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Master Thesis in Marketing

Content that Clicks: Comparing the Influence of User-Generated and Brand-Generated Content on Consumer Behavior with Brand Awareness as a Moderator.

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Abstract

This study investigates the influence of User-Generated Content (UGC) and Brand-Generated Content (BGC) on consumer purchase intention and engagement, as well as the moderating role of brand awareness. Using multiple linear regression models, survey data from 256 respondents were analyzed. The results revealed that UGC did not significantly differ in influence on purchase intention and engagement compared to BGC. Additionally, brand awareness did not moderate these relationships. These findings challenge the existing literature that often highlights the superiority of UGC in influencing consumer behavior due to its perceived authenticity and trustworthiness. Instead, the results suggest that a balanced content strategy incorporating both UGC and BGC is necessary to optimize marketing effectiveness. Education level, age, and online purchase frequency are among demographic factors that significantly influenced purchase intention and engagement, highlighting the importance of tailored marketing strategies to effectively target key consumer demographics. This study contributes to the digital marketing literature by providing empirical evidence on the effects of content types and brand awareness, offering practical insights for marketers to refine their content strategies.

Keywords: User-Generated Content, Brand-Generated Content, Purchase Intention, Consumer Engagement, Brand Awareness, Digital Marketing, Social Media Marketing.

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1. Introduction

“Content is king.” This famous statement by Bill Gates in his 1996 essay predicted the pivotal role that content would play in the growing internet landscape. Gates predicted a digital economy where content would drive economic value, much like it did with broadcasting at the time (Gates, 1996). At that time, the World Wide Web (WWW) had only been publicly available for three years, making Gates’ prediction seem optimistic at best. However, Gates also acknowledged potential challenges to his prediction, stating that although the long-term prospects are good, it may not work for some time, as he expected companies to struggle making money through advertising or subscriptions in the short-term (Gates, 1996).

Nearly 30 years later, digital content landscape has evolved dramatically, aligning closely with Gates’ prediction. Social media, barely a concept at the end of the 20th century, has grown into one of the most popular online activities. As of 2022, it possessed over 4.59 billion users globally, a number anticipated to reach close to six billion in 2027 (Dixon, 2023). Users spend an average of 151 minutes daily interacting, sharing, and consuming content on different social media platforms (Dixon, 2024b). Platforms such as Facebook, leading as the most popular network with close to 3 billion monthly active users in 2024, showcase the extensive reach of digital content and its profound impact on content creation and consumption (Dixon, 2024a).

Alongside the significant development of digital platforms, marketing strategies have also evolved. Social media marketing, particularly content marketing, has seen substantial growth, generating approximately 63 billion U.S. dollars in global revenue in 2022 alone (Dencheva, 2023). This figure is projected to increase to 72 billion in 2023, and is expected to continue growing, reaching 107 billion by 2026 (Dencheva, 2023). Today, terms such as ‘brand-generated content’ (BGC) and ‘user-generated content’ (UGC) dominate the digital marketing realm. BGC is content created and shared by brands themselves, while UGC is created by consumers, often featuring testimonials, reviews, or social media posts about the brand’s products (Müller & Christandl, 2019; Irelli & Chaerudin, 2020). Each type of content has its unique place and purpose, influencing consumer behaviors and preferences in distinctive ways.

Despite the growing reliance on these content types, a thorough understanding of their comparative impact on consumer behavior, particularly in terms of purchase intention and engagement, remains underexplored. Additionally, the role of brand awareness in moderating these effects is not well understood, posing a significant gap in the literature on digital marketing strategies. To address this gap, this study formulated four research questions:

1. How do user-generated content and brand-generated content differ in influencing consumer purchase intention?
2. How do user-generated content and brand-generated content differ in influencing consumer engagement?
3. How do different levels of brand awareness (high vs. low) moderate the influence of content type on consumer purchase intention?
4. How do different levels of brand awareness (high vs. low) moderate the influence of content type on consumer engagement?

The findings from this research aim to contribute to the existing literature of digital marketing by providing empirical evidence and deeper understanding of how different content types influence consumer behavior, particularly purchase intention and engagement. By examining the moderating effect of brand awareness, this study seeks to fill the research gaps in the current literature. Additionally, understanding how different content type and levels of brand awareness affect consumer behavior can provide valuable insights for marketers and brand managers, leading to more effective digital marketing strategies. Determining which type of content is more effective under different levels of brand awareness will guide brand managers and marketers in allocating their budgets effectively towards content that optimizes engagement and enhances return on investment.

To form a comprehensive analysis of the topic, this paper is divided into six chapters. Chapter 1 outlines the research questions, goals, and relevance. Chapter 2 provides a literature review, focusing on the roles of user-generated content (UGC) and brand-generated content (BGC). Chapter 3 discusses the data and methodology of this research, including the tools and approaches used to gather and analyze data. Chapter 4 presents the results, detailing the findings of the research and analysis. Chapter 5 includes a discussion and interpretation of these results, comparing them with existing theories and practices in digital marketing. The paper concludes with Chapter 6, which summarizes the research, highlights its contributions, acknowledges its limitations and suggests directions for future research on this topic.

2. Literature Review

This chapter discusses the theories and evidence necessary to answer the research questions outlined in the previous chapter. The first section discusses social media marketing. The second section explains brand-generated content (BGC) and its past research. The third section provides literature on user-generated content (UGC). The fourth section continues with consumer purchase intention. The fifth section discusses about the consumer engagement. The sixth section covers brand awareness and its moderating effect on engagement and purchase intention. The final section concludes this chapter with a conceptual framework and hypotheses development. Throughout these sections, four hypotheses are formulated to address the research questions introduced in the first chapter.

2.1. Social Media Marketing

As technology advances, social media platforms have gained popularity and significance in marketing practices. The growing influence of these platforms on consumer behavior has led brands to integrate social media marketing into their marketing mix (Godey et al., 2016; Mangold & Faulds, 2009). Studies have found that social media marketing significantly influences consumer behavior, particularly purchase intention and engagement (Husnain & Toor, 2017; Nguyen et al., 2020; Jaakonmäki et al., 2017).

Content is crucial element of social media marketing. Designing engaging and relevant content is pivotal for businesses as through more appealing advertising or campaigns, brands can maximize the impact of their social media marketing strategies (Jaakonmäki et al., 2017). Brand-generated content (BGC) and user-generated content (UGC) are two types of social media marketing content that have gained popularity in recent years. The main difference between the two lies in the nature of their creation and purpose. User-generated content (UGC) is created by consumers to reflect their personal experiences and opinions, often influencing purchase decisions based on credibility, while brand-generated content (BGC) is strategically produced by brands to engage and retain a defined audience, subtly guiding consumer behavior without direct promotion (Müller & Christandl, 2019). Although the influence of UGC and BGC differs in significance and strength on consumer behavior, it has been found that relying solely on BGC is not sufficient due to consumers' need for perceived originality to stimulate purchase intention (Müller & Christandl, 2019; Irelli & Chaerudin, 2020). Understanding which content works best for different types of consumers is essential to maximize the impact of social media marketing.

2.2. Brand-Generated Content (BGC)

Brand-generated content (BGC) is one of the largest and fastest-growing forms of social media marketing today (Dencheva, 2023). BGC is a type of content created by the brand themselves containing relevant and valuable content to be shared and published through the brand's own channels to attract, engage, and drive profitable actions from a clearly defined audience (Pulizzi, 2012; Du Plessis, 2017; Müller & Christandl, 2019). According to other study, BGC involves the creation and aesthetic curation of informational or promotional material by brands, designed to populate brands' business pages and effectively communicate product details or brand-centric messages (Irelli & Chaerudin, 2020). BGC's popularity among marketers is rising as it uses unobtrusive, pulling techniques rather than traditional, interruptive methods, enhancing brand engagement (Du Plessis, 2017). Technological advancements have made a wide range of information and knowledge more accessible, emphasizing the importance of digital strategies in educating and convincing consumers, which is often done by brands by publishing their own contents through social media platforms (Kee & Yazdanifard, 2015).

Numerous studies have investigated into the relationship between BGC and consumer behaviors such as purchase intention and engagement. Poulis et al. (2019) found that BGC positively impacts brand awareness, brand loyalty, electronic word of mouth, and purchase intention. They also noted a significant difference in the impact of BGC posted on Instagram compared to Facebook, with Instagram content impact users more positively than content on Facebook (Poulis et al., 2019). Contrarily, Joyosugito and Sobari (2020) found that while BGC positively affects brand awareness, loyalty, and electronic word of mouth, it does not necessarily influence purchase intentions, especially for well-known brands. This variation highlights a gap this study aims to further investigate.

Significant progress has been made in understanding different types of BGC and their impact on consumer engagement. Bai and Yan (2020) identified two types of brand-generated content, informative and persuasive. Informative BGC includes product-related content like products, deals, and locations, while persuasive BGC features brand personality content such as friendly reminders and emotional appeals (Bai & Yan, 2020). Their findings indicated that both informative and persuasive BGC significantly boost consumer engagement by satisfying information needs and enhancing brand identity. However, combining these content types can overwhelm consumers, potentially diminishing engagement due to information overload (Bai & Yan, 2020). Additionally, Meire et al. (2019) found that BGC significantly enhances consumer engagement by improving sentiment during experiential events. Informational BGC is particularly effective in positively influencing consumer sentiment during unfavorable event outcomes, while emotional BGC consistently boosts engagement regardless of the outcomes (Meire et al., 2019). This demonstrates BGC's ability to strategically influence consumer emotions and attitudes, thereby enhancing overall engagement with the brand. The recurring theme in these studies is that BGC enhances consumer engagement, reflecting a broader interest in identifying the factors that influence consumer engagement in marketing research.

2.3. User-Generated Content (UGC)

Technological advancements have significantly empowered consumers to share their personal experiences about products and services online through what is commonly known as user-generated content (UGC). According to Ridwan et al. (2017), UGC offers consumers the opportunity to share their experiences, opinions, and having online discussions about brands' products, seizing solitary control that brand managers used to have in managing brand image. Naab and Sehl (2016) define UGC as content created and published by users on digital platforms that allow significant personal input. They added that to foster broader discussions within society or specific groups, the content must be publicly accessible. Unlike professionally produced content, UGC emerges outside of professional routines and practices (Naab & Sehl, 2016).

Further defining UGC, Krumm et al. (2008) describe it as data, information, or media voluntarily contributed by individuals and displayed on digital platforms in ways that are useful or entertaining to others. According to them, UGC typically contains a wide array of forms such as ratings, reviews, testimonials, and social media posts. A notable aspect of UGC is its cost-effectiveness, as it is usually provided by users at no charge, allowing content creators to gain recognition for their contributions while offering consumers genuine insights from other users, unfiltered by traditional media channels (Krumm et al., 2008).

Among various types of UGC, reviews are extensively researched. These studies span across multiple industries and illustrate how UGC influences consumer purchase intention positively in sectors such as travel and tourism (Litvin, Goldsmith, & Pan, 2008; Mendes-Filho, Mills, Tan, & Milne, 2018; Ye et al., 2011), video games (Zhu & Zhang, 2010; Müller & Christandl, 2019), books (Chevalier and Mayzlin 2006), and restaurants (Luca, 2016). The effectiveness of UGC is underlined by several theories, including those that link UGC to increased consumer confidence in a brand mediated by brand trust, suggesting that UGC can significantly influence purchase decisions (Demba et al., 2019).

Sethna et al. (2017) highlight gender differences in the impact of UGC, finding that females are generally more influenced by UGC compared to males, suggesting that women may be more receptive to the opinions and reviews shared by other consumers online. This points to potential variations in marketing effectiveness across demographics. Trust, as noted by Sethna et al. (2017), plays a crucial role in this dynamic, with a higher level of trust in UGC correlating with increased purchase intentions for both genders.

Another reason why UGC has been influential on consumer behavior is that it acts as social proof, allowing consumers to share their real-life experiences and influence potential consumers to try products and services. This can help create trust in potential customers towards a product or brand while simultaneously creating a community and enhancing customer engagement and loyalty (Mathur et al., 2022).

