The Echoes of eWOM in the Metaverse

The Study of Sentiment's Effect on Participation Intention
in "NikeLand" Marketing Project

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ABSTRACT

With the advent of the Metaverse and the development of virtual reality technology, brands' digital marketing strategies have evolved, thus creating new opportunities for consumer-brand interaction. In this trend, electronic word-of-mouth (eWOM) on social media about a brand, product, or service remains one of the key factors influencing consumer behavior. Twitter, one of the mainstream social media platforms, was chosen for this study to investigate the impact of users' sentiment in eWOM, expressed in tweets, on other users' participation intention towards NikeLand, Nike's metaverse marketing program. This study is guided by the following research question: *To what extent does the sentiment in customers' tweets about the Nike Metaverse marketing project (NikeLand) impact other customers' intention to participate in NikeLand?* Nike has been chosen for this research because NikeLand is leading the NFT charge for big brands, and It carries significant value as it offers insights into the intricate interplay between virtual world environments and marketing strategies. A quantitative research approach was used in this study. First, data collection and sentiment analysis were conducted using SNScrape and SentiStrength. A total of 2152 tweets were analyzed, and the level of sentiment in them was evaluated and used to investigate the experimental conditions. Then, survey data were obtained from the participants as a survey, and regression analysis was performed to help analyze and answer the questions. This experimental design included four separate experimental groups, ultimately producing 258 valid responses. Based on the research findings, both positive and negative sentiments in customers' tweets significantly influence other customers' intentions to participate in the NikeLand project. However, contrary to expectations, the strength of this influence is not affected by the customer's gender or affiliation with Nike. Therefore, social media sentiment is critical in digital marketing campaigns, like NikeLand, irrespective of customer characteristics such as gender or brand loyalty. The findings from this study not only bridge the academic gap in the role of eWOM in brand metaverse marketing but also have strong social relevance. The conclusions shed light on how consumers' eWOM influences other users' consumption decisions and how companies can gain insights to effectively refine their digital marketing strategies. A further study of this relationship would be beneficial to explore the impact of other factors.

KEYWORDS: *Electronic Word-of-Mouth (eWOM), Metaverse Marketing, Participation Intention, Brand Behaviors, Sentiment Analysis*

Table of Contents

1. Introduction

Undoubtedly, the advent of Web 2.0 and the digital age have significantly transformed how consumers communicate and interact with brands and other consumers. One of the significant aspects of this change is the emergence of electronic word-of-mouth (Kudeshia & Kumar, 2017). Electronic word-of-mouth, or eWOM, refers to consumer reviews about a brand's products or services posted on social media platforms. In contrast to traditional word-of-mouth, which hinges on direct person-to-person social interaction, eWOM disseminates more swiftly and can reach a global audience (Babić Rosario et al., 2020). As communication technologies and social media platforms evolve, eWOM has solidified its role as a critical influencer of consumer behavior. It can determine consumers' participation or purchase intentions, yielding significant positive or negative impacts (Kudeshia & Kumar, 2017).

This evolution of communication style plays a vital role in the broader context of the digital marketing sector, and data-driven digital marketing has become a highly effective tool for businesses to market their products and services (Taylor, 2009). Specifically, Web 3.0 and the Metaverse - a form of an immersive 3D virtual world powered by the internet and social networks (Hollensen et al., 2022) - have opened brand new opportunities for businesses to engage with their audiences through Metaverse marketing (Dwivedi et al., 2022). This type of marketing leverages virtual and augmented reality to create immersive brand experiences and improve the overall user experience (Hollensen et al., 2022). By leveraging Metaverse marketing, companies can build communities, showcase products and create new revenue streams (Giang & Shah, 2023).

In the vanguard of these advancements, Nike launched NikeLand, a virtual world on the Roblox platform, in November 2021, replicating its global headquarters (Hollensen et al., 2022). By participating in the NikeLand and using virtual Nike products, players can wear virtual Nike products and play free games with pre-build and customizable games. In NikeLand, Nike products and sports are accessible to customers worldwide, and gamers can earn medals and ribbons for completing challenges. While many companies are doing virtual world marketing, the success of Nike and the successful implementation of NikeLand - with 7 million visitors from 224 countries - provide valuable insights for other brands looking to explore virtual world marketing strategies (Demir et al., 2023).

However, while embracing these novel marketing strategies, companies must also consider the impact of eWOM on social media platforms. This is particularly relevant when considering users' willingness to engage with a brand in the Metaverse (Liu et al., 2015; Kim

& Jung, 2022). According to Kim & Jung (2022), companies can leverage the power of eWOM to positively influence user engagement with their Metaverse campaigns, making it essential to consider the impacts of eWOM in Metaverse marketing for a successful marketing strategy in the Web 3.0 era.

Social media, particularly Twitter, has become a key platform for customers to express their opinions and feelings about brands and products (Wang et al., 2017). Wang et al. (2017) also state that the sentiment of customers' tweets can significantly influence their intention to participate in a brand or product. Naturally, positive customer sentiment in tweets can boost brand perception and participation intention, while negative sentiment can decrease it (Zhang et al., 2021).

The potential influence of sentiment expressed through social media highlights the need for a more in-depth exploration of its role in novel marketing contexts, such as Metaverse marketing. In particular, this study aims to examine the sentiment expressed in consumer tweets related to Nike's Metaverse marketing project, NikeLand. The ultimate objective is to comprehend how eWOM affects potential consumers' intention to participate in NikeLand, subsequently offering valuable insights that could assist other brands in refining their marketing strategies. Therefore, this study introduces the following research question:

RQ: *To what extent does the sentiment in customers' tweets about the Nike Metaverse marketing project (NikeLand) impact other customers' intention to participate in NikeLand?*

To address this research question, the researcher adopts a quantitative approach, drawing upon Friestad and Wright's persuasion knowledge model (1994) as a theoretical framework. The study's analysis comprises two phases. In the first phase, SNScrape is utilized to crawl Twitter for relevant data, following which the sentiment analysis software SentiStrength is employed to analyze the content of the 2,152 texts gathered automatically and to evaluate the intensity of positive and negative sentiment in the texts, rated on a scale of 5 to -5. Subsequently, the obtained sentiment analysis outcomes are imported into Tableau, a data visualization and analysis tool, to present precise percentages of positive and negative sentiment tweets. In the second phase, based on the ratings of the sentiments in the tweets, the researchers ranked the ratings from 5 to -5 and manually selected relevant tweets for the survey's experimental conditions. The survey is then administered through CloudResearch. The collected responses are subjected to regression analysis, enabling conclusions to be drawn.

1.1 Academic Relevance

In academia, numerous scholars have conducted studies on eWOM, focusing on areas such as the management of eWOM in the marketing domain (Babić Rosario et al., 2020) and the impact of the sentiment of consumers' reviews on Twitter (Pantano et al., 2018). As for research into online sentiments, various studies have extracted sentiment from texts to gain business insights into different domains. These include investigating gender equality in the workplace (Reyes Menendez et al., 2020) and enhancing resort business promotion (Philander & Zhong, 2016). However, despite Metaverse marketing developing rapidly, there appears to be a dearth of studies examining the impact of sentiment in online reviews (particularly on Twitter) on the consumers' intention regarding specific Metaverse marketing projects like Nike's NikeLand. As such, this study aims to contribute scientific insights to academia by filling this research gap.

1.2 Societal Relevance

This study has substantial societal relevance and promises to deliver value from several perspectives. Firstly, for consumers, this thesis' findings could further illuminate the mechanics behind eWOM and its influence on their consumption behavior. By understanding the impact of other consumers' online reviews and the sentiment expressed within these reviews, consumers could make more informed decisions when considering participation or purchasing products in reality or Metaverse (Babić Rosario et al., 2020). Secondly, this research can offer businesses valuable insights into the effects of online reviews on Twitter on the perception and reputation of their products or services. Based on these insights, companies can implement targeted strategies to enhance user experience and improve their eWOM reputation (Kim & Jung, 2022). Lastly, companies considering embarking on marketing or branding ventures in the Metaverse can benefit from the findings of this study. The research can facilitate a more comprehensive understanding of the industry and aid in assessing the feasibility of proposed projects, especially given that virtual and gamified environment are likely to take off given the continued development of VR technologies.

1.3 Chapter Outline

This thesis continues as follows. Chapter 2 begins by examining the theoretical underpinnings of eWOM and the sentiment expressed by customers through their tweets, as well as Nike's Metaverse marketing and customers' participation intentions, among other related theories. Chapter 3 provides an overview of the research design, including a description of the research methodologies employed to conduct the investigation and a discussion of operationalization. Chapter 4 presents, analyzes, and summarizes the investigation results, providing answers to the research questions and hypotheses posed. Additionally, potential research avenues and the study's limitations are discussed.

2. Theoretical Framework

2.1 eWOM

As eWOM has become an essential medium for consumers to share information about brands, products, and services, the digital era has fundamentally transformed the way they communicate about products and services (Liu et al., 2015). eWOM refers to customer reviews and statements about a product or company posted online (Babić Rosario et al.,2020). This contrasts with traditional word-of-mouth, which refers to passing information and opinions about products and services from person to person, and face-to-face in real (Jansen et al., 2009). Historically, traditional WOM was often regarded as more influential because it was based on direct social interactions between customers' families and friends. However, nowadays, eWOM has emerged as a distinct form of communication in the digital era because the perception of online comments has shifted, and eWOM is now perceived as more exciting and trustworthy than traditional WOM (Jansen et al., 2009).

Moreover, as technology has developed and social media has gained popularity, eWOM has become more critical in shaping consumer consumption behavior (Jansen et al., 2009). Also, the digitalization of media has significantly impacted customer brand-related behavior and purchase intentions, both positively and negatively (Liu et al., 2015). Overall, people are increasingly willing to accept and adopt product and service reviews from other online consumers on social media platforms (Cheung et al., 2008). Also, negative eWOM has more influence on consumers' decision-making than positive ones (Park & Lee, 2009).

Meanwhile, the growth of the internet and social media networks has also improved communication between customers, companies, and clients, thereby heightening the significance of eWOM in the marketing landscape (Rust, 2020). Given the impact of eWOM on consumer behavior, companies must pay attention to their eWOM reputation in the digital marketing era (Rust, 2020). Moreover, companies should proactively monitor and respond to eWOM feedback to maintain their brand reputation and avoid negative consequences (Liu et al., 2015).

eWOM benefits and challenges can be viewed from both consumer and company perspectives. On the one hand, consumers have access to more transparent brand information through eWOM. For instance, they can share their experiences with a product, whether positive or negative, through online channels, significantly impacting brand campaigns (Liu et al., 2015). Consequently, high proportions (> 80%) of consumers on some platforms have been found to make purchasing decisions based on other consumers' experiences (Rosario et al., 2020). This shift reflects how digitalization has changed how consumers access and share information.

On the other hand, for companies, eWOM can be a valuable tool to guide marketing efforts. Performing a positive reputation and using insights can improve transactions (Rosario et al., 2020). Since eWOM provides valuable information on consumer perceptions and preferences to refine marketing strategies (Liu et al., 2015). Furthermore, negative eWOM can lead to improvements, while positive eWOM can boost sales and recognition (Liu et al., 2015), making eWOM a powerful tool for driving business growth.

Although eWOM is an extremely beneficial marketing tool for brands, it presents several challenges and drawbacks. Judging the authenticity and credibility of eWOM can be challenging for consumers (Menkveld, 2013). Consumers may question overly positive reviews, suspecting they might be artificially planted or commissioned by companies (Martinez & Toral, 2019). Conversely, the validity of excessively negative reviews, potentially originating from competitors, can also be contested. Companies can artificially inflate a product or service's eWOM quantity and quality by utilizing "bots"—automated accounts—which can manipulate public opinion, skew user perceptions, and distort market trends (Menkveld, 2013). If exposed or discovered, this behavior could lead to a trust crisis among consumers toward the brand. Therefore, it is important for companies to manage eWOM effectively and ethically (Menkveld, 2013). It is also crucial for social media platforms to minimize bot-generated content and enhance the overall quality of content on the platform.

2.2 Persuasion Knowledge Model

Friestad and Wright's persuasion knowledge model (1994) is an influential marketing theory that has impacted advertising, marketing, and consumer behavior research. Various studies have applied this model to investigate the effects of online customer reviews and their persuasiveness in influencing consumer behavior (Evans & Park, 2015).

This model can serve as the theoretical foundation of this study. It suggests that customers are active participants who form their understanding based on prior knowledge and context (Evans & Park, 2015; Friestad & Wright, 1994). Their participation intention is shaped by their persuasion knowledge and the perceived credibility of online evaluations and reviews (Friestad & Wright, 1994). That is, customers consider the message's content and the source's credibility, trustworthiness, and expertise (Evans & Park, 2015). Hence, people are exposed to a persuasive message to activate and carry out defense mechanisms (Friestad & Wright, 1994).

