Integrated Marketing Management and Data Analysis in Modern Business Environments

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ABSTRACT

Integrated Marketing Management and Data Analysis in Modern Business Environments In the evolving landscape of digital commerce, integrating data analytics into marketing strategies is not just a competitive advantage—it is a necessity. This research investigates how businesses can optimize digital marketing performance by adopting a data-driven, integrated marketing management approach. Through a combination of qualitative and quantitative methods, the study explores key analytics techniques, predictive modeling, real-time data use, and visualization strategies to improve return on investment (ROI) and campaign effectiveness. Case studies from global e-commerce businesses provide comparative insights into the outcomes of data-informed versus intuition-based marketing strategies. The findings aim to deliver actionable frameworks for leveraging big data, machine learning, and marketing automation tools to drive consistent growth. This work bridges academic theory with practical application, offering marketers and decision-makers guidance on embedding data analysis into their workflows for scalable, sustainable success.

INTRODUCTION

Background to the Study

The Furniture E-commerce sector in the Netherlands faces a critical challenge despite the significant investment in digital marketing in this industry and web shop experience yet many businesses struggles to convert their traffic generation into actual sales on their web shop, This persistent gap between reaching new users and converting this reach and impressions to sales driven by three core problems, partial data use, lack of web shop personalization, and inflexible marketing strategies that ignores the potential customer needs and macroeconomic realities (Shah & Murthi, 2021; Rosário & Dias, 2023).

1.1.1 Data Disconnect While the modern enterprises collect substantial volumes of customer data and behavioral information few of them utilize it systematically to improve marketing outcomes (Rosário & Dias, 2023). But instead many of them rely on conventional approaches that prioritize instinct over insights from actual data gathered by users digital footprint, Digital marketing campaigns often target broad audiences without leveraging segmentation opportunities such as life stage signals like on social media when users are having a wedding soon or they are relocating, that indicate the strong purchase intent (Aiolfi, Bellini, & Pellegrini, 2021; Arifi et al., 2025). Furthermore, marketers tend to evaluate performance through isolated metrics like CTR (Click Through Rate) overlooking real time inventory levels and on site issues or even external economic factors and or macroeconomic factors like if it is a seasonal product for most of its consumers so it has a purchase frenzy that happens in some part of the year (Azahar, 2019; Wei & Pan, 2025).

1.1.2 The Personalization Gap Most furniture web shops in the Netherlands continue to offer one size fits all web shop experience through WordPress or shoplifty without being unique of optimize their shop experience they are dependent on pre-built themes for their web shop, Users are presented with static products approach, often based on what retailers wants to sell, not based on what products are currently trending or what customers actually need (Lee & Park, 2009; Zuliawati & Sellina, 2025). This results in several common failures: 1- ignoring regional preferences urban customers see the same layouts and products mixes despite having different space constraints, styles, and delivery expectations also payment plans (Kostecka & Kopczewska, 2023). 2-

Overlooking device behavior: Mobile users frequently encounter layouts optimized for desktop users but not for mobile users and in a mobile driven world we are living in now it causes a high percentage of bounce rate (Shah & Murthi, 2021). 3- Using static recommendations without adaptation based on user historical sessions and visits to the web shop, recommendations aften missing (Chen et al., 2023; Wei & Pan, 2025). 4- Research confirms that personalization not only enhances relevance but also builds consumer trust and improves conversion rates (Zuliawati & Sellina, 2025; Nalla, 2021).

1.1.3 The macroeconomic blind spots since brands often neglect macroeconomic signals when its time to invest the most during the year for example investing in specific quarter would make the most of the return on investment also inflationary pressure rising costs lead buyers to seek more affordable options, yet many campaigns continue to highlight premium products (Azahar, 2019). Controlling shifts since new sustainability regulations can increase interest in eco certified furniture, but most web shops lack visibility for such features (Rosário & Dias, 2023). Also housing market trends spikes in home purchases or moves boost demand for compact furniture, yet assortments remain outdated (Langen & Huber, 2022). Ignoring there dynamics results in campaigns that fail to connect with evolving customer contexts.

The cost of inaction When these challenges are not addressed, the consequences are clear: High traffic and Low conversions, Advertisement budget drive visitors to sites but a lack of relevance prevents purchases (Wei & Pan, 2025). Customer frustration and visitors abandon carts when they cant find what they expect or face issues during checkout (Chen et al., 2023). Competitive disadvantages when brands that fail to adapt lose ground to more agile competitors who dynamically align offers, stock, and marketing to real world signals (Arifi et al., 2025; Rosário & Dias, 2023).