Apart from purchase intention, studies have found that UGC significantly influences consumer engagement. However, various factors can determine this influence. For instance, Mohammad et al. (2020) found that the functional and emotional value of UGC positively affects brand engagement. To achieve this, UGC needs to be accessible and enjoyable to increase its functional and emotional value, hence boosting engagement (Mohammad et al., 2020). Moreover, the quality of UGC plays a crucial role in enhancing users' functional and emotional values. By having quality that is easy to understand unique, popular, and relevant to users' interests, UGC can encourage users to spend more time involved with the brand, connecting both cognitively and emotionally (Mohammad et al., 2020). Additionally, the tone of UGC also influences engagement, with positive posts found to attract more likes but fewer comments than neutral posts (Yang et al., 2019). Social media posts containing social complaints, on the other hand, receive more likes but fewer comments than posts related to quality or money issues (Yang et al., 2019). Furthermore, encouraging the creation of UGC can significantly influence consumer engagement positively, which in turn may enhance purchase intention (Malthouse et al., 2016). Malthouse et al. (2016) also suggest that hosting contests can incentivize participation and effectively boost engagement.

Drawing from existing research, UGC typically enhances consumer purchase intention and engagement by providing perceived authentic and trustworthy content, leveraging social proof and authenticity more effectively than traditional marketing content (Demba et al., 2019). Despite extensive research, gaps remain in understanding specific contexts or conditions under which UGC is most effective, highlighting the need of comprehensive models to predict when and why UGC leads to higher engagement.

2.4. Consumer Purchase Intention

Purchase intention measures consumer's likelihood of buying a particular product or service in the future (Wu et al., 2011). Various study found a positive correlation between purchase intention and the probability of an actual purchase, highlighting purchase intention's influence on consumer behavior, actions, and brand commitment (Fishbein and Ajzen, 1975; Dodds et al., 1991; Schiffman and Kanuk, 2007; Wu et al., 2011).

Engel et al. (1995, as referenced in Lee et al., 2019) classified purchase intentions into three categories: unintended, partially intended, and fully intended purchases, each characterized by different levels of pre-purchase deliberation. Unintended or impulse purchases or impulse purchases occur spontaneously when consumers decide to buy a product in-store, partially intended purchases involve pre-selecting a product category with final decisions made at the point of sale, and fully intended purchases are thoroughly planned with both product and brand decisions made prior to shopping (Engel el al., 1995). These purchasing behaviors are influenced by brand awareness and the strength of the brand image (Lee et al. 2019).

Moreover, purchase intentions and decisions, are found to be influenced by brand image, awareness, customer knowledge, trust, perceived risk, and perceived values such as ease of use, usefulness, and enjoyment (Shah et al., 2012; Younus et al., 2015; Kian et al., 2017; Martins et al., 2019). A thorough understanding of consumer purchase intentions, shaped by both emotional states and situational triggers (Kotler, 2003), is essential for crafting effective marketing strategies that resonate with consumer needs and preferences.

Studies also reveal the varying impacts of different content types on consumer purchase intention. As Generation Y, also known as millennials, increasingly utilizes social media to obtain information about products or brands, they tend to rely more on user-generated content (UGC) than brand-generated content (BGC) due to its perceived authenticity (Irelli & Chaerudin, 2020). According to Irelli and Chaerudin (2020), consumers believe that UGC provides more accurate information than BGC, parallel with the findings of Müller and Christandl (2019), who note that UGC is often perceived as more authentic and trustworthy as it comes directly from consumers rather than being created by the brand itself. However, BGC remains important for providing expertise, relevance, and credibility, qualities that often absent in UGC (Irelli & Chaerudin, 2020).

Mayrhofer et al. (2020) discovered that persuasive messages in content negatively affect consumer purchase intention. Their experiments suggested that UGC does not trigger persuasion knowledge or subsequent negative effects that persuasive messages in BGC do, leading to higher purchase intentions for UGC compared to BGC (Mayrhofer et al., 2020). In contrast, Müller & Christandl (2019) suggested that BGC and UGC contents are perceived similarly, even though BGC comes directly from the brands. Kajtazi & Zeqiri (2020) also found that in Kosovo, both BGC and UGC generated a solid positive impact on purchase intention, noting that the attractiveness of content can significantly enhance its influence on consumers (Kajtazi & Zeqiri, 2020).

Contrastingly, Al-Abdallah and Jumaa (2022) observed that in the Kurdistan Region of Iraq, BGC impacts the consumer buying process more significantly than UGC, potentially due to different characteristics of the BGC content in the region being lower in content valence and higher in information richness, which they found to be crucial in communication effectiveness. The study that was done by Al-Abdallah and Jumaa (2022) implies that industry-specific factors, cultural contexts, and the credibility of UGC creators might influence these outcomes, differing from findings by Irelli and Chaerudin (2020).

The focus of UGC and BGC is also different. UGC, as it comes directly from consumers, is typically outside brand control and often serves entertainment or education purposes, contrasting with BGC’s promotional focus (Müller & Christandl, 2019; Naab & Sehl, 2017).

Despite these contrasting findings, the trend in existing studies suggests that UGC generally has a more substantial positive influence on consumer purchase intentions than BGC. This observation has led to the formulation of the following hypothesis:

Hypothesis 1 (H1): User-Generated Content has a greater positive influence on consumer purchase intention compared to brand-generated content.

2.5. Consumer Engagement

Consumer engagement has become increasingly important because of the rapid development of social media and online content creation. According to Ibrahim et al. (2022), consumer engagement with social media content can be assessed through the number of likes, comments, and shares. Zailskaite-Jakste and Kuvykaite (2012) argued that consumer engagement is crucial for brands to enhance their brand presence and gain a competitive edge. Their findings suggest that engaging consumers online can lead to more active interactions on social media, help improve brand attributes, and attract loyal customers who are likely to advocate for the brand (Zailskaite-Jakste & Kuvykaite, 2012).

As enhancing consumer engagement becomes pivotal for brands on digital platforms, studies have analyzed the different impacts of content types on engagement, particularly between user-generated content (UGC) and brand-generated content (BGC). According to Ibrahim et al. (2022), UGC more effectively predicts 'likes' and 'shares' compared BGC, although BGC tends to generate more comments. Similarly, Aljarah et al. (2024) discovered that UGC is a more accurate predictor of consumer engagement compared to BGC. Their study added that consumer engagement significantly mediates online brand advocacy for unfamiliar brands, further highlighting the important influence that engagement has in building brands online.

It is also found that content types moderate the effect of consumer engagement in corporate social responsibility (CSR). Badenes-Rocha et al. (2019) reveal that CSR communications made by customers, which is referring to UGC, reinforce the impact of CSR messages on customer trust more significantly than those made by brands, indicating that UGC may have a stronger influence on engagement through enhanced trust levels compared to BGC. However, there is a lack of direct comparison between which content type is more effective in driving engagement.

Despite the growing presence of studies analyzing the influence of different content types on consumer engagement, there is a significant gap in literature comparing the significance of UGC and BGC on engagement in detail, despite more journals suggesting that engagement is a pivotal metric for brands. There is a trend, however, showing that UGC is a better predictor and driver of consumer engagement than BGC. With that, the following hypothesis is formulated:

Hypothesis 2 (H2): User-Generated Content has a greater positive influence on consumer engagement compared to brand-generated content.

2.6. Brand Awareness

Brand awareness refers to the degree to which consumers recognize and are familiar with a business and its products (Gustafson & Chabot, 2007). With the abundance of options and information on the internet, achieving high awareness is crucial for brands as it means that your brand is easily recognizable, a way to differentiate your brand from its competitors and gain a competitive edge (Gustafson & Chabot, 2007). Hameed et al. (2023) argued that customers with high brand awareness are more likely to recognize a brand when exposed to it, making it simpler for them to identify and recall the brand in specific circumstances.

As captured by Shahid et al. (2017), brand awareness significantly influences consumer purchase intention, as familiarity raises preference and trust, which are critical in the decision-making process. Customers tend to purchase from well-established companies that they find familiar and trustworthy, a tendency supported by studies on brand awareness which highlight that brand awareness not only enhances the likelihood of consumers on selecting known brands but also strengthens consumers' recall and preference in a market saturated with alternatives, ultimately influencing their purchase intentions (Sharma & Singh, 2021; Hameed et al., 2023). In addition, research by Kim and Kim (2016) found that consumers, when constantly exposed to a variety of brands, tend to retain and recall those that are popular, well-regarded, and prominent in the market. This level of brand recognition and the consumers' understanding of a brand's attributes significantly influence their likelihood of acquiring that brand (Kim & Kim, 2016).

There are various methods that brands can use to increase awareness. For instance, with the rise in prominence of social media, it has become crucial for brands to share content via social media to boost their marketing efforts. ElAydi (2018) discovered that engaging in social media marketing activities is important for businesses as it enhances brand awareness, which can subsequently result in higher sales revenue. Marzouk (2016) also supports this finding, noting that social media marketing assists firms in creating and boosting brand awareness, which subsequently leads to improved sales performance. Additionally, Shabbir et al. (2010) discovered brand awareness' role in mediating the relationship between marketing campaigns and consumer purchase intention, which might help explain the effect that brand awareness has in explaining or influencing the relationship between social media marketing and consumer purchase intention.

There is a noticeable gap in the existing literature regarding whether brand awareness levels (high vs. low) moderate the relationship of different content types (UGC vs. BGC) on consumer purchase intention and engagement. This study aims to address this gap by formulating hypotheses based on the existing literature that indirectly discusses these relationships.

When brand awareness level is low, UGC is believed to have stronger influence on consumer purchase intention and consumer engagement compared to BGC. Studies suggest that consumers rely more on UGC due to its perceived authenticity and trustworthiness when they are less familiar with a brand or product (Irelli & Chaerudin, 2020; Müller & Christandl, 2019). However, as brand awareness increases, the authenticity provided by UGC might become less critical, and the reinforcing effect of BGC becomes more prominent. BGC's credibility, relevance, and expertise can enhance consumer trust and influence purchase intentions more effectively when the brand is already well-known (Irelli & Chaerudin, 2020).

In terms of consumer engagement, UGC is more effective at engaging consumers through social proof and relatability when brand awareness is low (Ibrahim et al., 2022; Zailskaite-Jakste & Kuvykaite, 2012). Consumers are more likely to engage with content that reflects real-life experiences from other users, which helps to build trust and a sense of community. When brand awareness is high, the impact of BGC may be enhanced as established brands can leverage their recognition and reputation to maintain consumer engagement. Established brands can use BGC to highlight their strengths and maintain a consistent brand image, which can be crucial for long-term customer relationships (Aljarah et al., 2024; Badenes-Rocha et al., 2019).

With the above rationale from existing literature, the following hypotheses are formulated:

Hypothesis 3 (H3): Brand awareness levels (High vs. Low) moderate the relationship between content types (UGC vs. BGC) and purchase intention.

Hypothesis 4 (H4): Brand awareness levels (High vs. Low) moderate the relationship between content types (UGC vs. BGC) and engagement.

2.7. Conceptual Framework and Research Hypothesis

Based on the literature discussed in the previous sections, different content types are anticipated to have varying impacts on consumer purchase intention and consumer engagement. These relationships are summarized in Hypotheses 1 and 2. Additionally, brand awareness is expected to moderate the relationship between content types (UGC and BGC) and consumer purchase intention and engagement, as outlined in Hypothesis 3 and 4**.**

The conceptual framework (see ***Figure 1***) visually represents these relationships, illustrating the expected interactions between content types, brand awareness, purchase intention, and consumer engagement. This model serves as the foundation of the empirical analysis conducted in this study.