Therefore, this model can help to explain to what extent the customers' tweets impact other customers' intention to participate in the NikeLand marketing project. In order to better understand how product or band evaluations and sentiment in relevant tweets influence customers' perceptions regarding the marketing project, more study is needed.

2.3 Twitter

Web 2.0 and web technologies have brought about significant changes in social media platforms, and Twitter has established itself as one of the most influential platforms with the broadest number of users. Since its launch in 2006, Twitter has garnered over 353 million users globally (Statista, 2023). Furthermore, it is reported that over 500 million tweets are published on Twitter daily (Philander & Zhong, 2016). Regarding total time spent by users, Twitter ranks among the top three social media platforms, indicating a high level of user engagement (Sun et al., 2019). Owing to the inherently viral and interactive nature of Twitter, the platform is highly conducive to the spread of eWOM (Kwak et al., 2010). Kwak et al. (2010) also assert that a tweet, once retweeted, can potentially reach a thousand times more users. Consequently, the influence of Twitter and its user-generated content (UGC) on both companies and consumers is substantial and far-reaching.

As an interactive communications medium, Twitter provides users with multiple forms of interaction, including "interpersonal interactivity" and "machine interactivity." Interpersonal interactivity refers to the ability of users to generate their information, exchange information with organizations and other users, and cite and forward information to others. On the other hand, machine interactivity refers to Twitter's capacity for embedding hyperlinks within tweets. Through this embedded feature, users can easily access additional information or transfer to alternate platforms by clicking hyperlinks found within tweets (Burton & Soboleva, 2011).

The virality and interactivity of Twitter have enabled it to develop numerous features that have made it an indispensable tool for marketing management, promotion distribution communication, and market research (Philander & Zhong, 2016). These features, including instant post comments coupled with emotional reactions from anywhere at any time, allow users to exchange valuable insights with others during critical decision-making stages. As highlighted by Burton & Soboleva (2011), this feature also signifies the increasing popularity of Twitter as a source for brand reviews alongside product information sharing between fellow customers, broadening the range of communication across organizations-users' interfaces in social media.

Twitter's data availability is notably more liberal than other social media platforms (Philander & Zhong, 2016). As a result, not only can Twitter be used as one of the essential marketing communication channels in marketing and market research (Burton & Soboleva, 2011), but companies and media organizations are also interested in mining Twitter's data to study what consumer groups on Twitter say and feel about their products. This enables them to make targeted adjustments to products, services, and marketing strategies (Philander & Zhong, 2016; Kouloumpis et al., 2011).

2.3.1 Tweets on Twitter

Originally a microblogging site, Twitter emerged with a unique, condensed structure for posts or 'tweets,' which are both informative and convenient (Burton & Soboleva, 2011). Initially, users could only post messages up to 140 characters long. However, this limit was increased to 280 characters in 2017 (Völcker, 2020) and expanded to 4000 characters in 2023, enhancing users' writing and reading experience on the platform. The platform has the distinct advantage of capturing many users' real-time experiences and emotions about any topic (Sun et al., 2019). Users can express their thoughts through tweet content, highlight key points using hashtags, and send messages to specific users, making Twitter ideal for content and sentiment analysis (Philander & Zhong, 2016).

In market research, Twitter data is precious due to its open network structure and unique features like hashtags and tweets, which facilitate data mining and analysis (Philander & Zhong, 2016). However, in its early days, the real-time and voluminous nature of Twitter feeds posed a challenge. Monitoring and identifying user reviews amidst the massive amount of content was time-consuming and nearly impossible for companies to do manually (Philander & Zhong, 2016). Given these challenges, computer-aided sentiment analysis has emerged as a promising research area (Philander & Zhong, 2016). It assists in analyzing large quantities of online reviews more time and cost-effectively than traditional market research methods such as surveys and interviews (Sun et al., 2019; Philander & Zhong, 2016).

2.3.2 Sentiment of the Customers' Tweets

Tweets can be analyzed for content and sentiment analysis (Thakor & Sasi, 2015), as they can capture customers' in-the-moment experiences and sentiments and can provide a non-intrusive research model compared to traditional methods (Philander & Zhong, 2016).

The sentiment of customers' tweets refers to the emotions or opinions expressed in their tweets about a particular product, service, or brand. The sentiment can be positive, negative, or neutral (Medhat et al., 2014). Works of literature point out that positive sentiment in tweets can lead to increased consumer participation and brand loyalty (Medhat et al., 2014), while negative sentiment can lead to decreased participation and lower brand loyalty (Pantano et al., 2018). Thus, companies can use sentiment analysis to monitor their customers' tweets and respond appropriately, which can help improve customer engagement and satisfaction (Thakor & Sasi, 2015).

2.4 Metaverse Marketing

The metaverse, a pioneering idea, merges platforms accessible through the internet and social media to create a 3D digital universe. Giang Barrera & Shah (2023) deem it apt to revolutionize business and societal activities, similar to how the internet transformed our lives. The metaverse, representing users' real-life counterparts (Dwivedi et al., 2022), allows for interaction with others and their surroundings, offering experiences close to reality. For businesses, the metaverse can offer transformational opportunities. For instance, they can use the metaverse as a laboratory for branding and marketing, targeting younger demographics and providing them with new levels of user interaction and engagement, thus strengthening their relationship with consumers (Dwivedi et al., 2022).

Brands' marketing strategies stand poised for a significant overhaul with the advent of this all-new metaverse era (Dwivedi et al., 2022). The sheer size and diversity offered by this new world present a golden opportunity for companies to expand their audiences through fresh ideas utilizing immersive and interactive features within this realm (Giang & Shah, 2023). Additionally, with augmented reality elements taking center stage in marketing, unique experiences that stick long into consumer memories can be created, consequently building brand loyalty while improving brand rankings overall (Hollensen et al., 2022). Finally, gaining valuable data entry points for consumers is another perk these technological advancements provide. Collecting detailed insights produces tailored marketing plans made exclusively according to specific markets, resulting in products enjoyed far more keenly (Hollensen et al., 2022). Thus, companies must innovate before being left behind within this rapidly evolving landscape (Dwivedi et al., 2022).

However, despite much initial hype and being seen as the windfall of internet development, the metaverse is developing and being adopted more slowly than expected. Dwivedi et al. (2022) state that metaverse marketing is still highly experimental at this stage, posing a challenge for marketers that cannot be ignored. The extensive infrastructure required to support the metaverse, including hardware and software accessibility, data storage and processing capabilities, and high barriers to digital integration technologies, inhibit the possibility of true metaverse globalization (Hazan et al., 2022). In addition, user affordability of hardware costs, such as for VR and AR (e.g., glasses, headsets, and other electronic accessories), must also be considered (Demir et al., 2023). Finally, brands and platform companies must also consider users' social and cultural factors. Since users' skills and knowledge bases vary depending on their socio-cultural background, brands need to choose the optimal solution among different virtual worlds and their unique features and qualities (Dwivedi et al., 2022). Overall, while the promise and potential of the metaverse are enormous, many challenges remain to be addressed.

2.5 Nike

2.5.1 Nike's Metaverse Marketing

Although the scholarly literature on metaverse marketing remains limited, real-world applications are burgeoning in advertising, luxury, retail, and fashion (Dwivedi et al., 2022). In particular, fashion brands, which prioritize an immersive shopping experience enabled by the high interactivity of the virtual world, are at the forefront (Demir et al., 2023). These virtual realms provide consumers with personalized experiences and comfortable spaces that exceed their expectations.

In the metaverse world, consumers have various options, such as purchasing virtual currency NFTs or visiting online showrooms (Dwivedi et al., 2022). For instance, Gucci Garden, a unique event hosted by Gucci on the Roblox platform, allows visitors to explore a virtual garden and try out numerous digital goods (Kim & Bae, 2023). However, the user's gaming experience remains central in the metaverse (Demir et al., 2023). This shift has given rise to brand gamification, and users experience this gamified virtual marketing through sensory, interaction, pleasure, flow, and community relations dimensions (Luo et al., 2011), exemplified by initiatives like Nike's NikeLand and Samsung's 837x (Tayal & Rajagopal, 2023). Among all the examples, the Nike Metaverse marketing project, *NikeLand*, has significant research value, providing insights into the intersection of virtual worlds and marketing strategies (Hollensen et al., 2022). The case provides an opportunity to study the impact of the potential of metaverse platforms for business-to-consumer brands and the impact on brand awareness and customer engagement.

NikeLand, launched in November 2021, is a virtual world within the Roblox platform replicating Nike's global headquarters in Beaverton, Oregon (Hollensen et al., 2022). The metaverse offers opportunities for gamers to play pre-built or customized in-world games and wear virtual Nike products. Furthermore, the platform is free to enter and offers gamification elements where players earn medals and ribbons for completing challenges. Beyond gaming, NikeLand also presents an opportunity for customers worldwide to experience Nike products and sports without the cost of products and equipment. The metaverse also has a business model that includes payment through the sales of non-fungible tokens (CryptoKicks) for unique collectible digital shoes that can be connected to physical products. Thus, the success of Nike, with seven million visitors from 224 different countries, highlights the potential for metaverse platforms to bring people together globally (Demir et al., 2023).

2.6 Brand Awareness

Brand awareness refers to consumers' familiarity and recognition of specific goods or services under different conditions and is crucial in shaping consumers' preferences and behaviors toward brands (Barreda et al., 2015). This concept reflects the brand's prominence in consumers' minds and is defined as the personal significance attached to a specific brand in consumers' memory, encompassing all descriptive and pertinent information (Keller, 2009).

Two dimensions define brand awareness: intensity and degree. Intensity signifies the strength with which consumers retrieve the brand from their memory, gauging the ease with which consumers can recall brand information. Conversely, degree indicates the extent of consumers' prior exposure to the brand, or in other words, their level of knowledge about the brand (Barreda et al., 2015). These two dimensions aptly analyze the brand's strength in the consumer's mind, according to Keller (2009). Considering the influence of brand awareness in driving participation or purchase decisions (Foroudi, 2019), it becomes pivotal to understand its impact on consumers' intention formation, whether for participation or purchase. Moreover, exploring the moderating effects of eWOM in this context is also essential.

2.7 Brand Attitudes

Brand attitude, another significant concept related to consumer behavior, acts as a psychological variable that bridges consumers' attitudes with their actual consumption or participation behaviors (Kudeshia & Kumar, 2017). Keller (2009) asserts that consumers demonstrating positive attitudes toward brands tend to be willing to pay higher prices.

Existing literature predominantly explores whether eWOM impacts consumers' attitudes and subsequent purchase intentions toward brands. Some research suggests that positive attitudes toward a specific brand significantly influence a consumer's purchase intention (Keller & Lehmann, 2006). However, the inverse scenario has received less attention. Hence, investigating whether consumers' brand attitudes moderate the effect of eWOM on participation and purchase intentions offers an intriguing avenue of research.

2.8 Customers' Purchase Intention

Purchase intention is a crucial dimension of behavioral intention, embodying a consumer's conscious plan or resolve to purchase a specific product (Ali, 2016). This individual consumption behavior - significantly influenced by information and emotions - is often employed as a reliable indicator of actual purchase behavior (Carrington et al., 2010). Considerable academic research has underscored the impact of brand perception concepts - including brand awareness, brand attitude, and brand affiliation - on consumer purchase intention toward a brand's overall product line (Foroudi, 2019; Kudeshia & Kumar, 2017; Lu et al., 2014). However, the role of eWOM, specifically regarding individual products or projects, such as NikeLand, and its moderating effects on consumer behavior, has yet to be explored. To address the academic gap, this research incorporated an examination of consumer purchase intentions towards NikeLand and the broader range of Nike products. The aim was to comprehensively understand the nuanced interplay between eWOM related to specific products and broader brand perception and how these influence consumers' purchase intentions for the brand's complete product line. The results of this extended analysis were presented in the 'Other Findings' section.

2.9 Customers' Participation Intention

Participation intention refers to a customer's willingness to actively promote a brand, product or participate in a service. It is influenced by customers' brand perception, satisfaction, and perceived value (Jun et al., 2020). Understanding participation intention is important for businesses as it can predict future behavior and guides marketing strategies (Zhang et al., 2021).

