MASTERARBEIT | MASTER'S THESIS

Titel | Title

REDEFINING LUXURY: EXAMINING INCLUSION AND DIVERSITY IN LUXURY BRANDING

verfasst von | submitted by

Mona Pfohlmann B.Sc.

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2025

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 914
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Internationale Betriebswirtschaft
Betreut von | Supervisor:	Univ.-Prof. Christoph Fuchs PhD
Mitbetreut von | Co-Supervisor:	Lic. Mestr. Cátia Alves Ph.D.

Note of Thanks

First of all I want to start by thanking my family, especially my amazing parents. You've been and are my biggest supporters, not just during my degree but throughout my whole life. Your love, guidance, and endless encouragement mean everything to me. You've been there for every high and low, always ready with advice, reassurance, or just a hug or a call when I needed it most. Thank you for motivating me to keep pushing through, even when things felt impossible or neverending. I truly couldn't have done this without you.

To my friends, my chosen family away from home, thank you for being my rock in this whole process. You've been there for the late-night rants, the celebrations, and everything in between. Your love, laughter, and support have made all the difference, and I feel so lucky to have each of you in my corner.

This journey wasn't always easy, but knowing I had all of you cheering me on made it so much better. Thank you for believing in me and for being such an important part of my life.

Zuallererst möchte ich meiner Familie danken, insbesondere meinen großartigen Eltern. Sie waren und sind meine größten Unterstützer, nicht nur während meines Studiums, sondern mein ganzes Leben lang. Eure Liebe, Ratschläge und unermüdliche Ermutigung bedeuten mir alles. Ihr wart in allen Höhen und Tiefen für mich da, habt mir immer einen Ratschlag gegeben, mich beruhigt oder mich einfach nur umarmt oder angerufen, wenn ich es am meisten brauchte. Danke, dass ihr mich motiviert habt, weiterzumachen, auch wenn es sich unmöglich oder unendlich andauernd anfühlte. Ohne euch hätte ich das wirklich nicht geschafft.

Meinen Freunden - meine Familie fern der Heimat - danke ich dafür, dass ihr während dieses ganzen Prozesses mein Fels in der Brandung wart. Ihr wart bei den nächtlichen Aufregungen, beim Feiern und bei allem, was dazwischen lag, dabei. Eure Freundschaft, euer Lachen und eure Unterstützung haben den Unterschied ausgemacht, und ich bin so glücklich, euch alle an meiner Seite zu haben.

Diese Reise war nicht immer einfach, aber zu wissen, dass ihr mich alle unterstützt habt, hat sie so viel einfacher gemacht. Danke, dass ihr an mich geglaubt habt und dass ihr ein so wichtiger Teil meines Lebens seid.

Abstract - English

This master's thesis examines how consumer perceptions of videos on TikTok are influenced by diversity cues in branded social media content of luxury and non-luxury fashion brands. It includes two studies that examine how ethnic and gender diversity affects video performance (Study 1) and consumer sentiment in comments (Study 2).

Study 1 revealed that TikTok videos featuring diverse models, particularly in terms of ethnicity and gender, do not tend to perform better in terms of views. The only significant factor influencing views was luxury brand affiliation. Videos from luxury brands outperformed those from non-luxury brands, with the analysis showing that luxury branding contributed positively to higher view counts.

Study 2 demonstrates that diversity is associated with a slight increase in positive sentiment, particularly in terms of valence. Among racial categories, Asian representation had the most substantial impact on valence but significantly decreased emotionality. Conversely, White representation was negatively associated with valence but positively influenced emotionality, and Black representation showed mixed effects on sentiment.

This research highlights TikTok's unique role as a platform for studying diversity cues due to its dynamic engagement environment and viral content distribution. The thesis emphasizes the significance of inclusive advertising tactics by showing the concrete effects of diversity on video performance and sentiment. It offers practical advice to companies and marketing managers on how to authentically integrate inclusivity into their campaigns, balancing the tension between exclusivity and inclusivity in branding efforts. These results add to the expanding body of knowledge regarding diversity in marketing and how it influences customer attitudes and brand success.

Keywords: *Diversity in Advertising, TikTok Marketing, Luxury vs. Non-Luxury Brands, Consumer Sentiment Analysis, Social Media Engagement*

Abstract - Deutsch

In dieser Masterarbeit wird untersucht, wie die Konsumentenwahrnehmung von Videos auf TikTok durch Diversity- Cues in markeneigenen Social-Media-Inhalten von Luxus- und Nicht-Luxusmodemarken beeinflusst wird. Sie umfasst zwei Studien, die untersuchen, wie sich ethnische und geschlechtliche Vielfalt auf die Videoperformance (Studie 1) und die Konsumentenstimmung in Kommentaren (Studie 2) auswirkt.