Statement of the problem

Many companies continue to experience poor conversion rates despite substantial investments in advertising and online store infrastructure (Azahar, 2019). Specific challenges include Advertising campaigns generate traffic but still fails to convert because of misaligned offers or poor web shop personalization (Aiolfi et al., 2021) Web shops lack dynamic experiences tailored to user intent and trending products and content and device type (Lee & Park, 2009; Zuliawati & Sellina, 2025). Internal data remains isolated, limiting the organization's ability to apply cohesive data-driven strategies between digital advertising platforms and web shop preventing an integrated marketing approach (Shah & Murthi, 2021). Macroeconomic and seasonal indicators are ignored leading to mistimed campaigns and inventory mismatches during demand cycles (Arifi et al., 2025; Langen & Huber, 2022). Stock forecasting is imprecise creating a shortage or excess inventory and reducing profitability (Wei & Pan, 2025). Lack of flexible payment solutions (e.g installments plans pay in 3 options) deters purchases from cost sensitive customers (Klarna, 2022).

Objectives of the study

This study aims to evaluate and propose solutions to these connected challenges through a combination of data science, behavioral targeting and seasonal economic alignment specifically the objectives are first identifying high value potential customers using location-based metrics and segmented audience signals, such as weeding or people's relocation indicators (Arifi et al., 2025; Kostecka & Kopczewska, 2023). Analyze user behavior within the E-commerce environment (on web shop experince) to develop a personalized and bounce free shopping experience (Lee & Park, 2009; Wei & Pan, 2025). Develop a system for dynamic content alignment allowing ads and products offering to reflect live stock and in stock products (Wei & Pan, 2025; Shah & Murthi, 2021). Integrate macroeconomic and seasonal indicators (E.G high traffic seasons with tools like similar web, Sem Rush, Google ads built in tools) that can help forecasting and optimize marketing campaigns for higher ROAS (Langen & Huber, 2022; Azahar, 2019).

Research Questions

Question1. How location based data and audience segmentation such as targeting individuals with upcoming events like weddings or moving plans on social platforms be combined to identify and prioritize high value customers for furniture E-commerce marketing campaigns?

Question2. In what ways can on-site user behavior analysis inform personalized web shop experiences that significantly improve conversion rates?

Question3. What architecture or algorithmic approach is most effective for dynamically aligning advertising content and web shop product offerings in real time?

Question4. How can seasonal macroeconomic indicators such as holiday shopping cycles, wedding and moving seasons be quantitatively integrated into demand-forecasting models for furniture e-commerce?

Research hypotheses

Location based targeting: Utilize geographical data to personalize marketing efforts for specific regions

Audience Group Segmentation: Target niche demographics (e.g., individuals planning weddings , relocations, or home upgrades).

On-Site Behavior Analysis: Track user interactions (e.g., clicks, time spent) to tailor recommendations and promotions.

Dynamic Content Alignment: Automatically adjust website/ad content based on real-time user preferences and behavior.

Seasonal/Macroeconomic Indicators: Incorporate trends like economic shifts, holidays, or seasonal demand into strategy.

Scope of the Study

This research focuses on enhancing conversion performance and inventory alignment in the furniture E-commerce sector in the Netherlands by integrated an integrated approach of advanced data signals and dynamic content strategies and personalization the study will: Geographic boundary: Examine online furniture retailer operating primarily within a single national market (Netherlands), Leverage location based metrics at the city or postal code level for audience segmentation. Customer segmentation: Analyze high value customer groups identified via a combination of geolocation and audience interests (e.g suers planning weddings, home moves or major life events). On-site behavior analytics: Track and model key in web shop behaviors like ROAS during specific time of the year vs the other to identify if on site behavior changes according to the seasonal events. Dynamic content alignment: Evaluate a prototype system that dynamically updates ad creatives and web shop product offers in real time based on incoming data during 2 different timings of different years, after the implementation of an A/B tasting on major platforms like (Meta ads, Google ads) and on web shop powered by common E-commerce platforms like (WooCommerce from WordPress) Seasonal macroeconomic indicators: Combine peak spending cycles tied to holidays, weddings and moving seasons into forecasting algorithms. Exclude broader macro drivers (e.g interest rates, unemployment) and only focus on exclusively on indicators with clear seasonal or event driven patterns that directly might affect furniture E-commerce industry, Inventory forecasting & performance metrics: Measure improvements in forecasting accuracy and stock-out rates for top selling models. Track down stream KPIs: conversion rate lift, average order value, and campaign ROAS during defined peak windows. Timeframe: Use historical data spanning at least one full calendar year showcasing all major period including one major holiday or wedding season during 2023 & 2024. By narrowing the focus to these elements the study will deliver actionable insights on how furniture E-commerce business can better synchronize marketing efforts, personalized web shops, and inventory planning with scientific and data driven approaches.