Purchase intention, brand attitude, brand awareness, and customer participation intention are often interlinked (Jun et al., 2020). A high participation intention may indicate a strong interest in the brand and increase the likelihood of purchasing. Consumers who often check a company's social media pages, participate in online brand discussions, or provide product reviews may strongly imply or lead to their buying intention (Zhang et al., 2021). As mentioned above (in the Sentiments of Tweets section), the sentiments of reviews can influence the consumer's intention to the participant. Because expressions - such as social media posts - can concurrently harbor both positive and negative sentiments (Thelwall, 2013), each dimension is treated separately. Thus, based on the above theoretical evidence, the following hypotheses are suggested:

H1: *The positivity in customers' tweets has a significant positive effect on other customers' intention to participate in the NikeLand project.*

H2: *The higher negativity in customers' tweets has a significant negative effect on other customers' intention to participate in the NikeLand project.*

In this research, H1 and H2 analyze the effects of different aspects of customers' tweets sentiments (positivity and negativity, respectively) on other customers' intentions to participate in the NikeLand project. Both hypotheses aim to understand the impact of these two sentiment components (positive and negative) on participation intention. Additionally, H1a - a separate but related hypothesis - examines the effect of overall sentiment (a unidimensional range of sentiment) in customers' tweets about the NikeLand project on other customers' intention to participate. This hypothesis can provide a broader view and does not distinguish between positivity and negativity but instead looks at the overall sentiment conveyed in the tweets. So, while testing the individual effects of positivity and negativity (H1 and H2) is appropriate, placing sentiment into a single variable (H1a) on participation intention can reveal its overall effect. Through such an approach, it would be possible to gain a more comprehensive understanding of how different aspects of sentiment in tweets can affect participation intentions.

H1a*: The sentiment in customers' tweets about the NikeLand project has a significant positive effect on other customers' intention to participate.*

2.10 Gender's Role in Participation Intention

Gender information is critical in market research, providing valuable insights into consumer psychology and behavior (Xue et al., 2020). Distinctive attitudes and behaviors exhibited by consumers of different genders lead to variations in engagement and consumption levels (Tung et al., 2017). Therefore, understanding these differences is crucial in developing effective marketing strategies and gaining deeper market insights.

Research indicates that men and women possess different capacities for perceiving emotions. The empathizing-systemizing theory points out significant differences between male and female consumers' information-processing approaches (Darley & Smith, 1995; Xue et al., 2020). For instance, male consumers' psychology and behavior are predominantly influenced by cognition. In contrast, female consumers can perceive a broader range of emotions, and their psychology and behavior are more sentiment-driven (Xue et al., 2020). Furthermore, female consumers tend to focus more on subtle cues in the information, which emotionally influences their participation or purchase intention (Tung et al., 2017). Given these findings, it was postulated that gender differences might moderate the impact of tweets of different sentiments on participation intentions. Based on this conjecture, the following hypotheses were formulated:

H3*: The relationship between the positivity in customers' tweets about the NikeLand project and other customers' intention to participate is stronger for female customers than male customers.*

H4*: The relationship between the higher negativity in customers' tweets about the NikeLand project and other customers' intention to participate is stronger for female customers than male customers.*

2.11 Brand Affiliation

Brand affiliation refers to consumers' emotional connection or attachment to a brand. It can be influenced by factors such as the brand's image, reputation, values, and perceived quality (Yasin, 2013). Besides, the degree to which a consumer identifies with or feels a sense of belonging to a particular brand or organization is essential for customer participation intention or purchase intention (Kaufman et al., 2011). Therefore, the person's previous affiliation with the brand could moderate the effect of sentiment in tweets on the intention to participate with the brand.

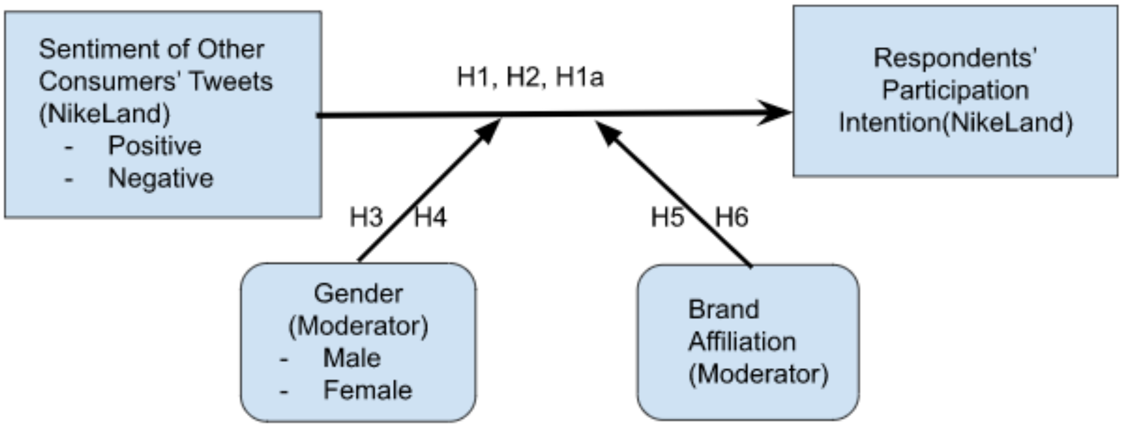
H5*: Positive tweets about the NikeLand project will have a stronger impact on participation intention for those who feel a strong affiliation with Nike.*

H6*: Negative tweets about the NikeLand project will have a weaker impact on participation intention for those who feel a strong affiliation with Nike.*

2.12 Conceptual Model

Below is a conceptual model that consolidates all of the hypotheses mentioned above (Figure 1). This model visually represents the relationships between various variables, ultimately addressing the corresponding research question.

Figure 1. *Conceptual Model*



3. Methods

3.1 Choice of Method and Justification

In order to test the hypotheses and answer the research question, the study employed a quantitative research approach, through which measurements could be obtained and compared as relationships between variables representing various concepts and constructs (Babbie, 2014). The effect of the findings on the sentiment of customers' tweets was subsequently tested on participation intention.

3.1.1 Sentiment Analysis of Tweets

The research was divided into two steps. To begin with, the researcher performed a sentiment analysis on selected customers' tweets about the NikeLand Metaverse project through SentiStrength (Thelwall, 2013). Sentiment analysis typically employs natural language processing techniques and machine learning algorithms to identify and classify sentiment in text data (Thelwall, 2013). This approach aims to determine the degree of both positivity and negativity in each tweet and classify it as positive, negative, or neutral (Pang & Lee, 2008). SentiStrength's algorithm addresses some of these issues by assessing sentiment based on arousal (low to high) and valence (positive to negative) (Thelwall, 2013). Therefore, the result can be used to understand customer opinions and attitudes toward products or services (Thelwall, 2013). In the end, the researcher selected comments that could be used as stimuli for the experiment.

3.1.2 Experimental Design

After the sentiment analysis of tweets, the method used to conduct the research is an online experimental design. This experiment was developed using Qualtrics, an online survey platform. The online experiment holds several advantages over offline experiments. Firstly, the online experiment is more convenient and can save significant time and monetary costs (Radford et al., 2016). Secondly, it dramatically reduces the potential for participants to be subject to researcher bias and interference (e.g., the observer effect). Thirdly, Qualtrics has the capability to assign a similar number of participants to each condition of the experiment, thereby ensuring that participants are automatically and randomly distributed evenly across all conditions.

3.2 Sample

3.2.1 Sampling for Sentiment Analysis of Tweets

A random sample of all historical tweets ($N = 2153$) - containing "NikeLand" or "#NikeLand " were obtained via the SNScrape (GitHub, n.d.). These were subjected to sentiment analysis via SentiStrength. The final set of tweets was gathered in March 2023. Several of these were selected from each sentiment rating (most positive, most negative, and neutral), and their sentiments were qualitatively verified by the researcher and appropriately adjusted for use as the manipulated stimuli of the experimental conditions: all tweets that were manually selected were styled/designed to appear as authentic tweets. Furthermore, anonymization was applied using fictitious usernames. The dates attached to these tweets were fabricated, and the texts of the tweets were slightly altered to maintain the privacy of the original tweets. Additionally, for negative tweets, any profanity was edited (e.g., "NikeLand on Roblox that’s f-cking dumb" and "definitely sh-t game" have been changed to "really, really dumb" and "totally useless") to prevent potentially alienating some respondents.

3.2.2 Sampling for Survey/ Experiment

The data collection for this study occurred between May 10 and 12, 2023. To answer the research question and test the hypotheses, the research units for the four conditions should consist of at least 30 respondents per condition. For the four conditions, a minimum of 120 respondents was required. However, to ensure a sufficient number of valid surveys, factoring in the potential exclusion of incomplete surveys and those screened out by the manipulation check, a total of $N = 316$ samples was collected for this experiment. The sample for this study was collected via the CloudResearch (Connect) survey crowd-sourcing platform and also via disseminating the survey link through the researcher’s own account on social media platforms such as Instagram, WeChat, and Facebook. Thus, the sampling was non-probability, purposive, and convenient and also included some snowball sampling (Etikan, 2016).

CloudResearch is an online crowdsourcing platform for labor that demands and anonymizes human opinions or attitudes (Douglas et al., 2023). CloudResearch presented several significant advantages. First, it allowed for faster data collection than offline labs. Moreover, because the researcher did not have direct contact with the participants, it minimized the influence of the experiment designer on the results (Douglas et al., 2023). Also, CloudResearch survey-takers are demographically more diverse than the average university sample, which made the results more representative of the general population (Crump et al., 2013). In this study, the compensation paid to each survey-taker on CouldResearch was set at 0.40 euros.

In addition, the researcher also used social media to distribute the survey for data collection to increase the sample size and diversity. However, this might have resulted in a slightly biased sample. All participants were assured of confidentiality, and their informed consent was obtained.

3.3 Survey Design and Procedure

This survey began with an informed consent form and an introduction to the study. Participants were informed that the research focused on examining the impact of sentiments in eWOM for the NikeLand project, along with their participation and purchase intentions. Also, participation was entirely voluntary. In addition, participants were assured that their data would be collected anonymously and used strictly for academic purposes. They were required to confirm their age as above 18 and agree to the terms to proceed with the survey. If not in agreement, they were directed to the survey's end immediately. After participants confirmed that they were older than 18 and agreed to begin the study, they first filled in the questions about their brand affiliation, brand awareness, and brand attitude about Nike. Then, they were randomly placed in one of four conditions, with three groups being exposed to manipulated stimuli and a control group receiving no stimuli. All groups watched the official "NikeLand" ad video before being subjected to the stimuli. The manipulated stimuli were tweets with solely positive sentiment, tweets with solely negative sentiment, or tweets with the neutral sentiment. This design was used for quantitative data analysis and allowed for direct comparisons between the conditions. The advantage here was the randomization of the participants. To ensure that the participants could watch the advertisement's video and the tweets being presented carefully, the researcher included a timer in the survey design.

Participants had to spend at least enough time watching the video and reading the tweets before moving on to the next step. Participants were then asked behavioral questions about the experimental variables. In total, the survey took an average of 8.2 minutes to complete. Before distributing the survey, the researcher pre-tested the survey/experiment with a few peers ($N = 5$) to test its usability and availability.

3.3.1 Manipulation Check

The respondents were asked near the end of the survey whether they saw the tweets and their perceptions of sentiment in the tweets as a manipulation check. The question was: "After watching the advertisement, did you see the tweets presented? If so, how would you define the overall sentiment expressed in the tweets you just read?". This question was included to check whether the participants had actually read the material presented in the experiment carefully. Research has shown that a manipulation check is crucial because it allows researchers to screen for valid responses, effectively improving the quality of the survey as well as the accuracy of the findings (Hauser et al., 2018). Finally, the underlying demographics of the participants were collected. Further details on the survey/experiment are discussed below. Also, see Appendix A for the full survey.

3.4 Operationalization

3.4.1 The Sentiment of Customers' Tweets of the NikeLand

The manipulated sentiment of customers' tweets regarding NikeLand was the main independent variable in this research. To measure this variable, the researcher first performed a sentiment analysis on selected customers' tweets ($N = 2153$) about the NikeLand Metaverse project using SentiStrength (Version 2.3; 2014). This produced a dual positivity and negativity score for each tweet: 0 to +4 for positivity and -4 to 0 for negativity. Tweets with high positivity and low negativity were candidates for the "positive" experimental condition, while the converse applied for the "negative" condition. The scraping approach also helped in acquiring a diversity of tweet content. Tweets exhibiting pure neutrality were candidates for the "neutral" condition. To make sentiment manipulation as effective as possible, six tweets per condition were provided in the experiment to ensure that the sentiment was sufficiently conveyed but also ensure that participants were not overwhelmed or exhausted.

Furthermore, after the sentiment analysis using SentiStrength, the data was imported into Tableau (Tableau 2023.1), a data analysis and visualization tool, for visualization. This resulted in a clear graphical representation of the percentage of tweets with positive, negative, and neutral sentiment in the overall tweets discussing NikeLand.

