-priced luxury products with price promotions, where consumers perceive higher quality and social status.
Jang & Moutinho, 2019; Truong et al., 2009	Effectiveness of price promotions depends on perceived social status, which tends to increase in relation to the price of accessible luxury products.
Chang, 2009; Rothschild & Gaidis, 1981; Taylor & Long-	Sales promotions can stimulate purchase behaviors in the short term.

Tolbert, 2002	

However, other research highlights the potential negative consequences of price promotions, particularly for luxury brands (Table 2). Deep price discounts can increase immediate price sensitivity, potentially undermining the long-term image of high-priced brands, which consumers typically buy for their perceived high quality and status (Fok et al., 2006; Bolton, 1989). Swani and Yoo (2010) suggested that price deals can damage brand uniqueness and image, leading to decreased behavioral intentions. Price promotions have been shown to lower quality perceptions (Rao and Monroe, 1988) and could create consumer confusion and instability, harming brand perception (Winer, 1986)

The long-term effects of price promotions on luxury brands are particularly concerning. While sales promotions can stimulate purchase behaviors in the short term (Chang, 2009), they are frequently found to erode brand associations and increase price sensitivity over time (Suri, Manchanda, and Kohli, 2000; Kalwani et al., 1990). Research suggests that while non-monetary promotions may reinforce brand equity, price promotions often result in lower future reference prices and brand image deterioration (Montaner et al., 2011). Price promotions vary with brand loyalty, as stronger brands get frequent but shallow discounts to retain their premium status (Allender & Richards, 2012).

Table 2. Negative effects of price promotions in luxury.

Author's	**Key findings**
Bolton, 1989; Fok et al., 2006	Deep price cut can increase price sensitivity, potentially undermining brand image.
Swani & Yoo, 2010	Price deals can damage brand uniqueness and image, leading to decreased behavioral intentions.
Blattberg & Neslin, 1990; Rao & Monroe, 1988	Price promotions have been shown to lower quality perceptions.
Villarejo-Ramos & Sanchez-Franco, 2005	Price promotions are negatively correlated with perceived brand quality and image.
Winer, 1986	Price deals create consumer confusion and instability, harming brand perception.

Overall, while the impact of promotions in the luxury sector yields mixed results, their role in other industries is well-documented, demonstrating positive effects on repurchase rates, particularly for full-price products (Mulhern & Padgett, 1995). Promotions also accelerate overall purchase rates (Neslin et al., 1985) and shift purchase decisions to the current period (Putsis, 1998). Building on studies that explore the effects of promotions across various sectors (Büyükdağ et al., 2020; Aguilar-Barrientos et al., 2021, Maier & Dost, 2024), this research seeks to clarify the influence of promotions on luxury consumer purchasing patterns by addressing two key questions and using different empirical methods as suggested by Lin (2012).

Our first research question is: *What purchase patterns are associated with the presence of promotions in the online luxury channel? (RQ1)* This question aims to explore how promotional activities relate to variations in purchase frequency and timing among luxury customers, drawing on prior evidence that promotions can influence engagement and re-purchase dynamics in other sectors (Hadi, 2021; Mulhern & Padgett, 1995).

The second one is: *What patterns characterize luxury customer purchasing behavior following promotional exposure? (RQ2)* This question seeks to identify whether customers who enter through promotions display distinct purchasing trajectories over time compared to those whose first purchase occurs at full price.

3. METHODOLOGY

For the study, data were collected from a European luxury company in the fashion sector. To ensure that the company's products can be considered luxury items, we compared the price, one of the defining elements of luxury (Jin & Cedrola, 2017), of two product categories, sneakers and derby shoes, with other well-known luxury brands such as Gucci, Prada, and Burberry. This comparison was conducted by analyzing specific price points within these categories to ensure that the products were directly comparable across brands. In this specific case, the price range is comparable to the brands examined, with the sneaker category ranging from €490 to €850 and the derby category ranging from €650 to €1700. Therefore, the available data can be considered representative of the high-end luxury sector.

For this study, data on transactions generated by customers on the company's direct e-commerce platform over four years (2020-2023) were collected. The use of big data is particularly relevant here, as it allows for a comprehensive analysis of customer behavior across a large and diverse set of transactions, providing insights that traditional data collection methods might not capture (DuBreuil & Lu, 2020). The promotions in this study were defined as discount price cuts ranging between 10-20%, offered during specific times of the year, such as seasonal sales or holiday events.

Upon completing the data collection, a thorough data cleaning procedure was performed. This iterative process included multiple steps such as analyzing the dataset, defining parameters, transforming data, establishing mapping rules, verifying consistency, and identifying outliers (Christen, 2012). As a result of this process, a final sample comprising 38.010 transactions from the brand's online store was obtained. The dataset includes variables such as buyer code, sales code, transaction date, item description, and whether a price discount was applied (yes/no). Based on this data, additional variables were calculated to identify the purchase path and behavior of the customers. Specifically, for each customer ID, the number of orders placed, the time elapsed between purchases, the total purchase value, and the average purchase value per transaction were measured. These variables were calculated using R, a statistical programming language, to ensure precision and efficiency in data analysis.

3.1 Analysis study 1

A detailed analysis of online customer transaction data was undertaken to understand the impact of promotions on shopping patterns, with a focus on subsequent purchases. This investigation is critical within the luxury sector, where promotional strategies could have substantial effects on customer acquisition, retention, and purchasing patterns. The analysis of buyer transactions in relation to price promotions was carried out using variables such as buyer code, sales code, transaction date, and promotion status (yes or no). This analysis focused on assessing whether promotions contribute to acquiring new buyers, specifically examining if their first purchase involved a discounted item. Additionally, it enabled the evaluation of repeat purchases driven by promotions over the buyer's entire purchasing journey.

To analyze user purchase history, considered as a sequence of transactions arranged in chronological order, we examined the dataset. We focused on "promo sequences," such as "Yes, No, No, Yes," where "Yes" denotes a purchase made during a promotion and "No" denotes a full-price purchase. This example sequence indicates a customer first purchased a promotional item, followed by two full-price items, and then another promotional item. Analyzing these promo sequences allows us to identify purchase patterns related to user behavior and understand the impact of promotions on both initial and repeat purchases. To this end, we employed SPA a well-established marketing technique for identifying specific consumer patterns (see Anderton et al., 1980; Rana & Cheah, 2019). Specifically, we used SPA of promotional and non-promotional purchases, adopting a consecutive subsequence approach. This method, as highlighted by Lu (2014), offers more accurate predictions of subsequent purchases compared to traditional SPA methods by explicitly considering purchase history. Our analysis involved examining all eligible subsequences from each user to develop a conditional probability model. This model, built using statistical techniques, calculates the likelihood of the next purchase being a promotional or non-promotional item based on the customer's preceding purchase sequence.

The extraction of subsequences follows a systematic process. Each user's purchase history, representing the ordered sequence of their transactions, is divided into all possible consecutive subsequences up to a maximum length of six. For example, from a purchase history such as [No, No, Yes, No, Yes], we generate subsequences like [No], [No, No], [No, No, Yes], [No, No, Yes, No], and [No, No, Yes, No, Yes]. It is important to note that only sub-sequences that appear consecutively within the original sequence are included. This means that, for instance, [No, Yes] would not be extracted from the example sequence, as the "Yes" is not immediately preceded by a "No" in the original sequence after the first two "No"s. The support of a subsequence P is then calculated to measure its prevalence within the dataset. Support is defined as the proportion of user purchase histories containing P to the total number of user purchase histories in the dataset.

To ensure the relevance of identified patterns, a minimum support threshold of 0.03 was applied. The selection of a minimum support threshold is a critical step in sequential pattern analysis, as it directly impacts both the quality, and the quantity of patterns discovered (Hikmawati et al., 2021). Setting this threshold too low can lead to an overwhelming number of patterns, many of which may lack statistical or practical significance. Conversely, a threshold that is too high risks excluding potentially meaningful but less frequent patterns (Yun, 2007). To balance these considerations, we adopted a minimum support threshold of 0.03 (3%), ensuring that only patterns with sufficient representation in the dataset were retained for analysis.

3.2 Analysis study 2

In the second stage of the analysis, we examined how promotional exposure is associated with variations in customers' purchase patterns over time, focusing on recurring sequences and temporal regularities. We created four distinct customer segments based on two criteria: (1) whether their initial purchase was a promotional or full-price item, and (2) whether they made at least one additional purchase in promotion over the observation period. This resulted in four groups: (a) promo-promo, first purchase and at least one subsequent purchase on promotion; (b) promo-full, first purchase on promotion and all subsequent purchases at full price; (c) full-promo, first purchase at full price, at least one subsequent purchase on promotion; (d) full-full, first purchase and all subsequent purchases at full price. Customers with a mix of promotional and non-promotional transactions were classified according to the presence of at least one promotional purchase after the first transaction. This rule was adopted to capture whether promotional exposure continued to play a role in a customer's later purchase path.