Studie 1 zeigt, dass TikTok-Videos mit diversen Models, insbesondere hinsichtlich ihrer ethnischen Zugehörigkeit und ihres Geschlechts, in Bezug auf die Aufrufe nicht besser abschneiden. Der einzige Faktor, welcher der die Aufrufe signifikant beeinflusste, war die Zugehörigkeit eines Videos zu einer Luxusmarke. Diese schnitten besser ab als solche von Nicht-Luxusmarken, wobei die Analyse zeigte, dass die Zugehörigkeit zu einer Luxusmarke positiv zu einer höheren Anzahl von Aufrufen beitrug.

Studie 2 zeigt, dass eine größere Vielfalt mit einem moderaten Anstieg positiver Stimmung verbunden ist, insbesondere hinsichtlich der Valenz. Unter den verschiedenen Kategorien der ethnischen Diversität hatte die Präsenz von asiatischen Models die stärkste Wirkung und führte zu einer signifikanten Verbesserung sowohl der Valenz, aber zu einer Verringerung der Emotionalität. Im Gegensatz dazu war die Darstellung von weißen Models negativ mit der Valenz assoziiert, aber positiv mit der Emotionalität verbunden, während die Darstellung von Personen afrikanischer Abstammung eine negative Wirkung auf die Valenz, aber eine positive Wirkung auf die Emotionalität hatte.

Diese Forschung unterstreicht die einzigartige Rolle von TikTok als Plattform für die Untersuchung von Diversity Cues aufgrund der dynamischen Interaktionsumgebung und der viralen Verbreitung von Inhalten. Die Arbeit unterstreicht die Relevanz inklusiver Werbetaktiken, indem sie die konkreten Auswirkungen von Vielfalt auf die Videoperformance und die Stimmung dieser aufzeigt. Sie bietet Empfehlungen für Unternehmen und Marketingmanager, die mit einer Vielzahl von Zielgruppen in den sozialen Medien interagieren und ein Gleichgewicht zwischen Exklusivität und Inklusivität in ihren Branding-Initiativen finden wollen. Diese Ergebnisse ergänzen das wachsende Wissen über Vielfalt im Marketing und wie sie die Einstellung der Kunden und den Erfolg der Marke beeinflusst.

Keywords: *Diversität in der Werbung, TikTok-Marketing, Luxus- vs. Nicht-Luxusmarken, Analyse der Verbraucherstimmung, Engagement in sozialen Medien*

Table of contents

1 Introduction 1

1.1 Background 2

1.1.1 Pretest 4

1.1.2 Pretest Results and Implications 5

1.2 Research Questions 6

1.3 Objectives and Significance of the Studies 8

2 Preliminary Remarks and Literature Review 9

2.1 Theoretical Framework 9

2.1.1 Social Identity Theory 9

2.1.2 Representation and Diversity in Media 9

2.2 Literature Review 11

2.2.1 Dimensions of Diversity 11

2.2.2 Social Media Advertising 19

2.2.3 Luxury Brands and Advertising 20

2.2.4 Celebrities in Advertising 24

2.3 Research Gap 25

3 Methodology 27

3.1 Research Objectives 27

3.2 Data Analysis Tools 28

3.3 Brand Selection 29

3.4 Study 1: Analysis of Video Performance 31

3.4.1 Data Collection 31

3.4.2 Variables 31

3.4.3 Hand Coding of Diversity Cues in Published Content 32

3.5 Study 2: Analysis of Consumer Sentiment 32

3.5.1 Data Collection 32

3.5.2 Variables 37

3.5.3 Sentiment Analysis of Comments 39

3.5.4 Hand Coding of Comments 41

4 Data Analysis and Results 43

4.1 Study 1: Impact of Diversity on Video Performance 43

4.1.1 Research Question 1: Effect of Diversity on Video Performance 43

4.2 Study 2: Impact of Diversity on Consumer Sentiment 48

4.2.1 Research Question 2: Effect of Diversity on Consumer Sentiment 48

4.2.2 Research Question 3: Sentiment Differences Between Luxury and Non-Luxury Brands 57
5 Discussion 64
5.1 Summary of Key Findings 64
5.2 Theoretical Implications 66
5.3 Practical Implications 68
5.4 Ethical Considerations 71
5.5 Limitations and Future Research 72
6 Conclusion 75
Bibliography VI
Annex XXXVII

List of Figures

Figure 1: Diversity Cues in Video Advertisements 5
Figure 2: Dimensions of Diversity 11
Figure 3: Distribution of Gender 13
Figure 4: Minorities in the European Union 16
Figure 5: Minorities in the United States 16
Figure 6: Presence of Model Attributes 43