3.4.2 Customers' Participation Intention

The intention for participating in the NikeLand Metaverse virtual project is adopted and integrated from Dodds et al. (1991) purchase intention scale and Bhattacherjee's (2001) Users' continuance participation intention scale, with a total of three items for both scales together. The questions were modified in order to fit the consumed objects, e.g. "My willingness to participate in this project is…"(from continuance participation intention scale), "The likelihood of participating in this project is…", "The probability that I would 'consider' participating in this project is…"(from purchase intention scale). Responses choices were posed as a 5-point Likert range (1=very low, 5 =very high).

3.4.3 Gender

Gender was included as a control variable to conduct a moderation analysis with the participation intention and provide support to the discussion of the impact of gender on the intention to participate. The term 'gender' here is not only determined by biological characteristics but also by social and psychological characteristics. This variable was converted into the survey via the question: "Please indicate your gender". Four gender groups were included: "Male", "Female", "Non-binary/third gender", and "Prefer not to say", to ensure the research-maintained inclusivity and sensitivity.

3.4.4 Brand Affiliation

Brand affiliation was measured using a four-item scale adapted from Enginkaya & Yılmaz (2014). The researcher tailored the questions in the scale to better align with the study's context. The revised questions included: "I generally follow Nike on social media which is congruent with my lifestyle.", "On social media, I follow Nike products that I might buy in the future, although I am not planning on buying right now.", "I follow Nike on social media which I consume and/or purchase often." and "I think that my talking about Nike on social media due to my satisfaction or dissatisfaction influences my friends in my social network." The questions utilized a 5-point Likert range. Participants were asked to choose the option that best represented their viewpoint from the following: "Strongly disagree" (=1), "Somewhat disagree" (=2), "Neither agree nor disagree" (=3), "Somewhat agree" (=4), "Strongly agree" (=5).

3.4.5 Brand Awareness

The scale for assessing customer brand awareness comprises four items, with a 5-point Likert range (1=strongly disagree, 5=strongly agree). The scale was designed to increase reliability by merging and editing questions from two different scales all named brand awareness. Two of the items were adapted from Yoo & Donthu (2001). The questions were, "I am aware of Nike products" and "I can recognize Nike products among other competing brands," The remaining two items were sourced from Lu et al. (2014). These questions were, "I know Nike" and "When it comes to (product), I can immediately recall Nike". By merging and editing these questions, a more reliable scale was formulated to measure brand awareness for Nike.

3.4.6 Brand Attitude

The measurement of brand attitude was based on a three-item scale adapted from Hsiao et al.'s (2014) brand attitude scale. This scale gauges consumers' comprehensive evaluation of a brand derived from their perceptions of the brand (Hsiao et al., 2014). The specific questions included "I feel Nike products are good," "I like Nike products," and "I feel Nike products are favorable." Responses were also structured with 5 points, ranging from 'strongly disagree' (1) to 'strongly agree' (5).

3.4.7 Customer Purchase Intention

The scale for assessing customer purchase intention, adapted from Lu et al. (2014) customer purchase intention scale, comprises three items. This scale gauges consumers' intentional readiness to purchase a product or engage in other forms of consumption (Lu et al., 2014). The questions were suitably modified based on the research population of interest for this study and were posed to respondents as: "I would consider buying Nike products," "It is possible that I would buy Nike products," and "I will purchase Nike products the next time I am in need." Responses were structured on a 5-point Likert range, with ratings from "Very low" (=1), "Low" (=2), "Neither high nor low" (=3), "High" (=4), to "Very high" (=5).

3.5 Data Analysis

SPSS 26.0 was used for processing the data, reliability tests, including factor analysis, the main hypotheses tests, namely multiple regression. For H1, H2, and H1a, several multiple linear regressions with the customers' participation intention as the primary dependent variable (DV) were employed. The primary predictors (IVs) are the two main types of sentiment in customers' tweets: positivity and negativity (i.e., separate tests for each type of sentiment, implicitly comparing each one to the remaining two categories). For H3 to H6, moderation analysis was employed with the participants' gender, and brand affiliation as moderators and customers' participation intention as the DV. The main predictor (IV) was the sentiment level in customers' tweets.

3.6 Validity/Reliability

The validity of the used scales is suggested by the use of validated scales from the literature. In this study, the reliability of each scale was ensured by achieving a Cronbach's α exceeding 0.8, deemed adequate for research purposes. Specifically, based on Dodds et al. (1991), the purchase intention scale demonstrated high reliability with a Cronbach's α of 0.95. The users' continuance participation intention scale, referring to Bhattacherjee (2001), exhibited a Cronbach's α of 0.83. The brand attitude scale showed exceptionally high reliability with Cronbach's α 0.97. The brand affiliation scale, adapted from Enginkaya & Yılmaz (2014), had a Cronbach's α of 0.85. As per Yoo & Donthu (2001), the brand awareness scale showed a Cronbach's α of 0.93. Lastly, the customer purchase intention scale, following Lu et al. (2014), had a Cronbach's α of 0.91. These tests include inspection of item deletion. To further ensure the reliability of each scale, both Cronbach's α and factor analysis were conducted on the collected data in the results section.

3.7 Dataset Cleaning and Preparation

The data collection for this study utilized two primary methods of participant recruitment. Both approaches yielded a total of 316 responses. The first method involved the use of CloudResearch. This method successfully recruited 167 participants, comprising 52.8% of the total respondents for the study. The second method of participant recruitment was a combination of snowball and convenience sampling. The second method helped secure the remaining 149 surveys, representing 47.1% of the total collected. By using these two strategies, the researcher managed to gather a diverse sample for the survey, incorporating both broad online recruitment via CloudResearch and more targeted dissemination within the researcher's social network. The data collection process significantly surpassed the initial target of 120, thereby allowing for a rigorous data-cleaning process. This process entailed discarding any incomplete or missing responses, accounting for 15.7% of the total responses. As a result of this procedure, a final dataset comprising 258 valid responses was produced. This refined dataset provided a sound basis for the subsequent data analysis.

The distribution of participants across the groups was automated by Qualtrics' randomizer, resulting in relatively balanced proportions. Specifically, 25.2% ($N = 65$) of the participants were assigned to the first group, where the sentiment of customer tweets was positive. Another 25.2% ($N = 65$) were sorted into the second group, characterized by neutral sentiment in customer tweets. The third group, marked by negative sentiment in customers' tweets, comprised 25.6% ($N = 66$) of the respondents. Finally, the fourth group, without stimuli, held 24% ($N = 62$) of the participants.

4. Results

4.1 Descriptive Statistics

4.1.1 Descriptive Statistics - Sentiment in Tweets

To assess the collective sentiment of consumers towards NikeLand, Nike's metaverse marketing initiative, sentiment analysis was conducted on a corpus of 2153 tweets using the SentiStrength software.

For descriptive analysis of the sentiment patterns surrounding NikeLand tweets, the data was imported into Tableau (Tableau 2023.1), a data analysis and visualization tool. This resulted in a clear graphical representation of the percentage of tweets with positive, negative, and neutral sentiment in the overall data. The researchers offset the sentiments value of 5 to -5 to 4 to -4 in order to better understand. Figure 2 revealed that a majority (57.2%) of the tweets displayed a neutral sentiment. This was closely followed by 21.1% of tweets that were slightly positive, with a positivity score of +1 and no negative sentiment.

In total, the tweets expressing positive sentiment (with no negativity) constituted 30.07%, while a mere 7.3% of tweets were negative (with no positivity). These statistics suggest that Nike's metaverse project, NikeLand, has been met with a predominantly positive response on Twitter.

Figure 2. *Sentiment Analysis of NikeLand Tweets*

	[Positive]-1				
[Negative]+1	0	1	2	3	4
0	57,20%	21,10%	7,11%	1,63%	0,23%
-1	5,58%	3,16%	1,02%	0,19%	
-2	1,30%	0,51%	0,14%	0,14%	
-3	0,33%	0,19%	0,09%		
-4	0,09%				

4.1.2 Descriptive Statistics - Survey

In total, 316 responses were collected and after cleaning the dataset from incomplete responses, the dataset consisted of 258 valid responses. Among participants, the age of respondents ranged from 18 to above 65. The age distribution of the sample was as follows:

the largest group comprised individuals aged between 25 and 34, comprising 41.5% (*N* =107) of the total sample. This was followed by the age group 18 to 24, which accounted for 26.4% (*N* = 68) of the sample. Subsequently, those aged between 35 to 44 represented 21.3% (*N* = 55) of the sample. Individuals between 45 and 54 years old constituted a smaller segment, making up 6.2% (*N* = 16) of the sample. Lastly, the smallest age group in the sample was those aged 55 and older, accounting for 4.7% (*N* = 12) of the total responses. The population was 53.1% (*N* = 137) female and 44.2% (*N* = 114) male, with four responses in the gender question being non-binary/ third gender (1.6%) and three responses being preferred not to say (1.2%).

The respondents' nationalities showed some diversity. A majority were American, comprising 56.2% (*N* = 145) of responses. This was followed by Chinese respondents, who accounted for 31% (*N* = 80) of the sample. The rest of the respondents hailed from various countries: 1.9% (*N* = 5) from Austria, 1.6% (*N* = 4) from the Netherlands, and 0.8% (*N* = 2) each from Belgium, France, and Spain. The remaining 18 responses were distributed across 18 different countries. As for education, 46.5% (*N* = 120) of the respondents obtained a bachelor's degree, 25.6% (*N* = 66) obtained a master's degree, 18.6% (*N* = 48) had some college as their highest degree, and 7.8% (*N* = 20) had 1.6% (*N* = 4) received a Ph.D.

4.2 Factor Analysis and Reliability Check of Scales

Factor analysis was the primary analysis that was undertaken on the cleaned dataset using SPSS. The aim was to identify, validate and confirm the unity and reliability of each scale, beginning with the scale of brand awareness, brand attitude, and brand affiliation. The 11 brand-related items which were Likert-scale based were entered into an exploratory/theoretically based factor analysis using principal components extraction with varimax rotation based on eigenvalues (> 1.00), $KMO = .85$, $\chi2$ ($N = 258, 55$) = 2300.19, $p < .001$. The resultant model explained 80.4% of the variance in brand questions. The factors found were labeled as Brand Awareness (with a *Cronbach's* α of .86), Brand Attitude (with a *Cronbach's* α of .92), and Brand Affiliation (with a *Cronbach's* α of .95). Upon reviewing the reliability of the scales, no single item, when removed, resulting in a significant increase (+.300 or more) in Cronbach's α, thereby validating the internal consistency and reliability of all the used scales in the study. Factor loadings of individual items are presented in Table 1.

The same procedure was followed for the customers' participation intention for the NikeLand project and purchase intention for Nike's products. The six items which were Likert-scale based were entered into an exploratory/theoretically based factor analysis using principal components extraction with varimax rotation based on eigenvalues (> 1.00), *KMO* = .83, $\chi 2$ (N = 258, 15) = 1679.63, $p < .001$. The resultant model explained 91.0% of participation and purchased behavior questions variance. The factors found were labeled as Participation Intention (with a *Cronbach's* α of .96) and Purchase Intention (with a *Cronbach's* α of .94). Factor loadings of individual items are presented in Table 2.

In general, all scales employed for assessing the dependent variables and the moderators exhibited reliability. Following the factor and reliability analysis, each scale's items were computed into new aggregated (average) fresh variables. This process yielded five new variables within the dataset, specifically, brand awareness (consisting of four items), brand attitude (comprising three items), brand affiliation (with four items), participation intention (consisting of three items), and purchase intention (comprising three items).