To compare these segments, we analyzed two metrics over a four-year period: the total number of orders per customer and the average time between consecutive purchases. These indicators provide a picture of each group's level of engagement and repeat activity. A greater number of orders and shorter intervals between purchases generally reflect more frequent interaction with the brand.

To analyze these metrics and detect statistically significant differences among the four customer segments, we employed ANOVA using R software. ANOVA is well-suited for comparing means of a continuous dependent variable (in our case, number of orders and time between purchases) across multiple independent groups (the four customer segments), allowing us to determine whether observed differences in purchasing patterns are statistically significant (Hair et al., 1998). We acknowledge that ANOVA assumes homogeneity of variance. To address potential concerns about these assumptions, we performed diagnostic tests, including Levene's test for homogeneity of variance, which confirmed that the assumption of equal variances was met. In R, we utilized packages such as stats for core statistical functions and dplyr for data manipulation and preprocessing, ensuring efficient and accurate analysis.

4. FINDINGS

The analysis was conducted on a sample of 24.032 online fashion buyers and 38.010 distinct purchases from Europe and North America (see Table 3). These transactions were distributed over the four years under review, with 12.2 % occurring in 2020, 22.2% in 2021, and 32.7% in both 2022 and 2023. Of the total transactions analyzed, 14% involved products sold at a direct discount ranging between 10% and 20% of the original price. The average price of products sold is €667, and the average number of orders placed per customer is 1.58, with 72% of customers making only one purchase during the period under review.

Table 3. Sample characteristics.

Variable	Value
Sample size (buyers)	24.032
Unique purchases	38.010
Region covered	Europe, North America
Time period	2020 - 2023
Percentage of transactions per year	2020: 12.2% 2021: 22.2% 2022: 32.7% 2023: 32.7%
Percentage of promotional sales	14%
Type of discount	Direct discount
Average product's price	667€
Average number of orders per customers	1.58 orders

4.1 Findings study 1

The sequential analysis of customer transactions highlights the stability of purchase patterns over time, especially for full-price purchases, while also revealing how promotional entries are associated with shifts in purchase sequences (see Table 4). The single-step pattern "[No]" exhibits the highest support (92.44%), indicating that most customers consistently avoid promotional purchases. This stability extends to the two-step pattern "[No, No]," which retains a high support level (86.05%) and confidence of 93.09%, suggesting a strong inclination to maintain full-price preferences over consecutive transactions. However, as the sequence lengthens, such as in "[No, No, No]" (42.23% support) and "[No, No, No, No]" (24.47% support), the frequency of consistent full-price purchases declines, though confidence remains moderate (49.07% and 57.96%, respectively).

Promotional patterns, in contrast, reveal a different dynamic. The single-step pattern "[Yes]" shows a support of 23.32%, while the two-step pattern "[Yes, Yes]" reaches 15.06% support and a confidence of 64.59%, indicating that customers engaging in promotional purchases exhibit a moderate tendency to repeat this behavior. Mixed patterns, such as "[No, Yes]" and "[No, No, Yes]," demonstrate lower support (13.72% and 7.61%, respectively) and confidence (14.84% and

8.84%, respectively), signaling that transitions from full-price to promotional purchases are relatively rare and unpredictable.

Table 4. Sequential pattern analysis results.

Support Count	Pattern	Support %	Confidence %
4400	[No]	92.43%	/
4096	[No, No]	86.05%	93.09%
2010	[No, No, No]	42.23%	49.07%
1165	[No, No, No, No]	24.47%	57.96%
1110	[Yes]	23.32%	/
726	[No, No, No, No, No]	15.25%	62.32%
717	[Yes, Yes]	15.06%	64.59%
653	[No, Yes]	13.72%	14.84%
510	[No, No, No, No, No, No]	10.71%	70.25%

Note: Min support = 0.003. Support (count) reports the number of customer purchase histories that contain a given pattern, while Support (%) is the share of all purchase histories that contain that pattern

4.2 Findings study 2

The second part of the analysis examined how the initial purchase condition (full-price or promotional) is linked to customers' subsequent purchase patterns over the long term. Results show that customers who made their first purchase at full price had a higher average number of orders per customer (1.61) compared to those who initially purchased on promotion (1.35) (Table 5). Customer distribution revealed that 89% of consumers started with a full-price purchase, while only 11% began with a promotional purchase. Notably, the repurchase rate, the percentage of customers making additional purchases, was also higher for full-price customers (30.1%) compared to promotion-first buyers (21.1%).

Table 5. Customer orders and repurchase rate.

First product bought	No. of orders	Percentage	% Repurchase
Full Price	1.61	89%	30.1
Promotion	1.35	11%	21.1

The analysis was expanded to examine purchase patterns, focusing on whether customers made their initial and subsequent purchases at full price or during promotions. As shown in Table 6, four distinct patterns emerged. The “FullPrice_FullPrice” group includes customers who consistently purchased at full price for both their initial and subsequent orders. The “FullPrice_Promo” group refers to those who made their first purchase at full price but switched to buying on promotion for subsequent purchases. Conversely, the “Promo_FullPrice” group includes customers who began with a promotional purchase but later bought at full price. Finally, the “Promo_Promo” group consists of customers whose purchases, both initial and subsequent, were made during promotions. The “FullPrice_Promo” group recorded the highest average number of orders at 3.84, indicating stronger engagement among customers who started with full-price purchases and later took advantage of promotions. The “FullPrice_FullPrice” group follows with 2.79 orders, reflecting a consistent purchasing pattern. In comparison, the “Promo_Promo” group shows a moderate level of engagement with an average of 2.79 orders, while the “Promo_FullPrice” group exhibits the lowest average number of orders at 2.48.

Differences also emerged in repurchase times. Customers in the “FullPrice_Promo” group exhibited the longest repurchase time, averaging 260 days, while those in the “Promo_Promo” group had the shortest time between purchases, with an average of 104 days. Customers in the “FullPrice_FullPrice” group took an average of 191 days to repurchase, while the “Promo_FullPrice” group displayed an intermediate average repurchase time of 122 days. Overall, the mean repurchase time across all patterns was 169 days.

In terms of customer distribution, most customers (74.1%) belong to the “FullPrice_FullPrice” group, indicating that most consumers consistently purchased at full price. The “FullPrice_Promo” group accounts for 17.9% of the customer base, while the “Promo_Promo” group represents 6.6%. Finally, the Promo_FullPrice group comprises only 1.4% of the total.

Table 6. Customer segments and repurchase metrics.

Purchase Pattern	**N° of orders (mean - SD)**	**Repurchase Time**	**Percentage**
FullPrice_FullPrice	2,79 (0,439)	191 days	74,1%
FullPrice_Promo	3,84 (0,498)	260 days	17,9%
Promo_FullPrice	2,48 (0,379)	122 days	1,4%
Promo_Promo	2,76 (0,411)	104 days	6,6%
Total	2,97	169 days	100%
ANOVA Analysis	***$p < 0.001$	***$p < 0.001$	/

Building on the analysis of purchase patterns, the ANOVA results (see Table 6) indicate that the differences observed across the four customer segments are statistically significant. The p-values for both metrics are below 0.001 ($p < 0.001$), suggesting that the variations among segments are unlikely to be due to random variation. These results show that the groups display distinct patterns in purchase frequency and timing, reflecting different levels of engagement with the brand.

5. DISCUSSION AND IMPLICATIONS

The results offer a picture of how luxury customers interact with price promotions over time. Across both analyses, a preference for full-price purchases clearly emerges. Customers whose first transaction occurs at full price tend to maintain similar purchasing patterns over time, showing a more consistent but slower repurchase rhythm and a relatively higher overall purchase frequency. The sequential analysis further indicates that full-price purchase patterns remain largely stable, with limited transitions between full-price and promotional transactions. By contrast, customers who engage with promotions form a smaller segment, displaying some internal consistency but a limited tendency to move toward full-price purchasing. These findings align with other existing research on luxury pricing strategies, particularly the notion that price serves as a marker of status and exclusivity. Studies by Kapferer and Bastien (2009, 2012) emphasized the role of price in creating “price-insensitive” consumers, a trend supported by the high frequency of full-price purchases observed in the data. This stability in full price purchasing patterns emphasizes the idea that these consumers are driven by the symbolic and experiential value of luxury goods, perceiving the value of these products as transcending monetary cost and purchasing them as expressions of social status and self-esteem (Jin & Cedrola, 2017; Woodside, 2012). Moreover, the low likelihood of customers switching from full-price to promotional purchases suggests that these consumers are largely immune to discounts, further reinforcing their insensitivity to price-based incentives. This aligns with research highlighting how luxury goods serve as indicators of wealth and power, with price acting as a proxy for exclusivity and brand prestige (Fok et al., 2006; Dubois, 2021).

