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Master Thesis Data Science and Marketing Analytics

Title: Does your reputation online matters? Assessing the Influence of Social Media on Brand Image Across Online Purchase Channels

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Abstract

Social media has transformed how consumers interact with brands and shape their purchasing decisions. This study explores the impact of social media electronic word-of-mouth (eWOM) on brand image, focusing on how different online purchase channels influence this dynamic. Initially designed for personal connections, social media has evolved into a crucial platform for brand-consumer interactions, influencing consumer choices and brand perception. While previous research has explored social media's role in brand awareness, this study investigates how social eWOM impacts brand image across direct (brand websites) and indirect (third-party platforms) channels. Using data from Sony Electronics, this research employs the Overall Brand Image Model (OBIM) and VARMAX modeling to analyze the temporal dynamics of these effects. Findings indicate that valence of social media eWOM significantly influences brand image across customers in the short term. Indirect channel customers show a stronger initial response to social media sentiment, but there is no substantial difference in impact between the purchase channels over time. Additionally, social media-derived brand image perceptions fluctuate between positive and negative impacts, showing no clear advantage for any purchase channel. The study highlights the imperative for brands to proactively manage social media sentiment and deeply understand their online audiences. To sustain a consistent brand image and safeguard their reputation across various platforms, brands must strategically navigate the evolving impacts of social media eWOM.

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1. Introduction

In the area of digital transformation, social media platforms have revolutionized how consumers interact with brands, share information, and make purchasing decisions (Hudson et al., 2016). These platforms were originally created to enable connections between friends; however, their scope has been widened to become important outlets for the production and exchange of information and news from both companies themselves but also from individual users (Tandoc et al., 2018). Unlike traditional media, social media platforms allow information to spread easily and amplify word-of-mouth effects, which can significantly boost consumer demand by increasing product awareness and influencing purchase decisions (Li & Wu, 2018). From initial product discovery to post-purchase reviews, social media acts as a dynamic hub where brands can directly engage with their audience while actively shaping their brand image.

Existing research provides valuable insights into various aspects of this relationship. For instance, Hudson et al. (2016) found that social media interactions enhance consumer–brand relationships, especially when brands are anthropomorphized. Colicev et al. (2018) highlighted the differing impacts of owned and earned social media on brand awareness, purchase intent, and customer satisfaction. Bruhn et al. (2012) demonstrated that while traditional media boosts brand awareness, social media significantly shapes brand image, with user-generated content having a notable influence on hedonic brand image. Babić Rosario et al. (2016) showed that electronic word-of-mouth (eWOM) positively affects sales, with its effectiveness varying by platform and product type.

Building on those findings, this study examines the effects of social media eWOM on brand image perceptions reflected in customer reviews, focusing on how these effects vary across direct and indirect online purchase channels. From Frasquet et al. (2015) it was found that both brand trust and brand attachment significantly influence loyalty towards online channels. This observation, combined with factors such as marketing channel preferences, inertia, and state dependence (Neslin et al., 2006; Valentini et al., 2011), builds the hypothesis that consumers purchasing directly from the brand's website exhibit stronger brand attachment. This stronger attachment is expected to moderate the impact of social media coverage on their brand image perception compared to consumers using third-party indirect online channels.

This research seeks to investigate how social media eWOM influences brand image, considering the moderating role of online purchase channels. Thus, the current research is guided by the following questions:

1. What are the effects of social media on brand image perception?
2. Which aspects of social media eWOM have the most significant impact on brand image among customers?

3. How does the impact of social media eWOM on brand image differ between consumers who purchase directly from the brand's website and those who purchase through third-party indirect online channels?

To explore these questions, data were collected over a 53-week period focusing on Sony Electronics, a leading provider of consumer electronics known for its innovative products and worldwide social media presence. Data sources included social media mentions on Sony products to measure social media eWOM, Amazon reviews of Sony products to measure the indirect online channels' brand image, and product reviews on Sony's official website to measure the direct online channels' brand image. To investigate the impact of social media coverage on brand image, the study employs the Overall Brand Image Model (OBIM) from Mitra & Jenamani (2020), which quantifies brand perception from both social media mentions and consumer reviews. Vector Autoregressive Moving Average with Exogenous Inputs (VARMAX) modeling is used to analyze the temporal dynamics and interactions among variables, allowing for a comprehensive assessment of how social media eWOM affects brand image while controlling for external factors.

The research findings indicate that social media eWOM significantly influences brand image on customer reviews, with varying impacts across different purchase channels. Our results showed that positive social eWOM valence initially enhances brand image as perceived in customer reviews, with a stronger short-term response observed in customers using indirect purchase channels compared to those using direct channels. However, despite these short-term differences, there is no significant moderation effect by purchase channel type. This suggests that both social media eWOM valence and brand image derived from social media have a consistent influence on brand perception across different channels. While the intensity of short-term impacts may vary, the fundamental effect of social media sentiment on brand perception remains uniform across channels.

Understanding these dynamics is essential for brands aiming to manage their online presence effectively. Companies can use these insights to proactively and quickly address negative eWOM and maintain a positive brand image among their online customers. Engaging with different audience segments and maintaining a unified brand message across channels will enhance customer engagement and protect brand perception. By focusing on these strategies, businesses can better navigate social media dynamics, optimize their brand presence, and mitigate risks associated with negative online discussions.

2. Theoretical Framework

2.1 The Role of Social eWOM on Brand Image

Social media platforms have become dominant channels of digital communication, changing how consumers discover, share information, and interact with brands they consider, purchase, and evaluate (Hudson et al., 2016). This evolution has fundamentally altered the landscape of brand communication to the public, prompting a reevaluation of brand image and its significance. Brand image, defined as the network of associations consumers hold in memory, is crucial in understanding brand perception and interaction (Keller, 1993; Mitra & Jenamani, 2020). Factors such as customer reviews and electronic word-of-mouth (eWOM) significantly shape brand image online, exerting tangible effects on brand loyalty, consumer trust, and purchase intention (Babić Rosario et al., 2016).

Research on consumer associations with brands has extensively explored concepts like brand identification (Bhattacharya & Sen, 2003), where brands align with consumers' self-concept, thereby fostering a connection between the brand and consumer identity (Escalas & Bettman, 2003). Yoo et al. (2013) support this by demonstrating that e-WOM impacts online shopping behavior through intrinsic rather than extrinsic factors. Given that social media platforms amplify these intrinsic factors, it is essential for retailers to maintain consistency in brand image to influence brand perception, mitigate perceived risk, and foster customer loyalty (Kwon & Lennon, 2009).

Marketing literature classifies social media into Owned social media (OSM) and Earned social media (ESM). OSM refers to a brand's communication on its own social network assets, such as Facebook fan pages, while ESM refers to the brand-related content that entities other than the brand, typically the consumers create, consume, and disseminate through online social networks. ESM includes User Generated Content (UGC) and eWOM, reflecting opinions about a product or company accessible online (Yoo et al., 2013). As consumer behavior shifts towards social media platforms, it underscores the necessity for companies to adapt their brand communication strategies to better engage with their target customers and achieve positive economic outcomes (Lim & Rasul, 2022).

A few seminal pieces have touched on the underlying dynamics of social eWOM. The study by Pauwels et al. (2016) quantified how Brand, Ad and Purchase related eWOM content are influenced by specific marketing strategies, driving traffic and performance. Interestingly, all eWOM types showed comparable long-term elasticity on online store traffic, emphasizing the importance of diverse eWOM content. Similarly, Colicev et al. (2018) explored owned and earned social media effects on consumer mindset metrics and shareholder value, revealing ESM's impact on brand awareness, purchase intent, and customer satisfaction.

Other researchers have studied the effects customer reviews have on brand performance metrics and financial valuation. Moe & Trusov (2011) investigated online product rating forums, finding that ratings behavior is influenced by previous ratings and their valence, directly affecting product sales. They also identified social influences and the product life cycle's role in consumer behavior, indicating the dynamic nature of consumer sentiment. Tirunillai & Tellis (2012) found that the volume of chatter significantly leads to abnormal returns. However, this effect is asymmetric, with negative reviews having a lasting negative impact, unlike positive reviews. Contrary to Moe & Trusov (2011)'s study, numerical ratings seem to not yield any significant impact on returns.

This literature raises the need for examining brand image within the specific context of online channels, as it influences many areas of the customer's journey creating a gap in exploring and measuring it in the digital landscape. Moreover, social media not only affects financial performance but also influences consumer behavior, emphasizing the importance of closely monitoring e-commerce market dynamics to enhance brand image and foster brand loyalty.

2.2 Consumer Dynamics in Online Purchase Channels

To explore further the complex digital landscape, it's crucial to gain a comprehensive understanding of the evolution of online channels into pivotal distribution platforms. Online commerce has steadily gained prominence since the beginning of the twentieth century. Mahadevan (2000) identified three key online commerce models: portals, market makers, and product/service providers. Of relevance to this research are market makers, like Amazon.com, facilitating transactions between buyers and sellers for a fee, and product providers directly engaging with clients in online commercial transactions. Direct online channels, such as brand websites, offer greater control over the content and communication with the consumers, influencing perceptions expectations, expectations, and loyalty (Kwon & Lennon, 2009). In contrast, indirect channels reach a wider audience but offer less control over the customer experience and brand perceptions (Lemon & Verhoef, 2016). Some other challenges include increased competition and low switching costs, potentially impacting customer loyalty (Neslin et al., 2006). Bei & Gielens (2023), on the other hand, highlighted these platforms' tendency to strip brands of differentiation, reducing brand awareness. Research on multichannel customer management states that customer channel preferences evolve over time, and given the potential risks associated with third-party e-commerce sites, it is important to cultivate long-term brand loyalty within direct online channels (Valentini et al., 2011; Kato; 2022).

As consumers search online, learn about products, and evaluate different alternatives, they are likely to encounter numerous online product reviews from other consumers (Mudambi & Schuff, 2010). Extensive research has been dedicated on understanding the effects of such eWOM on various aspects, including perceived product quality, purchase intention, brand loyalty and potential sales (Moe & Trusov, 2011; Neslin et al., 2014; Hoang & Tung, 2022). By examining the evolution of e-commerce models and the challenges they present for brands, we contribute to a deeper understanding of this complex landscape. Furthermore, investigating the influence of online product reviews on consumer behavior sheds light on their role in shaping perceptions, purchase intentions, and brand loyalty. This research aims to provide valuable insights into the interaction between online direct and indirect channels and consumer reviews on them, contributing the digital marketing and channel management knowledge.

Experts emphasized the importance of understanding how customers perceive different online shopping channels, which influences loyalty behaviors such as purchase intentions and eWOM (Frasquet et al., 2015). Seminal papers have set up the ground for our research to further investigate these themes. Chevalier & Mayzli (2006) studied the impact of customer reviews on sales at two different retailers, one third-party seller and the store's brand website. The study reveals that positive reviews boost sales on both third-party and brand websites, and that customers read review text rather than relying only on summary statistics. Recent research by Kato (2022) explores the impact of purchasing experience on brand loyalty by comparing purchases from third-party and brand e-commerce sites, indicating higher loyalty levels for purchases made on brand websites. Moreover, the experiments of Song et al. (2023), explored the effectiveness of different sales channels and the moderating role of review volume on consumers' purchase intention. The study showed that participants prefer own direct channels when review volume was low. These papers show the need to evaluate whether social media conversations influence customers' brand perceptions differently across purchase channels.

These insights discussed in this literature review collectively show the relationship between purchase channels, social media, and brand image, highlighting the need for retailers to strategically navigate these dynamics to optimize brand outcomes across diverse channels. While existing studies offer valuable insights, empirical research on the impact of social media coverage on brand image across diverse online purchase channels remains lacking. Table 1 shows the contribution of the present research to the current state of knowledge.

Table 1: Relevant literature on eWOM, Online Purchase Channels and this study's contribution

Author(s)	Type of eWOM	Source of Data	Distinction between Purchase Channels	Effect on	Main Findings
Pauwels et al. (2016)	ESM	Social platforms (Blogs, forums, Facebook, Twitter)	✓	Visitor traffic	All three kinds of eWOM affect online store traffic similarly, while brand-related content influences offline store traffic. eWOM has a greater impact than paid marketing on online store traffic.
Colicev et al. (2018)	OSM & ESM	Social platforms (Facebook, Twitter, Youtube)		Consumer Mindset metrics & Shareholder value	Social media actions influence consumer mindset metrics and shareholder value, particularly through brand fan following and engagement with ESM.
Moe & Trusov (2011)	Ratings	Retailer website		Sales	Ratings behavior (rating valence) is influenced by previous ratings and directly impacts product sales.
Tirunillai & Tellis (2012)	Reviews & ratings	Consumer reviews forums		Abnormal Stock Returns	UGC volume predicts abnormal returns. Negative UGC affecting returns negatively over time, while positive UGC has minimal impact.
Chevalier & Mayzli (2006)	Reviews	Amazon & Retailer websites	✓	Sales	Positive reviews drive sales, with one-star reviews having a stronger impact than five-star reviews. Customers value review content over summary statistics, and sales are influenced by the quantity and average rating.
Kato (2022)	None	Online survey	✓	Brand Loyalty	Consumers at the brand site are more willing to repurchase than those at the third-party site.
Song et al. (2023)	Reviews	Experimental studies	✓	Purchase Intention	Low review volume works better on the brands website, indicating a preference for perceived product quality. With high review volume, there's no significant difference in purchase intention between the brand's and third-party websites.
This study	Social eWOM & Reviews	Social platforms (Facebook, Twitter); Amazon & Retailer websites	✓	Brand Image	Valence of Social eWOM affects brand image on reviews similarly across both direct and indirect channels

2.3 Conceptual framework and hypothesis

The main effect hypothesis posits that social media eWOM significantly influences consumers' brand image perceptions. As social media has emerged as a powerful platform, our research aims to explore how different aspects of social media eWOM impact brand image. Building on seminal studies, we seek to assess both the valence of social media eWOM and the brand image perception calculated from social media itself, to identify which factor most profoundly impacts the brand image reflected in customer reviews. Colicev et al. (2018) complement Pauwels et al. (2016) by examining brand awareness through social eWOM, while our research will delve into how the valence of eWOM (i.e., the positivity or negativity of social media mentions) and the overall brand image perception on social media contribute to variations in brand image scores from customer reviews. Specifically, we aim to determine whether consumers are more influenced by the overall tone or sentiment conveyed by social media discussions or by the specific attributes and details mentioned within those discussions.