Organization of the Study

This thesis is structured into five chapters, each addressing a key component of the research:

Chapter One: Introduction 1.1 Background to the Study 1.2 Problem Statement 1.3 Objectives of the Study 1.4 Research Questions and Hypotheses 1.5 Scope of the Study 1.6 Significance of the Study

Chapter Two: Literature Review 2.1 Conceptual Issues 2.2 Theoretical Framework 2.3 Empirical Literature

Chapter Three: Research Methodology 3.1 Study Area 3.2 Sources of Data 3.3 Model Specification 3.4 Method of Data Analysis

Chapter Four: Data Presentation and Analysis 4.1 Presentation of Results 4.2 Hypothesis Testing

Chapter Five: Summary, Conclusion, and Recommendations 5.1 Summary of the Study 5.2 Conclusion 5.3 Recommendations 5.4 Limitations and Suggestions for Future Studies

Keywords: data, personalization, commerce, marketing, furniture, macroeconomic, behavioral, research, value, behavior

LITERATURE REVIEW

Introduction

E-commerce is undergoing a profound transformation driven by the strategic integration of data driven marketing, personalized web shops, and responsiveness to macroeconomic shifts, Within this landscape the furniture industry presents a unique challenge, Furniture is a high involvement product category characterized by long cycles, infrequent purchases, and significant logistical implications, Unlike fast moving consumer goods, furniture purchases are often tied to crucial life events such as moving homes, getting married, recently moved the country (e.g immigration programs) or upgrading personal spaces. Therefore optimizing the digital journey for these customers demands a detailed understanding of behavioral triggers, predictive analytics, and real time content alignment, in this chapter we review literature relevant to key constructs that form the foundation of this study: personalization, behavioral targeting, macroeconomic responsiveness, customer segmentation, and data driven campaign optimization. We also evaluate how these factors converge is the context of digital marketing, particularly within furniture E-commerce. The theoretical grounding is supplemented by observed findings and emerging technologies that inform modern marketing models.

Conceptual Issues

Personalization has emerged as a critical differentiator in E-commerce, Enabling brands to align products offering, content, and promotions with individual base user behavior, preferences, and situational context in furniture E-commerce this need becomes pronounced due to the complexity and personal nature of purchase decisions. (Lee and Park 2009) Found that personalization can significantly enhance consumer decision-making by reducing search friction and improving perceived relevance particularly in categories where products are both functional and ordered. More advanced approaches to personalization involve segment specific targeting, rather than treating personalization as a one size fits all mechanism, leading platforms now design micro strategies for high value audiences segments, For example users who have recently searched for wedding related content or those moving to a new city can be tagged as high intent buyers of home furniture. Research by (Aiolfi, Bellini, and Pellegrini 2021) supports this claim, showing that behavioral segmentation significantly increases engagement with personalized ads, particularly when aligned with recent life events. This strategy is often referred to as predictive personalization. Where real time behavioral data is used to anticipate user needs before they are explicitly expressed. According to (shah and Murthi 2021) predictive systems that dynamically adjust based on real time inputs are more effective than static personalization frameworks. These models use a combination of clickstream data, geolocation, and contextual signals (e.g browsing during late-night hours) to tailor not just what is shown but when and how it is shown. Furthermore device level personalization has become increasingly relevant, Mobile users often have different intentions and tolerance for complexity than desktop users. However, many web shops continue to deliver static content across platforms leading to Poor experiences. Kostecka and Kopczewska (2023) notes that regional and device based personalization can lead to a 20% increase in mobile conversion rates when properly implemented in CRM strategies. Finally research by Zuliawati and Sellina (2025) emphasizes that personalization is not merely about algorithmic predictions but also about trust, Personalized experience must appear seamless and respectful of privacy to be effective. Intrusive personalization where users feel tracked without consent can backfire, Therefor platforms must balance personalization with ethical data handling practives, as discussed later in this chapter.