Additionally, the study accentuates a key observation noted in previous literature: the luxury market comprises different consumer segments with varied attitudes toward price (Lim et al., 2012; Truong et al., 2009). It is not solely composed of wealthy, homogeneous buyers (Wiedmann et al., 2007; Vigneron, 2008) but also includes specific groups who seek luxury products during promotions and are attracted by deals (Lim et al., 2012). This segmentation is consistent with our findings, which highlight clear distinctions between full-price and promotion-oriented customers. The empirical results further support Lim et al.'s (2012) classification, extending it beyond psychographic traits such as prestige sensitivity, fashion leadership, and price mavenism. Specifically, customers who consistently purchase at full price can be likened to Lim et al.'s "Royal Shoppers", loyal customers who are largely insensitive to promotions and purchase at full price for the prestige, exclusivity, and intrinsic value of the brand (Jin & Cedrola, 2017; Wiedmann et al., 2007). In contrast there is a group of costumers who consistently purchase only during promotions are akin to the "Deal Hunters" described by Lim et al. (2012), customers who are highly price-sensitive and primarily focused on finding discounts, with less attachment to the brand's intrinsic value.

Price promotions are widely utilized in non-luxury markets to enhance sales and increase purchase frequency (Putsis, 1998; Mulhern & Padgett, 1995). However, their application in the luxury market is more nuanced and complex. The analysis suggests that while promotions tend to attract specific customer segments, they appear less relevant to the long-term purchasing patterns of traditional luxury buyers. Customers who consistently buy at full price often perceive their purchases as expressions of identity and social distinction, consistent with the notion of price-insensitive fans (Kapferer & Bastien, 2009, 2012). For this group, promotional activity may extend the time between purchases rather than stimulate additional buying, even though it can coincide with a slight increase in total spending. Such dynamics highlight the symbolic function of price in luxury contexts as a marker of exclusivity, prestige, and perceived brand quality (Keim & Wagner, 2018; Ailawadi et al., 2003).

Conversely, the analysis highlights a smaller segment of price-sensitive luxury customers who tend to respond more actively to promotional offers. Unlike full-price buyers, these customers relate to luxury brands in a more transactional and opportunity-driven way, placing greater value on immediate savings than on long-term brand prestige. Promotions are associated with more frequent short-term repurchases in this group, consistent with patterns observed in non-luxury markets (De Run & Jee, 2009; Chandon et al., 2000). However, this segment shows lower attachment to the brand and stronger sensitivity to price variations, dynamics that may challenge the perception of exclusivity and, over time, the symbolic value of luxury brands (Fok et al., 2006; Bolton, 1989).

The findings can also be interpreted through the lens of luxury democratization. While promotional initiatives may make luxury products somewhat more accessible to a wider audience, the prevailing tendency toward full-price purchases suggests that this democratization remains limited in scope. Despite the presence of discounts, perceptions of exclusivity and prestige still appear to guide the attitudes of core luxury customers. This highlights the delicate balance brands need to manage, using promotions to reach new segments while seeking to preserve their symbolic and aspirational value (Kapferer & Laurent, 2016). The modest movement observed between promotional and full-price segments suggests that, although there are signs of greater accessibility, most consumers seem to continue following purchasing patterns grounded in exclusivity. Those who approach the brand through promotions tend to show weaker long-term attachment and a more occasional or opportunity-driven engagement with the brand.

From a managerial standpoint, the findings provide useful indications for refining luxury brand strategies, particularly in the area of data-driven customer segmentation. The prevailing preference for full-price purchases suggests that maintaining premium price positioning remains essential for preserving exclusivity and perceived prestige. For this segment, brands may benefit from emphasizing non-price levers, such as heritage, craftsmanship, and distinctive experiences, to strengthen loyalty and reinforce brand meaning.

At the same time, promotional initiatives can serve a role in reaching more price-sensitive segments, but they should be employed selectively and with clear strategic intent, to avoid weakening the brand's symbolic value. Promotions might be most appropriate for specific objectives, such as managing seasonal inventory (Agrawal et al., 2022) or facilitating controlled customer acquisition. Leveraging data analytics and behavioral insights can help managers align promotional policies with each segment's characteristics, ensuring that short-term commercial goals remain consistent with the long-term maintenance of brand exclusivity.

6. LIMITATION AND FUTURE RESEARCH

While this study offers valuable insights into luxury consumer behavior and the impact of price promotions, it also has certain limitations that should be acknowledged. First, although the dataset is substantial and spans a four-year period, it is drawn from a single luxury company, which limits the generalizability of the findings. The preferences and behaviors observed in this specific company may not fully represent the entire luxury industry. Different luxury categories, such as automobiles or high-end services, might exhibit varying consumer behaviors. Future research should aim to include a broader range of luxury companies and product categories to ensure the findings apply more broadly across the luxury sector.

Second, this study focuses primarily on quantitative measures of consumer behavior, such as repurchase rates and sequential purchase patterns. While these metrics provide valuable information, they do not capture the underlying motivations or psychological factors driving consumer decisions. For example, the reasons why full-price consumers remain loyal to the brand or why promotional customers may shift to full-price purchases are not explored in depth. Qualitative research methods, such as interviews or focus groups, could be employed in future studies to provide a richer understanding of the psychological and emotional factors that influence luxury purchasing behavior.

Third, the data refer exclusively to purchases made through the online channel, while actual purchasing behavior may also include transactions in physical stores. Future research could incorporate this data to analyze in-store behavior and examine, using the same customer ID, potential alternation between purchases categorized as promotional or full-price across both channels.

Another limitation relates to the geographic and cultural context of the study. Consumer behavior in the luxury market can vary significantly across different regions and cultures due to differing attitudes toward wealth, status, and consumption. This study does not account for cultural differences, which may influence how price and promotions are perceived. For instance, luxury consumers in emerging markets may exhibit different sensitivity to price promotions compared to those in more mature luxury markets. Future research should explore cross-cultural comparisons to better understand how luxury consumers in different regions respond to pricing and promotional strategies.

Finally, the dataset used in this study lacks demographic information about the customers, such as age, profession, or income level. This limitation prevents a more granular analysis of how different demographic groups may respond to price and price promotions in the luxury sector. For instance, younger consumers or those with varying levels of disposable income might exhibit distinct purchasing behaviors compared to older or more affluent groups. Future research should aim to include demographic variables to better distinguish these consumer segments and assess how factors such as age, professional status, and economic background influence luxury purchasing decisions.

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CHAPTER 3

When Channels Complement (and When They Don't) in Luxury Retail

Abstract

Omnichannel retailing has transformed luxury distribution by connecting online and offline touchpoints, yet the dynamic interdependence among channels remains poorly understood. Prior research has largely examined cross-channel effects in static or dyadic settings, overlooking how interactions unfold over time and shape overall performance. This study addresses this gap by analyzing when and how channels reinforce or cannibalize one another within a governed luxury system. Drawing on Service-Dominant Logic and Market System Dynamics, the study conceptualizes channels as interdependent nodes embedded in institutional rules that define their capacity to transmit, absorb, or appropriate demand and value. Using weekly sales data from a luxury brand across three direct channels (e-commerce, boutiques, and outlets) a Vector Autoregression with exogenous regressors captures short-run propagation and system-wide outcomes. Results suggest limited and asymmetric interactions across channels. Most shocks dissipate rapidly, with only modest and context-dependent spillovers. Theoretically, the study advances a role-conditioned view of luxury omnichannel systems, emphasizing governance as the boundary mechanism that shapes how and where value can propagate across channels.

1. INTRODUCTION

Omnichannel retailing has reshaped how firms compete and how consumers navigate their purchase journeys. The increasing interconnection of online and offline touchpoints has made channel management a strategic rather than technological imperative (Cao & Li, 2015). Customers now expect continuity across platforms, moving effortlessly from information search to purchase and post-sale interaction (Sopadjieva et al., 2017; Verhoef et al., 2015). For firms, this convergence expands opportunities for engagement and data integration but also creates risks of overlap, margin erosion, and internal competition. An effective integration should, in theory, allow customers to switch media without friction while enabling firms to orchestrate pricing, assortment, and service decisions coherently. Yet, as recent work notes, integration is not purely technological but organizational and strategic: its effectiveness depends on what is coordinated, to what depth, and under which governance constraints (Thaichon et al., 2024). These tensions are particularly pronounced in luxury markets, where seamlessness must coexist with brand control, scarcity, and long-term value preservation. This paradox raises a broad question about when and under what conditions does integration across channels create expansion rather than conflict. Empirical research has only recently begun to examine this theme.

Emerging evidence shows that connecting or adding channels rarely leaves the system unaffected. Some interactions generate uplift through convenience and learning, while others displace demand or erode margins (Shankar & Kushwaha, 2021; Timoumi et al., 2022; Neslin, 2022). Studies using event-based or quasi-experimental designs often report aggregate gains-for example, offline openings boosting online sales, or mobile integration increasing purchase frequency (Pauwels & Neslin, 2015; Wang & Goldfarb, 2017; Narang & Shankar, 2019). Therefore, the extent to which integration delivers value depends on how channels interact in practice. (Maier & Wieringa, 2021; Van Crombrugge et al., 2025).