Furthermore, Moe & Trusov (2011) highlighted the role of social factors, which can be shaped by social media eWOM, in influencing ratings. We will explore these factors to understand their impact on consumer reviews. Tirunillai & Tellis (2012) underscore the importance of focusing on reviews rather than ratings, a perspective we will adopt in our study. Therefore, we hypothesize that while positive social media eWOM generally enhances brand image perception, both the valence of eWOM and the brand image perception calculated on social media play crucial roles in shaping the brand image reflected in customer reviews. In summary, the first hypothesis is:

H1a: Valence of social media eWOM positively influences brand image perception among customer reviews.
H1b: Brand image perception among social media eWOM positively influences brand image perception among customer reviews.

Building upon our main effect hypothesis, we propose a moderation hypothesis to further explore the dynamics of social media eWOM. We anticipate that the relationship between social media eWOM and brand image perception among customer reviews will be moderated by the type of online purchase channel used by consumers. Specifically, we expect the impact of social media eWOM on brand image to be weaker for consumers who purchase directly from the brand’s website compared to those who buy through third-party indirect online channels. This hypothesis is grounded in the understanding that consumer behavior and perceptions can vary significantly across different purchase channels, potentially influencing the extent to which social media eWOM affects brand image perception. Prior research, such as Chevalier & Mayzli (2006) and Kato (2022), has highlighted differences in sales and brand loyalty between direct and indirect purchase channels. These studies suggest that consumers who shop directly from a brand’s website may exhibit stronger brand attachment, which could reduce their sensitivity to social media eWOM compared to those purchasing through third-party channels.

Leveraging actual customer reviews as data, our research offers an authentic perspective on how consumers perceive brands from what social media portraits, considering the close relationship between brand loyalty and brand image. Findings from Frasquet et al. (2015) support the idea that brand trust and attachment influence consumer loyalty and behaviors towards specific online channels. Additionally, Song et al. (2023) emphasizes how review volume affects purchase intentions, revealing variations across different sales channels. By building on these insights, our study will examine whether sentiments expressed on social media are mirrored in customer reviews and how these reflections differ by purchase channel. In summary, we hypothesize that the type of online purchase channel moderates the effect of social media eWOM on brand image perception. Specifically, we expect that consumers purchasing through third-party marketplaces will be more influenced by social media eWOM compared to those purchasing directly from the brand's website, due to the stronger brand attachment associated with direct purchases. Based on these considerations, we hypothesize that the type of online purchase channel moderates the effects of social media eWOM valence and brand image perception on customer reviews. Specifically:

H2a: Purchasing through indirect channels (versus direct channels) positively moderates the impact of social media eWOM valence on brand image perception in customer reviews.

H2b: Purchasing through indirect channels (versus direct channels) positively moderates the impact of social media-derived brand image perception on brand image perception in customer reviews.

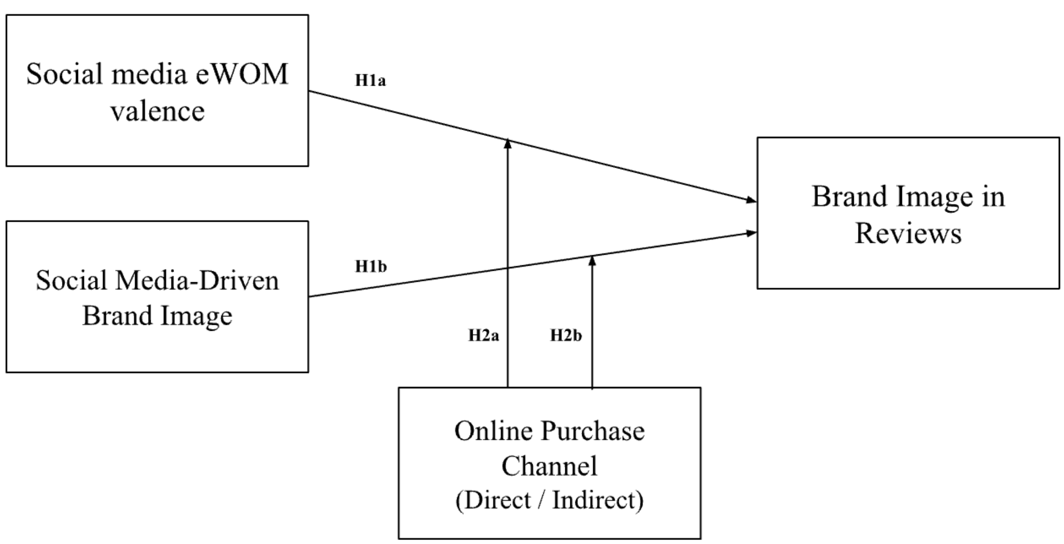

Figure 1: Conceptual framework of this research

3. Data

3.1 Data Sources

The data for this study on social media eWOM and brand image perception were collected from multiple sources for a time period of 53 weeks, ranging from May 23, 2023 to June 2, 2024 (henceforth referred to as the observation window). The brand which we focused on is Sony Electronics, an American leading provider of audio, video electronics and information technology products. Sony Electronics offers a wide range of consumer electronics products, including televisions, smartphones, cameras, audio equipment, and gaming consoles (Sony, 2024). This diversity allows for a wide variety of eWOM opinions across various product categories. Sony is known for its innovative products and technological advancements, which often generate buzz and discussions on social media. The data sources used in this study include social media mentions, Amazon reviews for the indirect online channel, and reviews from the official Sony Electronics website (Electronics.sony.com) as direct online channel.

Social media mentions were gathered using the Listen page from the Brandwatch tool. Brandwatch is a comprehensive platform that enables brands and agencies to make informed decisions and execute data-driven social strategies by monitoring their online presence (Brandwatch, 2019). The Listen feature allows tracking of online campaigns, competitors, new products, hashtags, and more through search queries. It covers a wide range of sources, including social media networks, blogs, review sites, and news sites (Brandwatch, 2024). To track mentions of Sony, the search query included keywords and phrases such as "Sony," "#Sony," and "@Sony," while excluding terms related to gaming and PlayStation to maintain focus on Sony Electronics.

Through Brandwatch, social media data was collected from Twitter, Reddit, and Facebook, chosen for their popularity and significant number of users discussing the brand, making them valuable sources of electronic word-of-mouth (eWOM). Each mentions the social listening tool gathered, includes text, media, date/time, author information, with the tool capable of detecting emotion, language, and location as well (Brandwatch, 2024). To uphold privacy standards, sensitive data was excluded during the subsequent cleaning steps. Additionally, despite Brandwatch's capability to detect emotional sentiment, we disregard it, and our study includes an independent sentiment analysis detailed in a later section. Finally, due to Brandwatch's export limit of 5000 mentions per day, we collected a random sample of 20,703 mentions for further analysis.

In addition to social media mentions, our study included customer reviews gathered from both Sony's indirect (Amazon.com) and direct online channel (Electronics.sony.com). To ensure comparability, we matched Product IDs from Sony's official website to those on Amazon, enabling us to collect reviews across a total of 61 unique SKUs, which were present in both channels. We collected indirect channel reviews using the Amazon Reviews Scraper from Junglee via Apify. Apify is a platform that facilitates web scraping, data extraction, and web automation (Apify, 2022). The Junglee scraper tool extracts detailed product reviews, including rating scores, review descriptions, reactions, and accompanying images, with careful exclusion of any sensitive user information, such as author name (Junglee, 2022). The scraper was configured to capture reviews within our observation window and could extract a maximum of 500 reviews per product. A random sample of 8,444 reviews were collected.

We collected direct channel reviews from the Sony direct online channel, specifically its official website, the Sony US site (Electronics.sony.com). We extracted the reviews manually on Python, gathering data such as Date Published, Headline, Review Body, and Rating Value.[1] To maintain privacy standards, sensitive information about the review authors was excluded from the extraction process. This method resulted in the collection of all reviews for these 61 SKUs, in total 10,024 reviews.

3.2 Preparing the Data

The data collected from each of the three sources was first saved into individual datasets for further analysis. To ensure data quality and relevance, a series of cleaning and preprocessing steps were implemented.

Initially, each dataset was translated to English using the Google Translate library in Python. Duplicate entries were then removed to eliminate redundancy. Then, the cleaning process involved expanding common abbreviations to their full forms, numerical digits were converted into their word equivalents, and repeated letters in words were reduced to a single occurrence to retain the original word form. Additionally, punctuation, non-ASCII characters, and extra whitespace were systematically removed. Emojis and standard stopwords were filtered out using NLTK's English stopwords corpus. Subsequently, the processed text was normalized and tokenized using NLTK's functionalities. Finally, the WordNet corpus from NLTK was employed to map POS tags to WordNet POS tags, ensuring accurate lemmatization of the text data. These comprehensive preprocessing steps were crucial in preparing the datasets for subsequent analysis.

3.3 Variable operationalization

Computation of Brand Image Score:

To measure the impact of social media coverage on brand image across different purchase channels, we adopted the Overall Brand Image Model (OBIM) developed by Mitra & Jenamani (2020). This approach allowed us to quantify brand image from social media mentions and consumer reviews for both indirect and direct channels and track its changes over time. The OBIM score for each brand association was calculated by multiplying its favorability, strength, and

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[1] This involved inspecting the elements of the product pages, specifically the HTML element with the ID #bv-jsonld-reviews-data, which contains the reviews data.

uniqueness scores, with the overall OBIM score for the brand being the sum of all aspect scores. This score provided a comprehensive measure of brand image perception, reflecting both the sentiment and the prominence of various aspects mentioned across the reviews. This multi-step process will be explained below, and more detailed calculations on Appendix A.

The OBIM process begins by extracting brand associations from consumer reviews using natural language processing techniques. Aspects, or brand associations, are identified by extracting opinion words using the VADER sentiment dictionary and employing dependency parsing with spaCy to identify syntactic structures. This ensures that the aspects accurately reflect the sentiment and associations in the reviews.

OBIM understands the concept of favorability as the positive or negative sentiment associated with a brand aspect. It measures favorability through an unsupervised lexicon-based sentiment analysis approach with VADER. The sentiment polarity score for each aspect is then calculated by averaging the sentiment scores of the associated opinion words. These measures result in a favorability score that reflects the overall sentiment towards each brand aspect.

The strength of each aspect is measured through co-word network analysis, which examines the frequency and context of co-occurrences within the text corpus. This co-occurrence matrix is then normalized to obtain the weights of the co-occurrences (edges) between words (nodes). The strength of each aspect is computed by averaging the edge weights connected to it, helping to understand how strongly each aspect is associated with the brand based on its frequency and context in the reviews. The strength score indicates how prominently each aspect is discussed in consumer reviews.

Uniqueness is quantified by analyzing the distinctiveness of each aspect within the co-word network. This involves calculating the importance of each edge in the network based on the degree of connected nodes and edge weights. The uniqueness score for each aspect is determined by summing its normalized degree and the contributions over its edges. This score highlights how unique or distinct each aspect is in the context of the brand's overall image.

Figure 2 is a visual representation of the calculation process for the OBIM score. The overall OBIM score for the brand is calculated by summing all aspect scores, providing a comprehensive measure of brand image perception that reflects both the sentiment, and the significance of various aspects mentioned across reviews. This comprehensive OBIM score helps in understanding the multidimensional nature of brand image and its perception among consumers.

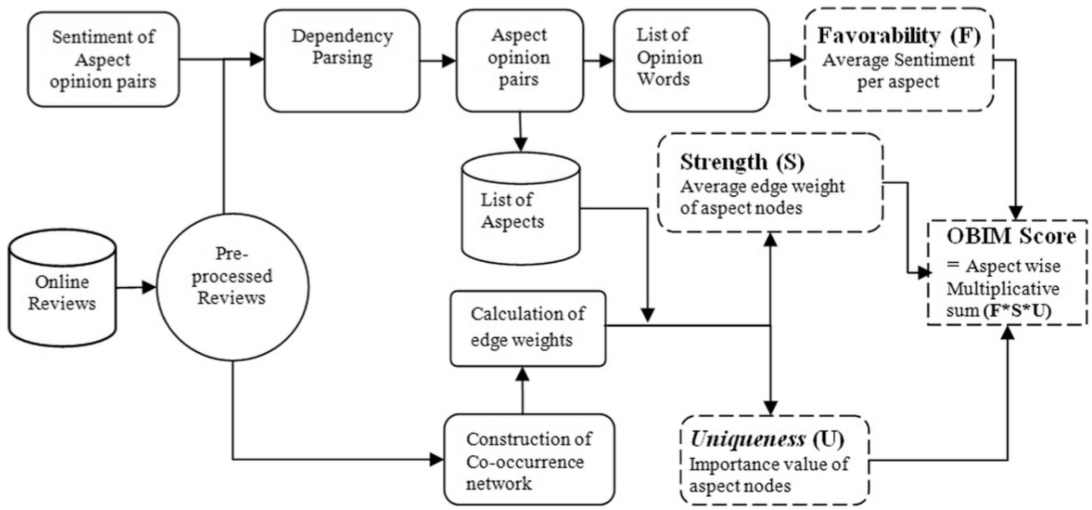

Figure 2: Computational Model of Online Brand IMage (OBIM)

Adapted Source: Mitra & Jenamani, 2020, p. 216

Given that the data points were collected weekly for this research, we obtained weekly OBIM scores across the three text corpora collected (social media mentions and customer reviews). This involved iterating through each weekly timestamp to create date ranges and filtering mentions and reviews within those ranges. For each week, the scores for favorability, strength, and uniqueness of each aspect were calculated and averaged to produce a weekly summary. This approach allowed for tracking changes in brand image over the study period on a weekly basis, providing detailed insights into how consumer perceptions evolved over time. During the calculation process, we noticed that datasets with more identified aspects, would result in higher OBIM scores due to the increased number of aspects contributing to the sum calculation, this is important to keep in mind when interpreting their results. Specifically, we identified 491 aspects for social media mentions, 334 aspects for customer reviews on Amazon (indirect online channel), and 290 aspects for customer reviews Sony's website (direct online channel).

3.4 Variables

With the data prepared, we incorporated them as variables to build our framework. The variables are detailed below per hypothesis tested, capturing both temporal effects and the dynamic role of social media eWOM on customer reviews.

Main Effect Hypotheses:

To investigate the main effect of social media eWOM on brand image perception on customer reviews, we proposed two hypotheses. Hypothesis H1a posits that valence of social media eWOM positively influences brand image perception among customer reviews. This will examine if social media mentions about Sony Electronics are positive, it enhances the overall brand image reflected in customer reviews. The independent variable created to include this information is Valence of Social eWOM Mentions (ValSt), which will provide insight into how the sentiment of social media discussions about Sony Electronics are. Hypothesis H1b proposes that high brand image scores calculated from social media mentions will result in higher brand image scores among customer reviews, indicating that favorable brand image perceived on social media eWOM translates into improved brand perception among Sony Electronics customers. The independent variable OBIM Scores for Social eWOM (OBIMst) will test this impact. The dependent variable for both hypotheses is OBIM Scores for reviews (OBIMrt), which represents the average brand image scores across both direct (Sony Electronics.com) and indirect (Amazon) online channels, measuring the overall perception of the brand as reflected in customer reviews. It enables us to examine the main impact of social media on customer reviews.