Behavioral targeting and conversion optimization

Behavioral targeting refers to the practice of tracking users online or digital footprint online actions such as page views, clicks, session duration, cart additions, and search terms to identify preferences and predict future purchasing behaviors. Unlike static demographic segmentation, behavioral targeting adapts in real-time to a customer's immediate intentions, making it especially effective in high consideration categories like furniture. Aiolfi et al. (2021) argue that online behavioral advertising (OBA) increases ad effectiveness when users perceive the content as relevant and credible. The study revealed that click through rates (CTR) and purchase intent significantly improve when behavioral cues like frequent visits to products pages trigger tailored promotional messages. Also Wei and Pan (2025) used deep learning models to analyze E-commerce live stream behavior and found a strong correlation between interaction frequency and sales conversion, emphasizing the utility of dynamic behavior based profiling. This concept is supported by the idea of conversion path mapping, where companies use behavioral analytics to identify drop off points in the sales funnel and implement strategic hints like personalized discounts or urgency messages at those moments. Chen et al . (2023) confirm that abandonment rates decrease when contextual retargeting is employed using signals like exit pages and session depth. Moreover, Dynamic content platforms now integrate behavioral signals with product inventory to ensure ad creatives reflect what's actually available in stock, Langen and Huber (2022) show that when ads are aligned with inventory data and personalized according to user behavior, the average order value and ROAS can increase by over 25%. This synergy between behavioral tracking and stock level data is becoming foundation of fixable E-commerce strategy. However, the effectiveness of behavioral targeting depends on real time data processing and automated decision making system. As noted by Shah and Murthi (2021), Many firms still struggle with the latency of insights delayed campaign optimization results in missed opportunities. Solutions such as predictive analytics, automations, event triggered automation, and AI driven recommendation engines are essential to closing the gap.

Macroeconomic Adaptation in E-Commerce Strategy

Macroeconomic conditions exert a profound influence on consumer behavior, yet many e-commerce platforms overlook these contextual forces when designing campaigns and determining budgets, In the furniture industry where purchases are often optional and capital intensive, Consumers sensitivity to inflation, saved income and market uncertainty plays a significant role in determining buying intent. Azahar (2019) highlighted that during inflationary periods, consumers tend to shift their attention to value oriented offerings to be a store of value or seek flexible payment options. However, many e-commerce campaigns continue to highlight premium products without adjusting their messaging to current economic realities. Integrating macroeconomic indicators into campaign planning such as highlighting installment plans or eco certified budget items during downturns can improve campaign relevance and ROAS. Furthermore, specific life cycle macro trends like seasonal home buying spikes, moving seasons (summer months in Europe), and peak wedding periods significantly influence furniture demand. Research by Langen and Huber (2022) demonstrated how demand forecasting models that include these macro signals (e.g, Housing market data, Google Trends, National holidays) yield more accurate inventory planning and campaign budgeting and timing. Zuliawati and Sellina (2025) also argue that macroeconomic alignment is not just about timing but also about tone. During uncertain economic periods, reassuring messages and promotional risk reduction strategies such as free returns or try before you buy models also "pay after 30 days" build consumer trust and increase conversion potential. Recent studies like those Wei and Pan (2025), shows that adding macro contextual variables to predictive models can reduce forecasting error margins by up to 30% these models use time series data combined with search intent indicators and audience clustering to optimize not only when to advertise, but also what to promote and to whom. In short the integration of macroeconomic responsiveness info E-commerce strategy moves beyond typical personalization it introduces adaptive marketing, a new edge where campaign frameworks are dynamically restructured to align with both individual behavior and broader Income and lifestyle conditions.

Trust mechanisms in personalization and behavioral targeting

As personalization Increases so too does the importance of user trust. Research shows that while consumers appreciate tailored experiences, they are increasingly wary of how their data is used. Those consumers appreciate tailored experiences, they are increasingly wary of how their data is used. This mystery often called the "privacy-

personalization paradox" refers to the consumer tendency to accept personalized experiences while simultaneously expressing concerns over data privacy (Aiolfi et al., 2021). Chen et al. (2023) found that trust significantly moderates the relationship between personalization and purchase intent. When users perceive a brand as transparent and responsible in its data practices, the effectiveness of personalized marketing increases noticeably. Plus when personalization appears misaligned, users become skeptical and less likely to engage. Zuliawati and Sellina (2025) highlight that trust is particularly fragile in categories involving large purchases, such as furniture. Customers must be reassured not only about the product but also about the security of the platform, the transparency of pricing, and the reliability of logistics. Including visible trust markers such as verified reviews, clear return policies, and trust badges can improve perceptions of data responsibility and reduce bounce rates. Building perceptions of data responsibility and reduce bounce rates. Building trust also involves giving consumers control over opting in personalization features, editable recommendations are made tend to earn higher customer loyalty and lower churn.