Although prior research has advanced our understanding of how channels interact, much of it captures static relationships rather than the dynamic evolution of entire channel systems. Only a limited number of studies have modeled channels jointly and traced how a shock in one node propagates through the portfolio over time using multivariate time-series approaches (Timoumi et al., 2022; Van Crombrugge et al., 2025). Such analyses are almost absent in luxury retail, where strong brand governance, curated assortments, and deliberate scarcity likely constrain and shorten these propagation effects. This underexplored domain motivates the empirical and theoretical focus of the present study.

To frame these dynamics conceptually, the study draws on Service-Dominant Logic (SDL) and Market System Dynamics (MSD). Together, these perspectives view markets as governed ecosystems in which channels operate as interdependent nodes and value circulates through feedback loops that are asymmetric and institutionally bounded. Guided by these perspectives, the study addresses the following questions

RQ1a. How do the brand's primary channels (e‑commerce, boutique, outlet) operate as an integrated dynamic system in luxury?

RQ1b. What is the direction, magnitude, and duration of the influence that a sales shock in one channel has on weekly outcomes in the others?

RQ2a. How does the luxury channel mix jointly determine the firm's aggregate weekly sales volume?

RQ2b. Do cross‑channel interactions yield a net synergistic (volume-expanding) or cannibalistic (volume-contracting) effect on total units sold in the luxury context?

We address these questions with a within-brand, weekly VARX design that treats direct channel sales as jointly endogenous and conditions on channel-specific promotions (Kilian & Lütkepohl, 2017). By answering these questions, the study will make three main contributions. First, it redefines the luxury omnichannel portfolio as an ecosystem of services shaped by feedback and governance dynamics, clarifying when cross-channel interactions constitute value co-creation versus co-destruction. Second, it provides weekly brand-internal and multichannel evidence from the luxury sector, a context largely absents from previous research. Third, it links short-term channel shocks to cumulative system-level outcomes, distinguishing sales expansion from redistribution.

The rest of the chapter is organized as follows. Section 2 develops the theoretical context and introduces role-based expectations for cross-channel propagation in SDL and MSD. Section 3 presents the research setup and VARX design. Section 4 reports the results of the estimates and dynamic analyses, quantifying the results at the ecosystem level. Section 5 discusses the results considering SDL and MSD, section 6 outlines the theoretical and managerial contributions, and section 7 concludes with limitations.

2. THEORETICAL BACKGROUND

2.1 Channel mix in luxury

In the luxury sector, the channel mix often includes boutiques, e-commerce and outlets, each of them playing a different strategic role in distribution and experience management (Mosca, 2014). Flagship stores and single-brand boutiques remain the primary locations for building identity, showcasing the brand's aura through architecture, location and service rituals. (Bastien & Kapferer, 2012; Dion & Borraz, 2017). In parallel, e-commerce has evolved from a marginal transactional extension to a governed digital storefront, where brands carefully curate access, symbolic codes, and premium service at scale (Okonkwo, 2009; Klaus, 2020). The third pillar, consisting of outlets and discount sales channels, ensures inventory management and controlled access to new consumer segments, but requires strict assortment limits and price discipline to avoid brand dilution (Ko & Megehee, 2012). To preserve coherence across channels, luxury firms rely on selective distribution and governance mechanisms (Cabigiosu, 2020).

To better understand the luxury channel mix, it is useful to first examine the three main channels individually. Each plays a different role in value creation, customer interaction with the brand, and management control by companies. Examining them separately provides the basis for later analyzing how they connect and influence each other in an omnichannel system.

2.1.1 Boutiques

As the most traditional and symbolically charged interface in the luxury channel mix, boutiques remain the primary point where brand identity is staged, performed, and experienced (Dion & Arnould, 2011). They infuse retail with artistic codes through gallery-like architecture, curated rituals, and the creative director's vision to create awe, preserve authenticity, and sustain prestige (Dion & Arnould, 2011). Contemporary flagships extend this logic: museum-quality spaces, art installations beside products, and sales staff acting as curators elevate the visit into a cultural experience that reinforces exclusivity and symbolic value (Joy et al., 2014). Boutiques also communicate corporate values beyond commerce. They materialize sustainability commitments via eco-materials, craftsmanship storytelling, and in-store messaging, turning the store into a credibility platform for social and environmental claims (Arrigo, 2018). From the consumer's point of view, satisfaction comes from personalized service and a multisensory atmosphere in line with the brand identity, which together foster feelings of importance, attachment and loyalty (Kauppinen-Räisänen et al., 2020). From a managerial perspective, clienteling protocols, service rituals, image care and cultural heritage programming shape this experiential core. By establishing quality and service standards for the system, boutiques can generate a halo effect demand that subsequently manifests itself online or, if governance is weak, disperses towards access formats.

2.1.2 E-commerce

Over the past decade, luxury brands have gradually shifted from cautious experimentation with online channels to a more deliberate and structured integration of e-commerce within their strategies. In the early stages, many firms faced what was often described as the "Internet Dilemma", the tension between maintaining exclusivity, personalization, and the symbolic aura of luxury while responding to the growing expectations of digital-first consumers (Kluge & Fassnacht, 2015; Bastien & Kapferer, 2012).

This uncertainty initially slowed adoption, as maisons feared that online visibility could lead to overexposure or loss of control. Over time, however, the perception of digital channels began to change. Empirical evidence shows a steady increase in online investments, with websites evolving from simple catalogues to fully transactional and service-oriented platforms (Hansen & Bjorn-Andersen, 2013; Geerts, 2013; D'Arpizio et al., 2024). As digital maturity advanced, the debate shifted from whether luxury brands should sell online to how they could do so without compromising prestige and perceived value (Chandon et al., 2016; Kim et al., 2015).

Recent studies suggest that online presence does not necessarily undermine profitability or exclusivity when it is governed by the right strategic and symbolic rules (Pruzhansky, 2014). In practice, most luxury e-commerce now operates as a curated digital storefront, designed to replicate the emotional and aesthetic codes of the boutique. Brands carefully control presentation, access, and pricing, while maintaining strict standards for authenticity and service quality (Klaus, 2020). This selective governance enables luxury firms to balance growth with control, expanding reach through digital channels while preserving the craftsmanship, heritage, and emotional depth that continue to define the essence of luxury (Cabigiosu, 2020; Sanz-Lopez et al., 2024).

2.1.3. Outlet

The outlet is a distinct interface with its own motives and expectations. Shoppers approach outlet malls with a mix of cognitive "value" attitudes and affective bargain-thrill emotions; fashion knowledge heightens the payoff, and consumers categorize outlets as fundamentally different from regular malls (Sierra & Hyman, 2011). On the supply side, manufacturers increasingly design made-for-outlet assortments with lower quality and price points to segment price-sensitive demand, rather than merely liquidate overstock (Li et al., 2017). This logic sits uneasily with strict luxury strategy: the anti-laws of luxury argue that institutionalized discounting erodes rarity and symbolic distance, making products comparable and weakening the “dream value” that supports margins (Kapferer, 2015; Bastien & Kapferer, 2012). Yet luxury outlet villages have evolved into carefully staged environments; atmospheric cues and commercial levers jointly convert attraction into “impulsive yet reasoned” purchases, while loyalty programs and staff interaction cultivate ongoing connection (Cao et al., 2024). Strategically, the outlet functions as governed access: it can widen penetration among aspirational customers but carries dilution and cannibalization risks if pricing, assortment, and service are not tightly coordinated with the core. Industry reporting underscores the format’s momentum and gateway role for value-seeking consumers (D’Arpizio et al., 2024) Consequently, outlet activity may replace full-price interfaces in the short term or foster future improvements when barriers and clienteling capture new entrants.

2.2 Omnichannel integration and cross-channel dynamics in luxury

As we saw in the previous section, boutiques, e-commerce and outlets play distinct roles, but their results are interdependent. To go beyond a simple description, the literature turns to omnichannel integration, which examines how coordinated channel design and governance influence value creation and performance. (Neslin et al., 2006; Verhoef et al., 2015). Building on this view, we introduce two complementary frameworks to conceptualize channels as interconnected elements of a dynamic system: Service-Dominant Logic and Market System Dynamics.

Service-Dominant Logic (SDL) conceptualizes value as co-created through service-for-service exchange among actors who integrate operant resources within institutional arrangements, implying that interfaces are inherently interdependent (Vargo & Lusch, 2004; Vargo et al., 2017). Market System Dynamics (MSD) complements this perspective by emphasizing how discourses, practices, and rules co-evolve through feedback processes, generating path-dependent change (Giesler & Fischer, 2017; Layton, 2015). Applied to omnichannel retail, these frameworks suggest that sales channels cannot be understood in isolation, but rather as components of a coupled system shaped by institutional rhythms, resource flows, and consumer learning over time (Avery et al., 2012; Verhoef et al., 2015).