Since sentiment scores are part of the OBIM score calculation, we conducted multicollinearity tests to ensure that including these variables together in the overall model would not compromise its effectiveness. The Variance Inflation Factor (VIF) score between ValSt and OBIMst is 1.20, indicating that multicollinearity is not a significant issue in this context, therefore we decided to include said variables together in the model.

Moderation Effect Hypotheses:

Hypothesis H2 suggests that the impact of social media eWOM on brand image scores is moderated by the purchase channel, with a stronger effect for customers purchasing through indirect channels than for those purchasing through direct channels. By exploring this moderation effect, we will discover whether social media has more influence on brand perception for Sony customers who buy from third-party websites compared to those who purchase directly from the brand's website. The variables used for this model include dependent variables such as OBIM Scores for Indirect online channel (OBIMrit), which measure the brand image as perceived through indirect purchase channels like customer reviews on third-party websites such as Amazon, and OBIM Scores for Direct online channel (OBIMrdt), reflecting the brand image from direct eWOM sources such as reviews on the brand's official website. The independent variable used for this test will be the most influential aspect of social media mentions on customer reviews, as derived from the results of H1a and H1b.

Control variables:

While the research hypotheses do not explicitly mention variables such as volume and valence of social eWOM or reviews, we find them crucial for a comprehensive analysis of brand image perception. Volume, indicated by the frequency of mentions and reviews, influences online site traffic, customer mindset, and shareholder value (Pauwels et al., 2016 & Colicev et al., 2018). Moreover, Kostyra et al. (2016) emphasize the moderating effect of review volume by valence, suggesting that products with positive reviews are more likely to be purchased when accompanied by a high volume of positive feedback. Therefore, by including volume information of each data source in the model of both hypotheses, it can more accurately capture the complexity of how social media eWOM impacts brand image, offering a more detailed analysis of brand perception dynamics.

In addition to the endogenous variables, we included two exogenous control variables: a weekly time trend increasing by one for each week in the data set (Wt) and the G20 Consumer Price Indices (CPIs)[2]. The Weekly trend variable captures temporal or seasonal effects on brand image, while the CPI provides insights into broader economic conditions that could impact consumer behavior and brand perception. We opted for the CPI aggregate for the G20 area, obtained from the OECD Data Explorer, due to its representation of major global economies. These control variables help isolate the effects of social media eWOM on brand image by accounting for external factors.

For each hypothesis test later in the Results section, we constructed a dedicated model by selecting the specific variables relevant to that hypothesis. The complete list of variables used to address the hypotheses are summarized in Table 2:

Table 2: Variable Description

Variable	**Description**	**Source**
Valence of Social eWOM Mentions ($ValS_t$)	Valence refers to the sentiment or tone of the social media mentions. It is a weekly measure whether the mentions are positive, negative, or neutral.	Brandwatch
OBIM Scores for Social eWOM ($OBIMs_t$)	Brand image scores calculated from social eWOM mentions. It provides a quantifiable measure of the brand image derived from social media mentions.	Brandwatch
OBIM scores on customer reviews (OBIMrt)	Average brand image scores across both direct (Sony) and indirect (Amazon) online channels.	Sony & Amazon Reviews Scrapper
OBIM Scores for Indirect online channel ($OBIMri_t$)	Brand image scores from indirect eWOM sources such as customer reviews on third-party websites (Amazon). It measures brand image as perceived through indirect online channels.	Amazon Reviews Scrapper
OBIM Scores for Direct online channel ($OBIMrd_t$)	Brand image scores from direct eWOM sources such as reviews on the brand's official website. It provides a measure of brand image from the direct online purchase channel.	Sony Reviews Scrapper

[2] Consumer Price Indices (CPI) measure changes in the prices of goods and services purchased by households, reflecting overall economic conditions (International Labour Office, 2004; OECD, 2024).

Volume of Social eWOM Mentions ($VolS_t$)	This variable captures the total weekly mentions of the brand on social media platforms. It provides a measure of the brand's visibility and the volume of eWOM.	Brandwatch
Volume of Amazon Reviews ($Volri_t$)	Total number of reviews the brand received each week on Amazon.	Amazon Reviews Scrapper
Volume of Sony Reviews ($Volrd_t$)	Total number of reviews the brand received each week on Sony's website.	Sony Reviews Scrapper
Week time trend (W_t)	Week number (1-53) capturing temporal effects	Own count
CPI monthly value (CPI_t)	Consumer Price Index (CPI) representing economic conditions across major economies (G20).	OECD Data Explorer

3.5 Descriptive statistics

With the dataset finalized, we proceed to examine it before embarking on the empirical analysis. Table 3 below show the descriptive statistics for all variables summarized above:

Table 3: Descriptive statistics of the variables used in this paper

Type	**Variable**	**Count**	**Mean per week**	**Std. Dev. per week**	**Min per week**	**Max per week**
Endogenous	Weekly Valence of Social eWOM Mentions ($ValS_t$)	53	0.27	0.07	0.05	0.46
	Weekly OBIM Scores for Social eWOM ($OBIMs_t$)	53	284.82	73.55	162.17	500.49
	Weekly OBIM scores on customer reviews ($OBIMr_t$)	53	191.03	36.66	90.33	257.27
	Weekly OBIM Scores for Indirect online channel ($OBIMri_t$)	53	213.66	52.88	109.10	335.67
	Weekly OBIM Scores for Direct online channel ($OBIMrd_t$)	53	168.40	48.36	64.72	268.00
	Volume of Social eWOM Mentions ($VolS_t$)	20703	385.04	141.98	37.00	929.00
	Volume of Amazon Reviews ($Volri_t$)	8444	155.13	48.54	48.00	236.00
	Volume of Sony Reviews ($Volrd_t$)	10024	188.19	47.22	91.00	306.00
Exogenous	Week time trend (W_t)	53	n/a	n/a	1	53
	CPI monthly value (CPI_t)	53	6.61	0.54	5.64	7.25

Examining the descriptive statistics in Table 3 provides insights into the dynamics of economic indicators, social media engagement, and consumer reviews over a 53-week period. The Consumer Price Index (CPI_t) exhibits an average value of 6.61, indicating stable pricing trends with a slight variability (standard deviation = 0.54). Weekly mentions of social media activity ($VolS_t$) average 385.04, ranging widely from 37.00 to 929.00 mentions per week, reflecting fluctuations in the volume of social eWOM over a year. Amazon reviews ($Volri_t$) and Sony reviews ($Volrd_t$) average 155.13 and 188.19 per week, respectively. The difference in review counts between Amazon and Sony website reviews can be attributed to the distinct data collection methods employed. Specifically, the Amazon reviews scraper has an extraction cap limit, whereas scraping reviews from the Sony website did not encounter such limitations. Weekly Valence of Social eWOM Mentions ($ValS_t$) averages 0.27, ranging from 0.05 to 0.46, indicating varying sentiment levels across weeks. OBIM scores also show variability: Brand image scores on social media averages 284.82, ranging from 162.17 to 500.49, while Brand image of reviews, on indirect channels, and direct channels average 191.03, 213.66, and 168.40, respectively, reflecting different scoring dynamics across channels.

As a final exploration of the data, we show the correlation between each of the variables below in Figure 3:

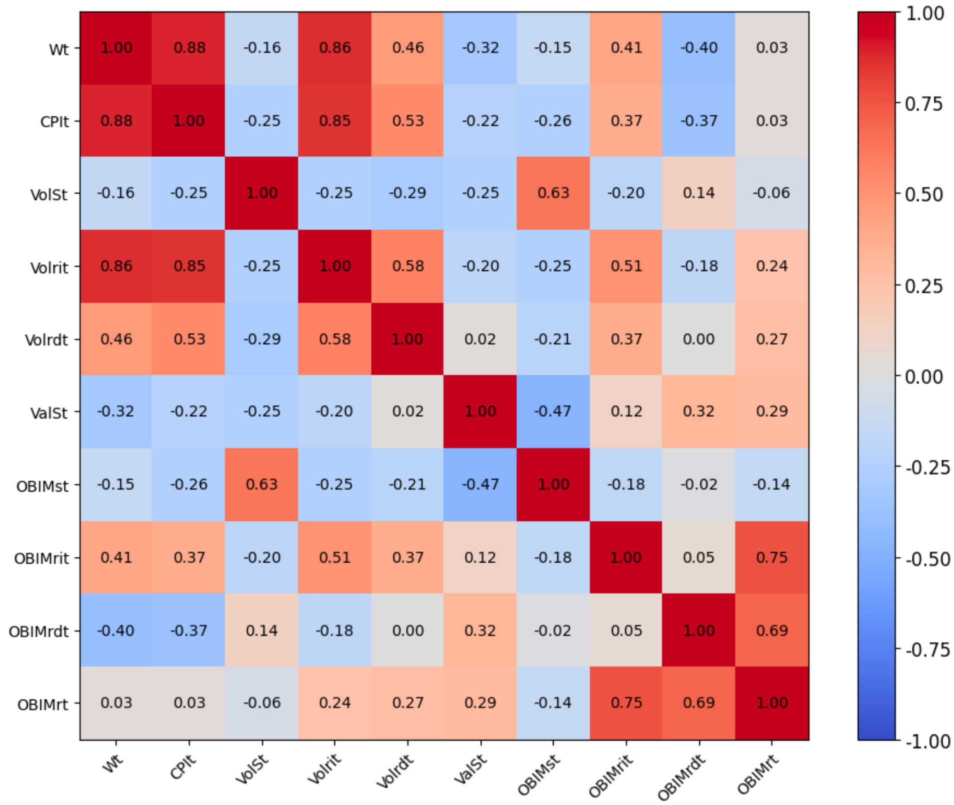

Figure 3: Correlation matrix including the variables used in this research

The correlation matrix reveals relationships among various metrics related to brand performance and consumer engagement. W_t shows a strong positive correlation with CPI_t, at 0.88, and with $Volri_t$, at 0.86. CPI_t also correlates positively with $Volri_t$, with a coefficient of 0.85, and with $Volrd_t$, at 0.53, suggesting similar patterns in consumer activity across different products. Conversely, $VolS_t$ exhibits negative correlations with CPI_t, at -0.25, and with ValSt, at -0.25, suggesting potential variations in consumer sentiment and engagement levels on social media. As for the brand image metrics, $OBIMri_t$ show moderate positive correlations with $Volri_t$ and $Volrd_t$, indicating alignment between brand perception on indirect channels and the volume of reviews on the purchase channels. Furthermore, $OBIMr_t$ demonstrate significant positive correlations with $OBIMri_t$, at 0.75, and with $OBIMrd_t$, at 0.69, which makes sense since it is a variable derived from those two variables. These correlations provide insights into how the various terms in the model interrelate.

4. Methodology

In this section, we discuss the methodology employed to test our hypotheses, focusing specifically on the Vector Autoregressive Moving Average with Exogenous Inputs (VARMAX) modeling. Our approach is designed to handle two critical aspects of our data: capturing the interactions among multiple time series variables to analyze the dynamic relationships between social media eWOM and brand image perception in customer reviews and integrating external factors as exogenous variables to control for influences beyond the primary variables of interest. We will outline the steps involved in applying the VARMAX model, including endogeneity tests, model estimation, and simulation analysis.

4.1 VARMAX Modeling

To explore the relationship between social media eWOM and brand image perception on customer reviews, we utilized Vector Autoregressive (VAR) modeling techniques. VAR modeling is well-suited for analyzing multivariate time series data by capturing temporal dependencies and interactions among variables. This approach enables us to examine how changes in social media eWOM influence brand image perception through a system of equations, where each variable is regressed on its own lagged values and those of other variables in the system (Korstanje, 2021). One characteristic of the VAR model is that it can be built upon to account for different types of processes. We used the VARMAX specification, which incorporates a moving average component, allowing for the inclusion of external, or exogenous variables. VARMAX allows us to explore how social media eWOM affects brand perception, while controlling for external factors with exogenous variables.

Several steps are involved in applying VARMAX modeling to this study, and several authors implement different methodological steps tailored to the nature of their research. Our approach incorporates analysis steps from Pauwels et al. (2016) and Srinivasan et al. (2010) to ensure a robust and comprehensive model. First, a time series data set for social media eWOM metrics and brand image scores was prepared by ensuring that all variables were measured at the same frequency (weekly) and covered the same time period. Next, to address potential endogeneity and formulate the model specification, we conducted two key tests. First, we checked for endogeneity within the full model using Granger causality test based on chi-square distribution ($\mathcal{X}^2$). This test determines if one variable provides useful information in forecasting another variable beyond its own past values, helping to assess the direction and strength of causal relationships (Granger, 1969 & Prabhakaran, 2019). For each hypothesis, we reviewed Granger causality results to see if social media eWOM significantly impacts brand image scores beyond what past brand image scores can explain, thus validating the need for a dynamic system model like VARMAX. Following the Granger causality test, the stationarity of the time series data was assessed using the Augmented Dickey-Fuller (ADF) test. Stationary variables have constant mean and variance over time, which is a prerequisite for reliable estimation in VARMAX modeling.