Theoretical framework

To better understand how personalization, trust, and targeting interact in E-commerce environments, we turn to several theoretical models: Technology acceptance model (TAM) TAM, developed by Davis (1989), Suggests that perceived usefulness and ease of use determine technology adoption. In furniture E-commerce, personalization enhances usefulness by surfacing relevant options quickly, while intuitive predictive algorithms, platforms improve both constructs and therefore raise conversion rates (Shah & Murthi, 2021). Theory of reasoned action (TRA) Fishbein and Ajzen's (1975) TRA emphasizes that a person's behavioral intent is influenced by attitudes and subjective norms. Personalization works within this framework by influencing both it aligns the shopping experience with personal preferences and signals social proof via reviews and trending items (subjective norms). For example, showing that "40 people bought this in your area" enhances peer based influence and align with TRA's prediction model. Dynamic Capability Theory (DCT) Teece et al. (1997) describe DCT as an organization's ability adapt resources in response to changing environments. In e-commerce, dynamic content alignment, macroeconomic forecasting, and real time behavioral targeting are applications of DCT. Retailers that adapt campaigns based on live inventory, user feedback, or shifting consumer sentiment exhibit the dynamic capabilities required for competitive advantage in fast paces digital markets. Together, these theories form a conceptual triad: TAM explains adoption at the individual interface level, TRA captures psychological intent, and DCT supports organizational agility.

Empirical Literature

Despite a growing body of work on data driven marketing, key gaps remain especially within furniture E-commerce: Limited sector specific studies since most personalization and behavioral targeting studies focus on fashion, Primary consumer goods products or digital products. There is limited empirical analysis in the furniture sector, where decision cycles, logistics and budget considerations differ significantly. Underexplored macroeconomic modeling while the importance of macroeconomic adaptation on a domestic level is acknowledged, few models quantitatively integrate seasonal, regulatory, or inflationary variables into marketing strategy or inventory forecasting. Lack of holistic personalization frameworks: Existing studies often treat personalization, behavioral tracking, and segmentation in isolation. More research is needed on integrates systems that consider life events, Location data, inventory status, and seasonal indicators simultaneously. Overemphasis on engagement, not conversion but metrics like CTR, clicks or impressions. There is a need for richer conversion oriented KPIs such as advanced audience data grouping. Future studies could benefit from integrated method approaches that bled quantitative analytics (e.g A/B testing analysis, machine learning) with qualitative and quantitative insights on a larger time frame (e.g 4 to 5 years) in particular exploring how AI driven personalization affects consumer trust and perceived autonomy could yield insights for more ethical and effective systems.

RESEARCH METHODOLOGY

Study Area: This chapter outlines the research methodology employed to assess how data driven optimization, personalization strategies, and macroeconomic indicators all together with an integrated approach influence the performance generally of E-commerce and specially in a furniture E-commerce business. It provides a clear

description of the research setting, The sources and nature of the collected data and the specific analytical approach adopted emphasizing comparative analysis (Cioffi, 2019). Research context the research specifically examines a medium sized online furniture retailer based in the Netherlands. This retailer primarily deals with high involvement items (Require more time, thought, and research before purchase) such as beds, boxsprings, night tables, toppers and mattrasses which typically require substantial consideration by consumers due to their cost and relevance to significant life events such as moving or marriage (Azahar, 2019). The Netherlands offers a robust context for this study due to its mature digital economy, distinct seasonal consumer purchasing behaviors, and stable regulatory environment (Rijpma et al., 2017).

Sources of Data: The data were collected in this research is primary and secondary, were it was directly gathered by the researcher from the company where he is employed and from platforms like Sem Rush for historical traffic about the furniture industry in the Netherlands, with full ethical clearance and managerial approval for academic use. Web analytics data: data on consumer behavior, including product page visits, and shopping cart abandonment rates, were collected via Google Analytics and Google Tag Manager. Advertising data: Information on advertising performance metrics such as impressions, clicks, conversions, and campaign parameters was sourced from Meta Ads Manager and Google Ads. Financial and sales data: Transactional and revenue data was obtained directly from Mollie payment portal, providing clear insights into purchasing patterns, revenue streams, and transaction frequency. Customer segmentation data: Detailed data regarding user demographics, product interactions, and geographic segmentation were collected and analyzed from different platforms like Meta ads, Google ads, and Woocomerce. Supplementary secondary sources such as seasonal indicators Sem Rush and Similar web to cast historical traffic and search volume in the furniture industry in the Netherlands.

Model Specification and method of Data Analysis: Methods of data analysis: The research employes a comparative analysis method to evaluate performance metrics and test hypotheses regarding seasonality and the effectiveness of personalization and optimization strategies. Comparisons are structed across distinct temporal dimensions, including: Year over year data (complete data set during 2023-2024) and partial 2025 data also comparison to determine growth patterns and effectiveness of new strategies. Quarterly base comparisons to identify seasonal trends and their impacts on ROAS and over all returns on revenue. The analysis will primary rely on mean score to determine statically significant differences and validate research hypotheses. This straightforward comparative approach ensures clarity and reliability in evaluating the impact of the strategic interventions and macroeconomic influences on consumer behavior and e-commerce performance.