Table 1. *Factor loadings explained the variance and reliability analyses for scales for brand awareness, brand attitude, and brand affiliation. (N = 258)*

Item	Brand Awareness	Brand Attitude	Brand Affiliation
Q1. I know Nike.	.84	-	-
Q2. I am aware of Nike products.	.89	-	-
Q3. When it comes to (product), I can immediately recall Nike.	.74	-	-
Q4. I can recognize Nike products among other competing brands.	.75	-	-
Q5. I feel Nike products are good.	-	.87	-
Q6. I like Nike products.	-	.84	-

Q7. I feel Nike products are favorable.	-	.89	-
Q8. I generally follow Nike on social media which is congruent with my lifestyle.	-	-	.92
Q9. On social media, I follow Nike products that I might buy in future, although I am not planning on buying right now.	-	-	.93
Q10. I follow Nike on social media which I consume and/or purchase often.	-	-	.94
Q11. I think that my talking about Nike on social media due to my satisfaction or dissatisfaction influences my friends in my social network.	-	-	.85
Variance explained	.46	.23	.11
Cronbach's α	.86	.92	.95
Eigenvalue	5.1	2.56	1.24

Table 2. *Factor loadings explained the variance and reliability analyses for scales for participation intention and purchase intention. (N = 258)*

Item	Participation intention	Purchase intention

Q1. My willingness to participate in NikeLand is...	.93	-
Q2. The likelihood of participating in NikeLand is...	.94	-
Q3. The probability that I would "consider" participating in NikeLand is...	.92	-
Q4. I would consider buying Nike products.	-	.93
Q5. It is possible that I would buy Nike products.	-	.93
Q6. I will purchase Nike products the next time when I am in need.	-	.86
Variance explained	.69	.22
Cronbach's α	.96	.94
Eigenvalue	4.1	1.3

4.3 Manipulation Check Results

In the survey, respondents from all four conditions were asked: "After viewing the advertisement, did you notice the tweets presented? If yes, how would you characterize the overall sentiment expressed in the tweets you just read?". The assigned condition group and their respective choices in the manipulation check were examined as two separate variables. A Pearson's Chi-Square test was performed using SPSS to identify the relationship between these two variables (Table 3). As per the calculated Pearson's Chi-square test, there was a significant interaction between the two variables, $\chi 2$ (9, $N = 258$) = 329.11, $p < .05$. The overall pass rate for the manipulation check was 67.1%. Interestingly, some notable things emerged.

The sentiment identification accuracy varied among the respondents based on the type of tweets they were shown. Among the respondents who were shown tweets with positive sentiment (group 1, $N = 65$), a majority (78.5%) accurately identified the positive sentiment, while the remaining respondents identified the sentiment as neutral (15.4%), negative (1.5%), or reported not seeing the tweets (4.6%). Likewise, respondents shown tweets with negative sentiment (group 3, $N = 66$) largely accurately identified the negative sentiment (83.3%), demonstrating an even higher correctness percentage than group 1.

For respondents who were shown purely neutral tweets (group 2, $N = 65$), discerning the conveyed sentiment proved more challenging. More than 58% of these respondents incorrectly perceived the tweets as having a positive sentiment, while 38% correctly identified the neutrality of the tweets. Previous research has suggested that individuals' interpretations of semantic emotional terms in text vary according to a multidimensional scale, influenced by their current mood and attention (Barrett, 1995). As such, neutral emotions in texts can often be perceived as positive. This could potentially explain why neutral tweets were frequently misinterpreted as positive by the participants in this study.

In the control group (group 4, $N = 62$), the majority of respondents (67.7%) correctly reported not seeing any tweets. Intriguingly, a small percentage of respondents selected either the positive or neutral sentiment options, despite no tweets being presented in this group. However, their responses were kept in the dataset. Some of these respondents provided feedback during the survey process, indicating that they felt influenced by the positive background music in the provided official advertisement video. Hence, their responses were still subject to some form of stimulus, and their data were considered valid. It is important to note that respondents who did not pass the manipulation check *did not necessarily* misunderstand the experiment or lack competency (Hauser et al., 2018). They may have responded differently to the stimulus provided. Excluding these respondents could introduce bias into the experimental results.

To ensure the validity and reliability of the experiment, the researchers conducted the analysis twice for testing. One analysis used data from all participants, and another only included data from participants who passed the manipulation check. This was to test the sensitivity of the results to the inclusion of these participants. Both analyses yielded similar results, indicating no significant differences or deviations (see Appendix B for the results for this test). Therefore, the data from all respondents ($N = 258$) was retained for subsequent analysis.

Table 3. *Distribution of Manipulation Checks Questions*

Conditional group	Choice- Positivity	Choice- Neutral	Choice- Negativity	Choice- No, didn't see
1.Positivity	**51**	10	1	3
2.Neutral	38	**25**	1	1
3.Negativity	3	6	**55**	2
4.No Stimuli	10	9	1	**42**

Note: The correct answers for each group are labeled in **bold**.

4.4 Hypothesis Testing

4.4.1 Effect of Positivity/Negativity in Customers' Tweets on Participation Intention (H1, H2)

To test *H1: The positivity in customers' tweets about the NikeLand project has a significant positive effect on other customers' intention to participate.* And *H2: The higher negativity in customers' tweets about the NikeLand project has a significant negative effect on other customers' intention to participate*, the researcher used two distinct analytical approaches for each H: ANOVA and regression analysis. Each method provides unique insight into how the positivity/negativity of customers' tweets affects other customers' intention to participate in the NikeLand project. Both were employed due to the dual quantitative/ ordinal nature of the IV. The following segments delve into the specifics of these two analytical methods and present numbers and corresponding analysis findings in the next two subsections.

The first method of analysis is ANOVA analysis. By comparing each sentiment condition separately, it can provide insight into the specific impact of each sentiment on participation intention. This analysis found a significant difference between the positivity and negativity conditions but no significant difference between the positivity and neutral or control conditions. Conversely, regression analysis focuses on the binary presence or absence of positive or negative tweets. As a result of this approach, both positivity and negativity in the tweets are significant predictors of participation intention, with positive tweets positively impacting participation intention and negative tweets negatively impacting participation intention.

Since the main hypotheses 1 and 2 revolve mainly around discerning the impact of positive or negative tweets. Regression analysis, the second method, provides a more applicable and relevant answer. It highlights the core differences between positive and negative sentiment tweets and the impact of each of these sentiments on other consumers' willingness to engage. The binary strategy utilized in the regression analysis simplifies the comparison between positive and negative sentiments, providing a closer alignment with the nature of the hypotheses. For the regressions, the stimuli as IV were treated as dummy/binary variables.

Furthermore, the results from the ANOVA analysis suggest a potential and more complex between the different emotional conditions interactions, which warrants further investigation. Specifically, the potential impact of neutral emotional tweets or lack of tweets (control condition) has yet to be fully explored and could be the focus of future research.

Given the above factors, regression analysis was considered the most appropriate for the subsequent hypothesis. The main focus was on the presence or lack of positive or negative tweets. This choice was also supported by the significant results generated by the regression analysis, providing a solid basis for exploring the further influence of other factors (moderators).

4.4.1.1 ANOVA Test

To test for differences between different conditions, a one-way ANOVA was conducted on Participation Intention. The conditions were labeled as Positivity (Group 1), Neutral (Group 2), Negativity (Group 3), and Control (Group 4).

ANOVA revealed a significant main effect for groups, $F(3, 254) = 3.496$, $p < .05$, partial $\eta^2 = .04$. This suggests significant differences in Participation Intention among the four groups. Tukey post hoc comparisons were then conducted to determine which specific groups differed from each other. These comparisons revealed that the Positivity condition ($M = 2.85$, $SD = 1.41$) resulted in significantly higher Participation Intention compared to the Negativity condition ($M = 2.21$, $SD = 1.11$), $p<.05$.

No other comparison between groups reached statistical significance. This suggests that the difference between the Positivity and Negativity conditions primarily drove the main effect observed in the ANOVA.

4.4.1.2 Regression

Also, to obtain a more comprehensive analysis result, the researcher conducted a multiple linear regression with 'Participation Intention' as the criterion. Predictors were two components derived from customer tweets about the NikeLand project: Positivity and Negativity.

For the Positivity model, the regression was found to be significant, $F(1, 256) = 5.799$, $p < .05$, with an R^2 of .022, indicating that about 2.2% of the variance in Participation Intention can be accounted for by Positivity. Positive tweets were found to significantly predict participation intentions ($b^* = .149$, $p < .01$, one-tailed), indicating that when Positivity is present (compared to the other conditions together - neutral, negativity, and control - that represent the regression's constant/intercept), the intention to participate also increases (a weak yet significant effect). Thus, H1 can be accepted.

For the Negativity model, the regression was also found to be significant, $F(1, 256) = 5.403$, $p < .05$, with an R^2 of .021, suggesting that about 2.1% of the variance in Participation Intention can be explained by Negativity. Negativity was found to be a significant predictor of Participation Intention ($b^* = -.144$, $p < .05$, one-tailed), demonstrating that when negativity is present, the intention to participate decreases (a weak yet significant effect). Thus, H2 can be accepted.

The analyses suggest that both the positive and negative customers' tweets about the NikeLand project have significant but small impacts on other customers' intentions to participate. Positivity positively affects participation intention, while Negativity has a negative effect.

4.4.2 Effect of Sentiment in Customers' Tweets on Participation Intention (H1a)

To test *H1a: The sentiment level (from negative to neutral to positive) in customers' tweets about the NikeLand project has a significant positive effect on other customers' intention to participate.* The researcher created a new variable that included sentiment levels operationalized as -1,0, and 1 (omitting the control group), and conducted a simple linear regression with 'Participation Intention' as the criterion. The predictor was the sentiment derived from customer tweets about the NikeLand project. The regression was found to be significant, $F(1, 194) = 8.832$, $p = .003$, with an R^2 of .044. This indicates that about 4.4% of the variance in 'Participation Intention' can be accounted for by the sentiment in customers' tweets. The sentiment in tweets was found to significantly predict participation intentions ($b^* = .209$, $p = .003$, $p < .01$), indicating that as the sentiment in customers' tweets about the

NikeLand project weakly increases towards positivity, the intention to participate also increases. Thus, H1a can be accepted.

4.4.3 Effect of Positive/Negative Tweets on Participation Intention and Gender as Moderator (H3 &H4)

To test *H3: The relationship between the positivity in customers' tweets about the NikeLand project and other customers' intention to participate is stronger for female customers than male customers.* And *H4: The relationship between the higher negativity in customers' tweets about the NikeLand project and other customers' intention to participate is stronger for female customers than male customers,* a moderation analysis was conducted. This analysis included gender as a moderator, participation intention as the dependent variable, and positivity and negativity from customer tweets as predictors. The data collected included four responses who identified as the third gender and three responses which preferred not to disclose their gender. These respondents were excluded during this moderation analysis for gender,- they were coded as missing data- resulting in a final sample size of $N = 251$ (Male = 144, Female = 137) for this analysis. The gender variable was binary coded with 0 = female and 1 = male.

Firstly, H3 was tested by including an interaction term between positivity and gender in the model (Table 4 and Figure 3). The model was found to be significant, $F(3,247) = 3.42$, $p = .018$, with an R^2 of .040, indicating that the predictors in the model can account for about 4% of the variation in Participation Intention. Notably, the interaction term between positive tweets and gender was significant ($b^* = .20$, $p = .034$, $p < .05$), suggesting that the effect of positive tweets on participation intention differs based on gender, the relationship between positive and participation intention is stronger for male customers than female customers. However, the direction of the interaction is opposite the hypothesized direction; this will be further discussed in Conclusions. Thus, H3 is unsupported.

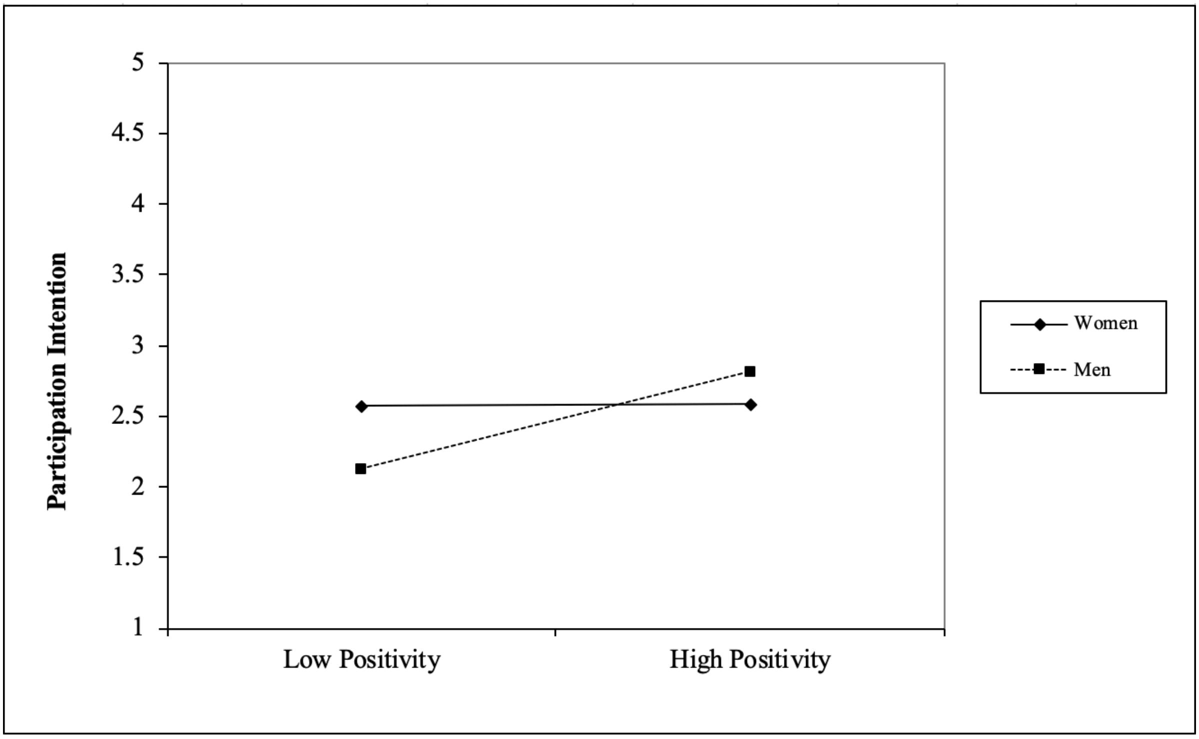
However, positivity alone was non-significant ($b^* = .02$, $p = .837$) when considered alongside gender and the interaction term. As a result, while positivity affects Participation Intention, its effect varies across genders. Table 4 clearly depicts positivity's effect on men alone, that gender is weakly significant $p < .10$ with women, in general, showing more PartInt (regardless of sentiment), but still a weak effect ($b^* = -.121$).