The broader retail literature supports this systemic view. Integration is defined as the joint design, coordination, and operation of interfaces and back-end processes to create customer value (Neslin et al., 2006; Verhoef et al., 2015). Two regularities emerge. First, cross-channel effects are real and asymmetric: actions in dissimilar interfaces tend to complement, while actions in similar interfaces more often substitute (Shankar & Kushwaha, 2021; Neslin, 2022). Second, outcomes are context-dependent: integration enhances value when it reduces search and risk without collapsing differentiation, but it can erode profits when costs increase or when products require touch-and-feel evaluation (Bell et al., 2015; Gallino & Moreno, 2014; Gu & Tayi, 2017; Forman et al., 2009; Ofek et al., 2011). Syntheses further show that adding online to stores typically raises total sales despite cannibalization, adding stores to online retailers increases both online and overall sales, and mobile adoption tends to lift purchase frequency and spend (Timoumi et al., 2022). At the same time, participation in marketplaces can expand reach while ceding customer relationships, with effects contingent on category and platform power (Maier & Wieringa, 2021).

In luxury, the retail patterns above typically play out under tighter governance as documented in prior work. Selective distribution, presentation rules, and service protocols make substitution across channels something the brand seeks to actively manage (Cabigiosu, 2020; Bai et al., 2024). Boutiques work as high-signal touchpoints that can spark online demand, while a well-governed e-commerce site lowers perceived risk and reinforces brand meaning (Wang & Goldfarb, 2017; Herhausen et al., 2015). The outlet channel then adds tension to this setup: routine discounting can narrow the symbolic gap with full price, yet for some customers it also serves as an on-ramp, encouraging trial, category exploration, and later full-price purchases (Bastien & Kapferer, 2012; Kapferer, 2015; Namin et al., 2022).

Retail research consistently shows that channels interact in asymmetric and context-dependent ways, and SDL-MSD provides a theoretical basis for expecting such interdependencies in luxury. Yet, within luxury, the available evidence is fragmented: most contributions focus on individual channels or on static comparisons, while the dynamics that link e-commerce, boutiques, and outlets as parts of the same system remain underexplored. As a result, we still lack systematic evidence on whether direct channels in luxury reinforce or erode one another when considered as an integrated ecosystem. For this reason, we empirically quantify how shocks propagate across e-commerce, boutiques, and outlets and what their system-level net effect is on total sales.

3. METHODOLOGY

3.1 Research setting

We study a mid-sized Italian luxury brand and focus on its domestic market, where the firm operates three direct channels: e-commerce, boutiques, and outlets. The boutique network consists of three flagship stores in Milan, one in Rome, and a seasonal boutique in Capri; the outlet channel comprises two locations in Northern and Central Italy. E-commerce serves the entire territory via nationwide shipping.

The observation window spans 72 consecutive weeks, from June 2022 to October 2023, based on weekly internal data. Our endogenous variables are the weekly units sold by channel, modeled jointly because shocks in one interface may propagate to the others through substitution or reinforcement. To isolate these dynamic interactions, we include two exogenous regressors capturing channel-specific promotions (boutique and e-commerce). These campaigns are planned by the firm in advance as part of broader marketing and merchandising calendars, defined under budgetary and assortment constraints that leave little room for short-term adjustments. Although our data capture the realized number of promotional units, we treat promotions as predetermined at the temporal frequency of our analysis. To limit simultaneity, they enter the model with a one-period lag, so that estimated coefficients reflect the conditional impact of lagged promotional intensity rather than any contemporaneous reaction to weekly sales. This specification aligns with how promotional decisions are operationally made and thus plausibly exogenous to short-run demand fluctuations. It should be noted that the outlet channel does not feature discrete promotional campaigns, as its pricing structure is permanently discounted; therefore, promotional variables are included only for e-commerce and boutiques.

Table 1 reports definitions, sources, transformations, and descriptive statistics for all variables.

Table 1. Descriptive statistics of model variables

Variable	Role	Description	Source	Mean (SD)
Weekly units sold (e-commerce)	Endogenous	Number of units sold through the online store	Company	39.7 (24.1)
Weekly units sold (boutiques)	Endogenous	Number of units sold through physical boutiques	Company	79.2 (25.5)
Weekly units sold (outlets)	Endogenous	Number of units sold through outlet stores	Company	90 (53.4)
Weekly promo units (e-commerce)	Exogenous	Units sold online under promotional campaigns	Company	3.7 (4.3)
Weekly promo units (boutiques)	Exogenous	Units sold in boutiques under promotional campaigns	Company	4.1 (4.9)

Note: period considered June 2022 - October 2023

To analyze dynamic interdependence, we estimate a Vector Autoregression with exogenous regressors (VARX). This framework allows each channel's sales to depend on its own and the others' past values while conditioning on promotional control, thereby capturing feedback loops without imposing them a priori (Kilian & Lütkepohl, 2017). The design directly maps onto our research questions. RQ1a is examined through the system's autoregressive structure, Granger and instantaneous causality tests, and forecast error variance decompositions (FEVDs), which together indicate how tightly the channels are interconnected. RQ1b is addressed through generalized impulse-response functions (IRFs), which trace the direction, magnitude, and duration of cross-channel propagation over time. RQ2a is investigated by back-transforming and aggregating IRFs across channels to estimate the system-wide change in total weekly sales following a one-standard-deviation innovation. Finally, RQ2b is assessed by decomposing this total into own- versus cross-channel contributions, identifying whether interactions produce net synergy (volume-expanding) or redistribution/cannibalization (volume-contracting) effects.

3.2 Model specification

Building on the design outlined above, this section details how the VARX framework is operationalized. All analyses were conducted in R, using a combination of packages for data manipulation, visualization, and econometric modeling. Specifically, we used readxl, dplyr, tidyr, and lubridate for data preparation and transformation, ggplot2 for exploratory visualization, and vars and urca for unit-root testing, cointegration analysis, and VARX estimation. Iterative routines and diagnostic checks were facilitated through purrr for functional programming and model evaluation. We begin by testing the time-series properties of the logged sales variables to ensure stationarity and to assess whether a cointegration structure is required. We then specify the deterministic components that capture trend and seasonal variation, define the inclusion and timing of exogenous regressors, and select the autoregressive order using information and diagnostic criteria. Finally, we evaluate overall model adequacy and residual behavior before moving to the dynamic analyses that address the research questions.

3.2.1 Stationary diagnostics

We model weekly units sold across channels using log-transformed variables to stabilize variance. Specifically, we apply $\log1p(y)=\log(1+y)$ to accommodate zeros in the raw counts without ad-hoc offsets.

Before specifying the VARX, we assessed the (trend-)stationarity of the logged series using a battery of complementary tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and KPSS (Kwiatkowski-Phillips-Schmidt-Shin). ADF test evaluates the null hypothesis that a series contains a unit root, that is, it follows a stochastic trend and is non-stationary (Dickey & Fuller, 1979). By including a drift and, when appropriate, a linear trend, the ADF accounts for deterministic components while controlling for serial correlation through lagged differences. The PP test also examines the null of a unit root but corrects for autocorrelation and heteroskedasticity in the error term using a nonparametric adjustment, making it a robustness check against potential misspecification in ADF regressions (Phillips & Perron, 1988). In contrast, the KPSS test reverses the hypotheses: its null assumes (trend-)stationarity, while rejection indicates the presence of a unit root (Kwiatkowski et al., 1992). Because the ADF and PP start from the assumption of non-stationarity whereas KPSS assumes the opposite, comparing their outcomes allows for a balanced assessment of the time-series properties (Kwiatkowski et al., 1992).

Table 2. Stationarity test for sales series

Series	ADF (drift) τ	ADF (trend) τ	PP (μ) Z-τ	PP (τ) Z-τ	KPSS μ	KPSS τ
E-commerce	−3.029 **	−2.975	−4.348 ***	−4.311 ***	0.053	0.053
Boutique	−2.182	−3.247 *	−4.083 ***	−5.055 ***	0.717 **	0.086
Outlet	−3.160 **	−3.180 *	−2.756 *	−2.737	0.094	0.097

Note: Significance codes: *** $p<0.01$, ** $p<0.05$, * $p<0.10$ (for ADF/PP → rejection of unit root). For KPSS, asterisks mark rejection of the null of stationarity.

The summarization in table 2 provides complementary evidence across tests. For e-commerce, both ADF (with drift) and PP reject the unit root and KPSS does not reject stationarity, indicating stable dynamics around a deterministic component. For boutiques, results are mixed but coherent with trend-stationarity: PP strongly rejects a unit root; ADF with trend is marginal; KPSS rejects level-stationarity but not trend-stationarity. For outlets, ADF rejects at conventional levels (drift/trend specifications), PP offers weaker support, and KPSS does not reject stationarity, again compatible with covariance stationarity around a deterministic path.

To further assess whether a Vector Error Correction Model (VECM) might be required, we applied Johansen's cointegration procedure (Johansen, 1995) using both trace and maximum eigenvalue statistics under constant and trend specifications. Across all lag structures examined, the null hypothesis of no cointegration could not be rejected at conventional significance levels. This indicates that the three logged series do not share a common stochastic trend, and a cointegrated VAR representation is therefore not required.

Taken together, unit-root evidence and the absence of cointegration support a VARX in levels with deterministic trend and seasonal controls. This choice preserves long-run information while maintaining covariance stationarity around the deterministic component. In the next subsections, we detail the deterministic terms (trend and Fourier seasonality), the treatment of exogenous regressors, and the selected lag structure.