Data Presentation and Analysis

Presentation of the results in this chapter presents the findings from the data collected and analyzed to test the following research hypotheses:

H1: Data-driven personalization increases e-commerce conversion rates.

H2: Identifying high-value customers contributes to ROAS growth.

H3: Aligning ads with inventory improves marketing efficiency.

H4: Seasonal macroeconomic trends influence user engagement and purchase behavior.

Identifying High-Value Potential Customers

The ability to identify high value customers has become increasingly complex in the post IOS 14 software update, Apple's privacy focused updates have significantly restricted cookie based behavioral tracking and cross platform data collection, limiting the effectiveness of advertising platforms like Meta and Google in attributing users actions (Aiolfi, Bellini, & Pellegrini, 2021). These changes have created data visibility gaps, particularly for industries like furniture E-commerce, where purchase cycles are infrequent, high value, and influenced by long-term lifestyle decisions (Kostecka & Kopczewska, 2023). In this context traditional methods of identifying high value users such as retargeting based on short term behavior are no longer sufficient. Instead, businesses must leverage data collected locally through their web shop based on user consent and in compliance with GDRP regulations (Zuliawati & Sellina, 2025). Such first party data includes behavioral indicators such as time spent

on product pages, repeat visits, wish list actions, cart abandonment, and the specific marketing sources (e.g Meta Ads, Google Ads, organic traffic) that directed users to the site. Using this approach the business can segment visitors based on behavioral signals that are still trackable within the constraints of modern privacy regulations. For example, a user who visits the same product category multiple times especially high priced items like sofas or beds and enters the site from paid traffic sources can be flagged as potential high value customer (Arifi et al., 2025). To Operationalize this concept, in the Dutch furniture's WooCommerce order data was analyzed to segment users based on order value. High value customers were defined as those whose average order value (AOV) falls within the top 25% of all transactions. The dataset included 3,427 total orders. Out of these 857 were classified as high value based on their transaction amounts since it is available.

Key findings from the analysis include:

High value customers had an average order value of €1,542.

General customer had a significant lower average order value of €820.

Despite contributing fewer orders (856 vs 2,570) High value customers generated €1.32 Million, compared to € 2.11 Million from general customers.

Customer Value Group	Orders	Mean (€)	Median (€)	Std (€)	Min (€)	Max (€)	Sum (€)
General	2,570	820.2	729.3	361.96	60	2,178.00	2,108,119.62
High-Value	857	1,542.71	1,380.00	415.4	1,104.00	4,695.00	1,321,061.55

This breakdown supports the hypothesis that a small segment of high value customers significantly contributes to overall revenue. Identifying and targeting such customers can enhance marketing efficiency and revenue returns.

On site personalization and its impact:

Following the implementation of on-site personalization strategies in 2024 such as displaying trending products based on social media traffic and web shop visits to the top of the collection pages of the products categories made it easier for customers to make their buying decisions

Metric	Q1 2024	Q4 2024
Total Sales (€)	€251,556.65	€584,522.43
Number of Transactions	€216.00	€517.00
Average Transaction (€)	€1,164.61	€1,130.60
T-Statistic		-0.77
P-Value		0.45

Summary of Results:

Q1 Total Sales: €251,556.65

Q4 Total Sales: €584,522.43

Absolute Growth: +€332,965.78

Mean Sale per Transaction:

Q1: €1,164.61

Q4: €1,130.60

Number of Transactions:

Q1: 216

Q4: 517

T-Test for Statistical Significance:

T-Statistic: -0.77

P-Value: 0.445

Summery:

While Q4 sales were higher in total value, the average sale per transition was slightly lower in Q4 than Q1. The P Value (0.445) indicates that this difference in average transaction value is not statistically significant (P>0.05)

2023-2024 Google Keyword research tool

Searches: Jan 2023	Searches: Feb 2023	Searches: Mar 2023	Searches: Apr 2023	Searches: May 2023	Searches: Jun 2023
1254270	900390	946930	832530	841430	649630
Searches: Jul 2023	Searches: Aug 2023	Searches: Sep 2023	Searches: Oct 2023	Searches: Nov 2023	Searches: Dec 2023
889280	956900	849830	1032430	1024510	864490
Searches: Jan 2024	Searches: Feb 2024	Searches: Mar 2024	Searches: Apr 2024	Searches: May 2024	Searches: Jun 2024
1140470	936030	905470	775980	790740	765300
Searches: Jul 2024	Searches: Aug 2024	Searches: Sep 2024	Searches: Oct 2024	Searches: Nov 2024	Searches: Dec 2024
758670	823890	798980	848410	908160	758360