Table 4. *Moderation of Customers' Gender (N = 251) on Participation Intention*

	B	*S.E.*	*b**	*t*	*P*
Positivity	.05	.25	.02	.21	.837
Gender	-.31	.19	-.12	-1.68	.095
PositivityxGender	.78	.37	.20	2.1	.034

R2 = .04, *F*(3, 247) = 3.418, *p* = .018

Figure 3. *Moderation Direction of Gender (Positivity, Male and Female) on Participation Intention*



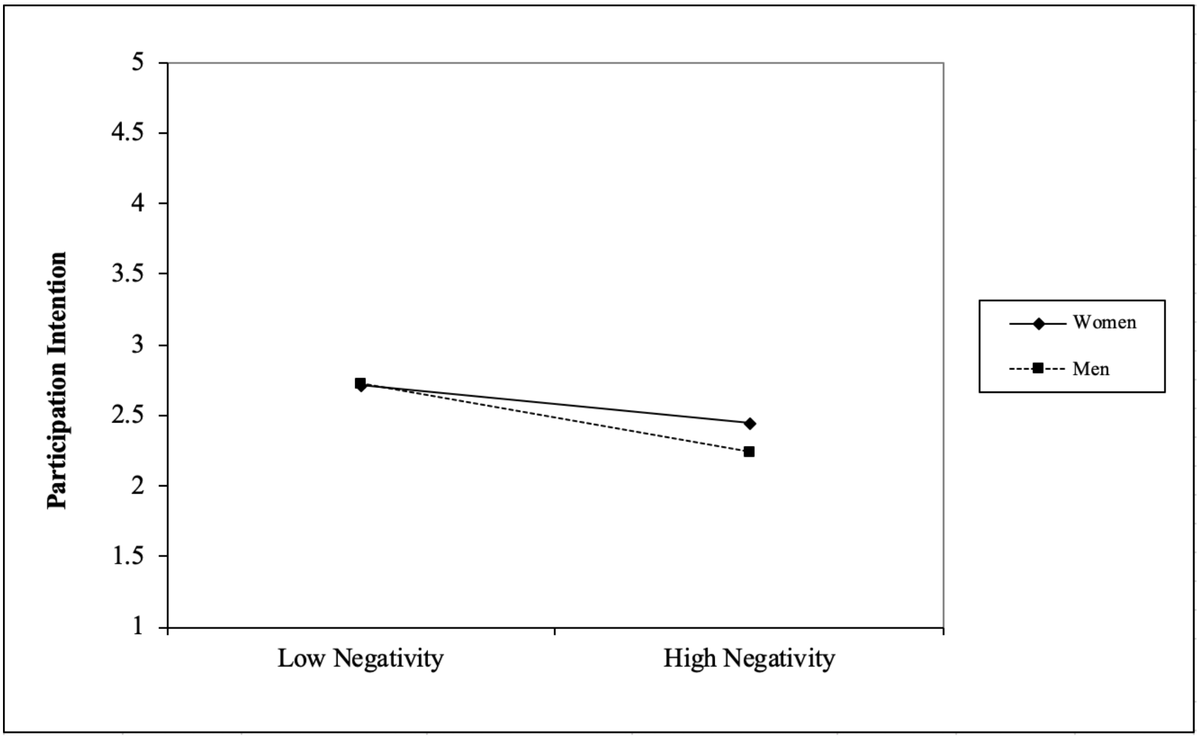
H4 proposed a similar moderating effect of gender but for the relationship between negativity in customers' tweets and other customers' intention to participate (Table 5 and Figure 4). However, the moderation model was not found to be significant, *F*(3,247) = 2.08, *p* = .103, and the interaction term between negative tweets and gender were also non-significant (*b** = -.06, *p* = .511). This indicates that gender does not significantly moderate the relationship between tweet negativity and participation intention. Thus, H4 is rejected. Still, the direction of the main effect of Negativity was in the expected direction as observed in H2.

Table 5. *Moderation of Customers' Gender (N = 251) on Participation Intention*

	B	*S.E.*	*b**	*t*	*P*
(Negativity)	-.32	.25	-.11	-1.26	.208
Gender	-.03	.19	-.012	-.16	.871
NegativityxGender	.25	.37	-.06	-.66	.511

R2 = .03, *F*(3, 247) = 2.08, *p* = .103

Figure 4. *Moderation Direction of Gender (Negativity, Male and Female) on Participation Intention*



4.4.4 Effect of Positive/Negative Tweets on Participation Intention and Brand Affiliation as Moderator (H5 &H6)

To test *H5: The impact of positive tweets about the NikeLand project on participation intention is stronger for those who feel a strong affiliation with Nike.* The researcher conducted a moderation analysis with customers' brand affiliation as a moderator and participation intention as the dependent variable. The predictor was the positivity of tweets (Table 6).

The interaction between the positivity of tweets and brand affiliation was insignificant (p = .465). Thus, H5 can be rejected. Therefore, customers' brand affiliation does not significantly moderate the impact of positive tweets about the NikeLand project on participation intention. However, the direction of the effect was in the hypothesized direction. The researcher also observed that brand affiliation itself is a moderate, positive, and significant predictor of participation intention (b^* = .58, p < .001, two-tailed).

Table 6. *Moderation of Brand Affiliation on Positive Tweets (N = 258)*

	B	*S.E.*	*b**	*t*	*P*
Positivity	.49	.14	.17	3.37	.001
Z(BrandAffiliation)	.74	.07	.58	10.1	.000
PositivityxZBrandAffiliation	.10	.14	.04	.73	.465

$R2$ = .388, F(3, 254) = 53.615, p <.001

To test *H6: The impact of negative tweets about the NikeLand project on participation intention is weaker for those who feel a strong affiliation with Nike.* The researcher conducted another moderation analysis with customers' brand affiliation as a moderator and participation intention as the dependent variable. The predictor was the negativity of tweets (Table 7).

The interaction between the negativity of tweets and brand affiliation was not found to be significant (p = .258). Thus, H6 can be rejected. The result is that customers' brand affiliation does not significantly moderate the impact of negative tweets about the NikeLand project on participation intention. However, the direction of the effect was in the hypothesized direction. And as expected from the H3 test, brand affiliation remains a positive, moderate, and significant predictor of participation intention.

Table 7. *Moderation of Brand Affiliation on Negative Tweets (N = 258)*

	B	*S.E.*	*b**	*t*	*P*
Negativity	-.58	.14	-.20	-4.06	.000
Z(BrandAffiliation)	.83	.07	.65	11.66	.000
NegativityxZBrandAffiliation	-.17	.15	-.06	-1.13	.258

$R2$ = .404, $F(3, 254) = 57.418$, $p < .001$

4.5 Summary of Statistical Results

An overview of the statistical results is provided in this table (Table 8).

Table 8. *Overview of Statistical Results*

Hypothesis	Supported or Rejected
H1	Supported
H2	Supported
H1a	Supported
H3	Rejected
H4	Rejected
H5	Rejected
H6	Rejected

4.6 Further Analysis and Additional Findings

4.6.1 Effect of Positive/Negative Tweets on Participation Intention and Brand Awareness, Brand Attitudes as Moderators

The other relevant brand variables – brand awareness and brand attitude – were also explored for their potential role as moderators of sentiments' impact on participation intention. Regression analyses with the other relevant brand variables - brand awareness and brand attitude - were carried out to explore potential moderation models further. In the moderation analysis of brand awareness, brand awareness served as a moderator, tweet sentiment (positivity and negativity) functioned as the independent variables, and participation intention was the dependent variable. The interaction model involving the positivity of tweets and brand awareness was statistically significant, $F(3, 254) = 3.625$, $p = .014$, $R^2 = .041$. However, the interaction term between positivity and brand awareness was insignificant ($b^* = .082$, $p = .224$), indicating that the influence of positivity on participation intention does not vary based on brand awareness levels. Nevertheless, positivity alone (main effect) was significant ($b^* = .127$, $p = .043$), as expected, when evaluated alongside brand awareness and the interaction term, highlighting its effect on participation intention. Similarly, the model investigating the interaction between the negativity of tweets and brand awareness was significant, $F(3, 254) = 3.836$, $p = .010$, $R^2 = .043$. However, the interaction term between negativity and brand awareness was not significant ($b^* = -.112$, $p = .139$), suggesting that the impact of negativity on participation intention remains constant irrespective of brand awareness levels. Had there been a justified hypothesis of this moderation, the effect could have been declared as weakly significant ($p < .10$). However, negativity itself (main effect) was significant ($b^* = -.141$, $p = .022$) when considered with brand awareness and the interaction term, affirming its influence on participation intention. Despite brand awareness not significantly moderating the relationship between tweet sentiment (positivity/negativity) and participation intention, the results emphasize the importance of tweet sentiment in shaping customer participation. The findings suggest that fostering a positive sentiment and curtailing negative sentiment in tweets about specific brand projects like NikeLand can enhance customer participation Intention, irrespective of brand awareness levels.

Circling back to the moderation analysis of brand attitudes, the result show parallels with the findings from the evaluation of brand awareness. This analysis employed brand attitudes as a moderator, tweet sentiment (positivity and negativity) as independent variables, and participation intention as the dependent variable. However, similar to the brand awareness analysis, the interaction term between tweet sentiment and brand attitudes was not statistically significant. Although the importance of brand awareness and brand attitudes in brand perception is recognized, the researcher found that the influence of tweet sentiment on participation intention does not differ based on varying brand attitudes (relevant SPSS report can be found in Appendix C).

4.6.2 Effect of Brand-Related Behaviors on Purchase Intention

The exploration of purchase intention as a dependent variable within the context of moderation analysis presents intriguing insights. Initially, the variables of brand affiliation, brand awareness, and brand attitudes were treated as independent variables, all of which significantly influenced purchase intention. The relevant outputs can be found in Appendix D. Interestingly, when the sentiment of tweets about the NikeLand project - either positive or negative - was incorporated into the analysis, these previously significant results were largely nullified. The exception was Brand awareness. The interaction model between the negativity of tweets and brand awareness was indeed statistically significant, $F(3, 254) = 15.346$, $p < .001$, accounting for 15.3% of the variance in purchase intention ($R^2 = .153$). This suggests that Brand Awareness moderates the effect of negative tweets on purchase intention. More specifically, for individuals with a higher level of brand awareness, the adverse impact of negative tweets on purchase intention is more pronounced. The result suggests that brand awareness is generally beneficial but may also increase customers' sensitivity to negative eWOM. Therefore, in situations with prevalent negative eWOM, brands may find it beneficial to moderate their awareness campaigns until the negative sentiment can be effectively addressed. Additionally, despite the fact that positive eWOM has universal benefits, its impact seems invariant to the level of brand awareness. Thus, while fostering positive eWOM remains a worthwhile pursuit for companies, it is equally crucial to manage and minimize negative eWOM.

In contrast, the sentiments (unidimensional variable) of tweets about the NikeLand project did not exhibit a significantly stronger influence on purchase intention for those who either had a strong affiliation with the brand or held positive brand attitudes. This lack of moderation is likely due to the lack of moderation with positivity (on the effects on purchase intention), as it was observed just above that negativity was indeed moderated by brand awareness. Thus, the effects of eWOM, specifically the NikeLand project, do not significantly influence customers' intention to purchase Nike's products. This suggests that, as regards NikeLand, feelings about the initiative might not translate directly into influence over purchasing decisions for the brand. However, it appears that this lack of effect is more related to positive sentiment, as negative sentiment showed some moderation by brand awareness.