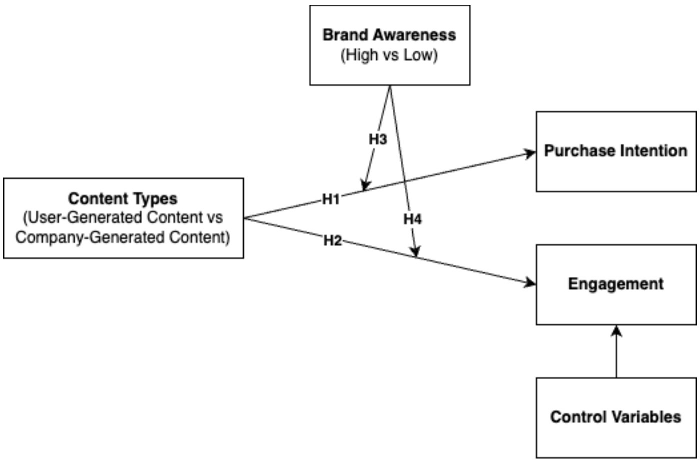

Figure 1. Research Framework

3. Data and Methodology

This chapter outlines the data collection and methodology used in this study. The first section covers data collection and the sample. The second section elaborates on the measures of the variables. The third section explains the data analysis process, including the regression model. The fourth section presents descriptive statistics of the data. The fifth section details the creation of dummy variables for the regression analysis. Finally, the sixth section examines the reliability of the measurement scales.

3.1. Data Collection and Sample

This study investigates the influence of different content types in social media marketing (brand-generated content and user-generated content) and the moderating effect of brand awareness on consumer purchase intention for vacuum cleaners, a home appliance product. To recruit participants, social media platforms such as LinkedIn, Instagram, Facebook and WhatsApp were utilized, employing snowball and voluntary sampling. Additionally, convenience sampling was used initially to gather pretest results and initial respondents. These methods aimed to achieve a diverse representation across different consumer segments and demographics with varying levels of brand awareness.

To capture responses of consumers in different types of scenarios, the survey is designed as an experimental between-subjects with a 2x2 model (BGC vs. UGC) x (High vs. Low Awareness), resulting in the creation of four scenarios such as follows:

1) Low brand awareness with user-generated content
2) Low brand awareness with brand-generated content
3) High brand awareness with user-generated content
4) High brand awareness with brand-generated content

Using an experimental survey allows for controlled manipulation of the variables (content types and brand awareness levels), which helps establish causal relationships between these variables and consumer behavior (Mosleh et al., 2021). Furthermore, experimental design would also be beneficial for the study as it can simulate real-world scenarios while maintaining a controlled environment, thus providing high internal validity (Kuru & Pasek, 2016).

There are multiple reasons to why this study preferred a between-subjects design over a within-subjects design. First, it eliminates the risk of carryover effects, where participants' responses to one condition could influence their responses to another (Brunk, 1958). This is particularly important when examining variables like brand awareness and content types, where exposure to one scenario could alter perceptions and behavior in subsequent scenarios. Second, it reduces the likelihood of fatigue or boredom that participants might experience if required to complete multiple scenarios, thus maintaining the integrity and accuracy of their responses (Sauermann & Roach, 2012). Lastly, a between-subjects design simplifies the survey process for respondents, reducing complexity and potential confusion, leading to more reliable data (Pozzar et al., 2020).

The survey questionnaires were created using Erasmus Qualtrics. This survey was published with a target to obtain a minimum of 120 respondents evenly distributed across the four scenarios. When entering the survey, participants were informed that the survey focused on social media marketing content types and consumer behavior. Information regarding the survey structure and estimated completion time was provided upfront. Additionally, instructional information about how the survey would be conducted and a privacy notice assuring confidentiality of their responses for scientific purposes were included before proceeding to the survey.

The survey employed criteria for data cleaning and analysis purposes, such as requiring respondents to complete every question for their responses to be considered valid. An attention check question was included mid-survey to ensure respondents were attentive, with failure to pass this check resulting in invalidation of their responses. This criterion helps ensure that only respondents who are paying attention and answering the questions according to the facts and scenarios presented are included in the final analysis.

3.2. Measures

To measure the influence of different social media marketing content types on consumer purchase intention and engagement, as well as the moderating effect of brand awareness, a series of questions using categorical items, and a standard 5-point Likert scale were formulated. During the survey, respondents ranked their reactions to purchase intention and consumer engagement in response to brand-generated and user-generated content. The scale ranged from 1 (Strongly Disagree) to 5 (Strongly Agree), comparable to similar studies (Balakrishnan et al., 2014; Pandey et al., 2018; Athapaththu & Kulathunga, 2018; Ceyhan, 2019). The survey concluded with demographic questions such as age group, income, education, gender, Instagram usage frequency, and online shopping frequency. More of this can be seen in the below table and ***Appendix B***.

Variables	Items	Description	Source
Purchase Intention	PI-1	How likely are you to purchase this vacuum cleaner	Adopted from Dodds et al., 1991
	PI-2	If you needed a vacuum cleaner, how probable is it that you would consider buying this product?	
	PI-3	My willingness to buy this product is…	
Consumer Engagement	CE-1	How likely are you to like this post on Instagram?	Adopted from Deng et al., 2021
	CE-2	How likely are you to share this post with your friends or family?	

3.3. Data Analysis

To analyze the correlation between variables derived from the survey responses, several statistical analyses were employed using SPSS. Descriptive analysis showcased basic characteristics of the data, such as the mean, standard deviation, and frequency. Cronbach's Alpha test assessed the reliability and internal consistency of the survey scales, following methods used in similar studies (Dewi et al., 2022; Almohaimmeed, 2019).

To test the hypotheses, multiple regression analysis was employed to examine the direct effect of content types on purchase intention and consumer engagement, as well as the moderating effect of brand awareness on these relationships. The following regression models were formulated:

Equation 1. Regression Model for Purchase Intention

$$PI = \beta_0 + \beta_1 CT + \beta_2 BA + \beta_3 (CT \times BA) + \beta_5 Control\,Variables + \epsilon$$

Equation 2. Regression Model for Consumer Engagement

$$CE = \beta_0 + \beta_1 CT + \beta_2 BA + \beta_3 (CT \times BA) + \beta_5 Control\,Variables + \epsilon$$

Where:

- PI = Consumer Purchase Intention
- CE = Consumer Engagement
- CT = Content Type (1 for UGC, 0 for BGC)

- BA = Brand Awareness (1 for High, 0 for Low)
- ϵ = error term
- Control Variables = Demographics (i.e. Age, Education, etc.)

Multiple regression analysis was selected for the analysis of this study for several key reasons. Firstly, it allows for the inclusion of multiple independent variables while also accounting for the moderating role of brand awareness simultaneously (Dumirescu et al., 2012). A study by Mason and Perreault (1991) confirms that this method is particularly robust for examining interaction effects, which is essential for understanding how brand awareness influences the relationship between content types and consumer behaviors such as consumer engagement and purchase intention. Additionally, multiple regression analysis effectively controls for potential confounding variables, ensuring that the observed effects are specifically attributable to the variables of interest (Rust, 1988; Mishra et al., 2010). This robustness makes it an ideal choice for the complexity of the relationships being studied.

3.4. Descriptive Statistics

After publishing the survey via Qualtrics from June 3rd, 2024, to June 13th, 2024, a total of 467 responses were acquired. Out of these, only 350 responses were usable, as 117 respondents did not complete the survey. Additionally, 94 responses were dropped because respondents failed the attention check or consent question, resulting in 256 valid responses for analysis.

Out of the 256 valid responses, respondents were evenly distributed across the four scenarios, except for scenario 1 where it has about 18 respondents less compared to the other scenarios. ***Table 1*** shows the frequency distribution of the survey scenarios.

Table 1. Frequency Table of Survey Scenarios

Scenario	Frequency	Percent	Cumulative Percent
1	50	20%	20%
2	69	27%	46%
3	69	27%	73%
4	68	27%	100%
Total	256	100%	

Descriptive statistical analysis on the dependent variables, Purchase Intention and Consumer Engagement, provided insights into central tendency and dispersion within the dataset.

Table 2. Dependent Variables Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Purchase Intention	256	1.00	5.00	3.5404	.76760	.589	-.528	.152	.779	.303
Consumer Engagement	256	1.00	5.00	2.9277	1.07176	1.149	-.124	.152	-.733	.303

The mean score for Purchase Intention was 3.54 (SD = 0.77), indicating a moderate to high intention to purchase. The distribution was slightly left-skewed (Skewness = -0.528), with a slight peak (Kurtosis = 0.779), within normal distribution limits (-2 to +2).

The mean score for Consumer Engagement was 2.93 (SD = 1.07), indicating moderate engagement. The distribution was nearly normal with slight left skew (Skewness = -0.124) and a flatter distribution (Kurtosis = -0.733). Variability was higher in Consumer Engagement, suggesting diverse engagement levels among respondents.

Table 3. Frequency of the Categorical Variables

Variable	Category	Frequency	Percent
Brand Awareness	Low Awareness	119	46.5%
	High Awareness	137	53.5%
Content Type	Brand Generated Content	119	46.5%
	User Generated Content	137	53.5%
Instagram Usage Frequency	Never	11	4.3%
	Once a week	10	3.9%
	2-3 times a week	25	9.8%
	4-6 times a week	23	9.0%
	Daily	187	73.0%
Household Appliances Online Purchase Frequency	Never	18	7.0%
	Sometimes	154	60.2%
	About half the time	37	14.5%
	Most of the time	38	14.8%

Variable	Category	Frequency	Percent
	Always	9	3.5%
Age Group	Under 18	9	3.5%
	18 – 24	77	30.1%
	25 – 34	58	22.7%
	35 – 44	35	13.7%
	45 – 54	70	27.3%
	55 – 64	6	2.3%
	75 – 84	1	0.4%
Gender	Male	124	48.4%
	Female	124	48.4%
	Non-binary / third gender	3	1.2%
	Prefer not to say	5	2.0%
Education	Less than high school	7	2.7%
	High school graduate	33	12.9%
	Some college	32	12.5%
	Associate's Degree	1	0.4%
	Bachelor's degree (HBO or University)	124	48.4%
	Master's degree (HBO or University)	57	22.3%
	Doctorate (PhD)	2	0.8%
Income	Less than €1,500	110	43.0%
	€1,500 – €2,500	63	24.6%
	€2,501 – €3,500	41	16.0%
	€3,501 – €5,000	27	10.5%
	€5,000 – €10,000	10	3.9%
	More than €10,000	5	2.0%

Descriptive statistics of the categorical variables show a balanced distribution in brand awareness and content type exposure. For instance, 46.5% of the responses were recorded for low brand awareness, and 53.3% respondents were recorded for high brand awareness manipulation. Similarly, the content type distribution was balanced, with 46.5% for brand-generated content, and 53.5% for user-generated content. This balance indicates that both content types are equally represented in the sample, providing a solid basis for comparing their effects on consumer behavior.

Furthermore, the descriptive statistics highlight a high daily Instagram usage among the sample, with 73% of respondents using Instagram daily. The household appliance online purchase frequency among the sample is varied, with 60.2% purchasing household appliances online occasionally (sometimes). Gender representation was balanced, with an identical number of both male and female respondents. Most respondents are highly educated (bachelor’s degree or higher) and fall into lower income brackets, which could influence their purchasing power and preferences.

3.5. Creation of Dummy Variables

To facilitate the regression analysis, several control variables were converted into dummy variables, assigning binary values (0 or 1) to different categories. This conversion allowed their inclusion in the regression models.

The initial sample of 256 respondents included non-binary or third gender and non-disclosed gender respondents, but these groups were excluded from the final analysis due to their small size, which could lead to unreliable estimates and biases. Consequently, the final sample size for regression analysis excluded these respondents. Two dummy variables for male and female respondents were then made.

Several age groups were combined to address underrepresentation. For instance, respondents under 18 years old and those aged 18-24 were combined, as the under 18 group had only 9 respondents. Similarly, the 55-64 and 75-84 age groups were merged with the 45-54 group to form an older age group. Additionally, the 25-34 and 35-44 age groups were combined. These combinations helped simplify the regression analysis and ensure sufficient representation.

In terms of education, dummy variables were created by merging several education levels. The new categories were "High School or Less" (combining "Less than high school" and "High school graduate"), "Some College/Associate's Degree" (combining "Some college" and "Associate's Degree"), "Bachelor’s Degree" (remaining the same), and "Postgraduate" (combining "Master’s degree" and "Doctorate").