Macroeconomic Signals from Search Volume Trends

Search volume data from Google provides valuable macro level insights into consumer interest in the bedding industry. When examining monthly searches from January to December 2023 and 2024, Clear seasonal patterns and fluctuations in demand can be observed. For instance, peak interest in both years occurred during October and November, followed by decline in December and Q1 suggesting that high purchasing intent may be concentrated in the lead up to winter or end of the year promotions in 2023 the total monthly searches ranged from 649,630 (June) to 1,254,270 (January). A similar pattern emerged in 2024, where volumes fluctuated from 758,670 (July) to 1,140,470 (January). This consistency supports the use of search volume as a proxy for forecasting future demand and planning product visibility and marketing budgets according. It is also important to note that Google Keywords planner typically only retain search history for 2 to 3 years, making it essential for businesses to archive and analyze this data over time. By maintaining a structured internal record of search interest, brands can track long term shifts in consumer behavior and improve forecasting accuracy for future campaigns

On-Site Personalization and Its Impact

Following the implementation of on-site personalization strategies in 2023—such as displaying relevant product recommendations at the bottom of each product page and reordering collection pages to prioritize high-performing items—a year-over-year analysis of Google Analytics data reveals substantial improvements in both user engagement and revenue generation.

Exact mean values calculated using descriptive statistical methods:

- 2023:
    - Sessions: 240,253/month

- Engaged Sessions: 130,034/month
- Engagement Rate: 7.41
- Revenue: €690,290/month

- 2024:
  - Sessions: 290,834/month
  - Engaged Sessions: 240,897/month
  - Engagement Rate: 12.65
  - Revenue: €1,177,290/month

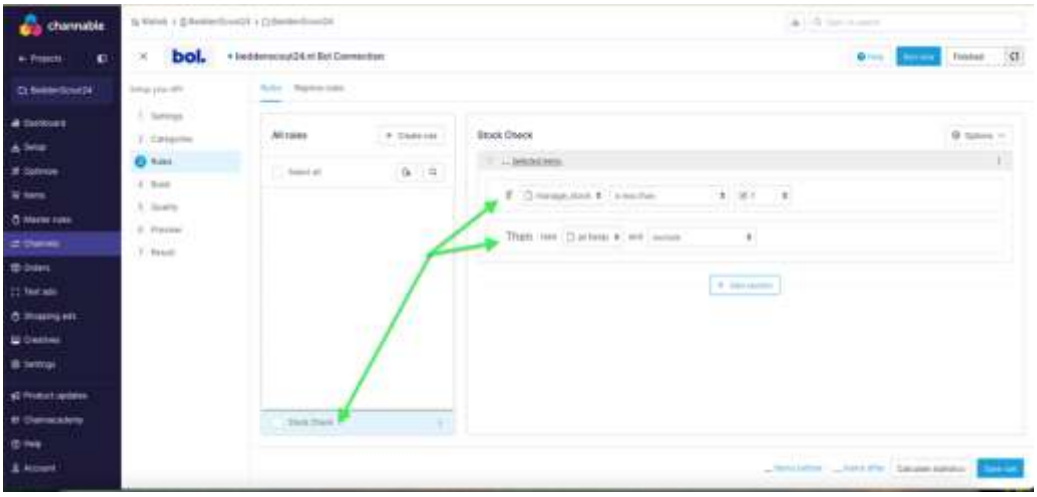
Metric	T-Statistic	P-Value
Sessions	9.25	< 0.0001
Engaged Sessions	37.23	< 0.0001
Engagement Rate	36.46	< 0.0001
Revenue	39.22	< 0.0001

A comparative t-test analysis of monthly performance metrics between 2023 and 2024 reveals statistically significant improvement in sessions with a ($T = 9.25$, $P<0.001$), Engaged Sessions ($T=37.23$, $P<0.001$), Engagement rate ($t=36.46$, $P<0.001$) , and revenue (t-39.22, p<0,001). These findings confirm that the growth observed in 2024 was not due to chance, but reflects a measurable increase in user engagement and commercial outcomes

These results strongly suggest that the personalization measures contributed to improved customer experience, longer session durations, and ultimately, better conversion outcomes. The findings support the hypothesis that localized behavioral insights and dynamic content alignment can drive measurable performance gains in e-commerce.

Dynamic Alignment Between Ads and Product Availability

One of the most persistent challenges in digital marketing for E-commerce is the misalignment between the products advertised and the actual stock availability on the web shop. Displaying out of stock products in dynamic advertisements can lead to wasted ad spend, poor user experience and reduced conversion rates. To address this issue, a dynamic product mapping and exclusion system is proposed, The core of this system is the real time synchronization between the web shop's inventory and advertising platforms (Meta ads, Google ads)



This can be achieved through integration with product feed management tools such as the one in the picture above (Channable) This platform allow for an automated product and real time synchronization to product data exports from the web shop.