3.2.2 Deterministic components and seasonality

Consistent with the stationarity evidence, we include a deterministic linear trend to capture low-frequency drifts, and we model seasonality with a parsimonious Fourier approximation. Weekly luxury sales exhibit smooth, recurrent cycles (e.g., holidays, summer peaks, collection launches) that are poorly represented by coarse monthly dummies and would require dozens of calendar indicators to track intra-month patterns, leading to over-parameterization and loss of degrees of freedom. By contrast, a small set of sine-cosine pairs flexibly approximates these cycles without imposing stepwise breaks, while mitigating multicollinearity and preserving power.

In practice, we consider K = 0-3 Fourier harmonics (always including a linear trend). For each K, we select the autoregressive order by the Schwarz criterion and then assess model adequacy on: (i) information criteria, (ii) system stability (all roots inside the unit circle), (iii) residual whiteness via the Portmanteau test at lag 8, and (iv) the joint relevance of the seasonal block using Wald tests. This procedure provides a compact seasonal specification that matches the weekly data structure and as shown in Table 3, yields a significant seasonal block with clean residual diagnostics

Table 3. Comparison of deterministic specifications (trend + Fourier terms)

K	Lag (SC)	BIC	Max root	Portmanteau p (lag 8)	Wald p (E / B / O)
0	1	178.6	0.8122	0.414	-
1	1	195.7	0.7891	0.278	0.319 / 0.253 / 0.612
2	1	173.5	0.4497	0.182	0.006 / 0.009 / 0.000
3	1	188.5	0.4337	0.069	0.027 / 0.002 / 0.0003

As shown in Table 3, the specification with K = 2 provides the most balanced representation of seasonal dynamics. It achieves the lowest BIC among all stable alternatives (BIC = 173.5; max root = 0.4497), satisfies residual whiteness according to the Portmanteau test ($p = 0.182$), and displays strong joint significance of the seasonal block across the three equations (Wald p-values: E = 0.006, B = 0.009, O < 0.001). Specifications with K = 0-1 clearly underfit seasonal variation, yielding higher information criteria and statistically irrelevant Fourier components, while K = 3 increases complexity without substantive gains in fit and introduces mild residual autocorrelation (Portmanteau $p = 0.069$). For these reasons, the K = 2 model is retained as the baseline deterministic structure, offering a parsimonious yet empirically adequate representation of seasonal behavior in weekly luxury sales.

3.2.3 Lag order selection and model adequacy

Building on the deterministic specification established above the model incorporates promotional variables expressed as log1p(promo) at lag 1 for e-commerce and boutiques as exogenous regressors. This lagged formulation mitigates simultaneity and enhances the short-run identification of shocks, providing a more reliable representation of weekly dynamics as discussed before.

The autoregressive order was then selected using standard information criteria over p = 1–3. All criteria (AIC, HQ, BIC, and FPE) consistently favored p = 1, with the BIC showing the clearest minimum. Accordingly, the final specification is a VARX (1) including a linear trend, Fourier terms (K = 2), and the promotional variables at lag 1.

Based on this baseline structure, we next assess the model's overall adequacy (Table 4). The system satisfies the stability condition, with all characteristic roots well inside the unit circle (max |root| = 0.407). Residual diagnostics indicate no significant autocorrelation up to eight lags (Portmanteau χ^2 (63) = 78.30, p = 0.093) and no evidence of conditional heteroskedasticity (multivariate ARCH χ^2 (180) = 201.73, p = 0.128). The multivariate Jarque–Bera test detects mild departures from normality (χ^2 (6) = 13.94, p = 0.030), driven primarily by skewness (χ^2 (3) = 7.997, p = 0.046), while kurtosis remains nonsignificant (χ^2 (3) = 5.948, p = 0.114). As commonly observed in weekly retail data, these deviations are moderate and are addressed through bootstrap-based inference for impulse response and variance decomposition analyses.

Table 4. Final model adequacy tests

Test	Statistic (χ^2)	p-value
Portmanteau (8 lags)	78.30	0.093
ARCH (multivariate)	201.73	0.128
Jarque-Bera (overall)	13.94	0.030
Skewness test	7.997	0.046
Kurtosis test	5.948	0.114

With the baseline model in place, we now turn to the dynamic evidence that addresses our research questions. The analysis unfolds in four steps. First, we present the VARX parameter estimates to provide a structural overview of short-run own- and cross-channel effects. Second, we trace shock propagation through generalized impulse response functions (GIRFs), computed with residual-based bootstrap confidence bands (thousands of replications) to account for small-sample distortions and the documented non-normality. This approach produces ordering-invariant and statistically reliable responses, ensuring robust inference even under non-Gaussian residuals

(Pesaran & Shin, 1998; Kilian, 1998). Third, to gauge the relative importance of cross-channel dynamics, we report 12-week forecast error variance decompositions (FEVDs), which attribute each channel's forecast uncertainty to own versus cross-channel innovations, and complement them with Granger and instantaneous causality tests to establish whether spillovers systematically improve predictability (Lütkepohl, 2005). Fourth, we move to the ecosystem level by back-transforming GIRFs into units for a one-standard deviation innovation in each channel and then aggregating responses across channels. We adopt this scaling because a one-standard deviation shock is a conventional normalization in VAR analysis that benchmarks the effect of a typical historical disturbance, making responses comparable across channels (Lütkepohl, 2005). This allows to quantify whether interdependencies translate into net synergy or cannibalization in total weekly sales.

4. RESULTS

This section presents the empirical findings from the baseline VARX model, organized to progressively link the short-run estimates to the dynamic propagation of shocks across channels. We begin by examining the estimated coefficients to outline the immediate relationships among e-commerce, boutique, and outlet sales, and then trace how these relationships evolve over time through impulse-response analysis.

4.1 Estimation results and impulse response analysis

The estimated coefficients reported in Table 5 offer a concise picture of the short-run dynamics across channels. On the autoregressive side, outlets display marked persistence, as lagged outlet sales are positively associated with current outlet performance (0.471***). A similar link appears from outlets to e-commerce (0.290*), suggesting that outlet activity may precede modest increases in online sales. Other cross-channel lags are small and not statistically significant at conventional levels, indicating limited evidence of systematic short-run feedback among the three interfaces.

Table 5. Parameter estimates of the VARX model

	Ln (Ecom)	Ln (Boutique)	Ln (Outlet)
Endogenous variables			
Ln (Ecom) (t-1)	-0.124	0.204	-0.025
Ln (Boutique) (t-1)	0.246	0.127	-0.187
Ln (Outlet) (t-1)	0.290*	0.118	0.471***

Exogenous variables			
Promo Ecom (t-1)	0.096*	-0.047	-0.022
Promo Boutique (t-1)	-0.099	-0.007	0.102*
Trends			
const	1.868*	2.376*	2.966**
trend	-0.005	0.006**	0.004*
S1	-0.026	0.068	0.056
C1	-0.091	0.097*	0.121*
S2	-0.374**	-0.169*	0.041
C2	0.273*	0.011	0.310***
R²	0.526	0.547	0.797

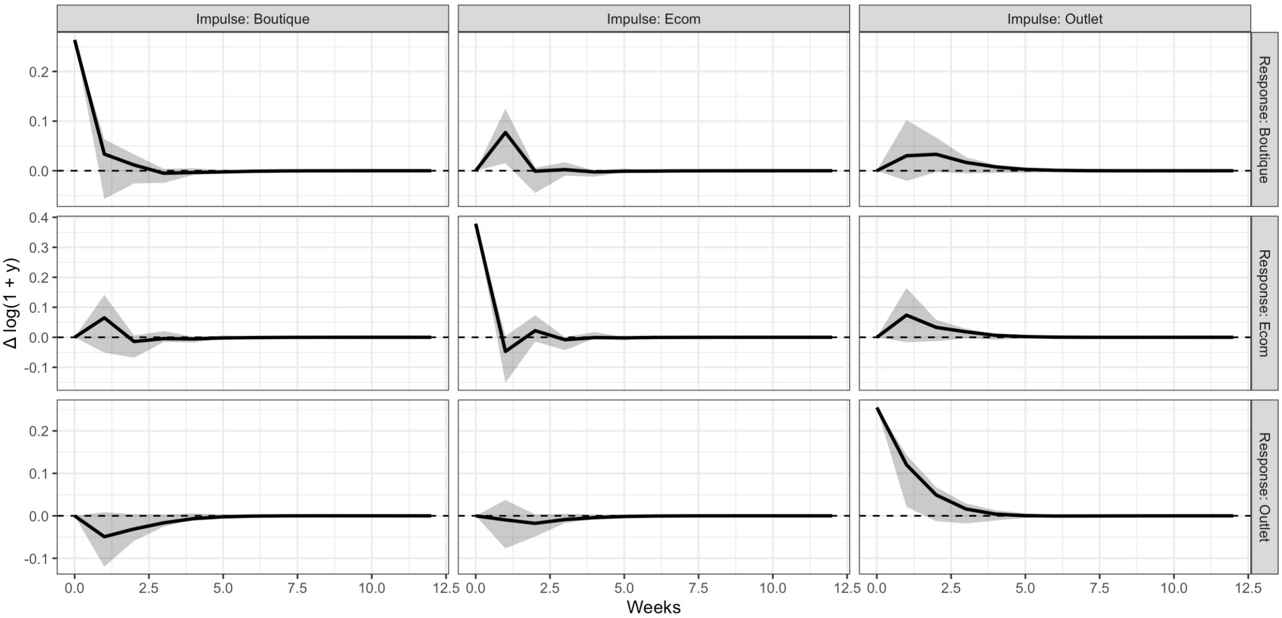
Note. * $p < .10$; ** $p < .05$. VARX(1) with constant, trend, and seasonal Fourier terms ($K = 2$) among the deterministic components; exogenous variables as specified. Sample: 72 weeks. All characteristic polynomial roots are < 1, indicating stability.