For income, the new distribution of the dummy variables included "Low Income" (combining "Less than €1,500" and "€1,500 – €2,500") and "High Income" (combining "€2,501 – €3,500", "€3,501 – €5,000", "€5,000 – €10,000", and "More than €10,000"). Furthermore, Instagram usage frequency was categorized into "Low Usage" (combining "Never", "Once a week", and

"2-3 times a week") and "High Usage" (combining "4-6 times a week" and "Daily"). Finally, online purchase frequency was categorized into "Low Purchase" (combining "Never" and "Sometimes") and "High Purchase" (combining "About half of the time", "Most of the time", and "Always"). These dummy variables simplified the regression analysis and helped avoid underrepresentation.

3.6. Reliability Analysis

Cronbach's Alpha was utilized to assess the internal consistency of the scales. High reliability indicates that the items within each scale constantly measure the same underlying construct, crucial for the validity of the findings (Bravo & Potvin, 1991).

Table 4. Cronbach's Alpha Table of Dependent Variable's Measurement Scale

Variable	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Purchase Intention	.808	.809	3
Consumer Engagement	.721	.721	2

The Purchase Intention scale exhibited good internal consistency, with a Cronbach's Alpha of 0.809 (see ***Table 4***). The corrected item-total correlations ranged from 0.406 to 0.716, indicating that all items were sufficiently correlated with the overall scale. Notably, the item "My willingness to buy this product is…" had the highest corrected item-total correlation (0.716), suggesting it was particularly representative of the overall construct. Removing any item would not significantly improve the overall alpha, indicating that each item contributed positively to the scale's reliability.

Table 5. Item-Total Statistics for Variable Purchase Intention

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
How likely are you to purchase this vacuum cleaner?	7.21	2.481	.626	.406	.772
If you needed a vacuum cleaner, how likely is it that you would consider buying this product?	6.76	2.749	.631	.421	.762
My willingness to buy this product is…	7.27	2.521	.716	.515	.674

The Consumer Engagement scale, consisting of two items, exhibited acceptable internal consistency with a Cronbach's Alpha of 0.721 (see ***Table 4***). The corrected item-total correlations for both items were 0.564, indicating a moderate correlation with the overall scale.

Table 6. Item-Total Statistics for Variable Consumer Engagement

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
How likely are you to like this post on Instagram?	2.79	1.443	.564	.318	.
How likely are you to share this post with your friends or family?	3.06	1.494	.564	.318	.

The results confirm that the scales employed in this study are both reliable and internally consistent, thus providing a robust basis for further analysis. The acceptable and good levels of Cronbach's Alpha for Consumer Engagement and Purchase Intention, respectively, indicate that the items within each scale reliably measure the same underlying construct.

4. Results

This chapter presents the results of the statistical analyses conducted to test the hypotheses outlined in the previous chapters. The outcomes of the analysis examining the influence of user-generated content (UGC) against brand-generated content (BGC) on consumer purchase intention and engagement will be discussed. Additionally, the moderating role of brand awareness on these relationships will be explored.

The analyses were performed using multiple linear regression, incorporating various demographic and behavioral control variables to account for their potential influence on the dependent variables. Interaction term was included in the two of the models to test the moderation effects of brand awareness.

4.1.Hypotheses Testing

4.1.1. Hypothesis 1

A multiple linear regression was performed to test Hypothesis 1, using purchase intention as the dependent variable, content type as the independent variable, and various demographic and usage control variables. The model summary table indicates that this set of predictors explains 13.7% of the variance in purchase intention, or approximately 9.7% after adjusting for the number of predictors.

Table 7. Model Summary of Hypothesis 1 Regression Model

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.370	.137	.097	.71054	.137	3.408	11	236	<.001

Predictors: (Constant), High Online Purchase Frequency, Content Type, Male Respondents, Education: Some College/Associate's Degree, 25-34 years old, Low Income: <€2,500, Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Bachelor’s Degree, <24-years old

The ANOVA table confirms that the model implemented in Hypothesis 1 testing is statistically significant, meaning that the predictors collectively have a significant impact on Purchase Intention.

Table 8. ANOVA Table of Hypothesis 1 Regression Model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	18.929	11	1.721	3.408	<.001
Residual	119.149	236	.505		
Total	138.079	247			

Dependent Variable: Purchase Intention

Predictors: (Constant), High Online Purchase Frequency, Content Type, Male Respondents, Education: Some College/Associate's Degree, 25-34 years old, Low Income: <€2,500, Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Bachelor's Degree, <24-years old

The regression result indicates that content type is not a significant predictor of consumer purchase intention. It suggests that UGC negatively affects consumer purchase intention by 0.051 (B = -0.051, p = 0.584), although this is not statistically significant. Hence, the insignificance of content type explains that the data do not have sufficient evidence to conclude whether UGC and BGC differ in their influence on purchase intention within the context of this study. Therefore, **Hypothesis 1 is not supported** by the regression analysis results.

Table 9. Coefficients of Hypothesis 1 Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.567	.154		23.149	<.001
Content Type	-.051	.093	-.034	-.549	.584
<24-years old	-.355	.136	-.224	-2.609	.010
25-34 years old	-.311	.135	-.174	-2.300	.022
35-44 years old	-.231	.149	-.108	-1.545	.124
Male Respondents	-.084	.096	-.056	-.881	.379
Education: High School or Less	.213	.170	.103	1.255	.211
Education: Some College/Associate's Degree	.371	.163	.169	2.280	.024
Education: Bachelor's Degree	.221	.123	.148	1.790	.075
Low Income: <€2,500	-.006	.106	-.004	-.059	.953
Low Instagram Usage: Never to 3 times a week	-.168	.124	-.086	-1.362	.175
High Online Purchase Frequency	.403	.101	.251	3.994	<.001

The regression results also found that demographic factors such as age, education, and online behaviours play a crucial role in shaping consumer purchase intention. For instance, younger consumers (under 34 years old) are associated with lower purchase intention compared to the reference group (45 years old and older). Specifically, being 24 years old or younger is associated with purchase intention that is lower by 0.355 (B = -0.355, p = 0.010) units compared to being 45 years old and older. Similarly, being 25 to 34 years old is associated with purchase intention that is lower by 0.311 (B = -0.311, p = 0.022) units compared to the same reference age group.

Education level is another significant predictor of purchase intention in this model. Consumers with some college or an associate's degree are associated with purchase intention that is higher by 0.371 units (B = 0.371, p = 0.024) compared to consumers who have postgraduate degrees. Moreover, online purchase frequency is another significant predictor of purchase intention, with consumers who have high online purchase frequency being associated with a higher purchase intention by 0.403 units (B = 0.403, p < 0.001) compared to those with low online purchase frequency. These results suggest that while content type does not significantly influence purchase intention, demographic factors such as age and education, as well as online purchase frequency, are crucial in shaping consumers' purchase intentions.

4.1.2. Hypothesis 2

To test Hypothesis 2, a similar multiple linear regression was conducted with consumer engagement as the dependent variable instead of purchase intention. The model summary table indicates 23.7% of the variance in consumer engagement is explained by the model or 20.2% after adjusting for the number of predictors.

Table 10. Model Summary of Hypothesis 1 Regression Model

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.487	.237	.202	.95576	.237	6.672	11	236	<.001

Predictors: (Constant), High Online Purchase Frequency, Content Type, Male Respondents, Education: Some College/Associate's Degree, 25-34 years old, Low Income: <€2,500, Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Bachelor's Degree, <24-years old

The ANOVA table confirms that the model implemented in Hypothesis 2 testing is statistically significant, meaning that the predictors collectively have a significant impact on consumer engagement.

Table 11. ANOVA Statistics of Hypothesis 2 Regression Model

	Sum of Squares	df	Mean Square	F	Sig.
Regression	67.038	11	6.094	6.672	<.001[b]
Residual	215.582	236	.913		
Total	282.620	247			

Dependent Variable: Consumer Engagement

Predictors: (Constant), High Online Purchase Frequency, Content Type, Male Respondents, Education: Some College/Associate's Degree, 25-34 years old, Low Income: <€2,500, Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Bachelor's Degree, <24-years old

The regression result shown in the coefficients table (see ***Table 12***) indicates a positive, though not statistically significant, effect of content type on consumer engagement (B = 0.121, p = 0.334). This suggests that there is no sufficient evidence to conclude that UGC and BGC differ in their influence on consumer engagement within the context of this study. Therefore, **Hypothesis 2 is not supported** by the regression analysis results.

Table 12. Coefficients of Hypothesis 2 Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.141	.207		15.151	<.001
Content Type	.121	.125	.056	.968	.334
<24-years old	-.810	.183	-.357	-4.432	<.001
25-34 years old	-.949	.182	-.372	-5.225	<.001
35-44 years old	-.235	.201	-.077	-1.171	.243
Male Respondents	-.144	.129	-.067	-1.117	.265
Education: High School or Less	.349	.229	.118	1.527	.128
Education: Some College/Associate's Degree	.614	.219	.196	2.810	.005
Education: Bachelor's Degree	.072	.166	.034	.434	.665
Low Income: <€2,500	.169	.142	.074	1.186	.237
Low Instagram Usage: Never to 3 times a week	-.524	.166	-.187	-3.149	.002
High Online Purchase Frequency	.467	.136	.204	3.441	<.001

Dependent Variable: Consumer Engagement

The regression result shown in ***Table 12*** also shows that demographic factors such as age, education, online purchase frequency, and social media usage play a crucial role in shaping consumer engagement. The result suggests that being 24 years old or younger (B = -0.810, $p < 0.001$) and being between 25-34 years old (B = -0.949, $p < 0.001$) are both associated with significantly lower consumer engagement compared to being 45 years old and older. Education is the next significant predictor of consumer engagement with the regression result suggesting that having some college or an associate's degree is associated with significantly higher consumer engagement (B = 0.614, p = 0.005) compared to having a post-doctorate degree. Social media usage, which in the context of this study is specified to Instagram, is also another significant predictor with low Instagram usage being associated with lower consumer engagement (B = -0.524, p = 0.002) compared to high Instagram usage. Lastly, high online purchase frequency is associated with significantly higher consumer engagement (B = 0.467, $p < 0.001$) compared to low online purchase frequency.

4.1.3. Hypothesis 3

Hypothesis 3 investigates the moderating effect of brand awareness on the effect of content type on purchase intention. A slightly different multiple linear regression model is implemented with two new variables introduced in the form of brand awareness and the interaction term between brand awareness and content type. The model summary table indicates that 14.7% of the variance in purchase intention is explained by the model or 10.0% after adjusting for the number of predictors.

Table 13. Model Summary of Hypothesis 3 Regression Model

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.383	.147	.100	.70950	.147	3.100	13	234	<.001

Predictors: (Constant), High Online Purchase Frequency, Interaction Term (CT*BA), Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Some College/Associate's Degree, Male Respondents, Low Income: <€2,500, 25-34 years old, Brand Awareness, Education: Bachelor's Degree, <24-years old, Content Type

The ANOVA table confirms that the model implemented in Hypothesis 3 testing is statistically significant, meaning that the predictors collectively have significant impact on consumer engagement.

Table 14. ANOVA Statistics of Hypothesis 3 Regression Model

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	20.286	13	1.560	3.100	<.001[b]
Residual	117.793	234	.503		
Total	138.079	247			

Dependent Variable: Purchase Intention

Predictors: (Constant), High Online Purchase Frequency, Interaction Term (CT*BA), Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Some College/Associate's Degree, Male Respondents, Low Income: <€2,500, 25-34 years old, Brand Awareness, Education: Bachelor's Degree, <24-years old, Content Type

The regression analysis reveals that the interaction term between content type and brand awareness is not statistically significant (B = 0.064, p = 0.727), indicating that brand awareness does not moderate the relationship between content type and purchase intention. Additionally, neither content type (B = -0.097, p = 0.479) nor brand awareness (B = 0.120, p = 0.338) are significant predictors of purchase intention on their own. Therefore, **Hypothesis 3 is not supported** by the regression analysis results.