Including non-stationary variables in the model can cause regression issues, so we applied first differencing to those variables that were not stationary, specifically Volrit and OBIMrit (See ADF results in Appendix B). Additionally, since OBIMrdt is one of our focal variables for H2a and H2b in the moderation analysis versus OBIMrit, we also differenced this variable to ensure comparability of their results. With endogeneity and stationarity confirmed, we finalize the model specifications as follows: Equation (1) for testing H1a and H1b, and Equation (2) for testing H2. The model's equations were formulated to account for lagged effects and error terms, providing a framework to analyze the temporal dynamics between these variables.

$$\begin{bmatrix} OBIMr_t \\ ValS_t \\ OBIMs_t \\ VolS_t \\ d(Volri_t) \\ Volrd_t \end{bmatrix} = \begin{bmatrix} C_{OBIMr} \\ C_{ValS} \\ C_{OBIMs} \\ C_{VolS} \\ C_{Volri} \\ C_{Volrd} \end{bmatrix} + \sum_{j=1}^{J} \begin{bmatrix} \Phi_{11}^{j} & \Phi_{12}^{j} & \cdots & \Phi_{16}^{j} \\ \Phi_{21}^{j} & \Phi_{22}^{j} & \cdots & \Phi_{26}^{j} \\ \vdots & \vdots & \ddots & \vdots \\ \Phi_{61}^{j} & \Phi_{62}^{j} & \cdots & \Phi_{66}^{j} \end{bmatrix} \begin{bmatrix} OBIMr_{t-j} \\ ValS_{t-j} \\ OBIMs_{t-j} \\ VolS_{t-j} \\ d(Volri_{t-j}) \\ Volrd_{t-j} \end{bmatrix} + \begin{bmatrix} \theta_{OBIMr} \\ \theta_{ValS} \\ \theta_{OBIMs} \\ \theta_{VolS} \\ \theta_{d(Volri)} \\ \theta_{Volrd} \end{bmatrix} \begin{bmatrix} W_t \\ CPI_t \end{bmatrix} + \begin{bmatrix} \epsilon_{OBIMr,t} \\ \epsilon_{ValS,t} \\ \epsilon_{OBIMs,t} \\ \epsilon_{VolS,t} \\ \epsilon_{Volri,t} \\ \epsilon_{Volrd,t} \end{bmatrix} \qquad \text{Eq. (1)}$$

$$\begin{bmatrix} d(OBIMri_t) \\ d(OBIMrd_t) \\ ValS_t \\ OBIMs_t \\ VolS_t \\ d(Volri_t) \\ Volrd_t \end{bmatrix} = \begin{bmatrix} C_{OBIMri} \\ C_{OBIMrd} \\ C_{ValS} \\ C_{OBIMs} \\ C_{VolS} \\ C_{Volri} \\ C_{Volrd} \end{bmatrix} + \sum_{j=1}^{J} \begin{bmatrix} \Phi_{11}^{j} & \Phi_{12}^{j} & \cdots & \Phi_{17}^{j} \\ \Phi_{21}^{j} & \Phi_{22}^{j} & \cdots & \Phi_{27}^{j} \\ \vdots & \vdots & \ddots & \vdots \\ \Phi_{71}^{j} & \Phi_{72}^{j} & \cdots & \Phi_{77}^{j} \end{bmatrix} \begin{bmatrix} d(OBIMri_{t-j}) \\ d(OBIMrd_{t-j}) \\ ValS_{t-j} \\ OBIMs_{t-j} \\ VolS_{t-j} \\ d(Volri_{t-j}) \\ Volrd_{t-j} \end{bmatrix} + \begin{bmatrix} \theta_{d(OBIMri)} \\ \theta_{d(OBIMrd)} \\ \theta_{ValS} \\ \theta_{OBIMs} \\ \theta_{VolS} \\ \theta_{d(Volri)} \\ \theta_{Volrd} \end{bmatrix} \begin{bmatrix} W_t \\ CPI_t \end{bmatrix} + \begin{bmatrix} \epsilon_{OBIMri,t} \\ \epsilon_{OBIMrd,t} \\ \epsilon_{ValS,t} \\ \epsilon_{OBIMs,t} \\ \epsilon_{VolS,t} \\ \epsilon_{Volri,t} \\ \epsilon_{Volrd,t} \end{bmatrix} \qquad \text{Eq. (2)}$$

Where:

- $OBIMr_t, OBIMri_t, d(OBIMrd_t), ValS_t, OBIMs_t, VolS_t, d(Volri_t), Volrd_t$ are the endogenous variables, with $d(OBIMr\text{i}_t), d(OBIMrd_t)$ and $d(Volri_t)$ being differenced.
- C are the intercept coefficients for each target variable.
- Φ_{ij}^{j} are the autoregressive coefficients (with subscripts denoting the variable relationships and the superscript j indicating the lag).
- θ are the coefficients for the exogenous variables.
- W_t and CPI_t are the exogenous variables (Weekly time trend and CPI monthly value, respectively).
- ϵ_t represents the white-noise disturbances, the error terms for each equation at time t (Korstanje, 2021).

We log-transformed all endogenous variables, which allows direct interpretation of impulse response functions (IRFs) as elasticities. This facilitates comparison of effect sizes in a VARMAX context where changes in variables are influenced by shocks (Maier & Wieringa, 2021, p. 320 & Pauwels et al., 2016, p. 8).

Then, model selection is carried out using the defined models for each hypothesis. The optimal lag length for the VARMAX model was determined using criteria such as the Akaike Information Criterion (AIC). This criterion is a famous KPI for goodness of fit of a model and it helps identify the number of lags that best capture the relationships between the variables without overfitting the model (Akaike, 1974). Once the optimal lag length is determined, the estimation phase begins. Using Ordinary Least Squares (OLS) regression, the VARMAX model was then estimated based on the selected lagged values of social media eWOM metrics and brand image scores. To confirm the model's validity, a portion of the dataset was reserved as a test sample, specifically 20% of the data, to calculate forecast error metrics such as Mean Absolute Percentage Error (MAPE). MAPE measures the forecast's accuracy by calculating the average absolute percentage error between predicted and actual values. This metric provides an easily interpretable percentage error, helping us assess the predictive accuracy of the model, for forecasting brand image scores based on social media eWOM metrics.

Finally, simulation analysis was performed using the Orthogonalized Impulse Response Functions (OIRFs) and Forecast Error Variance Decompositions (FEVD) from the VARMAX estimates. We relied on OIRFs because the order of the variables is theoretically mandated (e.g., social media mentions must come before reviews), and because certain effects are delayed rather than instantaneous. For example, customers usually take multiple days to convert even on one website, and even longer to write a review for the product (Maier & Wieringa, 2021). Based on these estimations, the impulse response function estimates the net effect of a shock to one variable on the others relative to their baselines (Pesaran & Shin, 1998). We identified shock contributors using the orthogonalized approach, which decomposes shocks into independent components. We generated impulse response functions by performing Cholesky decomposition of the error terms to address contemporaneous correlations (Vieira et al., 2019, p. 1094). These techniques showed how shocks in our independent variables determined in the hypotheses, namely social media eWOM metrics (ValSt, OBIMst), affect our dependent variables, brand image scores on reviews (OBIMrt, OBIMrit, OBIMrdt). We reported both short-term and long-term effects. Short-term effects are measured over a 2-week period, reflecting immediate, 1-week, and 2-week impacts on our dependent variables, such as brand image scores on reviews. Two weeks is an appropriate timeframe to measure short-term effect, as customers typically take several days to make a purchase decision and write a review[3]. Long-term effects were assessed at week 8, capturing the sustained impact over a longer timeframe. The 8-week timeframe represents a reasonable timeframe within which consumers might still remember social media interactions, beyond which their memory and the influence of such interactions may fade. Cumulative OIRFs (e_{cum}) were reported for significant periods to clarify the duration of impacts. Elasticities, also referred as OIRF estimate, were calculated for both short-term and long-term effects, each with its standard error and are presented in elasticity tables. Estimates with a t-value (the ratio of the estimate to its standard error) greater than 1 were considered statistically significant, following criteria of existing research (Pauwels et al., 2016, p. 8). To ensure the accuracy of these estimates, we performed bootstrapping with 1000 iterations to compute sample standard errors.

While the OIRFs allow us to calculate the performance effect of a unit change in the social media eWOM metrics, it is also good to know the overall importance of these metrics on customer reviews. For this we calculated FEVD, which measures the cumulative impact over time of shocks from each variable (Pauwels, 2004). It calculates the percentage of variation in brand image scores due to changes in each variable, clarifying how social media eWOM influences perceptions of the brand. This approach offers a robust statistical framework to analyze the impact of social media eWOM on brand image. The results from VARMAX modeling, OIRFs, and FEVD tests explored hypothesized relationships and the causal dynamics between variables over time.

[3] Customers average 9.2 days to make an online purchase decision (Li & Kannan, 2014).

5. Results

This section presents the findings of the study, focusing on the hypotheses defined earlier. The results are organized to address each effect, beginning with the main and moderation effect hypothesis, respectively.

Main Effect Results:

The first analysis investigated the influence of social media eWOM on brand image perception. It specifically examines the relationship between positive social media mentions and customer review scores, as well as the impact of high brand image scores from social media mentions on brand image scores in customer reviews.

The VARMAX model built from Eq. (1), used an optimal lag length of 1 with an AIC of 6.471. This lag length aligns with typical VAR applications in marketing, allowing for complex wear-in and wear-out patterns spanning several weeks (Pauwels et al., 2016, p. 8). As a robustness check for the forecasting model, it achieved a Model Accuracy of 91.66%, suggesting that the model performs reasonably well on unforeseen data. For H1a, the Granger causality test (See Appendix C) and VARMAX model results (Appendix D) showed that social eWOM valence does not significantly affect brand image scores, with p-values of 0.4319 and a coefficient of -0.0287, respectively. Similarly, H1b was not supported, as the Granger test and model showed no significant relationship between social media brand image scores and customer review scores, with p-values of 0.4874 and a coefficient of -0.1568.

First, the simulation analysis results for H1a, as shown in Figure 4.A, indicate that the Orthogonalized Impulse Response Functions (OIRFs) reveal a positive initial response in brand image scores in customer reviews following a shock to ValSt. We computed OIRFs based on the estimated VARMAX system for all endogenous variables in the order of Eq. (1) and obtained 95% confidence intervals through bootstrapped residuals (n = 1000). The elasticity at moment 0 is 3.22×10^{-02}, and at week 1 it peaks to 3.41×10^{-02}. However, by week 2, the elasticity drops to 4.18×10^{-03}, becoming not statistically significant. Right after, this effect diminishes and stabilizes around the zero line. The cumulative impact of social media valence is positive (6.13×10^{-2}). Over the long term (8 weeks), the elasticity turns slightly negative, with a very small value of $-2.096433 \times 10^{-07}$. This indicates that while positive eWOM initially boosts brand image perception, this effect diminishes and may become slightly negative over time. This evolution is highlighted in Tables 4 & 5 and the complete elasticities tables for short and long term in Appendix E.

Finally, the Forecast Error Variance Decomposition (FEVD) analysis (Figure 5) reveals that cumulatively by week 8, approximately 5.5% of the variation in brand image scores among reviews can be attributed to past changes in social media eWOM sentiment. Therefore, these results indicate that valence of social media eWOM (ValSt) will positively influence brand image perception, resulting in higher brand image scores amongst customer reviews (OBIMrt) (H1a).

Table 4: Short-Term Effects of ValSt and OBIMst on OBIMrt

Impulse	Week	Response: OBIMrt (Elasticity)
ValSt	Week 0	3.22×10^{-2} (2.19×10^{-02})*
	Week 1	3.41×10^{-02} (2.92×10^{-02})*
	Week 2	4.18×10^{-03} (9.79×10^{-03})
OBIMst	Week 0	1.07×10^{-02} (3.68×10^{-02})
	Week 1	-3.58×10^{-02} (2.99×10^{-02})*
	Week 2	1.04×10^{-02} (9.79 x $10\text{-}03$)*

Values are reported with two decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8). The full table, including all variables in the model, is in Appendix E.

Table 5: Long-Term Effects of ValSt and OBIMst on OBIMrt

Impulse	Response: OBIMrt (Elasticity)
ValSt	-2.096×10^{-07} (1.09×10^{-04})
OBIMst	2.35×10^{-06} (9.83×10^{-05})

Values are reported with two decimal places. Long-term elasticities (8-week period) include standard errors in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8). The full table, including all variables in the model, is in Appendix E.

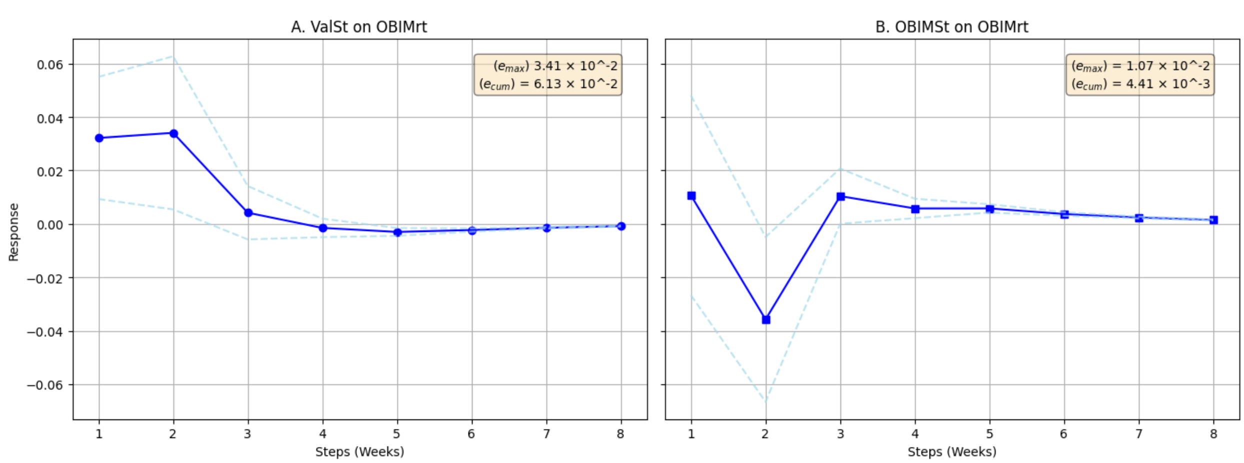

Figure 4: Orthogonalized Impulse Response Functions (OIRF) plots of Impulse Variables ValSt and OBIMst on OBIMrt

For Hypothesis H1b, we focused specifically on the impact of high brand image scores from social media mentions (OBIMst) on brand image scores among customer reviews. At week 0, the elasticity is 1.07×10^{-02}, which is not statistically significant (See Table 4). Then, the OIRF plot indicates a significant negative impact of OBIMst on OBIMrt, reaching its lowest point around the first week after the impulse, an impact of -3.58×10^{-02} (See Figure 4.B). This initial response rejects H1b, suggesting that higher brand image scores from social media mentions may initially lead to lower brand image perception on customer review. By week 2, the elasticity becomes positive at 1.04×10^{-02}, and this value is statistically significant, indicating a positive adjustment in customer review scores following the initial negative impact. Over time, the effect of OBIMst on OBIMrt stabilizes around zero and shows a slight positive impact. The cumulative elasticity (e_{cum}) of 4.41×10^{-03} suggests a very small total effect over time. Additionally, the long-term elasticity (See Table 5) shows a small and insignificant positive impact of OBIMst on OBIMrt (2.35×10^{-06}). This suggests that while initial social media brand image scores may have a short-term negative effect, this impact diminishes over time, and any long-term effects are minimal and not statistically significant.