Regarding the exogenous regressors, e-commerce promotions at lag 1 are positively related to online sales in the following week (0.096*), while boutique promotions show a positive association with outlet sales (0.102*), consistent with potential cross-format sensitivity to full-price activity.

Among the deterministic components, the estimates indicate a mild upward trend in boutiques (0.006**) and outlets (0.004*), while seasonal patterns are concentrated in the second harmonic: the second sine term is negative for e-commerce (-0.374**) and boutiques (-0.169*), whereas the second cosine term is positive and significant for outlets (0.310***), consistent with distinct timing of peak activity across channels.

The impulse-response analysis (Figure 1) broadly reflects these patterns. A boutique shock produces a sharp on-impact increase in boutique sales that quickly dissipates, with negligible propagation to other channels. An e-commerce shock generates a modest, short-lived self-response and minimal cross-channel effects. In turn, an outlet shock corresponds to a large immediate rise in outlet sales, followed by a gradual decline, with small and occasionally positive spillovers to the other formats. All impulse responses are scaled to one-standard-deviation innovations and reported with bootstrap confidence intervals.

Figure 1. IRF (Bootstrap 95%)

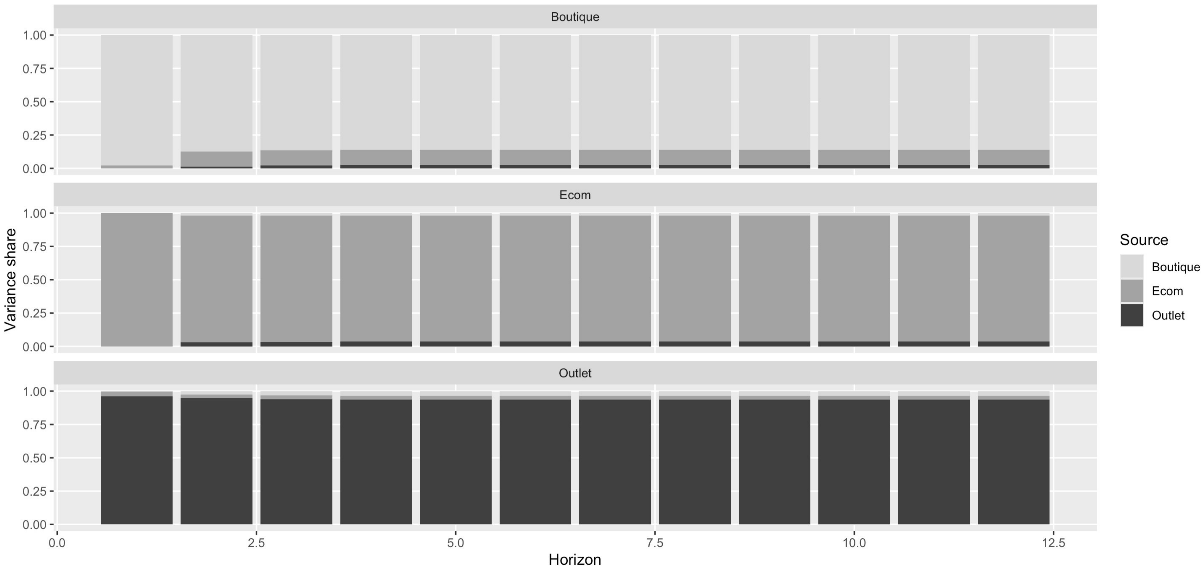


Taken together, these estimates suggest that short-run interactions among the brand's channels are relatively contained, with most adjustments occurring within each format. To further assess whether such patterns hold beyond immediate effects, we next examine the direction, magnitude, and persistence of cross-channel dependencies through variance decomposition and causality tests.

4.2 Asymmetric interdependence and directionality across channels

To complement the impulse-response evidence, we analyze FEVDs over a 12-week horizon. This approach quantifies the relative contribution of each channel's own history and of shocks originating in the others, providing a broader view of interdependence and asymmetry across the omnichannel system. Figure 2 summarizes the results.

Figure 2. FEVD



The variance decomposition results point to moderate asymmetries in how channels depend on their own versus external shocks. E-commerce appears largely self-driven, with 92.5% of its forecast error variance explained by its own innovations, and only limited contributions from boutiques (3.2%) and outlets (4.3%). Boutiques show comparatively greater exposure to external influences: 85.7% of their variance is explained by own shocks, while 11.5% stems from e-commerce and 2.8% from outlets. Outlets fall in between, with 93.5% of variance driven by their own dynamics, 3.0% attributable to e-commerce, and 3.5% to boutiques.

Formal tests of directionality are consistent with these patterns. Granger causality tests do not indicate systematic predictive links across channels (E-commerce: $p = 0.35$; Boutique: $p = 0.11$; Outlet: $p = 0.15$), and instantaneous causality tests, which capture same-week co-movements beyond the autoregressive structure, similarly fail to reject independence (E-commerce: $p = 0.18$; Boutique: $p = 0.39$; Outlet: $p = 0.27$).

4.3 Ecosystem-wide impact: cumulative total response in units

To assess whether cross-channel dynamics result in overall expansion or merely redistribution of sales, the back-transformed generalized impulse responses are aggregated across the three channels and cumulated over a 12-week horizon ($H = 12$). Table 6 reports the cumulative totals, the peak total value, defined as the maximum system-wide response observed within the horizon, and the cumulative contribution of the non-originating channels.

Table 6. Cumulative ecosystem impact of channel-specific shocks

Impulse	Cum. Total (1→H)	Peak Total Volume	Cumulative spillover from other channels (1→H)
Boutique	19.5	24.9	−8.10
Ecom	20.7	19.8	2.39
Outlet	59.4	27.3	13.6

Boutique shocks generate a modest aggregate volume effect, with a cumulative gain of 19.5 units over 12 weeks and a peak of 24.9 units in the first week. The spillover component is negative (−8.1 units), suggesting that the system-wide gain is driven entirely by boutiques themselves. E-commerce shocks produce a similar cumulative volume gain of 20.7 units, peaking at 19.8 units on impact. In this case, however, the contribution of the other channels is slightly positive (+2.39 units), pointing to limited but genuine reinforcement outside the origin channel. Outlet shocks stand out as the largest source of aggregate volume expansion: the cumulative effect reaches 59.4 units, with a peak of 27.3 units on impact, and the other channels contribute an additional +13.6 units, confirming that outlet disturbances propagate positively beyond their own domain.

Overall, two regularities emerge. First, the cumulative effects are front-loaded, with responses peaking early and decaying rapidly, implying that observed volume expansion or redistribution occurs mainly through short-run impulses. Second, the sign of the spillover component aligns with the asymmetries noted earlier: boutiques exhibit mild cannibalization effects, e-commerce shows modest positive reinforcement and outlets act as the main transmitter capable of expanding the system's aggregate volume.

5. DISCUSSION

This section discusses how the findings answer each research question, integrating evidence from the VARX analyses with the theoretical lenses of SDL and MSD. We first address RQ1a and RQ1b, which concern the dynamic structure and propagation mechanisms across channels, and then turn to RQ2a and RQ2b, which examine the aggregate and net system-level outcomes.

Regarding RQ1a and RQ1b, the findings reveal that the brand's direct channels form a lightly coupled and asymmetric system. Most of the variation in future sales comes from each channel's own past, while interactions between channels are weak and fade quickly. Among the statistically significant links, only the lagged pathway from outlet to e-commerce emerges consistently suggesting that access-driven activity can precede modest increases in online sales, while other cross-effects quickly dissipate.