5. Conclusion

The current study aims to understand how the sentiment of tweets (positive or negative) about the NikeLand program influences the participation intentions of potential customers and how this relationship is moderated by their level of brand awareness (brand attitude and brand affiliation in other findings). This is explored through the following research questions and relevant hypotheses. By investigating these dynamics, this study aims to reveal the complex interplay between eWOM, brand-related behaviors, and consumer participation intentions in the context of innovative marketing initiatives (e.g., NikeLand) in virtual worlds.

RQ: *To what extent does the sentiment in customers' tweets about the Nike Metaverse marketing project (NikeLand) impact other customers' intention to participate?*

5.1 Summary of Findings

In summarizing the findings from the SPSS analysis, H1-H2 are accepted within this study. Conclusions for H1, H2, and H1a suggest a significant influence of positive and negative sentiments in customers' tweets about the NikeLand project on the participation intentions of other customers. This finding is consistent with that of Zhang et al. (2021), who concluded that consumers' exposure to eWOM on social media platforms can significantly influence their consumption behavior, including participation intention and purchase intention.

The test for H3's moderating effect indicates that the relationship between positivity in customers' tweets about the NikeLand project and other customers' intention to participate is stronger for male customers than female counterparts, opposite to what H3 posed. This suggests that male customers may be more responsive to positive eWOM regarding the NikeLand project. It also hints at the increased impact of such positivity on their decision to engage in the metaverse marketing program. This finding contradicts the conclusions drawn by Xue et al. (2020), who started from the premise that female consumers can perceive a broader range of emotions and that their psychological and behavioral responses are more varied. However, this study implies that men might be more influenced by or responsive to positive sentiments concerning innovative marketing campaigns by brands. A possible explanation is that the difference in response to positive eWOM between male and female consumers could be attributed to Nike's brand perception. According to Miller (2019), women have historically been excluded from sneaker culture, sneakers had a more male-biased target audience in the early years, and there was this implicit and meaningless discrimination against female consumers (Miner, 2009). This perception may explain why men were more responsive to positive sentiments about NikeLand. In contrast, brands such as Adidas have a different brand personality, are perceived as more "friendly" and "practical" (Arora & Stoner, 2009), and are equally appealing to both genders. This suggests that brand perceptions play an essential role in shaping responses to eWOM. This interpretation adds another layer of complexity to the understanding of the role of gender in meta-border marketing and underscores the importance of considering brand perceptions in future research.

Additionally, the moderating effect of H4 did not support the notion that the relationship between higher negativity in customers' tweets about the NikeLand project and other customers' intention to participate is stronger for female customers than for males. This finding proposes that negativity expressed in tweets about NikeLand impacts both genders equivalently, this result also contradicts the conclusions drawn by Xue et al. (2020). This leads to the conclusion that negative sentiment disseminated via social media affects both genders equally. Negative eWOM regarding the NikeLand project did not have a more significant effect on the participation willingness of female customers than it did on males. In summary, the role of gender in the impact of eWOM on consumer behavior may be more nuanced than initially presumed. While men may be more influenced by positive sentiments expressed in tweets about initiatives like NikeLand, their reactions to negative sentiments align with those of women. These findings contribute a novel perspective to studying gender-specific responses to differing sentiments in eWOM. Collectively, they could aid researchers and companies in further understanding the role of gender in Metaverse Marketing.

Following the previous analysis, hypotheses H5 and H6 did not find support. It was not found that the impact of positive tweets about the NikeLand project on participation intention is stronger for those with a strong affiliation with Nike (H5). Furthermore, the impact of negative tweets about the NikeLand project on participation intention was not found to be weaker for those with a strong affiliation with Nike (H6). These findings differ from Kaufman et al. (2011), who state that brand affiliation can influence participation intention, including acting as a moderator. These findings indicate that the influence of both positive and negative tweets on participation intention in NikeLand remains consistent, irrespective of the strength of individuals' affiliation with Nike. This outcome presents an intriguing perspective and can be understood from two angles.

From one perspective, the universality of positive sentiments expressed in tweets is apparent, not subject to alteration by the individual consumers' brand affiliations. Similarly, negative feedback propagated via social media exerts a universal impact on consumers, independent of their brand affiliation. This finding highlights the potential impact of negative eWOM, suggesting the broad reach of eWOM in shaping consumer behavior and intentions, whether brand affiliation is high or low. Therefore, businesses should put effort into managing the eWOM for their brands, products, and services effectively. Another interpretation hinges on the distinction between the brand affiliation scale used in the study, which pertains to Nike and its overall products, and the eWOM, which specifically addresses the NikeLand program. This distinction might imply that consumers' sense of brand affiliation does not moderate the effect of eWOM on their intention to engage with individual products. Consumers might distinguish between their feelings towards the brand and their responses to specific items or product lines within that brand. As a result, even consumers who exhibit a strong sense of brand affiliation can be significantly influenced by positive or negative eWOM associated with a specific product or product line. This insight underscores the nuanced role of eWOM in driving consumer engagement with specific initiatives like NikeLand.

In addition, among other findings, brand awareness moderated the effect of negative tweets on purchase intentions. Interestingly, for those with high brand awareness, tweets with negative sentiment had an even more significant negative impact on purchase intentions. While companies generally know that increased brand awareness is often beneficial, this study found that it may also make customers more susceptible to negative eWOM. The impact of positive eWOM is consistent regardless of brand awareness. This suggests that while encouraging positive eWOM benefits companies, controlling and reducing negative eWOM is equally essential. In a more profound sense, these findings underscore the dual role of brand awareness: In the brand-consumer relationship, it can amplify the benefits of positive eWOM and exacerbate the damage of negative eWOM.

5.2 Theoretical and Practical Implications

Overall, this study offers numerous theoretical and practical implications across several areas. Firstly, regarding eWOM and brand specificity, this research demonstrates that consumers distinguish between their general feelings towards a brand and their reactions to a specific product or service within that brand. This finding enriches the theoretical understanding of consumer brand perception and highlights its complexity. Additionally, the study reveals the influential role of gender in eWOM reception. The finding that male consumers are more likely to be influenced by positive sentiments about innovative marketing campaigns (e.g., NikeLand) expressed in eWOM opens a new avenue in understanding how gender affects eWOM perception. While previous research has examined gender differences in emotional text perception (Xue et al., 2020), this research provides fresh insights into gender's role in eWOM. This study also incorporates brand affiliation, brand awareness, and brand attitude as moderators, investigating their impact on the relationship between tweet sentiment, consumer participation, and purchase intentions. This nuanced exploration of eWOM influence adds depth to our existing knowledge of marketing theories.

From a practical perspective, this research can encourage brands to refine their management strategies, given that maintaining a positive perception of a specific brand initiative in eWOM enhances customers' participation intentions, regardless of their awareness of the product. Furthermore, the findings on gender differences in eWOM responses can aid companies in formulating gender-specific marketing strategies, particularly for innovative campaigns like Metaverse marketing. Finally, given the amplified impact of negative eWOM, this research underscores the need for businesses to invest more resources in managing and mitigating the effects of negative eWOM. In summary, this study offers critical insights that can inform theoretical discussions and practical strategies in marketing.

5.3 Limitations

Certain findings from the current study were unable to substantiate the hypotheses drawn from the existing literature. These discrepancies could be attributed to several limitations inherent in the study design and the data collection process.

Firstly, the focus of this study, Metaverse Marketing, is a relatively nascent field, particularly concerning NikeLand, a metaverse game program launched by Nike in recent years. Due to this novelty, a relative dearth of comprehensive research exists on this specific topic. Existing studies have primarily examined eWOM concerning generic products or services (Babić Rosario et al., 2020), the influence of eWOM sentiments on consumers' participation and purchase intentions (Liu et al., 2015), and aspects of brand behavior (Kaufman et al., 2011). The scarcity of studies bridging all these elements addressed in this thesis underscores the innovative nature of the research. However, it also limits the amount of supporting literature to frame the research questions and hypotheses.

Another potential limitation lies in the geographical distribution of the survey respondents. According to Babbie (2014), statistical conclusions are based on samples that ideally reflect the population profile. In this study, a large majority of responses were from the United States and China, constituting 87.2% of the total sample and offering some generalizability in terms of Eastern and Western perspectives. However, this skewed representation might have introduced a particular bias, as the concentration of responses from these tech-affluent countries may not adequately represent global attitudes and does not broadly reflect the global population profile. However, in the context of Nike's target consumer base, this sample might be represented as it can likely encompass individuals with some degree of disposable income. Future studies should aim for a more diverse and geographically representative sample. Also, the total count of 258 valid responses in this study was divided among four experimental groups, which resulted in a small, less-than-ideal sample size for each group.

Lastly, despite its strengths, the current study design could have been more optimal for several reasons. The existing experiment included groups that expressed pure sentiments (positive, negative, neutral). However, a more comprehensive research design would encompass additional groups reflecting a mix of sentiments or bidirectional sentiments – complexity in sentiments highlighted by Thelwall (2013) - offering a more holistic perspective on the research question. Future studies should consider this enhanced design to provide deeper insights and add more dimensions to the research.

5.4 Recommendations and Directions for Future Research

This study provides several avenues for future research based on its findings. In addition to expanding the sample size and diversity and incorporating groups with mixed sentiments, there are other noteworthy perspectives to consider.

On the one hand, future studies could benefit from exploring the role of eWOM across other social media platforms, including Facebook, YouTube, and Instagram. The platform selected for this study, Twitter, is recognized for its fast-paced, concise nature and real-time communication (Völcker, 2020). Conversely, Facebook is characterized by its closely-knit community-based networks of friends (Alhabash & Ma, 2017), while Instagram is predominantly visual, with eWOM often disseminated through vibrant images and multimedia content (Alhabash & Ma, 2017). YouTube, focusing primarily on video sharing (Bärtl, 2018), allows for the rich and detailed showcase of products, further facilitating the spread of eWOM. The characteristics and usage patterns of each social media platform are unique (Burton & Soboleva, 2011). Expanding the scope to include these platforms would provide a more comprehensive understanding of how different platforms impact eWOM, thus enriching the research framework.

On the other hand, it may be beneficial for future studies to examine the landscape of Metaverse marketing projects in more depth. While this study focused on one brand, Nike, and one specific project, NikeLand, an increasing number of brands, such as Samsung, Gucci, and Adidas, have also initiated popular Metaverse projects. Each brand caters to a different group of consumers who may respond differently to eWOM. For instance, Adidas and Nike are sports brands with similar product categories (Weking et al., 2023) and may produce similar eWOM results. However, outcomes can also be influenced by other factors such as specific brand history, preferred consumer gender, reputation base, and consumer economic level (Weking et al., 2023). It is worth noting that Nike has faced several scandals and brand PR crises in past decades (Lee, 2016), which may explain the interplay between brand awareness, negative eWOM, and consumer participation intention that emerged in this study. Moreover, in the case of Gucci, for example, its primary consumer audience consists predominantly of high-income individuals due to its product characteristics and luxury brand positioning (Jebarajakirthy et al., 2020). Therefore, a different kind of eWOM may be generated. Mainly if different income groups are considered, low-income consumers may harbor stronger negative sentiments towards luxury and fashion brands like Gucci, thereby amplifying the influence and spread of negative eWOM (Bhatia, 2018). Hence, broadening the scope of the investigation to include these other brands could provide researchers and companies with a more holistic view of the market, paving the way for more effective strategies and interventions.

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Appendix
Appendix A: Qualtrics Survey

Introduction

Dear respondent,

Thank you for your interest in this graduate's thesis research. I'm Feng Ye, a master's student, majoring in Media and Business. The purpose of this study is to investigate how the sentiment of customers' tweets about the Nike Metaverse project (NikeLand, a free- to- play virtual world) influences other customers' participation intention.

In this questionnaire, I will describe some behaviour to you. I would like to ask you to evaluate each answer. The questionnaire will take approximately 5 minutes to fill in. Please answer each question carefully and honestly, I am sincerely interested in your personal opinions. There are no right or wrong answers.

CONFIDENTIALITY OF DATA
All research data remain completely confidential and are collected in anonymous form. We will not be able to identify you. There are no foreseeable risks or discomforts associated with participating in this research.

VOLUNTARY
If you now decide not to participate in this research, this will not affect you. If you decide to cease your cooperation while filling in the questionnaire, this will in no way affect you either. You can cease your cooperation without giving reasons.

FURTHER INFORMATION
If you have questions about this research, in advance or afterwards, please feel free to contact me by email: {593772fy@eur.nl}. If you want to invoke your rights or if you have a question concerning privacy about this study, you can also contact me via email.

Skip to
End of Survey if I do not agree Is Selected

If you are above 18, and If you understand the information above and freely consent to participate in this study, click on the "I agree" button below to start the questionnaire.