Moreover, the FEVD analysis, in Figure 5, up to 8 weeks shows that brand image scores on social eWOM contribute 3.6% to the forecast error variance of brand image on customer reviews. This contribution indicates a lower impact than the valence of social media mentions. The FEVD analysis thus supports the notion that while social media brand image scores do influence customer review scores to some extent, their relative impact is smaller compared to other factors, such as the valence of the social media mentions.

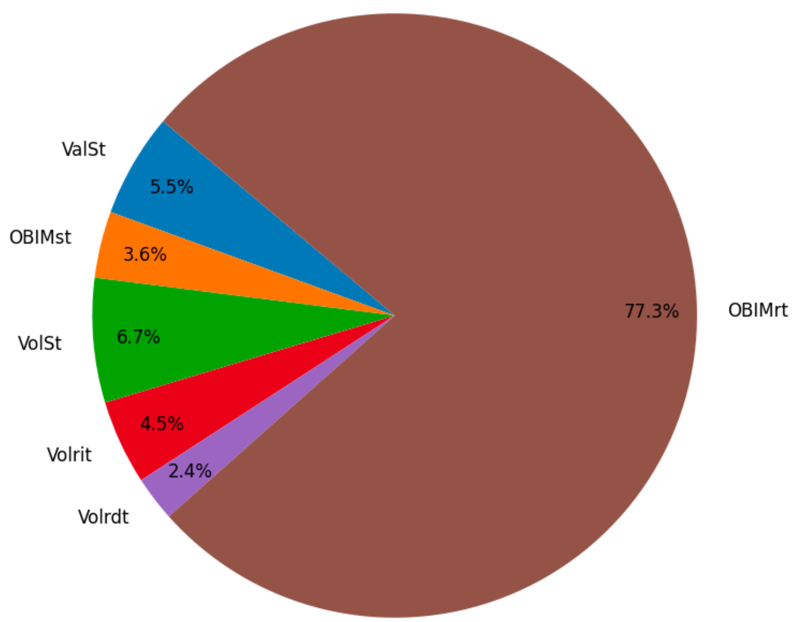

Figure 5: Cumulative Forecast Error Variance Decomposition (FEVD) for OBIMrt (up to 8 weeks)

In summary, H1a is supported in the short-term (2 weeks), showing that social media eWOM valence positively impacts brand image scores in reviews, peaking at 0.034 in the first week. However, no long-term impact was detected. The FEVD analysis confirmed this, attributing 5.5% of review score variation to social media sentiment. In contrast, H1b is rejected; social media brand image scores initially negatively impacted review scores by -3.58×10^{-02} in the first week, but this effect became positive by Week 2. Given the initial impact is negative and considering the relatively small contribution of social media brand image scores to the variance in review scores (as per the FEVD analysis), the hypothesis H1b is not supported. The influence of social media brand image perception on customer review scores is not consistently positive and is relatively minor in terms of overall impact.

These findings suggest that consumers, in general, are more influenced by the overall sentiment of social media rather than specific details. The OBIM scores extract brand associations from textual data, considering both the frequency and importance weights of these associations relative to others. Customers seem to form a general impression of the brand, which affects their reviews, rather than focusing on specific aspects. This highlights the need for brands to maintain a positive sentiment across social media, as isolated brand associations alone may not significantly alter consumer perceptions.

Moderation Effect Results:

Given the findings from H1, which highlighted the significant impact of social media eWOM on customer reviews, H2 examined how this impact is moderated by the online purchase channel. This hypothesis posits that consumers purchasing through indirect channels (OBIMrit) will be more influenced by social media eWOM due to the stronger brand attachment associated with direct purchases (OBIMrdt).

Granger causality test results (Appendix F) showed that social media eWOM (ValSt) does not significantly influence brand image scores for either direct (OBIMrdt) or indirect (OBIMrit) purchasing channels, with p-values of 0.1783 and 0.9734, respectively. Social media-derived brand image scores (OBIMst) do not significantly affect direct channel scores (p-value 0.1918) but do impact indirect channel scores significantly (p-value 0.0254). The VARMAX model derived from Eq. (2) (See Appendix G), with a lag length of 1 and an AIC of 98.306, shows no significant effect of ValSt on brand image scores in either channel but indicates a significant impact of OBIMst. The model's accuracy, with a MAPE of 70.40%, reflects a moderate explanatory power.

In the simulation analysis for H2a, tests such as OIRF and FEVD provided insights into the individual contributions and dynamic effects of valence of social media eWOM (ValSt), on its relationship with OBIM scores across both indirect and direct channels. Due to the differencing of both focal variables, the interpretation of the elasticities is in the form of growth rates.

Additionally, the differencing only allowed us to report the short-term effects for weeks 1 and 2. The OIRF analysis (shown in Figure 6.A) reveals that social media valence does not significantly impact the growth rate of brand image scores for either channel initially. Short-term elasticities (Table 6) show that for week 1 the impact is non-significant and negative for both direct (-4.64 x 10^{-02}) and indirect (-4.297 x 10^{-03}) channels. By week 2, ValSt shows their highest impact on both channels, a non-significant positive effect on OBIMrdt (1.18 x 10^{-02}) and a significant positive effect on OBIMrit (2.49 x 10^{-02}). The cumulative effect (e_{cum}) of social eWOM valence on the direct channel is negative (-4.17 x 10^{-02}), suggesting a negative relationship. In contrast, the indirect channel shows a cumulative effect of -2.42 x 10^{-02}, indicating a more significant overall positive influence on growth rates for indirect customers.

As Maier & Wieringa (2021, p. 323) highlight, the absence of a standardized statistical test is addressed by examining overlapping confidence intervals of the OIRFs, which reveal no statistically significant difference between the two channels in the immediate impact of social eWOM valence on customer reviews growth rates. Both channels' responses diminish and stabilize by week 4, indicating similar and non-significant long-term effects (Table 7).

The FEVD results (see Figure 7) show that by Week 8, social media valence accounts for 7.1% of the variance in brand image scores for direct channels (graph on the left). This percentage indicates that customers using direct channels are considerably influenced by social media sentiment in their perception of the brand. In contrast, it only contributes 1% to the variance for indirect channels (graph on the right). These findings underscore that social media valence has a more pronounced impact on the variability of brand image scores for direct channel customers compared to those using indirect channels by the 8th week.

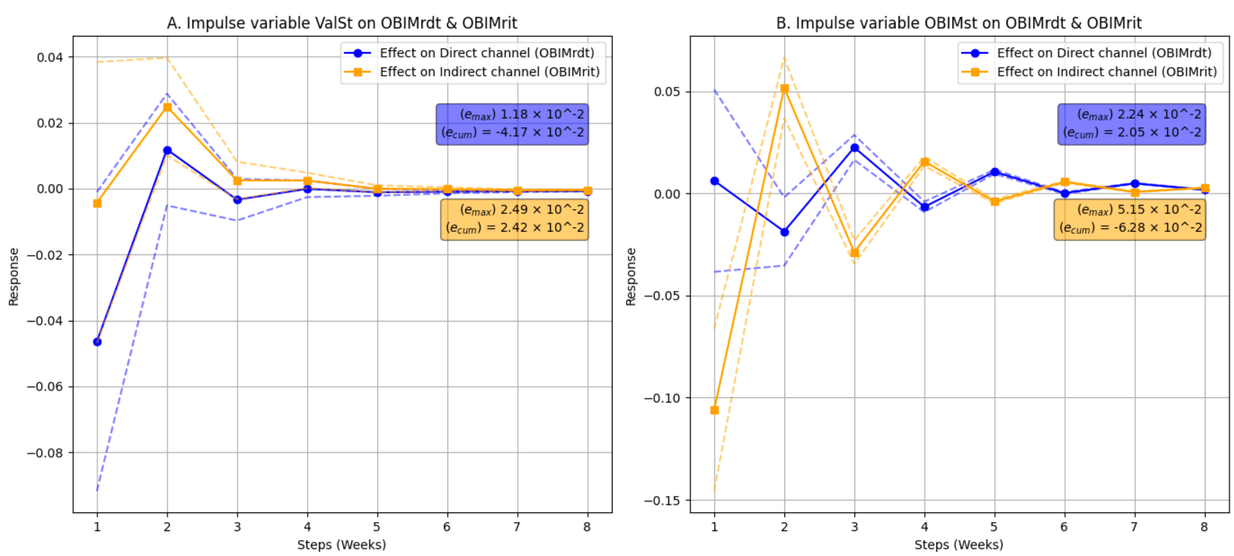

Figure 6: Orthogonalized Impulse Response Functions (OIRF) plots for Impulse variable ValSt and OBIMst

Regarding H2b, OIRF and FEVD evaluated the role of social media-derived brand image perception (OBIMst) and its effect on OBIM scores across both indirect (OBIMrit) and direct (OBIMrdt) channels. The OIRF analysis (see Figure 6.B) indicates that the influence of OBIMst on brand image scores differs by channel. Table 6 shows that in Week 1, the direct channel (OBIMrdt) shows a small and statistically insignificant elasticity of 6.18×10^{-03}, suggesting a small immediate impact. In contrast, the indirect channel (OBIMrit) displays a significant negative elasticity of -1.06×10^{-01}, indicating an inverse effect on brand image scores. By week 2, the direct channel's elasticity shifts to -1.87×10^{-02}, indicating a significant negative impact. On the other hand, the indirect channel shows a significant positive elasticity of 5.15×10^{-02}. Table 7 shows that by Week 8, both channels exhibit very small elasticities (9.97×10^{-06} for direct and 5.92×10^{-06} for indirect), indicating minimal long-term effects of social media-derived brand image perception. The cumulative effect for the direct channel is 2.05×10^{-02}, while the indirect channel shows a negative cumulative effect of -6.28×10^{-02}. This suggests that, in the short term, social media-derived brand image perceptions negatively impact direct channels but have a positive influence on indirect channels.

The FEVD analysis (Figure 7) supports these findings by illustrating the relative contributions of social media-derived brand perceptions to customer reviews. Specifically, social media-derived perceptions account for 0.71% of the variance in brand image scores for reviews on the direct channel and 13.1% for the indirect channel. This indicates that while brand image perceived on social media have a modest impact on the direct channel's variance, they play a more significant role in explaining the variance for the indirect channel.

The OIRF plot indicates that while social media-derived brand image perceptions have a notable short-term impact on both channels, the response fluctuates between positive and negative over time. The indirect channel shows a stronger immediate positive response at week 2 compared to the direct channel; however, this does not translate into sustained positive effects in subsequent weeks. This suggests that while there is a short-term enhancement of brand image perception in indirect channels, it is not consistent over the long term. The FEVD findings confirm that brand image perceptions on social media contribute more substantially to the variance in brand image scores for indirect channels, highlighting their differential impact based on the channel. Consequently, although there is some short-term support for the hypothesis that indirect channels enhance the impact of social media-derived brand perceptions, the lack of consistent long-term effects means that the hypothesis cannot be fully accepted. The dynamic nature of the impact underscores the complexity of social media's influence on brand image perceptions.

Table 6: Short-Term Effects of ValSt & OBIMst on OBIMrdt & OBIMrit

Impulse	**Week**	**Response: OBIMrdt**	**Response: OBIMrit**
ValSt	Week 1	-4.64×10^{-02} (4.45×10^{-02})*	-4.297×10^{-03} (4.20×10^{-02})
	Week 2	1.18×10^{-02} (1.61×10^{-02})	2.49×10^{-02} (1.54×10^{-02})*

OBIMst	Week 1	6.18×10^{-03} (4.44×10^{-02})	-1.06×10^{-01} (4.01×10^{-02})*
	Week 2	-1.87×10^{-02} (1.57×10^{-02})*	5.15×10^{-02} (1.49×10^{-02})*

Values are reported with two decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8). The full table, including all variables in the model, is in Appendix H.

Table 7: Long-Term Effects of ValSt & OBIMst on OBIMrdt & OBIMrit

Impulse	Response: OBIMrdt (Elasticity)	Response: OBIMrit
ValSt	-1.04×10^{-05} (1.80×10^{-04})	1.404×10^{-05} (1.43×10^{-04})
OBIMst	9.97×10^{-06} (1.38×10^{-04})	5.92×10^{-06} (1.34×10^{-04})

Values are reported with two decimal places. Long-term elasticities (8-week period) include standard errors in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8). The full table, including all variables in the model, is in Appendix H.

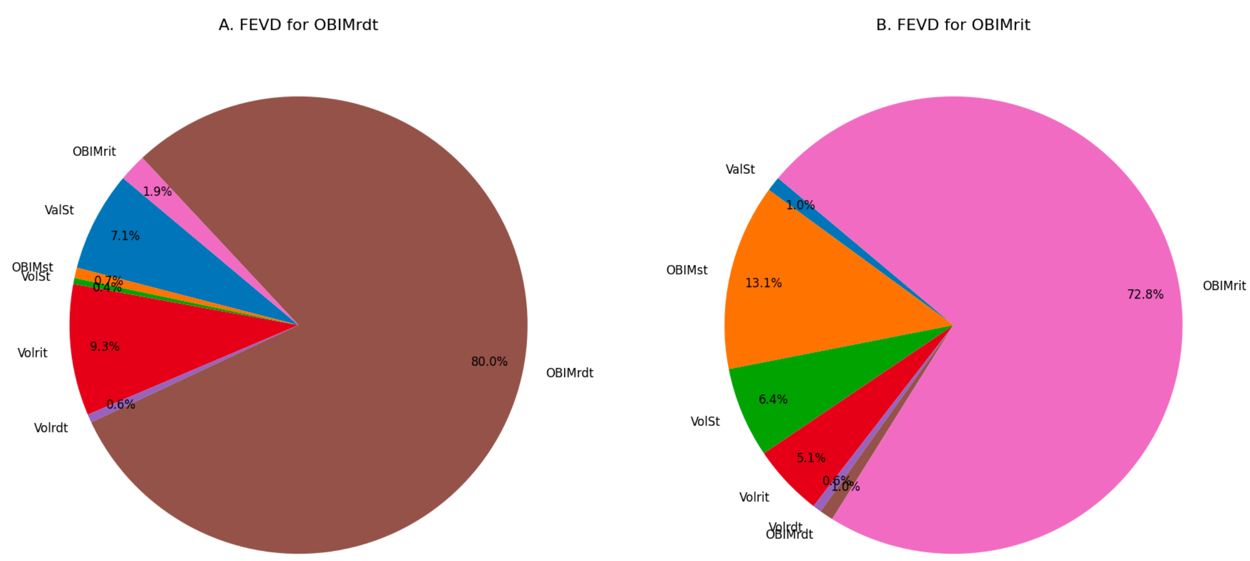

Figure 7: Cumulative Forecast Error Variance Decomposition (FEVD) for OBIMrdt and OBIMrit (up to 8 weeks)

In summary, H2a, suggesting that purchasing through indirect channels (vs direct) positively moderates the impact of social media eWOM valence on brand image perception in customer reviews, is not supported. The overlapping confidence intervals demonstrate no significant difference across channels, meaning no moderation effect was found. However, in the short term, indirect channels show a greater response to social media eWOM valence compared to direct channels. Furthermore, H2b, which posits that purchasing through indirect channels (versus direct channels) positively moderates the impact of social media-derived brand image perception on brand image perception in customer reviews, is not supported. Although social media-derived brand image perceptions have a notable short-term impact, the effects are inconsistent, with fluctuations between positive and negative. No clear moderation effect was found as the values oscillate and do not show a consistent pattern across channels.