Table 15. Coefficients of Hypothesis 3 Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.523	.163		21.596	<.001
Content Type	-.097	.137	-.065	-.708	.479
Brand Awareness	.120	.125	.080	.960	.338
Interaction Term (CT*BA)	.064	.184	.038	.350	.727
<24-years old	-.350	.136	-.221	-2.578	.011
25-34 years old	-.297	.135	-.167	-2.202	.029
35-44 years old	-.233	.150	-.109	-1.561	.120
Male Respondents	-.068	.096	-.045	-.705	.482
Education: High School or Less	.204	.170	.099	1.202	.231
Education: Some College/Associate's Degree	.336	.164	.153	2.050	.041
Education: Bachelor's Degree	.196	.124	.131	1.574	.117
Low Income: <€2,500	-.014	.106	-.009	-.134	.893
Low Instagram Usage: Never to 3 times a week	-.190	.124	-.097	-1.526	.128

High Online Purchase Frequency	.397	.101	.248	3.944	<.001

a. Dependent Variable: Purchase Intention

The regression result also shows that demographic factors such as age, education, as well as online purchase frequency play a crucial role in shaping consumer engagement. Starting with age, being 24 years old or younger (B = -0.350, p = 0.010) and being between 25-34 years old (B = -0.297, p = 0.010) are both associated with significantly lower purchase intention compared to being 45 years old and older. With education, having some college or an associate's degree is associated with significantly higher purchase intention (B = 0.336, p = 0.041) compared to having a postgraduate degree. In online purchase frequency, high online purchase frequency is associated with significantly higher purchase intention (B = 0.397, p < 0.001) than consumers with low online purchase frequency.

4.1.4. Hypothesis 4

To test Hypothesis 4, similar multiple linear regression model with Hypothesis 3 was implemented with consumer engagement as the dependent variable instead of purchase intention. Similar to Hypothesis 3 regression model, brand awareness and its interaction term with content type were also introduced in the model to test the moderating effect of brand awareness on the effect of content type on consumer engagement. The model summary table indicates 23.9% of the variance in consumer engagement is explained by the model or 19.6% after adjusting for the number of predictors.

Table 16. Model Summary of Hypothesis 4 Regression Model

R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
.489	.239	.196	.95894	.239	5.642	13	234	<.001

Predictors: (Constant), High Online Purchase Frequency, Interaction Term (CT*BA), Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Some College/Associate's Degree, Male Respondents, Low Income: <€2,500, 25-34 years old, Brand Awareness, Education: Bachelor’s Degree, <24-years old, Content Type

The ANOVA table confirms that the model implemented in Hypothesis 4 analysis is statistically significant, meaning that the predictors collectively have significant impact on consumer engagement.

Table 17. ANOVA Statistics of Hypothesis 4 Regression Model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	67.443	13	5.188	5.642	<.001[b]
Residual	215.177	234	.920		
Total	282.620	247			

Dependent Variable: Consumer Engagement

Predictors: (Constant), High Online Purchase Frequency, Interaction Term (CT*BA), Low Instagram Usage: Never to 3 times a week, Education: High School or Less, 35-44 years old, Education: Some College/Associate's Degree, Male Respondents, Low Income: <€2,500, 25-34 years old, Brand Awareness, Education: Bachelor’s Degree, <24-years old, Content Type

The regression results shown in ***Table 18*** illustrate that the interaction term between content type and brand awareness is not statistically significant (B = 0.022, p = 0.928). Neither content type (B = 0.102, p = 0.582) nor brand awareness (B = 0.073, p = 0.568) are significant predictors of consumer engagement on their own. This suggests that there is no evidence to support that brand awareness moderates the relationship between content type and consumer engagement. Hence, **Hypothesis 4 is not supported** by the regression analysis results.

Table 18. Coefficients of Hypothesis 4 Regression Model

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.113	.220		14.120	<.001
Content Type	.102	.186	.048	.551	.582
Brand Awareness	.073	.169	.034	.429	.668
Interaction Term (CT*BA)	.022	.249	.009	.090	.928
<24-years old	-.808	.184	-.356	-4.403	<.001
25-34 years old	-.942	.183	-.369	-5.158	<.001
35-44 years old	-.236	.202	-.077	-1.168	.244
Male Respondents	-.135	.130	-.063	-1.038	.300
Education: High School or Less	.344	.230	.116	1.499	.135
Education: Some College/Associate's Degree	.595	.221	.189	2.691	.008
Education: Bachelor’s Degree	.058	.168	.027	.344	.731
Low Income: <€2,500	.165	.143	.072	1.151	.251
Low Instagram Usage: Never to 3 times a week	-.536	.168	-.192	-3.189	.002
High Online Purchase Frequency	.464	.136	.202	3.403	<.001

Dependent Variable: Consumer Engagement

The regression results also show demographic factors such as age, education, as well as online purchase frequency and social media usage play a crucial role in shaping consumer engagement. For instance, being 24 years old or younger ($B = -0.808$, $p < 0.001$) and being between 25 to 34 years old ($B = -0.942$, $p < 0.001$) are both associated with significantly lower consumer engagement compared to being 45 years old and older. In education, having some college or an associate's degree is associated with significantly higher consumer engagement ($B = 0.595$, $p = 0.008$) compared to having a postgraduate degree. Instagram usage behavior also significantly predict consumer engagement, with low Instagram usage associated with significantly lower consumer engagement ($B = -0.536$, $p = 0.002$) compared to high Instagram usage. Finally, high online purchase frequency is associated with significantly higher consumer engagement ($B = 0.464$, $p < 0.001$) compared to lower online purchase frequency.

4.2.Robustness Check

To test the validity and robustness of the results shown by the OLS regression of Hypotheses 1 to 4 previously, analyses such as multicollinearity, residual, and autocorrelation check were done. The results shown by these tests indicate that the regression results to test the hypotheses are all valid and robust.

4.2.1. Multicollinearity Check

To ensure the stability and reliability of the regression models conducted to test the four hypotheses, multicollinearity diagnostics were conducted.

Table 19. Collinearity Statistics of Purchase Intention Model

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Content Type	.433	2.309
Brand Awareness	.521	1.918
Interaction Term (CT*BA)	.304	3.285
<24-years old	.497	2.010
25-34 years old	.636	1.572
35-44 years old	.749	1.336
Male Respondents	.881	1.135
Education: High School or Less	.542	1.846
Education: Some College/Associate's Degree	.657	1.523

Education: Bachelor’s Degree	.525	1.904
Low Income: <€2,500	.829	1.207
Low Instagram Usage: Never to 3 times a week	.901	1.110
High Online Purchase Frequency	.921	1.086

Dependent Variable: Purchase Intention

The Variance Inflation Factor (VIF) and Tolerance values for the model with purchase intention as the dependent variable are within acceptable limits. Specifically, the VIF values were below 10, and Tolerance values were above 0.1 for all predictors, indicating no severe multicollinearity. The interaction term between content type and brand awareness, while higher than other variables, remained within acceptable limits (VIF = 3.285, Tolerance = 0.304).

Similarly, the VIF and Tolerance values for the model with consumer engagement as the dependent variable were within acceptable limits. All predictors had VIF values below 10 and Tolerance values above 0.1, indicating no severe multicollinearity. The interaction term between content type and brand awareness showed higher values but remained within acceptable limits (VIF = 3.285, Tolerance = 0.304).

Table 20. Collinearity Statistics of Consumer Engagement Model

Model	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Content Type	.433	2.309
Brand Awareness	.521	1.918
Interaction Term (CT*BA)	.304	3.285
<24-years old	.497	2.010
25-34 years old	.636	1.572
35-44 years old	.749	1.336
Male Respondents	.881	1.135
Education: High School or Less	.542	1.846
Education: Some College/Associate's Degree	.657	1.523
Education: Bachelor’s Degree	.525	1.904
Low Income: <€2,500	.829	1.207
Low Instagram Usage: Never to 3 times a week	.901	1.110
High Online Purchase Frequency	.921	1.086

Dependent Variable: Consumer Engagement

The multicollinearity diagnostics for both regression models indicate that multicollinearity is not a concern. All predictors have acceptable VIF and Tolerance values, ensuring the stability and reliability of the coefficient estimates. This validation step enhances the robustness of the findings and supports the interpretations and conclusions drawn from the regression analyses.

4.2.2. Residual Analysis – Linearity and Homoscedasticity Check

Residual analysis was conducted to validate the linearity and homoscedasticity assumptions of the OLS regression models conducted to test the hypotheses.

The scatter plot of standardized residuals versus standardized predicted values for the purchase intention model shows that the residuals are randomly dispersed around the horizontal axis without any visible pattern, indicating that the assumptions of linearity and homoscedasticity are satisfied. A few outliers were identified; however, they did not form a systematic pattern, indicating they might not heavily influence the overall model.

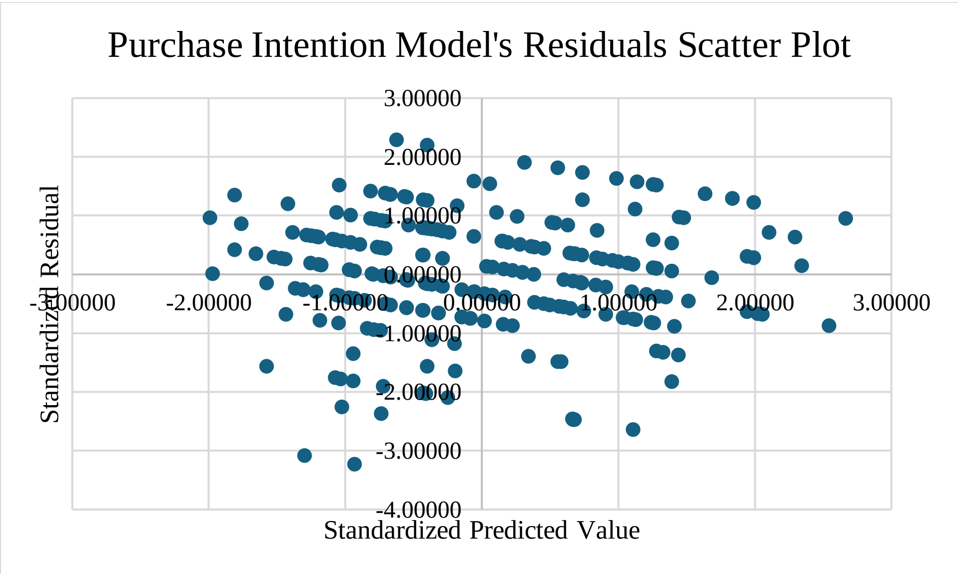

Figure 2. Purchase Intention Model Residuals Scatter Plot

Similarly, the scatter plot for Model 2 showed that the residuals were randomly scattered around the horizontal axis, with no clear pattern or structure. This indicates that the assumptions of linearity and homoscedasticity were satisfied for this model as well. Some potential outliers were identified and should be further investigated to ensure they do not disproportionately affect the model's results.

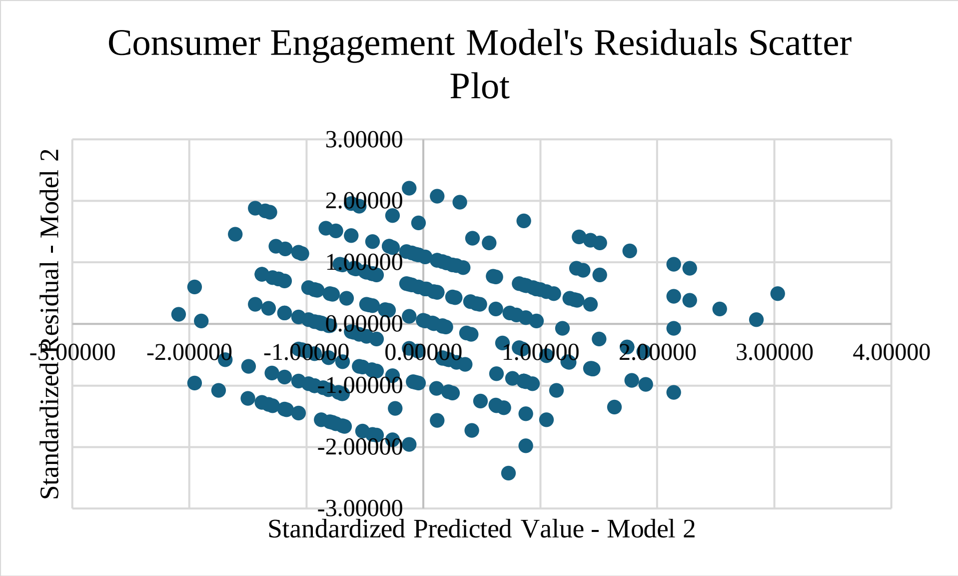

Figure 3. Consumer Engagement Model Residuals Scatter Plot

Conclusively, the residual analysis confirmed that the assumptions of linearity and homoscedasticity were reasonably met for both regression models, thereby enhancing the credibility and validity of the regression results and supporting the robustness of the conclusions derived from the analyses.