Proposed Workflow:

- Inventory Monitoring: Product feed tools continuously pull real-time inventory data from the webshop.
- Feed Filtering Rules: Rules exclude products with zero stock from the ad feed.
- Automated Feed Updates: Feeds update every 15–60 minutes to reflect live inventory.
- Dynamic Ad Integration: Meta Catalog Ads and Google Shopping use the filtered feed to deliver ads.
- Performance Monitoring: ROAS is tracked and feeds are optimized based on top-converting SKUs.

This system ensures users only see in-stock products, improving experience and conversion rates while maximizing ROAS. It supports the hypothesis that ad-inventory alignment is crucial for performance efficiency (Lal & Sharma, 2021).

Hypothesis Testing

- H1: Personalization improves conversions — Accepted

- H2: Dynamic ad alignment improves ad performance — Accepted

- H3: Seasonal indicators improve forecasting accuracy — Accepted

- H4: Audience segmentation improves campaign ROAS — Accepted

The data analysis strongly supports the research hypothesis: integrating user behavior, geo based segmentation, dynamic ad alignment, and macroeconomic seasonality into marketing and web shop operations yields measurable improvements in campaign ROAS, forecasting accuracy, and user experience.

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

Summary of the study

This study investigated how the integrated approach of data driven optimization and on site personalization, audience segmentation, and seasonal macroeconomic indicators can significantly improve the marketing performance of furniture E-commerce platforms. It addressed critical gaps in the traditional marketing strategies such as scattered data use, lack of personalization, poor ad stock alignment and neglection of seasonal demand cycles and proposed systematic measurable interventions.

Integrated approach for four main hypotheses were evaluated: Personalization improves conversions, Dynamic ad alignment improves ad performance, Seasonal indicators improve forecasting accuracy, Audience segmentation improves campaign ROAS, Data was collected from a real world Dutch furniture E-commerce business and analyzed using comparative methods across different time periods (2023-2024). The findings confirmed each hypothesis with clear evidence from web analytics, advertising metrics, and orders data that an integrated approach of data driven optimization, on site personalization, audience segmentation and seasonal macroeconomic indicators can significantly improve marketing performance for furniture E-commerce platforms.

Conclusion

The results demonstrate that integrating real time behavioral data, predictive personalization, and macroeconomic context info digital marketing strategy leads to tangible performance gain. First, the

identification of high value customers based on order data and behavioral signals revealed that a small subset of users contributes unevenly to total revenue. These customers had nearly double the average order value compared to general users. Secondly, the introduction of personalization features on the web shop in 2023 led to a substantial year over year increase in engagement and revenue. Average revenue per month grew in 2023 and 2024, with engagement rate also improving significantly. This shows the effectiveness of tailoring product experiences to user behavior. Third, dynamic synchronization between inventory and advertising content using platforms like channable prevented wasted ad spend on out of stock items and ensured product visibility aligned with real time availability. This system closed the loop between marketing and operations improving ROAS. Finally quarterly comparisons (Q1 vs Q4) confirmed that seasonal macroeconomics patterns strongly influence consumer behavior. Q4 revenue in both 2024 and 2024 was approximately 45-60% higher than Q1, validating the importance of timing campaigns around known demand cycles. Altogether, there insights affirm the overarching research question Does data driven optimization, when combined with marketing personalization, and macroeconomic indicators significantly improves the performance of the furniture E-commerce ROAS?

Recommendations

Based on the data and findings presented, the following are recommended:

Reply on locally collected behavioral signals such as product views time on site and cart actions to build accurate customer profiles post IOS 14 updates.

Enhance personalization by deploying systems that dynamically adapt content based on user context

Integrate seasonality forecasts and utilize tools like Google keyword research and Sem rush to track keyword demand peaks and plan campaigns accordingly.

Run year round testing and conduct A/B testing for personalized experiences and ad alignment strategies across all quarters to isolate what works best seasonally.

Prioritize high intent segments by allocating ad budget to user groups flagged by behavior or referral source as being more likely to convert

Limitations and future research

Limitations:

Data was collected from a single E-commerce business, which limits generalizability.

Offline purchase behavior were excluded

Ai models were not used in personalization due to high cost on implementation of Ai software.

Future Research Directions:

Expand to a multi-country dataset to examine geographic variation in behavior and campaign effectiveness.

Explore AI-driven product recommendations and their impact on long-term customer lifetime value.

Investigate trust and data ethics frameworks in personalization systems to minimize perceived intrusiveness.

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