Overall, social media valence does not lead to significant or sustained changes in brand image scores across purchase channels. While the indirect channel shows a stronger short-term response, this effect fades over time. Social media-derived brand image impacts brand image scores inconsistently and fluctuates between channels, showing no clear long-term advantage for either purchase channel.

The main findings of all hypotheses are summarized in Table 8, below.

Table 8: Summary of Hypothesis Testing Results

Test Conducted \ Hypothesis		**H1a: Valence of social media eWOM positively influences brand image perception among customer reviews.**	**H1b: Brand image perception among social media eWOM positively influences brand image perception among customer reviews.**	**H2a: Purchasing through indirect channels (versus direct channels) positively moderates the impact of social media eWOM valence on brand image perception in customer reviews.**		**H2b: Purchasing through indirect channels (versus direct channels) positively moderates the impact of social media-derived brand image perception on brand image perception in customer reviews.**	
				Direct Channel	Indirect Channel	Direct Channel	Indirect Channel
Granger causality test (p-value)		0.4319	0.4874	0.1784	0.9734	0.1918	0.0254
Orthogonalized Impulse Response Functions (OIRFs)	e_{cum}	6.13 × 10^{-02}	4.41 × 10^{-03}	-4.17 x 10^{-02}	2.42 x 10^{-02}	2.05 x 10^{-02}	-6.28 x 10^{-02}
	Week 0 elasticity	3.22 x 10^{-02}*	1.07 x 10^{-02}	n.a	n.a	n.a	n.a
	Week 1 elasticity	3.41 x 10^{-02}*	-3.58 x 10^{-02}*	-4.64 x 10^{-02}*	-4.297 x 10^{-03}	6.18 x 10^{-03}	-1.06 x 10^{-01}*
	Week 2 elasticity	4.18 x 10^{-03}	1.04 x 10^{-02}*	1.18 x 10^{-02}	2.49 x 10^{-02}*	-1.87 x 10^{-02}*	5.15 x 10^{-02}*
	Long term elasticity	-2.096 x 10^{-07}	2.35 x 10^{-06}	-1.04 x 10^{-05}	1.404 x 10^{-05}	9.97 x 10^{-06}	5.92 x 10^{-06}
Forecast Error Variance Decomposition (FEVD)		5.5%	3.6%	7.1%	1.0%	0.71%	13.1%
Hypothesis Result		**Accepted in the short term**	**Rejected**	**Rejected**		**Rejected**	

6. Discussion

6.1. Valence Impact on Reviews vs. Brand Image Scores

The findings from H1a and H1b highlight that the overall tone of social media discussions has a more substantial impact on customer reviews than the specific attributes captured by OBIM scores. This indicates that consumers are more influenced by the general sentiment of social media rather than detailed brand attributes that users talk about. One possible explanation for this is that, due to the information overload characteristic of social media, consumers may rely on the overall tone as a simplifying strategy. This behavior aligns with the concept of satisficing, where individuals form opinions rapidly without engaging in comprehensive analysis (Schwartz et al., 2002). Additionally, the anchoring effect could be at play as well, where the tone of the first information they find on social media serves as a significant anchor that shapes and influences subsequent conversations about the brand (Wansink et al., 1998). The overall sentiment thus acts as a powerful cue, it tends to persist in consumers' minds, overshadowing the specific topics of individual conversations they encounter. However, it is important to note that the significant effect of social media tone on consumer behavior is mainly observed in the short term. While it can strongly influence initial perceptions and reviews, these effects tend to diminish over time. Prior research (Colicev et al., 2018) has supported the broader impact of social media actions on consumer mindset metrics through engagement with electronic social media. Our study complements these findings by highlighting that the influence of social media tone is particularly significant in the short term. These findings add evidence to the importance of managing social media tone to influence consumer reviews effectively in the short term.

6.2 Short-Term Social Media Impacts on Direct and Indirect Channels

Both direct and indirect channels experience greater impacts from social media influences in the short term. Our analysis indicates that both channels are most significantly affected by social media shocks (valence and brand image scores) within the first three weeks following an impulse. This underscores the importance for marketers to implement strategies that capitalize on these short-term boosts. Brands should be prepared to leverage these short-term surges in sentiment and discussions to drive immediate engagement and sales. However, these influences tend to fade over time. To manage this dynamic effectively, brands should engage continuously and proactively by maintaining regular interaction with followers and promptly addressing any negative feedback. This approach should be applied consistently across both social media platforms and online customer reviews.

6.3. Effects of social media eWOM on Brand Perception Across Channels

The results for Hypothesis 2 also indicated that while the valence of social media eWOM impacted brand image perception across both direct and indirect purchase channels, no significant moderation effect by channel type was found. This consistency suggests that consumers process and react to social media sentiment in a similar manner, regardless of whether they are purchasing directly from the brand or through third-party platforms. This finding is consistent with Song et al. (2023), which found no significant difference in purchase intention between a brand's own website and third-party websites when review volume is high. A closer look reveals that indirect channel customers are a bit more responsive to social media valence compared to direct channel customers. This aligns with findings from Kato (2022), which suggest that consumers at the brand site are more willing to repurchase than those at third-party sites. Similarly, Pauwels et al. (2016) discuss how different types of eWOM affect online store traffic, and our study extends this understanding by providing a slightly different perspective on the short-term impact of the overall tone of social media discussions on customer reviews and brand perceptions. The dynamics of social media-derived brand image perceptions differ markedly between the two channels, with indirect channel customers showing significant but fluctuating effects, while direct channel customers demonstrate more stable responses.

Overall, the findings highlight the importance of timely and strategic management of social media sentiment. For brands like Sony Electronics, it is crucial to address social media impacts promptly to capitalize on short-term boosts, mitigate potential negative effects to maintain a positive brand image across both direct and indirect purchasing channels.

6.4. Consumer Behavior and Social Media Influence Across Purchase Channels

Although our findings suggested that there is no significant moderation effect by channel type, differences in consumer responses to social media eWOM exist and can be strategically leveraged by the brand.

Customers purchasing through direct online channels, such as Sony's own website, exhibit high sensitivity to social media eWOM valence. A significant portion of the variance in their brand image scores is attributed to social media sentiment, yet the accumulated elasticity indicates a negative long-term impact. This suggests that direct purchasers, due to their closer relationship with the brand and higher expectations, may develop critical views if those expectations are not met over time. As Kato (2022) and Magnini & Karande (2011) findings, customers who choose to buy directly from the brand's website, such as Sony's own site, can have stronger loyalty and maintain a direct relationship with the brand. Direct purchasers might also perceive social media information with skepticism, viewing it as marketing-driven rather than genuine feedback. This skepticism is increasing due to the prevalence of questionable practices, such as offering rewards for positive reviews, which contributes to the rise of persuasion knowledge among consumers (Román et al., 2023). In this context, brands should focus on maintaining high levels of customer satisfaction and managing expectations through proactive engagement and personalized communication. Addressing skepticism through transparent and authentic interactions can be a way to mitigate potential negative impacts on brand perception (Connors et al., 2015).

In contrast, customers engaging through indirect purchase channels, such as third-party retailers, seem to develop a more comprehensive and sustained impression from social media eWOM. The FEVD of 1% suggests that the immediate influence of social media valence on these indirect channels is less pronounced. This implies that indirect purchasers' perceptions may be shaped by a broader array of factors, such as price, convenience, and overall market conditions. These customers tend to be less reactive to short-term fluctuations in social media sentiment. However, they do demonstrate a higher sensitivity to social media-derived brand image, as evidenced by a high FEVD of 13.1%. This aligns with Jindal et al. (2021), who emphasize that online customers are often influenced by competitive factors such as convenience and price, making them more susceptible to the narratives shaped by social media. This broader influence can significantly affect their overall brand perception.

Understanding these nuanced consumer behaviors is essential for effective social media management. While there may not be a need for tailored strategies per channel, recognizing these behavioral differences can help brands better manage overall social media sentiment while improving online customer experience. This study provides a foundation for future investigations into how social media and customer reviews influence brand perception. Previous studies, such as those by Li & Hitt (2008) and Yin et al. (2016), have established that past reviews significantly impact potential buyers' perceptions of product quality. Future research could explore whether reviews on a brand's site are perceived as more filtered or controlled by the brand, potentially affecting consumer trust and perceived objectivity. For consumers without a strong attachment to the brand, third-party sites may offer a more impartial perspective. Moreover, exploring cross-channel spillover effects could yield valuable findings, whether exposure to reviews on third-party platforms influences consumers to visit the brand's own website, exploring how different sources of information impact their decision-making process.

6.5. Managerial Implications

This research has provided insights regarding the impact of social media sentiment on brand perception. To leverage on these findings, brands should adopt proactive crisis management practices by investing in sophisticated social media listening tools to track sentiment in real-time. Given that social media sentiment and discussions notably affect both channels within the first three weeks following an impulse, brands need to adopt agile and responsive strategies. Investing in sophisticated social media listening tools to track real-time sentiment shifts will allow brands to quickly respond to both positive and negative trends. By promptly identifying and responding to shifts in sentiment, brands can mitigate negative eWOM effects effectively. Research on crisis management strategies suggests that brands can use a strategic silence approach to manage online firestorms, which involves refraining from responding to negative sentiment to prevent escalation. Alternatively, a sympathetic response strategy can be employed, where showing empathy and understanding can potentially trigger more positive engagement from users (Qu et al., 2023).

Moreover, instead of allocating budgets to develop tailored engagement strategies for different online channels, brands should focus on delivering a unified message that resonates across all platforms. This approach not only reinforces the brand's core values and identity but also ensures that consumers receive consistent messaging. This consistency can strengthen brand associations and loyalty, safeguarding the brand against potentially damaging social media discussions. Engaging content, such as user-generated posts and testimonials, can be utilized to shape consumer perceptions and improve brand image across multiple channels (Roma & Aloini, 2019). By reinforcing brand concept consistency, brands can enhance consumers' evaluations and build a more cohesive and compelling brand presence online (Lanseng & Olsen, 2012).

Both purchase channels experience significant short-term impacts from social media influences. To capitalize on these boosts and prevent negative brand perceptions, brands should maintain high levels of satisfaction and manage expectations proactively, especially for direct purchasers who are highly sensitive to social media sentiment and may encounter negative information online. Transparent communication and prompt issue resolution are critical, along with personalized engagement to foster strong relationships. Indirect purchasers, influenced by broader factors, react less immediately to social media valence but are more affected by cumulative brand image. Brands should enhance their overall narrative and reputation through a consistent and positive social media presence.

7. Conclusion

This study provided valuable insights into the interplay between social media eWOM, brand image perception, and online purchase channels. Our main effect findings demonstrate that positive social eWOM valence initially enhances brand image perceived on customer reviews, indicating that consumers are influenced more by the general tone of social media discussions rather than by specific details. Additionally, customers using indirect purchase channels exhibit a more pronounced short-term response to social media influences compared to those using direct channels. However, despite these short-term differences, there is no significant moderation effect by channel type, suggesting that both social media eWOM valence and brand image derived from social media have a consistent influence on brand perception across different channels. Thus, while the intensity of short-term impacts may vary, the fundamental effect of social media sentiment on brand perception is uniform across channels.

Moreover, there are some limitations regarding the methodology used. The sampling process, sample size, and scope were constrained to external factors, which may impact the generalizability of the findings. Additionally, the metrics used to assess brand image may have inherent biases or inaccuracies, which could affect the results. The study’s use of primarily quantitative methods might overlook qualitative aspects within social media sentiment and customer review creations. Incorporating methods such as content analysis could offer deeper insights into how eWOM specifically impacts brand image on reviews. Furthermore, the timeline from a user's social media interaction to their purchase decision and review is a black box, and our assumption might not fully capture the true duration of this process, which could influence the accuracy of the findings. Other influential factors, including marketing campaigns, price competition, or product quality changes, were not controlled for, potentially leading to confounding effects in our dependent variable. Finally, the focus on Sony Electronics, with its unique brand characteristics, might limit the applicability of the findings to other brands or industries. Future research should address these limitations by expanding the sample size and study period, and including a diverse range of brands and industries, to provide a more comprehensive understanding of social media’s impact on consumers brand perception.

In summary, this research contributes to the broader understanding of social media eWOM's role in brand management, offering both theoretical evidence and practical recommendations for brands. It provides actionable insights for brands to navigate social media challenges effectively, refining strategies for immediate brand image management, and enhancing brand reputation in the short term.

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9. Appendix

Appendix A. Detailed Computation of Brand Image Score

OBIM Score Formula. The OBIM score of each aspect is obtained by multiplying its favourability, strength, and uniqueness scores. The overall OBIM score for the brand is then calculated by summing all the OBIM values of the aspects.

Favourability. Aspects mentioned in consumer reviews are identified as brand associations using natural language processing techniques. This process involves extracting opinion words from each review using the VADER sentiment dictionary and employing dependency parsing with spaCy to identify the syntactic structure of each sentence. Aspects are defined as nouns modified by opinion words, and rules are applied to identify them within the text corpus. We used two primary rules: if the opinion word is directly related to the target word or a word associated with the target word through an adjective or noun modifier, the target word is selected. To handle various sentence structures, additional rules are applied to manage adverbial modifications, comparative and superlative forms, and negations associated with nouns. This approach ensures that the extracted aspects accurately reflect the sentiment and associations in the consumer reviews.

In the next calculation step, sentiment scores are assigned to each aspect to measure favorability. This is achieved by using an unsupervised lexicon-based sentiment analysis approach, VADER, to analyze the sentiment of each opinion word associated with an aspect. The sentiment polarity score for each aspect is then calculated by averaging the sentiment scores of the opinion words.