4.2.3. Autocorrelation Check

The Durbin-Watson statistic was utilized to detect autocorrelation in the residuals. The results are presented in the table below:

Table 21. Autocorrelation Statistics of Hypothesis Models

Hypothesis (Model)	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.370	.137	.097	.71054	2.021
2	.487	.237	.202	.95576	2.071
3	.383	.147	.100	.70950	2.030
4	.489	.239	.196	.95894	2.079

For all four hypotheses models, the Durbin-Watson statistics are very close to 2 (ranging from 2.021 to 2.079), suggesting no significant autocorrelation were found in the residuals. This implies that the residuals are independent, which is an important assumption for the validity of the regression models. Overall, the lack of significant autocorrelation in the residuals indicates that the models are robust, and the assumption of independent residuals holds true.

Conclusively, this analysis confirms that the models do not suffer from autocorrelation issues, which supports the reliability of the regression results presented in the study.

4.3. Sensitivity Analysis

To investigate the stability, and therefore robustness, of the models conducted to test the hypotheses, sensitivity analysis was performed. By systematically adding control variables, sensitivity analysis helps understanding the stability of the observed effects and identify any potential confounding factors.

4.3.1. Hypothesis 1

Table 22. Sensitivity Analysis Table for Hypothesis 1

Model	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Content Type	-0.026 (0.095)	-0.029 (0.096)	-0.029 (0.096)	-0.027 (0.095)	-0.029 (0.096)	-0.031 (0.095)	-0.051 (0.093)
<24-years old	-	-0.316** (0.118)	-0.316** (0.118)	-0.385** (0.134)	-0.368** (0.139)	-0.396** (0.140)	-0.355** (0.136)
25-34 years old	-	-0.287** (0.131)	-0.287** (0.131)	-0.250 (0.134)	-0.236 (0.139)	-0.266* (0.139)	-0.311** (0.135)
35-44 years old	-	-0.195 (0.153)	-0.195 (0.153)	-0.181 (0.154)	-0.236 (0.154)	-0.194 (0.154)	-0.231 (0.149)
Male Respondents	-	-	-0.119 (0.096)	-0.100 (0.097)	-0.102 (0.098)	-0.078 (0.099)	-0.084 (0.096)
Education: High School or Less	-	-	-	0.254 (0.174)	0.261 (0.175)	0.275 (0.175)	0.213 (0.170)
Education: Some College/Associate's Degree	-	-	-	0.399** (0.164)	0.413** (0.168)	0.412** (0.167)	0.371** (0.163)
Education: Bachelor's Degree	-	-	-	0.314** (0.124)	0.320** (0.125)	0.312** (0.125)	0.221 (0.123)
Low Income: <€2,500	-	-	-	-	-0.049 (0.108)	-0.064 (0.108)	-0.006 (0.106)
Low Instagram Usage: Never to 3 times a week	-	-	-	-	-0.199 (0.127)	-0.199 (0.127)	-0.168 (0.124)
High Online Purchase Frequency	-	-	-	-	-	-	0.403** (0.101)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.576*** (0.065)	3.774*** (0.098)	3.835*** (0.119)	3.592*** (0.146)	3.613*** (0.153)	3.667*** (0.157)	3.567*** (0.154)

Note: ** p<0.05; *** p<0.01

Seven models were tested to examine the correlation between different content types (UGC and BGC) and purchase intention. Each model incrementally includes different control variables to account for demographic and behavioral factors. The sensitivity analysis confirms that the primary finding, content type (UGC vs. BGC) does not significantly influence purchase intention, holds across various model specifications. Age and educational level emerge as consistent significant predictors of purchase intention. These findings underline the importance of considering demographic factors when analyzing consumer behavior.

4.3.2. Hypothesis 2

Table 23. Sensitivity Analysis Table for Hypothesis 2

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.876*** (0.093)	3.304*** (0.135)	3.464*** (0.162)	3.165*** (0.199)	3.105*** (0.208)	3.256*** (0.209)	3.341*** (0.207)
Content Type	0.159 (0.136)	0.164 (0.132)	0.162 (0.131)	0.143 (0.130)	0.150 (0.130)	0.144 (0.127)	0.121 (0.125)
<24-years old	-	-0.654*** (0.163)	-0.727*** (0.167)	-0.732*** (0.182)	-0.780*** (0.189)	-0.858*** (0.186)	-0.810*** (0.183)
25-34 years old	-	-0.835*** (0.180)	-0.886*** (0.182)	-0.775*** (0.183)	-0.814*** (0.187)	-0.897*** (0.185)	-0.949*** (0.182)
35-44 years old	-	-0.179 (0.210)	-0.225 (0.211)	-0.151 (0.209)	-0.154 (0.209)	-0.193 (0.205)	-0.235 (0.201)
Male Respondents	-	-	-0.235 (0.133)	-0.210 (0.132)	-0.204 (0.133)	-0.137 (0.132)	-0.144 (0.129)
Education: High School or Less	-	-	-	0.400 (0.237)	0.381 (0.237)	0.421 (0.233)	0.349 (0.229)
Education: Some College/Associate's Degree	-	-	-	0.709** (0.224)	0.667** (0.228)	0.662** (0.223)	0.614** (0.219)
Education: Bachelor’s Degree	-	-	-	0.218 (0.169)	0.200 (0.170)	0.178 (0.167)	0.072 (0.166)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low Income: <€2,500	-	-	-	-	0.143 (0.147)	0.102 (0.144)	0.169 (0.142)
Low Instagram Usage: Never to 3 times a week	-	-	-	-	-0.559*** (0.170)	-0.524** (0.166)	-0.524** (0.166)
High Online Purchase Frequency	-	-	-	-	-	-	0.467*** (0.136)

Note: ** $p<0.05$; *** $p<0.01$

Another seven model specifications were also employed for Hypothesis 2, showing several key findings across the seven models. Across all models, the content type variable (UGC vs. BGC) remains insignificant, indicating that content type does not have a statistically significant impact on consumer engagement. Control variables such as age groups, gender, education, income, Instagram usage, and online purchase frequency remain stable in effect and significance through the iterations of the seven models. The analysis highlights the stability of the model through the various model specifications, indicating the robustness of the model.

4.3.3. Hypothesis 3

Table 24. Sensitivity Analysis Table for Hypothesis 3

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	3.490*** (0.092)	3.685*** (0.119)	3.737*** (0.137)	3.592*** (0.146)	3.561*** (0.165)	3.611*** (0.167)	3.523*** (0.163)
Content Type	0.073 (0.141)	0.071 (0.142)	-0.067 (0.142)	-0.063 (0.142)	-0.068 (0.142)	-0.067 (0.141)	-0.097 (0.137)
Brand Awareness	0.172 (0.129)	0.166 (0.128)	0.163 (0.128)	0.123 (0.129)	0.122 (0.129)	0.144 (0.129)	0.120 (0.125)
Interaction Term (CT*BA)	0.058 (0.191)	0.052 (0.190)	0.044 (0.188)	0.041 (0.187)	0.052 (0.190)	0.044 (0.189)	0.064 (0.184)
<24-years old	-	-0.313** (0.118)	-0.337** (0.122)	-0.379** (0.127)	-0.360** (0.139)	-0.390** (0.140)	-0.350** (0.136)
25-34 years old	-	-0.266** (0.131)	-0.283** (0.134)	-0.250** (0.139)	-0.222** (0.138)	-0.253** (0.139)	-0.297** (0.135)
35-44 years old	-	-0.195 (0.153)	-0.212 (0.154)	-0.181 (0.154)	-0.182 (0.154)	-0.196 (0.154)	-0.233 (0.150)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Male Respondents	-	-	-0.374 (0.097)	-0.100 (0.097)	-0.089 (0.098)	-0.061 (0.099)	-0.068 (0.096)
Education: High School or Less	-	-	-	0.243 (0.174)	0.261 (0.175)	0.264 (0.174)	0.204 (0.170)
Education: Some College/Associate's Degree	-	-	-	0.364** (0.166)	0.379** (0.175)	0.373** (0.168)	0.336** (0.164)
Education: Bachelor's Degree	-	-	-	0.288 (0.124)	0.295 (0.126)	0.283 (0.124)	0.196 (0.124)
Low Income: <€2,500	-	-	-	-	-0.055 (0.108)	-0.071 (0.108)	-0.014 (0.106)
Low Instagram Usage: Never to 3 times a week	-	-	-	-	-	-0.222 (0.127)	-0.190 (0.124)
High Online Purchase Frequency	-	-	-	-	-	-	0.397** (0.101)

Note: ** $p<0.05$; *** $p<0.01$

The sensitivity analysis results for Hypothesis 3 show that across seven models, the significance of each of the variables, including the moderating variable, remains consistent. Conclusively, across seven different model specifications, brand awareness does not moderate the relationship between content type and purchase intention. The analysis highlights the importance of age, education, and online purchase frequency on purchase intentions as these control variables were consistent in effect and significance throughout various model specifications of the test. These results further strengthen the conclusion drawn from the regression analysis in the previous section, suggesting the importance of focusing on demographic and behavioral factors rather than content type and brand awareness to enhance purchase intentions.

4.3.4. Hypothesis 4

Table 25. Sensitivity Analysis Table for Hypothesis 4

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	2.833*** (0.132)	3.261*** (0.164)	3.419*** (0.189)	3.148*** (0.211)	3.086*** (0.225)	3.216*** (0.223)	3.113*** (0.220)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Content Type	0.062 (0.203)	0.109 (0.196)	0.120 (0.177)	0.122 (0.197)	0.136 (0.193)	0.138 (0.189)	0.102 (0.186)
Brand Awareness	0.085 (0.186)	0.077 (0.186)	0.074 (0.177)	0.040 (0.176)	0.043 (0.176)	0.100 (0.172)	0.073 (0.169)
Interaction Term (CT*BA)	0.154 (0.274)	0.084 (0.263)	0.063 (0.262)	0.031 (0.259)	0.019 (0.259)	0.002 (0.254)	0.022 (0.249)
<24-years old	-	-0.652*** (0.163)	-0.723*** (0.168)	-0.733*** (0.182)	-0.777*** (0.190)	-0.855*** (0.187)	-0.808*** (0.183)
25-34 years old	-	-0.821*** (0.181)	-0.872*** (0.182)	-0.775*** (0.183)	-0.809*** (0.188)	-0.897*** (0.185)	-0.949*** (0.182)
35-44 years old	-	-0.182 (0.211)	-0.225 (0.211)	-0.153 (0.210)	-0.154 (0.210)	-0.193 (0.205)	-0.236 (0.201)
Male Respondents	-	-	-0.226 (0.122)	-0.210 (0.132)	-0.199 (0.133)	-0.127 (0.133)	-0.144 (0.130)
Education: High School or Less	-	-	-	0.396 (0.236)	0.377 (0.239)	0.414 (0.233)	0.344 (0.229)
Education: Some College/Associate's Degree	-	-	-	0.696** (0.227)	0.655** (0.231)	0.639** (0.226)	0.595** (0.221)
Education: Bachelor's Degree	-	-	-	0.209 (0.171)	0.191 (0.172)	0.160 (0.169)	0.058 (0.168)
Low Income: <€2,500	-	-	-	-	0.141 (0.147)	0.098 (0.145)	0.165 (0.143)
Low Instagram Usage: Never to 3 times a week	-	-	-	-	-0.573** (0.170)	-0.559** (0.170)	-0.524** (0.166)
High Online Purchase Frequency	-	-	-	-	-	-	0.464** (0.136)

Note: ** p<0.05; *** p<0.01

The sensitivity analysis for Hypothesis 4 shows consistent results across seven different model specifications of the Hypothesis 4 regression model. Hence, it can be concluded that the model is robust and stable, further strengthen the conclusion that brand awareness does not moderate the relationship between content type and consumer engagement. The analysis also highlights the importance of age, education, and online purchase frequency on consumer engagement, suggesting the importance of focusing on demographic and behavioral factors rather than solely on content type and brand awareness to enhance consumer engagement.