Viewed through SDL theory, this pattern suggests that channels operate as service interfaces with differentiated resource-exchange roles. The outlet functions as an access node that facilitates price and assortment discovery, reducing perceived risk and stimulating subsequent digital engagement. This mechanism aligns with luxury's emphasis on controlled accessibility and institutionally bounded value co-creation (Vargo & Lusch, 2004; Bastien & Kapferer, 2012). From the perspective of MSD theory, such directionality reflects the governance rules and feedback loops that direct bargain-oriented demand toward conversion-efficient nodes while preserving symbolic distance (Giesler & Fischer, 2017). Previous research portrays outlet shoppers as value-seeking consumers responsive to curated atmospherics; when assortments and pricing are tightly fenced, these interactions can promote trial without eroding brand equity (Sierra & Hyman, 2011; Cao et al., 2024). Therefore, the outlet's ability to transmit value depends critically on institutional control: selective distribution and disciplined governance define whether its impulses act as bridges or leakages within the system (Cabigiosu, 2020). In contrast to the outlet's transmissive behavior, e-commerce plays a contained and absorptive role. Its shocks are modest and largely confined to the channel itself, consistent with the behavior of a governed, low-friction interface designed to reduce search effort and reinforce trust while maintaining curated scarcity (Okonkwo, 2009; Klaus, 2020). Prior studies indicate that well-managed digital touchpoints in luxury strengthen brand meaning rather than trigger broad spillovers (Herhausen et al., 2015; Wang & Goldfarb, 2017), a pattern mirrored in our short-run dynamics. Finally, boutiques act primarily as identity nodes, capturing rather than transmitting value. Shocks in boutiques peak sharply and dissipate within a week, showing minimal reinforcement outside the origin channel. This local appropriation aligns with their symbolic and experiential nature: boutiques stage brand aura through ritualized service, spatial curation, and clienteling (Dion & Arnould, 2011; Joy et al., 2014). Within the observed horizon, the value generated in boutiques is realized in situ, consistent with luxury's logic of authenticity, exclusivity, and relationship-based meaning (Bastien & Kapferer, 2012; Arrigo, 2018; Kauppinen-Räisänen et al., 2020). Having established how channels interact dynamically (RQ1a-b), we now examine whether these differentiated roles translate into measurable performance outcomes at the system level (RQ2a-b).

Answering RQ2a, which investigates whether the interaction among channels translates into short-term aggregate performance gains, the evidence points to heterogeneous and transient effects. Shocks originating in the outlet channel produce the largest overall increases in total units sold, accompanied by modest positive spillovers to other channels. E-commerce shocks also generate incremental but contained effects, reinforcing demand primarily within their own domain, while boutique shocks raise immediate sales locally but are followed by slight compensatory declines elsewhere, signaling short-run redistribution rather than true expansion. Consistent with the short-horizon dynamics observed in RQ1, these aggregate responses peak quickly and fade within a few weeks, suggesting that volume expansion in luxury retail emerges mainly through rapid reallocations across controlled interfaces rather than through enduring, diffusive processes (Vargo & Lusch, 2004; Giesler & Fischer, 2017).

While RQ2a focuses on the short-term aggregate effects of individual channel shocks, RQ2b evaluates the net balance of these interactions, that is, whether cross-channel dynamics ultimately generate synergistic or cannibalistic outcomes for total sales. The results reveal small and asymmetric net effects, suggesting that, in luxury retail, such interactions rarely produce sustained expansion or contraction of overall volume. Synergy emerges only under tightly controlled access conditions, particularly when outlet traffic stimulates incremental demand later captured online, while in other cases redistribution prevails. E-commerce stabilizes demand by absorbing short-term fluctuations, and boutiques primarily appropriate value locally without diffusing it across the system.

These findings echo evidence from general retailing, where dissimilar interfaces tend to complement one another and similar ones more often substitute (Shankar & Kushwaha, 2021; Neslin, 2022) and where adding online or physical formats typically raises total sales despite partial cannibalization (Gallino & Moreno, 2014; Timoumi et al., 2022). However, the smaller magnitude and shorter persistence of effects observed here likely reflect the governance intensity of luxury portfolios, in which selective distribution, price boundaries, and codified service protocols keep channel roles distinct and limit systemic propagation (Verhoef et al., 2015; Cabigiosu, 2020; Bai et al., 2024).

6. CONTRIBUTION

Much of the omnichannel literature acknowledges that channels interact but often leaves unclear the mechanisms through which such effects arise and the institutional conditions that shape them (Shankar & Kushwaha, 2021; Neslin, 2022; Verhoef et al., 2015). This ambiguity is especially evident in luxury, where selective distribution, strict governance, and differentiated channel roles complicate the translation of general retail insights (Bastien & Kapferer, 2012; Cabigiosu, 2020). Our study provides several theoretical contributions by extending SDL/MSD.

First, we articulate a role-conditioned propagation view: channels are institutionally distinct nodes whose ability to transmit value depends on their role and the rules that structure interaction (Vargo & Lusch, 2004; Vargo et al., 2017; Giesler & Fischer, 2017). In this mapping, access nodes (outlets) can transmit demand by lowering perceived risk and enabling price/assortment learning (Sierra & Hyman, 2011; Li et al., 2017); digital nodes (brand e-commerce) primarily absorb demand through governed convenience and curated scarcity, with limited outward transmission (Okonkwo, 2009; Klaus, 2020); identity nodes (boutiques) mostly appropriate value in place via ritualized service and symbolic staging (Dion & Arnould, 2011; Joy et al., 2014). This role-based account refines broad claims that "dissimilar interfaces complement" by offering micro-foundations for where complementarities are more likely in luxury (Shankar & Kushwaha, 2021; Neslin, 2022).

Second, we frame governance as a theory-consistent boundary condition for these mechanisms. Selective distribution, price/assortment fences, and service protocols keep roles distinct and limit the extent of propagation (Verhoef et al., 2015; Cabigiosu, 2020; Bai et al., 2024). Under such conditions, and consistent with a tightly managed portfolio, outlet activity need not be inherently dilutive: when protected by strong fences and staged environments, outlets can function as controlled transmitters that seed demand later captured online. This interpretation nuances the "anti-laws" view by showing that, in well-governed contexts, access formats may support rather than erode the system (Bastien & Kapferer, 2012; Kapferer, 2015).

Finally, we link node-level dynamics to ecosystem outcomes by distinguishing between net expansion and redistribution of total units over short horizons. This ecosystem-level distinction between net expansion and redistribution addresses a gap in the literature, where most studies focus on dyadic effects or adoption events (Timoumi et al., 2022). It also helps qualify omnichannel claims for luxury, showing that complementarities are conditional, bounded, and time-sensitive, shaped by channel role and institutional guardrails (Shankar & Kushwaha, 2021; Verhoef et al., 2015).

Building on these theoretical contributions, we now turn to the managerial implications, translating the role-conditioned dynamics we identified into priorities for luxury channel governance and portfolio design. First, expand outlets selectively rather than uniformly. Our short-run, volume-based evidence indicates that outlet activations can lift system sales, but this effect is contingent on governance quality. Managers should treat format choices, assortment policy, and pricing discipline as structural decisions: only where institutional "fences" are credible should an outlet be used as a growth lever. Practically, this means privileging locations and partner arrangements that preserve brand distance (e.g. factory outlet or outlet villages), enforcing assortment rules that clearly separate outlet stock from full-price lines, and maintaining price ladders that avoid continuous deep discounting. In such conditions, the outlet can generate short-run uplifts and, at the margin, seed demand that is later absorbed online; where these conditions are absent, additional outlet capacity is more likely to reallocate sales than to expand them.

Second, use e-commerce as a stabilizing instrument to stimulate demand without disturbing the channel mix. In our setting, online sales respond to promotions but transmit little to other channels. This recommends treating the brand site as a reliable, self-contained lever for incremental volume rather than as a vehicle to trigger cross-channel ripples.

Third, manage boutiques primarily as identity anchors, not as engines of system-wide volume growth. Boutique shocks peak on impact and tend to be absorbed locally, consistent with their role in staging service, curation, and symbolic value. The managerial implication is to evaluate boutique initiatives by their reputational and relational outcomes rather than by short-run unit lifts. Activations should privilege experiences that enhance authenticity and attachment, with digital follow-through (e.g., curated online access) designed to capture value without displacing sales across physical stores.

7. LIMITATIONS

As with any empirical, single-study design, our findings should be interpreted considering several scope and identification caveats. First, the evidence derives from one luxury brand in a single country observed over 72 consecutive weeks, a relatively short window for time-series analysis. While this horizon is adequate to uncover short-run dynamics and immediate channel interdependencies, it may not fully capture slower seasonal cycles, structural adjustments or long-term equilibria. The limited span could also affect the power of unit-root and stationarity tests and make the estimated coefficients more sensitive to transient shocks or local instability. Future research should therefore extend the temporal coverage and assemble multi-brand, multi-country panels to test whether the observed short-run patterns persist, attenuate, or reverse over longer horizons and under different governance regimes or luxury tiers.

Second, we model only the firm's direct channels (e-commerce, boutiques, outlets), excluding marketplaces, wholesale partners and resale. Extending the architecture to the full interface portfolio would permit mapping displacement and reinforcement across the entire ecosystem rather than within the direct triad alone.

Third, governance is theorized as the boundary condition that delimits propagation, yet we do not observe it directly. Subsequent work should operationalize a channel-level governance index and test its moderating role on the direction, magnitude, and duration of cross-channel effects.

Fourth, promotions are lagged to curb simultaneity, but residual endogeneity and measurement limits remain; our modeling choices temper, but do not eliminate, these risks (Kilian & Lütkepohl, 2017; Lütkepohl, 2005).

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