Strength. The strength of each aspect within the review corpus is measured using co-word network analysis, where each element represents the frequency of co-occurrence of two words. This analysis helps in understanding how strongly each aspect is associated with the brand based on the frequency and context of its occurrence in the reviews.

The network consists of a set of vertices $G = \{w_1, w_2, ..., w_n\}$ where $\{w_1, w_2, ..., w_n\}$ are the words appearing in the entire corpus, along with a set of edges $E = \{e_{11}, e_{12}, e_{13}, ..., e_{nn}\}$ where e_{ij} exists if both the i^{th} and j^{th} words appear in the same context of the corpus. This co-occurrence matrix is then normalized to obtain the edge weights between nodes (words). The strength of each aspect is computed by averaging the edge weights connected to it, reflecting the frequency and significance of its co-occurrence with other words in the reviews.

Uniqueness. The distinctiveness of each aspect within the co-word network is quantified to determine its uniqueness in the context of the brand's overall image. To quantify the distinctiveness, the importance of each edge in the co-word network is calculated based on the degree of the connected nodes and the edge weight. The contribution of each node (aspect) over its connected edges is then computed, and the uniqueness score for each aspect is determined by summing its normalized degree and the contributions over its edges.

Appendix B. Stationarity results (ADF test)

Table B1: ADF test results for Eq.(1) variables

Variable	ADF Statistic	p-value	Status
ValSt	-5.598	0.000	Stationary
OBIMst	-2.836	0.053	Non-Stationary
OBIMst (differenced)	-3.855	0.002	Stationary
VolSt	-4.642	0.000	Stationary
Volrit	-3.362	0.012	Stationary
Volrdt	-4.067	0.001	Stationary
OBIMrt	-4.459	0.000	Stationary

Table B2: ADF test results for Eq.(2) variables

Variable	ADF Statistic	p-value	Status
ValSt	-5.598	0.000	Stationary
OBIMst	-2.835	0.053	Non-Stationary
OBIMst (differenced)	-3.855	0.002	Stationary
VolSt	-4.641	0.000	Stationary
Volrit	-3.362	0.012	Stationary
Volrdt	-4.067	0.001	Stationary
OBIMrdt	-2.418	0.136	Non-Stationary
OBIMrdt (differenced)	-7.252	0.000	Stationary
OBIMrit	-1.352	0.604	Non-Stationary
OBIMrit (differenced)	-4.261	0.001	Stationary

Appendix C. Granger Causality Test Results for H1a & H1b (p-values)

Cause \ Effect	**ValSt _x**	**OBIMst _x**
OBIMrt _y	$\mathcal{X}^2$ = 0.6178 (0.4319)	$\mathcal{X}^2$ = 0.4824 (0.4874)

Note: $\mathcal{X}^2$ values
∗∗∗p<0.001, ∗∗p<0.01, ∗p<0.05, ′p<0.1

Appendix D. VARMAX Model Results for Eq(1)

Table D1: VARMAX Model Results for Equation OBIM scores on customer reviews (OBIMrt)

Variable	Coefficient	Std Error	z Value	p-value	[0.025	0.975]
Intercept	3.1788	0.131	24.222	0.000***	2.922	3.436
L1.valence_social_ewom	-0.0287	0.126	-0.228	0.819	-0.275	0.218
L1.obim_scores_BW	-0.1568	0.192	-0.816	0.415	-0.534	0.220
L1.mentions_per_week	0.1076	0.174	0.618	0.537	-0.234	0.449
L1.num_reviewsAM	0.0384	0.308	0.125	0.901	-0.565	0.642
L1.num_reviewsSONY	0.1265	0.242	0.523	0.601	-0.348	0.601
L1.obim_scores_reviews	0.3236	0.280	1.154	0.248	-0.226	0.873
beta.Week	-0.0007	0.011	-0.068	0.946	-0.022	0.021
beta.CPI_VALUE	-0.0396	0.144	-0.275	0.783	-0.322	0.243

Note: $***p<0.001$, $**p<0.01$, $*p<0.05$, $'p<0.1$

Appendix E. Full Short and Long-term Elasticity tables for Eq.(1)

Table E1: Short-Term Elasticities for Model in Eq.(1) at Week 0

	ValSt	OBIMst	VolSt	Volrit	Volrdt	OBIMrt
ValSt	3.443495×10^{-1} $(7.361168 \times 10^{-2})$*	-1.085809×10^{-1} $(4.021585 \times 10^{-2})$*	-5.601315×10^{-2} $(5.397649 \times 10^{-2})$*	-2.088447×10^{-2} $(4.204254 \times 10^{-2})$	1.819507×10^{-2} $(2.994480 \times 10^{-2})$	3.216588×10^{-2} $(2.187294 \times 10^{-2})$ *
OBIMst	0.000000 (0.000000)	1.782620×10^{-1} $(2.762062 \times 10^{-2})$*	1.047313×10^{-2} $(1.020958 \times 10^{-1})$	-5.071647×10^{-3} $(7.967191 \times 10^{-2})$	3.270443×10^{-2} $(5.536215 \times 10^{-2})$	1.066510×10^{-2} $(3.657993 \times 10^{-2})$
VolSt	0.000000 (0.000000)	0.000000 (0.000000)	1.404039×10^{-1} $(8.278371 \times 10^{-2})$ *	-6.812377×10^{-3} $(1.238843 \times 10^{-1})$	-2.734194×10^{-2} $(7.575301 \times 10^{-2})$	3.061908×10^{-2} $(4.196671 \times 10^{-2})$
Volrit	0.000000 (0.000000)	0.000000 (0.000000)	0.000000 (0.000000)	1.654396×10^{-1} $(5.228848 \times 10^{-2})$ *	6.362315×10^{-3} $(4.813140 \times 10^{-2})$	3.972266×10^{-2} $(3.844665 \times 10^{-2})$ *
Volrdt	0.000000 (0.000000)	0.000000 (0.000000)	0.000000 (0.000000)	0.000000 (0.000000)	1.742140×10^{-1} $(1.659139 \times 10^{-2})$ *	1.430028×10^{-2} $(2.931448 \times 10^{-2})$
OBIMrt	0.000000 (0.000000)	0.000000 (0.000000)	0.000000 (0.000000)	0.000000 (0.000000)	0.000000 (0.000000)	1.567858×10^{-1} $(1.758334 \times 10^{-2})$ *

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).

Table E2: Short-Term Elasticities for Model in Eq.(1) at Week 1

	ValSt	**OBIMst**	**VolSt**	**Volrit**	**Volrdt**	**OBIMrt**
ValSt	7.442245×10^{-2} $(4.431336 \times 10^{-2})$ *	-5.280881×10^{-2} $(3.410790 \times 10^{-2})$ *	-1.275697×10^{-1} $(6.189116 \times 10^{-2})$ *	-1.456929×10^{-2} $(5.292205 \times 10^{-2})$	3.515347×10^{-2} $(3.762774 \times 10^{-2})$	3.408125×10^{-2} $(2.917856 \times 10^{-2})$ *
OBIMst	-8.345604×10^{-2} $(4.804428 \times 10^{-2})$ *	4.361364×10^{-2} $(3.316714 \times 10^{-2})$ *	1.568095×10^{-1} $(6.043148 \times 10^{-2})$ *	-2.393380×10^{-2} $(5.164631 \times 10^{-2})$	-5.013300×10^{-3} $(3.723400 \times 10^{-2})$	-3.576341×10^{-2} $(2.992405 \times 10^{-2})$ *
VolSt	2.964483×10^{-2} $(4.969014 \times 10^{-2})$	-2.969124×10^{-3} $(3.374491 \times 10^{-2})$	$-8.860870 \times 10-3$ $(5.463067 \times 10^{-2})$	-2.103662×10^{-3} $(5.370662 \times 10^{-2})$	8.657698×10^{-3} $(4.012440 \times 10^{-2})$	3.924667×10^{-2} $(2.916644 \times 10^{-2})$ *
Volrit	-4.753768×10^{-2} $(4.981216 \times 10^{-2})$	-2.533208×10^{-2} $(3.439537 \times 10-2)$	-1.651777×10^{-2} $(5.981326 \times 10^{-2})$	1.186523×10^{-1} $(5.054777 \times 10^{-2})$ *	5.988637×10^{-2} $(3.668070 \times 10^{-2})$	2.384288×10^{-3} $(2.929117 \times 10^{-2})$
Volrdt	2.750042×10^{-2} $(5.064466 \times 10^{-2})$	-2.822365×10^{-2} $(3.680482 \times 10^{-2})$	-4.556230×10^{-2} $(6.018692 \times 10^{-2})$	2.609430×10^{-2} $(5.043783 \times 10^{-2})$	3.836935×10^{-2} $(3.563548 \times 10^{-2})$ *	2.673517×10^{-2} $(2.788871 \times 10^{-2})$
OBIMrt	2.944012×10^{-2} $(5.112861 \times 10^{-2})$	-2.562832×10^{-2} $(3.436350 \times 10^{-2})$	-4.819265×10^{-3} $(5.863565 \times 10^{-2})$	2.112918×10^{-2} $(5.125910 \times 10^{-2})$	3.825361×10^{-2} $(3.706594 \times 10^{-2})$ *	5.945977×10^{-2} $(2.894916 \times 10^{-2})$ *

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).

Table E3: Short-Term Elasticities for Model in Eq.(1) at Week 2

	ValSt	**OBIMst**	**VolSt**	**Volrit**	**Volrdt**	**OBIMrt**
ValSt	2.286543×10^{-2} $(1.734274 \times 10^{-2})*$	-2.526802×10^{-2} $(1.150053 \times 10^{-2})*$	-4.986181×10^{-2} $(2.009966 \times 10^{-2})*$	5.315998×10^{-4} $(1.699507 \times 10^{-2})$	1.233743×10^{-2} $(1.241210 \times 10^{-2})$	4.176246×10^{-3} $(9.793969 \times 10^{-3})$
OBIMst	3.698505×10^{-3} $(1.609539 \times 10^{-2})$	2.257639×10^{-02} $(1.126981 \times 10^{-2})*$	3.436547×10^{-2} $(2.030525 \times 10^{-2})*$	-2.034001×10^{-2} $(1.660371 \times 10^{-2})*$	-1.635370×10^{-2} $(1.196903 \times 10^{-2})*$	1.038615×10^{-2} $(9.785488 \times 10^{-3})*$
VolSt	1.041886×10^{-2} $(1.532897 \times 10^{-2})$	-9.680205×10^{-3} $(1.100513 \times 10^{-2})$	-7.598184×10^{-3} $(2.072081 \times 10^{-2})$	3.433537×10^{-3} $(1.812391 \times 10^{-2})$	1.257621×10^{-2} $(1.269287 \times 10^{-2})$	1.528390×10^{-2} $(1.021225 \times 10^{-2})*$
Volrit	-2.328417×10^{-2} $(1.588195 \times 10^{-2})*$	-2.632891×10^{-2} $(1.064876 \times 10^{-2})*$	-4.272551×10^{-2} $(1.910625 \times 10^{-2})*$	9.582227×10^{-2} $(1.806996 \times 10^{-2})*$	4.475799×10^{-2} $(1.299057 \times 10^{-2})*$	3.330109×10^{-4} $(9.767794 \times 10^{-3})*$
Volrdt	8.763360×10^{-3} $(1.527452 \times 10^{-2})$	-2.127199×10^{-2} $(1.146305 \times 10^{-2})*$	-3.621917×10^{-2} $(1.956797 \times 10^{-2})*$	2.832173×10^{-2} $(1.725450 \times 10^{-2})*$	2.308325×10^{-02} $(1.192852 \times 10^{-2})*$	9.841745×10^{-3} $(9.259552 \times 10^{-3})*$
OBIMrt	2.273593×10^{-2} $(1.609311 \times 10^{-2})*$	-2.625065×10^{-2} $(1.133417 \times 10^{-2})*$	-3.908200×10^{-2} $(2.036685 \times 10^{-2})*$	2.946909×10^{-2} $(1.781358 \times 10^{-2})*$	3.206520×10^{-2} $(1.226857 \times 10^{-2})*$	3.088578×10^{-2} $(1.000009 \times 10^{-2})*$

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).

Table E4: Long-Term Elasticities for Model in Eq.(1) at Week 8

	ValSt	**OBIMst**	**VolSt**	**Volrit**	**Volrdt**	**OBIMrt**
ValSt	-9.400028×10^{-6} $(2.485027 \times 10^{-4})$	3.820279×10^{-7} $(1.442653 \times 10^{-4})$	-3.646363×10^{-6} $(2.305255 \times 10^{-4})$	5.283482×10^{-6} $(1.847751 \times 10^{-4})$	4.648559×10^{-6} $(1.385317 \times 10^{-4})$	-2.096433×10^{-7} $(1.094316 \times 10^{-4})$
OBIMst	-5.956222×10^{-6} $(1.862041 \times 10^{-4})$	$-1.599797 \times 10^{-}6$ $(1.465872 \times 10^{-}4)$	9.121506×10^{-6} $(2.210738 \times 10^{-4})$	9.504419×10^{-6} $(1.898835 \times 10^{-4})$	2.795844×10^{-6} $(1.178794 \times 10^{-4})$	2.347581×10^{-6} $(9.833486 \times 10^{-5})$
VolSt	-4.302776×10^{-6} $(1.987045 \times 10^{-4})$	1.711842×10^{-6} $(1.339138 \times 10^{-4})$	-7.561989×10^{-6} $(2.823430 \times 10^{-4})$	6.343572×10^{-6} $(2.066226 \times 10^{-4})$	5.700663×10^{-6} $(1.247484 \times 10^{-4})$	-6.292481×10^{-7} $(1.017003 \times 10^{-4})$
Volrit	5.208534×10^{-6} $(1.797696 \times 10^{-4})$	-2.303165×10^{-7} $(1.150537 \times 10^{-4})$	-3.324219×10^{-6} $(2.098892 \times 10^{-4})$	6.268340×10^{-7} $(2.081167 \times 10^{-4})$	-3.837039×10^{-8} $(1.232007 \times 10^{-4})$	-1.802198×10^{-7} $(1.002827 \times 10^{-4})$
Volrdt	1.065236×10^{-6} $(1.462515 \times 10^{-4})$	-3.917053×10^{-6} $(1.237172 \times 10^{-4})$	-8.427392×10^{-7} $(2.339637 \times 10^{-4})$	2.273275×10^{-6} $(1.885504 \times 10^{-4})$	-5.525062×10^{-6} $(1.710833 \times 10^{-4})$	-2.797780×10^{-7} $(9.627708 \times 10^{-5})$
OBIMrt	6.384531×10^{-6} $(2.016628 \times 10^{-4})$	-3.889844×10^{-6} $(1.260146 \times 10^{-4})$	-4.299083×10^{-6} $(2.538496 \times 10^{-4})$	-4.057208×10^{-6} $(2.187436 \times 10^{-4})$	-1.835627×10^{-6} $(1.340709 \times 10^{-4})$	-1.207482×10^{-5} $(1.432311 \times 10^{-4})$

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).