○ I agree
○ I do not agree

Q3

The following statements focus on the brand awareness you have with the Nike brand. Please indicate the extent of your agreement or disagreement with the statements below.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I know Nike.	○	○	○	○	○
I am aware of Nike products.	○	○	○	○	○
When it comes to (product), I can immediately recall Nike.	○	○	○	○	○
I can recognize Nike products among other competing brands.	○	○	○	○	○

Q4

The following statements focus on the brand attitudes you have with the Nike brand. Please indicate the extent of your agreement or disagreement with the statements below.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I feel Nike products are good.	○	○	○	○	○
I like Nike products.	○	○	○	○	○
I feel Nike products are favorable.	○	○	○	○	○

Q5

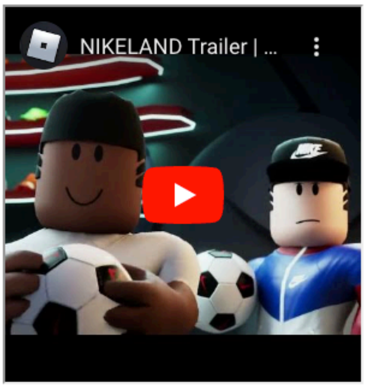
The following statements focus on your affiliation with the Nike brand. Please indicate the extent of your agreement or disagreement with the statements below.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I generally follow Nike on social media which is congruent with my life style.	○	○	○	○	○
On social media, I follow Nike products that I might buy in future, although I am not planning on buying right now.	○	○	○	○	○
I follow Nike on social media which I consume and/or purchase often.	○	○	○	○	○
I think that my talking about Nike on social media due to my satisfaction or dissatisfaction influences my friends in my social network.	○	○	○	○	○

Q6

Nike has built a virtual world called "Nikeland" in Roblox using a tool called Roblox Studio. Nikeland is a 3D space made for people who love sports and gaming, and it was inspired by Nike's original headquarters. In Nikeland, users can do many things like try on virtual products, buy NFTs, play mini-games, and shop for Nike clothes and accessories in a digital showroom.

In the following short video, an official advertisement for “NikeLand” will be presented. Please watch the video carefully.



Q7

This question lets you record and manage how long a participant spends on this page. This question will not be displayed to the participant.

Condition 1: positive sentiment

Q8

Next, some tweets about this Metaverse project will be presented. Please read the tweets carefully.

IamSann
@IamSann

It's such a fun game, and I loved getting to build my own yard! Check out NIKELAND for yourself here!

12:23 PM · Dec 6, 2021

Raja
@rajatweets

Visited #nikeland in #roblox. Pretty cool way in which brands can interact with users in virtual worlds. You can get awesome merchs like shoes & jackets for your avatar from the store.
Will be interesting to see how the virtual and physical worlds come together!

6:43 AM · Dec 21, 2021

BlackLLC
@BlackLLC

This is an awesome collaboration between #Nike and #Roblox! Nike implemented a new Roblox world.

12:06 PM · Jun 6, 2022

Wallaroo M
@WallaroM

Loving the integration of web3 in @Nike's flagship store! #Nikeland #Roblox #web3 #HouseOfInnovation #metaverse

8:06 AM · Feb 18, 2022

Liferzz
@4466liferzz

@Nike @Roblox Personally, I think it was very smart on how they advertised the Roblox and Nike collaboration where they made the Drake music video in Roblox.

Also, love the Nikeland game, it's amazing!

11:31 AM · May 10, 2022

Miami
@2Miammmm

Check out the new #Nikeland in the Roblox ecosystem! Experience a uniquely immersive virtual environment built with the same technology.
Get ready for a mini metaverse inspired by Nike HQ! #Roblox #Metaverse #DigitalTransformation #RobloxNike

7:20 PM · Jan 11, 2023

Q9

This question lets you record and manage how long a participant spends on this page. This question will not be displayed to the participant.

Condition 2: Neutral sentiment

Q10

Next, some tweets about this Metaverse project will be presented. Please read the tweets carefully.

Jesse
@Jesse

NIKE teams up with ROBLOX to create a virtual world called 'NIKELAND'

$NKE $RBLX

8:01 AM · Jan 7, 2022

ypulse
@ypulse

In more Roblox news, Nike is building out 'Nikeland' for users to participate in mini-games and interact with the brand.

7:46 AM · Nov 18, 2021

Tech Junkie
@ TechJunkie

Nikeland debuts on #Roblox as its latest persistent #gaming space.

6:17 AM · Nov 28, 2021

Roy
@ Roy

About to jump onto #Nikeland @Nike on #Roblox @Roblox

6:45 AM · Nov 19, 2021

Roy
@ Roy

If anyone is looking for me I am running hurdles in Nikeland #Metaverse @Nike

4:20 PM · Aug 31, 2022

Pete
@ @BreadAm

Imagine actually being a part of #Nikeland

8:00 PM · Oct 18, 2022

Q11

This question lets you record and manage how long a participant spends on this page. This question will not be displayed to the participant.

Condition 3: negative sentiment

Q12

Next, some tweets about this Metaverse project will be presented. Please read the tweets carefully.

gavvv
@gavvvv

Roblox "Nikeland" killed my laptop.

3:34 PM · Feb 24, 2023

Aleks
@Aleks

#roblox __If you want to see how should not be a game.... come to Nikeland full of bugs it's a shame for #Nike definitely shit game!

8:00 PM · Sep 7, 2022

Paul
@paul

Well I just tried Nikeland on Roblox -- Metaverse UX!
I'd rather just play Minecraft frankly.
And I hate Minecraft (except the music).

12:07 PM · Feb 17, 2022

hiki
@hikimaru

Nikeland never fails to remind me why I disliked their game what a pain this hat is to earn.

8:16 PM · Mar 8, 2022

Mia
@2Miammmm

Nikeland on Roblox that's really really dumb.

5:20 PM · Jul 22, 2022

Mia
@2Miammmm

Nikeland. Totally useless

7:20 PM · Nov 7, 2022

Q13

This question lets you record and manage how long a participant spends on this page. This question will not be displayed to the participant.

Condition 4: no tweets and sentiment

Participation intention

Q14

The following statements focus on your participation intention with the NikeLand Metaverse project. Please answer each statement by indicating how low or high your participation intention might be.

	Very high	High	Neither high nor low	Low	Very low
My willingness to participate in Nikeland is...	○	○	○	○	○
The likelihood of participating in Nikeland is...	○	○	○	○	○
The probability that I would "consider" participating in Nikeland is...	○	○	○	○	○

Q15

The following statements focus on your purchase intention with the Nike product. Please answer each statement by indicating how low or high your purchase intention might be.

	Very high	High	Neither high nor low	Low	Very low
I would consider buying Nike products.	○	○	○	○	○
It is possible that I would buy Nike products.	○	○	○	○	○
I will purchase Nike products the next time when I am in need.	○	○	○	○	○

Manipulation check

Q16

After watching the advertisement, did you see the tweets presented? If so, how would you define the overall sentiment expressed in the tweets you just read?

- ○ Yes, I saw the tweets and the sentiment was positive
- ○ Yes, I saw the tweets and the sentiment was neutral
- ○ Yes, I saw the tweets and the sentiment was negative
- ○ No, I did not see the tweets after watching the advertisement

demographics

Q17

Please indicate your gender

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

Q18

How old are you?

- ○ Under 18
- ○ 18-24 years old
- ○ 25-34 years old
- ○ 35-44 years old
- ○ 45-54 years old
- ○ 55-64 years old
- ○ 65+ years old

Q19 | List of Countries

What is your nationality?

Afghanistan

Q20

What is the highest level of education you have completed or the highest degree you have received?

- ○ Less than high school
- ○ High school graduate
- ○ Some college
- ○ Bachelor degree
- ○ Master degree
- ○ Doctorate

Appendix B: Manipulation Check Test Result

With manipulation check question as the filter:

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Positivity[b]	.	Enter

a. Dependent Variable: ParticipationIntention

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.290[a]	.084	.079	1.25432

a. Predictors: (Constant), Positivity

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.713	1	24.713	15.708	.000[b]
	Residual	269.039	171	1.573		
	Total	293.752	172			

a. Dependent Variable: ParticipationIntention

b. Predictors: (Constant), Positivity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.178	.114		19.176	.000
	Positivity	.829	.209	.290	3.963	.000

a. Dependent Variable: ParticipationIntention

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Negativity[b]	.	Enter

a. Dependent Variable: ParticipationIntention

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.177[a]	.031	.026	1.29006

a. Predictors: (Constant), Negativity

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.164	1	9.164	5.506	.020[b]
	Residual	284.588	171	1.664		
	Total	293.752	172			

a. Dependent Variable: ParticipationIntention

b. Predictors: (Constant), Negativity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.579	.119		21.717	.000
	Negativity	-.494	.211	-.177	-2.347	.020

a. Dependent Variable: ParticipationIntention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24.259	3	8.086	5.030	.002[b]
	Residual	260.421	162	1.608		
	Total	284.680	165			

a. Dependent Variable: ParticipationIntention

b. Predictors: (Constant), Positivity, Please indicate your gender, PositivityXGender

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.230	.162		13.734	.000
	Please indicate your gender	-.096	.236	-.037	-.408	.684
	PositivityXGender	.337	.429	.093	.784	.434
	Positivity	.645	.306	.226	2.113	.036

a. Dependent Variable: ParticipationIntention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.695	3	3.565	2.108	.101[b]
	Residual	273.985	162	1.691		
	Total	284.680	165			

a. Dependent Variable: ParticipationIntention

b. Predictors: (Constant), NegativityXGender, Please indicate your gender, Negativity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.519	.167		15.129	.000
	Please indicate your gender	.154	.243	.059	.633	.528
	Negativity	-.380	.313	-.134	-1.213	.227
	NegativityXGender	-.293	.438	-.082	-.668	.505

a. Dependent Variable: ParticipationIntention

Appendix C: Brand Attitudes as Moderator

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	77.471	3	25.824	19.217	.000[b]
	Residual	341.318	254	1.344		
	Total	418.789	257			

a. Dependent Variable: ParticipationIntention

b. Predictors: (Constant), PositivityxZBrandAttitude, Positivity, Zscore (BrandAttitude)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.440	.084		29.199	.000
	Zscore(BrandAttitude)	.454	.082	.356	5.518	.000
	Positivity	.294	.168	.100	1.746	.082
	PositivityxZBrandAttitude	.244	.175	.090	1.390	.166

\ a. Dependent Variable: ParticipationIntention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	79.270	3	26.423	19.768	.000[b]
	Residual	339.519	254	1.337		
	Total	418.789	257			

a. Dependent Variable: ParticipationIntention

b. Predictors: (Constant), Negativity, Zscore(BrandAttitude), NegativityxZBrandAttitude

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.619	.083		31.376	.000
	Zscore(BrandAttitude)	.577	.085	.452	6.796	.000
	NegativityxZBrandAttitude	-.224	.161	-.092	-1.387	.167
	Negativity	-.383	.165	-.131	-2.317	.021

a. Dependent Variable: ParticipationIntention

Appendix D: Effect of Brand-Related Behaviors on Purchase Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	41.590	3	13.863	15.346	.000[b]
	Residual	229.467	254	.903		
	Total	271.058	257			

a. Dependent Variable: PurchaseIntention

b. Predictors: (Constant), Zscore(BrandAwareness), Negativity, NegativityxZBrandAwareness

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3.589	.069		52.293	.000
	Negativity	.005	.136	.002	.038	.970
	NegativityxZBrandAwareness	-.346	.126	-.195	-2.747	.006
	Zscore (BrandAwareness)	.484	.073	.471	6.648	.000

a. Dependent Variable: PurchaseIntention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	150.774	3	50.258	106.129	.000[b]
	Residual	120.283	254	.474		
	Total	271.058	257			

a. Dependent Variable: PurchaseIntention

b. Predictors: (Constant), Zscore(BrandAttitude), Positivity, PositivityxZBrandAttitude

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.605	.050		72.664	.000
	Positivity	-.040	.100	-.017	-.405	.686
	PositivityxZBrandAttitude	.111	.104	.051	1.065	.288
	Zscore(BrandAttitude)	.741	.049	.722	15.176	.000

a. Dependent Variable: PurchaseIntention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	151.886	3	50.629	107.909	.000[b]
	Residual	119.171	254	.469		
	Total	271.058	257			

a. Dependent Variable: PurchaseIntention

b. Predictors: (Constant), Zscore(BrandAttitude), Negativity, NegativityxZBrandAttitude

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.587	.049		72.546	.000
	NegativityxZBrandAttitude	-.176	.096	-.090	-1.841	.067
	Negativity	.036	.098	.015	.371	.711
	Zscore(BrandAttitude)	.814	.050	.793	16.184	.000

a. Dependent Variable: PurchaseIntention