4.3.5. Sensitivity Analysis: Conclusion

To assess the robustness of the regression results, sensitivity analyses were conducted by incrementally introducing various control variables. The key variables of interest, particularly content type and brand awareness were examined across different model specifications to ensure the stability of the findings.

The results demonstrate that the main findings of the study are robust and consistent across different model specification. For instance, content type variable consistently remained insignificant across all regression models for both purchase intention and consumer engagement. These consistent results suggest that the primary conclusion, indicating that content type does not significantly impact consumer behavior, is stable and not influenced by the inclusion of additional controls. Similarly, brand awareness, both as an individual predictor and as a moderator, showed consistent minimal impact across models. This further strengthens the conclusion drawn in the previous section that the level of brand awareness does not moderate the relationship between content type and consumer behavior.

Lastly, the control variables exhibited expected patterns of significance and direction consistently. For instance, younger age groups consistently showed lower purchase intention and engagement, while higher education levels were consistently associated positively with consumer engagement and purchase intention. The stability of the magnitude of the effect and significance of the control variables across models reinforces the validity of the findings.

In conclusion, the sensitivity analyses confirm that the regression results are robust. The consistent findings across various model specifications provide assurance in the validity and reliability of the conclusions drawn from the study. This robustness underlines the importance of demographic factors such as age and education in influencing consumer behavior, while the type of content (UGC or BGC) and brand awareness appear to have a lesser to no impact within the studied context.

5. Discussion

This study investigated how different content types, user-generated and brand-generated content, influence consumer behavior, particularly purchase intention and engagement, with an additional focus on the moderating effect of brand awareness.

The analysis showed that content type does not significantly influence consumer purchase intention, contrasting with existing literature that suggests UGC often drives higher purchase intentions due to its perceived authenticity and trustworthiness (Müller & Christandl, 2019; Irelli & Chaerudin, 2020). This discrepancy might be due to the specific context of home appliances, or the sample population used in this study. This suggests that while UGC is often assumed to have a strong impact on purchase intention, its effectiveness may be context-dependent, emphasizing the need for marketers to consider contextual factors when designing content strategies. Therefore, marketers should consider both UGC and BGC in their strategies to balance authenticity with controlled brand messaging. For instance, BGC can be utilized to provide consistent and controlled brand messaging, while UGC can be leveraged for authenticity and social proof. This strategy ensures that different aspects of consumer needs and perceptions are addressed, which may enhance overall marketing effectiveness.

Similarly, the analysis found that content type does not significantly influence consumer engagement. Although UGC showed a slight positive effect on engagement, it was not statistically significant. This finding deviates from previous studies emphasizing UGC's engagement potential due to its relatability and act as a social proof (Ibrahim et al., 2022; Aljarah et al., 2024; Malthouse et al., 2016). Therefore, a combined approach of using both UGC and BGC might be more effective in driving engagement by catering to different consumer preferences. For example, brands can encourage customers to create and share content, which can be featured alongside professionally produced content on brand platforms. This dual approach can cater to different consumer preferences and enhance engagement by offering a variety of content forms.

The analysis also found that brand awareness did not moderate the relationship between content type and purchase intention or engagement. This indicates that the effectiveness of UGC and BGC is consistent regardless of brand awareness levels. This finding challenges the assumption that high brand awareness would enhance the effectiveness of content types especially BGC due to increased consumer trust and familiarity (Sharma & Singh, 2021; Hameed et al., 2023).

Consequently, marketers should focus on the quality and relevance content rather than relying on brand awareness. This means even lesser well-known brands can compete effectively by producing high-quality, engaging content. For more well-known brands, it is important to maintain the standard of content to ensure consistent engagement and preference from consumers. This finding supports the notion of the universal appeal of engaging content (Aljarah et al., 2024; Zailskaite-Jakste & Kuvykaite, 2012), regardless of brand awareness levels. This further strengthens the importance of creating content that resonates with your audience and target consumers. For well-known brands, leveraging UGC can provide a sense of community and authenticity, while BGC can reinforce brand messaging. On the other hand, brands that are lesser known can use UGC to build credibility and BGC to ensure brand consistency and help educating consumers of their products.

Given the conclusion drawn from the analyses for the four hypotheses, marketers should not overly rely on a single type of content, UGC or BGC, but rather integrate both to address different consumer segments and contexts. Understanding the demographic and behavioral characteristics of the target audience is crucial for designing effective content strategies. For example, brands could utilize UGC for its authenticity and relatability, while employing BGC for consistent brand messaging and promotional activities. Given that this study discovered that brand awareness does not moderate the effects of content types on consumer behaviors such as consumer engagement and purchase intention, marketers should focus on creating high-quality and engaging content regardless of the brand's current awareness level among the consumers. Strategies to enhance brand awareness should be pursued parallelly but should not be done at the expense of content quality. This means that even lesser-known brands can compete effectively by producing compelling content.

Demographic factors and online usage behavior also provide deeper insights into the factors influencing consumer purchase intention or engagement. Younger consumers (<24 years old) showed a significantly lower purchase intention compared to older age groups. This might be due to financial constraints or differing priorities. This highlights the importance for marketers to tailor their strategies differently across age groups. Marketers targeting younger demographics should consider strategies that resonate with this age group’s preferences and financial constraints. For example, offering promotions, discounts, or creating value-driven campaigns can attract younger consumers. Additionally, using platforms and content formats popular among younger audiences, such as Instagram Reels, Instagram Stories, or TikTok

Videos, can enhance engagement and potentially drive purchase intentions from consumers in this age group.

Education level also emerged as a significant predictor, with consumers having some college or an associate's degree showing higher purchase intention and engagement compared to those with postgraduate degrees. This suggests that intermediate education levels are more responsive to social media marketing efforts, possibly due to higher engagement with these platforms and reliance on them for product information and recommendation. For marketers, this finding emphasizes the importance of understanding the education level of their target consumers. With certain educational demographics more likely to interact with and be influenced by contents published on social media, recognizing these characteristics allows marketers to create more targeted and effective campaigns.

Consumers' social media usage frequency also appeared to be another significant predictor of purchase intention and engagement, where consumers with low Instagram usage (never to 3 times a week) negatively associated with both purchase intention and engagement. Active social media users are more positively influenced by online content which might be contributed by their heavy engagement to the platform. This underlines the importance of targeting active social media users through frequent, interactive posts and engagement strategies. For brands, it could help build a loyal community of consumers and enhance both engagement and purchase intention. For less active users, marketers might need to diversify their strategies, utilizing alternative digital marketing channels like targeted advertisement, search engine optimization, and email marketing.

Lastly, online purchase frequency emerged as a significant predictor of purchase intention and engagement. Consumers who frequently buy products online, which in the case of this study is for home appliances products, have higher purchase intentions and engagement compared to those who do so infrequently. This finding highlights the importance of targeting frequent online shoppers, who are likely more receptive to digital marketing efforts. For this group, both UGC and BGC can be highly effective if tailored correctly. UGC can leverage the trust and authenticity that frequent online shoppers seek, while BGC can provide consistent and informative content that supports their decision-making process. Marketers should emphasize creating content that resonates with these high-frequency online shoppers by showcasing product reviews, user testimonials, and detailed product information, while also showcasing convenience, exclusive online deals, and loyalty programs that reward frequent purchases.

The findings suggest that an integrated content strategy combining UGC and BGC, tailored to different demographics, social media usage levels, and online purchase frequencies, can enhance marketing effectiveness. Marketers should not rely solely on brand awareness but focus on producing high-quality, engaging content to drive consumer behavior.

6. Conclusion

This study investigated the impact of user-generated content (UGC) and brand-generated content (BGC) on consumer purchase intention and engagement, as well as the moderating role of brand awareness. Contrary to many existing studies, the findings show that UGC's influence on purchase intention and engagement does not significantly differ compared to BGC, in the context of vacuum cleaners. Additionally, brand awareness did not moderate these relationships.

These results suggests that while UGC is often perceived as more authentic and trustworthy, its effectiveness may vary depending on the context. Therefore, marketers should not rely solely on UGC in their marketing efforts but should instead adopt a balanced content strategy that includes both UGC and BGC. This approach can address various consumer needs, preferences, and characteristics, which potentially can enhance the overall marketing effectiveness.

The study also highlighted the significant impact of demographic factors such as age, education, social media usage and online purchase frequency on consumer behavior. Younger consumers and those with some college or an associate's degree demonstrated distinct purchase intentions and engagement patterns. Furthermore, frequent online shoppers demonstrated higher purchase intentions and engagement compared to infrequent online shoppers, emphasizing the importance of targeting this demographic with tailored content strategies. On the other hand, consumers with low social media usage demonstrated significantly lower engagement with content on social media compared to active social media users, highlighting a key consumer target to drive content engagement on social media.

In summary, this research contributes to the digital marketing literature by providing empirical evidence on the influence of content types and brand awareness on consumer behavior. The results indicate that brand awareness does not moderate the impact of content types on consumer behavior, suggesting that high-quality and engaging content is crucial regardless of brand recognition among consumers. These insights offer hands-on guidance for marketers to refine their content strategies, ensuring they cater to diverse consumer segments and optimize their marketing efforts.

6.1.Limitation of the Study

While this study provides valuable insights, there are several limitations to consider. Firstly, although the sample size was adequate for the analyses conducted, it may not reflect the diversity of the broader consumer population. Future research should incorporate larger and more diverse samples to improve the generalizability of the results. Secondly, this research focused solely on vacuum cleaners as the product category, which might limit the applicability of the results to other product types. Investigating a range of product categories could provide a more comprehensive understanding of how UGC and BGC influence consumer behavior across different contexts. Thirdly, the study depended on self-reported data, which is prone to biases including social desirability and recall bias. Employing a mixed methods approach or incorporating objective measures of engagement and purchase behavior could enhance the robustness of the findings.

6.2.Suggestion for Future Research

Future research should explore various directions to build on the findings of the study. One potential direction is to examine the long-term effects of UGC and BGC on consumer behavior, considering factors such as brand loyalty, followers or subscribers' growth and conversion rate, and repeat purchases. Additionally, researchers could investigate the impact of emerging social media platforms and new content formats, such as short-form videos, on consumer engagement and purchase intention. Another interesting area of study is the role of cultural differences in shaping consumer responses to UGC and BGC, as cultural factors can significantly influence consumer behavior.

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Appendix

Appendix A. Survey Instrument

<u>Introduction</u>

Dear Participant,

Thank you for taking the time to participate in this research study. Your insights are incredibly valuable and will help us understand **how different types of social media content influence consumer behavior and brand engagement**.

My name is **Ariq Fatah**, and I am conducting a survey for my master thesis in Marketing at Erasmus School of Economics.

What to Expect:

Shortly, you will be randomly assigned to one of four scenarios in this survey, each presenting a unique combination of content type and brand awareness level. After viewing the content, you will be asked to answer a series of questions about your perceptions, engagement, and purchase intentions related to the brand. You will be able to go back and forth between questions.

It is of high importance that you read every piece of information given in this survey carefully before moving to the next step. **<u>Try to base your answers solely on the information provided</u>**. There are no right or wrong answers, only your opinion matters.

This survey should not take longer than **3 minutes.**

Your Privacy:

Your responses will be kept confidential, anonymous and will be used solely for academic purposes. Participation in this survey is voluntary, and you may withdraw at any time without any consequences. Once your personal data is no longer needed, it will be deleted from the system.

Informed Consent:

By proceeding with this survey, you consent to participate in this study. If you have any questions or concerns, please feel free to contact us at ariq@student.eur.nl.