Appendix F. Granger Causality Test Results for H2 (p-values)

Table F1: Granger Causality Test Results for OBIM Scores and Social media Valence (p-values)

Cause \ Effect	**ValSt_x**
OBIMrdt _y	$\mathcal{X}^2$ = 1.8499 (0.1783)
OBIMrit _y	$\mathcal{X}^2$ = 0.0011 (0.9734)

Note: $\mathcal{X}^2$ values
∗∗∗p<0.001, ∗∗p<0.01, ∗p<0.05, ′p<0.1

Appendix G. VARMAX Model Results for Eq(2)

Table G1: VARMAX Model Results for Equation OBIMrdt

Variable	Coefficient	Std Error	z Value	p-value	[0.025	0.975]
Intercept	-1.2542	0.009	-138.008	0.000***	-1.272	-1.236
L1.valence_social_ewom	0.0859	0.111	0.772	0.440	-0.132	0.304
L1.obim_scores_BW	0.3306	0.074	4.475	0.000***	0.186	0.475
L1.mentions_per_week	0.3308	0.051	6.531	0.000***	0.232	0.430
L1.num_reviewsAM	0.0106	0.051	0.209	0.835	-0.089	0.110
L1.num_reviewsSONY	-0.1896	0.050	-3.807	0.000***	-0.287	-0.092
L1.obim_scores_direct	-0.4415	0.069	-6.428	0.000***	-0.576	-0.307
L1.obim_scores_indirect	0.0274	0.084	0.328	0.743	-0.136	0.191
beta.Week	-0.0036	0.005	-0.759	0.448	-0.013	-0.934
beta.CPI_VALUE	-7.321	0.012	-616.623	0.049*	0.000	0.132

Note: ∗∗∗p<0.001, ∗∗p<0.01, ∗p<0.05, ′p<0.1

Table G2: VARMAX Model Results for Equation OBIMrit

Variable	Coefficient	Std Error	z Value	p-value	[0.025	0.975]
Intercept	2.7517	0.018	149.094	0.000***	2.716	2.788
L1.valence_social_ewom	-0.0099	0.071	-0.138	0.890	-0.150	0.130
L1.obim_scores_BW	-0.2694	0.100	-2.687	0.007**	-0.466	-0.073
L1.mentions_per_week	-0.0064	0.065	-0.099	0.921	-0.134	0.121
L1.num_reviewsAM	-0.5364	0.051	-10.494	0.000***	-0.637	-0.436
L1.num_reviewsSONY	0.2415	0.070	3.438	0.001**	0.104	0.379
L1.obim_scores_direct	0.1242	0.089	1.396	0.163	-0.050	0.299
L1.obim_scores_indirect	-0.4831	0.094	-5.147	0.000***	-0.667	-0.299
beta.Week	0.0151	0.006	2.528	0.011	0.003	0.027
beta.CPI_VALUE	-0.2596	0.094	-2.758	0.006**	-0.444	-0.075

Note: ∗∗∗p<0.001, ∗∗p<0.01, ∗p<0.05, ′p<0.1

Appendix H. Full Short and Long-term Elasticity tables for Eq.(2)

Table H1: Short-Term Elasticities for Model in Eq.(2) at Week 1

	ValSt	OBIMst	VolSt	Volrit	Volrdt	OBIMrdt	OBIMrit
ValSt	7.862641×10^{-2} (4.5499×10^{-2}) *	-5.547194×10^{-2} (3.320055×10^{-2}) *	-1.287548×10^{-1} (4.234699×10^{-2}) *	-1.568515×10^{-2} (5.113855×10^{-2})	4.531897×10^{-2} (3.785848×10^{-2}) *	-4.641581×10^{-2} (4.448608×10^{-2}) *	-4.296566×10^{-3} (4.200157×10^{-2})
OBIMst	-9.7157×10^{-2} (4.68169×10^{-2}) *	4.592869×10^{-2} (3.188390×10^{-2}) *	1.624072×10^{-1} (4.062208×10^{-2}) *	-1.282550×10^{-2} (4.834046×10^{-2})	-5.109367×10^{-3} (3.598384×10^{-2})	6.178858×10^{-3} (4.437526×10^{-2})	-1.060138×10^{-1} (4.013019×10^{-2}) *
VolSt	7.976838×10^{-3} (4.67176×10^{-2})	-2.407850×10^{-3} (3.393209×10^{-2})	-3.559770×10^{-3} (4.132004×10^{-2})	2.806312×10^{-2} (4.864871×10^{-2})	8.087973×10^{-4} (3.570392×10^{-2})	-1.214362×10^{-3} (4.561188×10^{-2})	-4.073602×10^{-2} (3.928723×10^{-2}) *
Volrit	-3.7087×10^{-2} (4.98656×10^{-2})	-2.656000×10^{-2} (3.306299×10^{-2})	-1.584147×10^{-2} (4.104285×10^{-2})	1.098799×10^{-1} (4.752059×10^{-2}) *	5.158721×10^{-2} (3.537441×10^{-2}) *	-4.490920×10^{-2} (4.636672×10^{-2})	-7.150406×10^{-2} (4.140561×10^{-2}) *
Volrdt	4.053846×10^{-2} (4.87224×10^{-2})	-3.064720×10^{-2} (3.219×10^{-2})	-4.484590×10^{-2} (4.174×10^{-2}) *	1.305070×10^{-2} (4.983×10^{-2})	4.669242×10^{-2} (3.506×10^{-2}) *	-5.290443×10^{-2} (4.391055×10^{-2}) *	3.015558×10^{-2} (4.057100×10^{-2})
OBIMrdt	6.077712×10^{-2} (4.98155×10^{-2}) *	-1.341376×10^{-2} (3.276959×10^{-2})	-7.870477×10^{-3} (4.178130×10^{-2})	-5.266956×10^{-2} (4.778605×10^{-2}) *	3.444969×10^{-2} (3.528317×10^{-2})	-1.304446×10^{-1} (4.378569×10^{-2}) *	4.667856×10^{-2} (4.027704×10^{-2}) *
OBIMrit	-6.7870×10^{-3} (4.91054×10^{-2})	-2.250430×10^{-2} (3.413×10^{-2})	-8.693519×10^{-3} (4.118×10^{-2})	7.046151×10^{-2} (4.827×10^{-2}) *	7.445434×10^{-2} (3.599×10^{-2})	2.225501×10^{-2} (4.513×10^{-2})	-1.066000×10^{-1} (3.828×10^{-2}) *

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).

Table H2: Short-Term Elasticities for Model in Eq.(2) at Week 2

	ValSt	OBIMst	VolSt	Volrit	Volrdt	OBIMrdt	OBIMrit
ValSt	2.376421×10^{-2} $(1.726780 \times 10^{-2})$*	-2.441082×10^{-2} $(1.203983 \times 10^{-2})$*	-5.951470×10^{-2} $(1.504591 \times 10^{-2})$*	-3.435385×10^{-3} $(1.844721 \times 10^{-2})$	1.015522×10^{-2} $(1.316263 \times 10^{-2})$	1.182332×10^{-2} $(1.611824 \times 10^{-2})$	2.485731×10^{-2} $(1.536068 \times 10^{-2})$*
OBIMst	1.834206×10^{-3} $(1.777138 \times 10^{-3})$	3.169659×10^{-2} $(1.250233 \times 10^{-2})$*	4.639179×10^{-2} $(1.532529 \times 10^{-2})$*	-4.092144×10^{-2} $(1.715647 \times 10^{-2})$*	-1.522237×10^{-2} $(1.375122 \times 10^{-2})$*	-1.868263×10^{-2} $(1.572776 \times 10^{-2})$*	5.154232×10^{-2} $(1.488091 \times 10^{-2})$*
VolSt	-9.064506×10^{-3} $(1.811011 \times 10^{-2})$	-4.013647×10^{-4} $(1.240345 \times 10^{-2})$	-2.554425×10^{-3} $(1.554829 \times 10^{-2})$	9.512719×10^{-3} $(1.759281 \times 10^{-2})$	7.431267×10^{-3} $(1.309751 \times 10^{-2})$	-7.609114×10^{-3} $(1.571345 \times 10^{-2})$	5.376923×10^{-3} $(1.504619 \times 10^{-2})$
Volrit	-2.688844×10^{-2} $(1.871550 \times 10^{-2}$*	-1.902615×10^{-2} $(1.227443 \times 10^{-2})$*	-3.691641×10^{-2} $(1.492313 \times 10^{-2})$*	8.119286×10^{-2} $(1.843697 \times 10^{-2})$*	3.667297×10^{-2} $(1.338700 \times 10^{-2})$*	-1.797863×10^{-2} $(1.620211 \times 10^{-2})$*	6.816158×10^{-3} $(1.422411 \times 10^{-2})$
Volrdt	6.458500×10^{-3} $(1.825852 \times 10^{-2})$	-2.150021×10^{-2} $(1.240648 \times 10^{-2})$*	-4.113665×10^{-2} $(1.512558 \times 10^{-2})$*	3.222028×10^{-2} $(1.773881 \times 10^{-2})$*	1.602113×10^{-2} $(1.326319 \times 10^{-2})$*	8.873033×10^{-3} $(1.669756 \times 10^{-2})$	-1.149447×10^{-2} $(1.438812 \times 10^{-2})$
OBIMrdt	7.686576×10^{-3} $(1.795904 \times 10^{-2})$	-5.140227×10^{-3} $(1.216972 \times 10^{-2})$	-1.982618×10^{-2} $(1.520650 \times 10^{-2})$*	-2.738532×10^{-3} $(1.892922 \times 10^{-2})$	-1.421750×10^{-2} $(1.313366 \times 10^{-2})$*	5.729871×10^{-2} $(1.628635 \times 10^{-2})$*	-1.808952×10^{-2} $(1.437286 \times 10^{-2})$*
OBIMrit	-7.335003×10^{-3} $(1.778966 \times 10^{-2})$	-6.555625×10^{-3} $(1.214418 \times 10^{-2})$	-2.247627×10^{-2} $(1.532380 \times 10^{-2})$*	2.238676×10^{-2} $(1.706295 \times 10^{-2})$*	2.261638×10^{-2} $(1.234104 \times 10^{-2})$*	-3.350376×10^{-2} $(1.597763 \times 10^{-2})$*	3.547937×10^{-2} $(1.492932 \times 10^{-2})$*

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).

Table H3: Long-Term Elasticities for Model in Eq.(2) at Week 8

	ValSt	**OBIM st**	**VolSt**	**Volrit**	**Volrdt**	**OBIMrdt**	**OBIMrit**
ValSt	4.747129×10^{-5} $(2.941845 \times 10^{-5})$	-1.53339×10^{-5} (1.81296×10^{-4})	- 1.324344 10^{-5} (1.43769×10^{-4})	-5.161871×10^{-6} $(1.760540 \times 10^{-4})$	$5.815372 \times 10^{-6}(2.2419 \times 10^{-4})$	$-1.034653 \times 10^{-5}(1.8501 \times 10^{-4})$	$1.403998 \times 10^{-5}(1.426 \times 10^{-4})$
OBIM st	-4.254980×10^{-6} $(1.802604 \times 10^{-4})$	3.108958×10^{-5} (1.52755×10^{-4})	1.902355×10^{-5} (1.52732×10^{-4})	-2.176972×10^{-5} $(1.642797 \times 10^{-4})$	-1.380163×10^{-5} (1.398933x10-	$9.966635 \times 10^{-6}(1.3570 \times 10^{-4})$	5.922989×10^{-6} $(1.341980 \times 10^{-4})$
VolSt	7.090201×10^{-6} $(1.579741 \times 10^{-4})$	1.137181×10^{-6} (1.19136×10^{-4})	3.219811×10^{-5} (1.65020×10^{-4})	$-2.059788 \times 10^{-5}(1.823 \times 10^{-4})$	-1.352158×10^{-5} $(1.240905 \times 10^{-4})$	$6.744519 \times 10^{-6}(1.3908 \times 10^{-4})$	2.432655×10^{-6} $(1.520532 \times 10^{-4})$
Volrit	6.849860×10^{-6} $(1.746461 \times 10^{-4})$	-6.18477×10^{-6} (1.26590×10^{-4})	-2.76496×10^{-6} (1.26968×10^{-4})	$4.188107 \times 10^{-5}(2.169 \times 10^{-4})$	$2.141114 \times 10^{-5}(1.4684 \times 10^{-4})$	$1.227909 \times 10^{-6}(1.2852 \times 10^{-4})$	$-1.636766 \times 10^{-6}(1.444 \times 10^{-4})$
Volrdt	9.658656×10^{-6} $(3.561739 \times 10^{-4})$	-3.97534×10^{-6} (2.18194×10^{-4})	-4.83355×10^{-6} (1.64528×10^{-4})	$9.827934 \times 10^{-6}(1.929 \times 10^{-4})$	$3.494677 \times 10^{-5}(2.8411 \times 10^{-4})$	$-1.425065 \times 10^{-5}(1.9790 \times 10^{-4})$	$1.052023 \times 10^{-5}(1.668 \times 10^{-4})$
OBIM rdt	-6.920816×10^{-6} $(1.667968 \times 10^{-4})$	8.188768×10^{-6} (1.06326×10^{-4})	3.673044×10^{-6} (1.04695×10^{-4})	$-4.921620 \times 10^{-6}(1.421 \times 10^{-4})$	$-5.834649 \times 10^{-6}(1.1676 \times 10^{-4})$	$3.293329 \times 10^{-5}(1.4088 \times 10^{-4})$	-1.377468×10^{-6} $(1.080695 \times 10^{-4})$
OBIM rit	-1.093974×10^{-6} $(1.483171 \times 10^{-4})$	-2.46817×10^{-6} (1.13069×10^{-4})	5.150167×10^{-5} (1.17157×10^{-4})	$3.963645 \times 10^{-6}(1.507 \times 10^{-4})$	$1.755749 \times 10^{-6}(1.2473 \times 10^{-4})$	1.315543×10^{-6} $(1.279342 \times 10^{-4})$	3.277470×10^{-5} $(1.907548 \times 10^{-4})$

Values are reported with six decimal places. Standard errors are provided in parentheses. Elasticities with a t-value > 1 are marked with an asterisk (*) to indicate statistical significance (Pauwels et al., 2016, p. 8).