Scenarios:

Scenario 1: Low Brand Awareness and User-Generated Content

Description:

Imagine that you are searching online for a new vacuum cleaner, and **you come across an Instagram post from a user named @HomeCleanGuru** who is sharing their experience with a new vacuum cleaner from a brand called ***'CleanMaster'***. **You have never heard of this brand before**.

In the post, @HomeCleanGuru showcases the new ***'CleanMaster'*** vacuum cleaner they recently bought, highlighting its advanced features such as its 2-in-1 functionality as both a dry and wet vacuum cleaner and as a wet mop, something not found in other brands. The post demonstrates how it can effectively clean different surfaces and offers better results compared to competitors. @HomeCleanGuru mentions how these features can make your cleaning routine more efficient and enjoyable. Apart from attaching the brand's official Instagram page, the post ends with a link to buy the new ***'CleanMaster'*** vacuum cleaner from the official website.

Scenario 2: Low Brand Awareness and Brand-Generated Content

Description:

Imagine that you are searching online for a new vacuum cleaner, and **you come across an Instagram advertisement from a brand** called ***'CleanMaster'***. **You have never heard of this brand before**.

In the advertisement, the brand showcases the new ***'CleanMaster'*** vacuum cleaner, highlighting its advanced features such as its 2-in-1 functionality as both a dry and wet vacuum cleaner and as a wet mop, something not found in other brands. The advertisement demonstrates how it can effectively clean different surfaces and offers better results compared to competitors. The brand mentions how these features can make your cleaning routine more efficient and enjoyable. Apart from attaching the brand's official Instagram page, the advertisement ends with a link to buy the new ***'CleanMaster'*** vacuum cleaner from the official website.

Scenario 3: High Brand Awareness and User-Generated Content

Description:

Imagine that you are searching online for a new vacuum cleaner, and **you come across an Instagram post from a user named @HomeCleanGuru** who is sharing their experience with a new vacuum cleaner from a brand called ***'CleanMaster'***. **You are already familiar with this brand.**

In the post, @HomeCleanGuru showcases the new ***'CleanMaster'*** vacuum cleaner they recently bought, highlighting its advanced features such as its 2-in-1 functionality as both a dry and wet vacuum cleaner and as a wet mop, something not found in other brands. The post demonstrates how it can effectively clean different surfaces and offers better results compared to competitors. @HomeCleanGuru mentions how this feature can make your cleaning routine more efficient and enjoyable. Apart from attaching the brand's official Instagram page, the post ends with a link to buy the new ***'CleanMaster'*** vacuum cleaner from the official website.

Scenario 4: High Brand Awareness and Brand-Generated Content

Description:

Imagine that you are searching online for a new vacuum cleaner, and **you come across an Instagram advertisement from a brand** called ***'CleanMaster'***. **You are already familiar with this brand.**

In the advertisement, the brand showcases the new ***'CleanMaster'*** vacuum cleaner, highlighting its advanced features such as its 2-in-1 functionality as both a dry and wet vacuum cleaner and as a wet mop, something not found in other brands. The advertisement demonstrates how it can effectively clean different surfaces and offers better results compared to competitors. The brand mentions how these features can make your cleaning routine more efficient and enjoyable. Apart from attaching the brand's official Instagram page, the advertisement ends with a link to buy the new ***'CleanMaster'*** vacuum cleaner from the official website.

Measuring Variables (Question):

Purchase Intention (Adopted by Dodds et al., 1991)

1. How likely are you to purchase this vacuum cleaner
   - o Very Unlikely (1) to Very Likely (5)
2. If you needed a vacuum cleaner, how probable is it that you would consider buying this product?
   - o Very Improbable (1) to Very Probable (5)
3. My willingness to buy this product is…
   - o Very Low (1) to Very High (5)

Engagement

According to Deng et al. (2021), customer engagement in social media is shaped and can be measured by the number of likes and shares of a social media post.

1. How likely are you to like this post on Instagram? (Adopted by Deng et al., 2021)
   - o Very Unlikely (1) to Very Likely (5)
2. How likely are you to share this post with your friends or family? (Adopted by Deng et al., 2021)
   - o Very Unlikely (1) to Very Likely (5)

Manipulation (Attention) Check

1. What is the brand of the Vacuum Cleaner mentioned in the scenario?
   - o Dyson
   - o CleanMaster
   - o HomeCleanGuru
   - o Hoover

Demographic and Control Variables

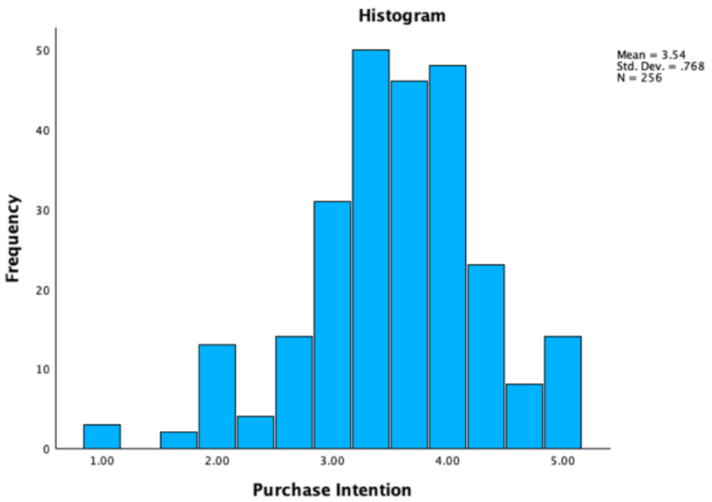
1. How often do you use Instagram?
   - o Daily
   - o Weekly
   - o Monthly

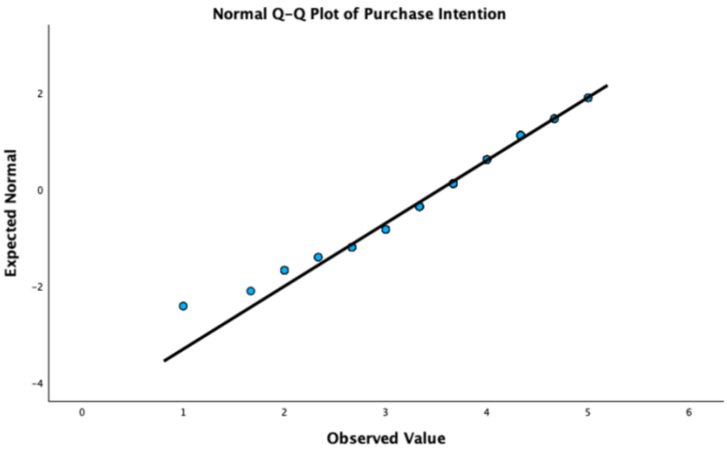
- Rarely
- Never

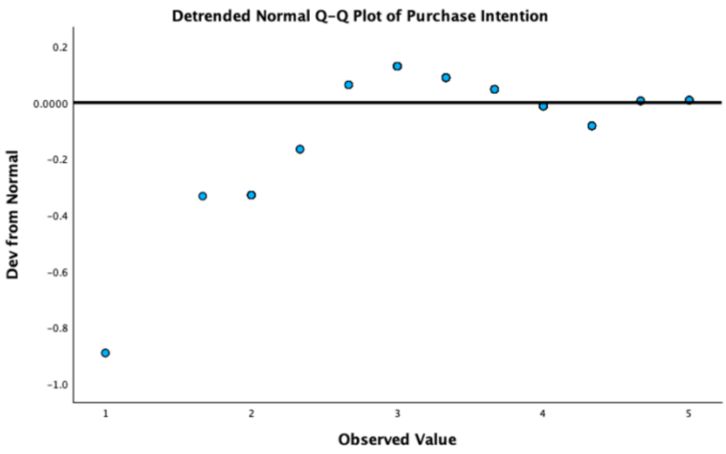
2. How often do you purchase household appliances online?
   - Frequently
   - Occasionally
   - Rarely
   - Never
3. Which age group are you in?
   - ≤ 17 years old
   - 18-24 years old
   - 25-34 years old
   - 36-44 years old
   - 45-54 years old
   - 55-64 years old
   - 65 years old and above
4. Which gender do you identify as?
   - Male
   - Female
   - Non-binary
   - Prefer not to say
5. What is the highest level of education you have attained (not including the degree you are currently pursuing)?
   - High school degree or equivalent
   - Associate’s degree
   - Bachelor’s degree (HBO or University)
   - Master’s degree (HBO or University)
   - Doctoral degree (or PhD)
   - Others
6. What is your monthly income (in euro or equivalent)
   - €1,500 or less
   - €1,501 – 2,500
   - €2,501 – 3,500
   - €3,501 – 5,000

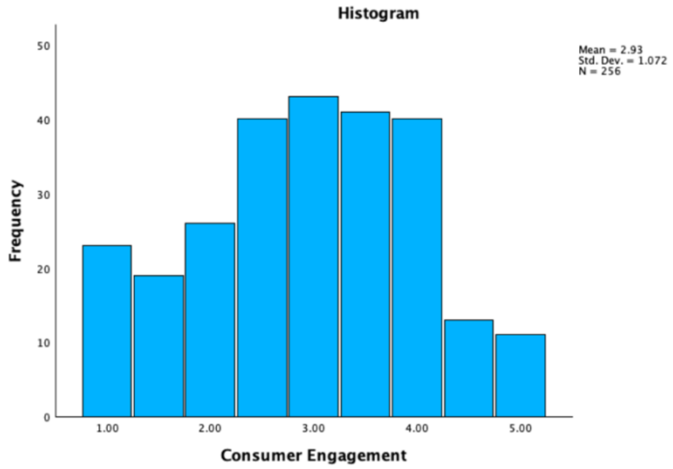
- €5,001 – 10,000
- €10,000 and above

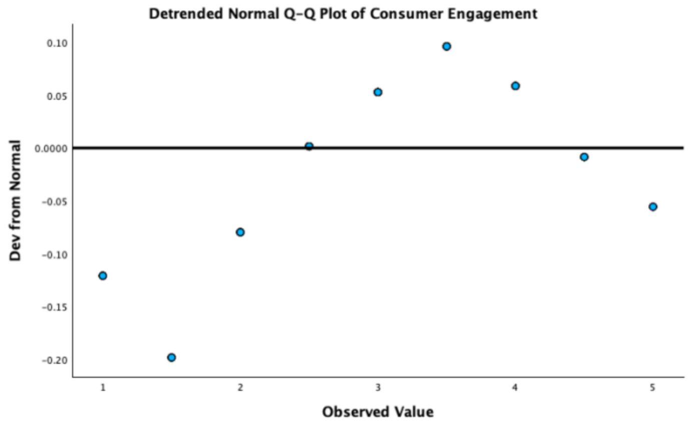
Appendix B. Histogram and Q-Q Plots of Purchase Intention and Consumer Engagement Variables.

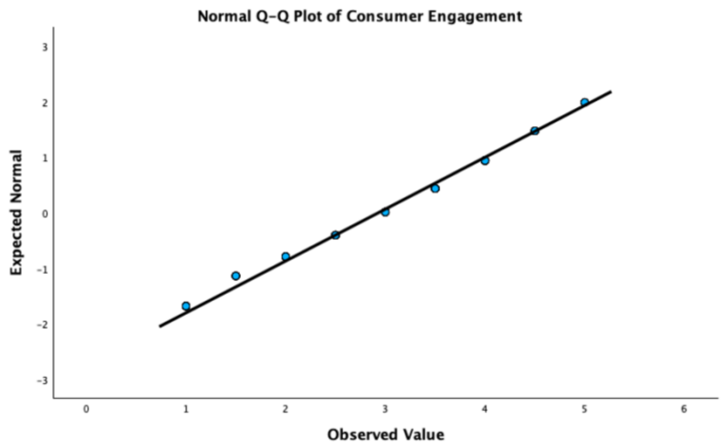







Histogram
Mean = 2.93
Std. Dev. = 1.072
N = 256
Frequency
Consumer Engagement


Detrended Normal Q-Q Plot of Consumer Engagement
Dev from Normal
Observed Value


Normal Q-Q Plot of Consumer Engagement
Expected Normal
Observed Value