List of Tables

Table 1: Parameters Hand Coded in Pretest 4
Table 2: Pretest Results 5
Table 3: Breakdown of Brand Selection Rationale 30
Table 4: TikTok Brand Metrics: Followers and Total Likes on 04.06.2024 30
Table 5: Variables Study 1 31
Table 6: Breakdown of Variable Hand Coding 32
Table 7: 59 Videos Suitable for In-Depth Analysis as of 04.06.2024 36
Table 8: Variables Study 2 39
Table 9: Presence of Model Attributes 43
Table 10: Summary Linear Regression RQ1 46
Table 11: Summary Linear Regression Lexical Suite Average Sentiment Score RQ2 ... 48
Table 12: Summary Linear Regression Hand Coded Variables RQ2 51
Table 13: Summary Multi Linear Regression Interaction Lexical Suite Average Sentiment Score and Brand Type RQ2 54
Table 14: Summary Linear Regression Lexical Suite Average Sentiment Score RQ3 ... 57
Table 15: Summary Linear Regression Hand Coded Variables RQ3 60
Table 16: Summary Multi Linear Regression Interaction Lexical Suite Average Sentiment Score and Celebrity Presence RQ3 62

1 Introduction

Social media has transformed the way brands and consumers interact, positioning itself as a central tool in the digital communication strategies of modern companies. In particular, brands are leveraging social media platforms not only to promote their products but also to showcase their commitment to diversity, equity, and inclusion (DEI) practices, which are increasingly critical in today's market. For instance, Corey Smith, Head of Diversity & Inclusion at LVMH, emphasizes that DEI is integral to the luxury conglomerate's core operations. LVMH has implemented specific measures to increase representation not only within its workforce but also among its suppliers and leadership, demonstrating a commitment to evolving alongside its increasingly diverse consumer base (Cosenza, 2024). This includes reaching younger, unconventional buyers who have often been overlooked by traditional luxury marketing. The role of DEI in social media advertising has gained significant traction, with brands incorporating diverse representation and inclusive messaging to resonate with a broader, more diverse audience. The managerial relevance of this shift is underscored by the fact that DEI-focused content is shown to enhance consumer engagement, fostering stronger brand loyalty and emotional connection, particularly in a landscape where consumers are more aware of social justice issues.

Previous research has largely focused on how interactive content, storytelling, and influencers drive engagement on social media (Voorveld et al., 2018; Sussman et al., 2022; Sun, 2024). While these studies have provided valuable insights, there is a gap in understanding the specific impact of diversity representation on consumer interaction, especially in the comment sections where real-time opinions are voiced. Some studies suggest that diverse representation positively influences engagement, while others show contrasting evidence (Liaukonytė et al., 2015; Golub et al., 2022). Thus, there is a need for more targeted research examining how various aspects of diversity affect consumer responses on social media.

Given this, the present research explores how diversity elements, such as ethnicity, gender, and inclusivity in social media advertisements, influence customer engagement. Specifically, this study analyzes the nature of consumer comments to understand how diversity representation impacts the sentiment, frequency, and depth of online interaction. Our findings indicate that brands incorporating diversity in their advertising not only garner higher engagement but also tend to elicit more positive emotional responses from consumers, further amplifying brand loyalty and social visibility.

Theoretical contributions of this research include a deeper understanding of the intersection between DEI practices and consumer behavior in the digital sphere. Practically, the insights derived from this study offer actionable strategies for brands aiming to enhance their online engagement through inclusive advertising, thus aligning business goals with evolving societal values.

1.1 Background

Brand Awareness and Consumer Choice

Brand awareness is a key factor in consumer decision-making, as it simplifies the process by allowing consumers to rely on recognizable brands (Hoyer & Brown, 1990). Consumers' perceptions of a brand's image, personality, and culture also strongly influence their preferences and buying behavior (Zhang, 2023; Freling & Forbes, 2005). Brands that effectively communicate their values, personality, and cultural relevance foster consumer loyalty and preference.

Luxury vs. Non-Luxury Brands and Diversity

Over the last 25 years, luxury and non-luxury brands have evolved differently in their approach to diversity cues. Luxury brands face the challenge of expanding their consumer base while maintaining exclusivity and high pricing (Oeppen & Jamal, 2014). The democratization of luxury, driven by social media and e-commerce, has made luxury fashion more accessible to a broader demographic (Franco et al., 2019; Matić & Bajs, 2022). Younger generations, especially Millennials and Gen Z, are key drivers of this trend, valuing emotional connections and experiences with brands (Tang, 2023; Bhagaskara, 2023; Xue-shan & Vijayan, 2023). These consumers also seek personal expression through luxury purchases (Eckhardt et al., 2014).

Luxury brands now emphasize sustainability, craftsmanship, and heritage to appeal to ethically conscious consumers (Franco et al., 2019; Bhagaskara, 2023). However, they must balance appealing to wider audiences while preserving exclusivity. Integrating diversity into branding strategies helps luxury brands enhance recognition and foster a sense of belonging among diverse consumers, increasing engagement and loyalty (Rubaca, 2023).

The Role of Diversity in Advertising

Race and gender diversity in advertising have become increasingly important. Consumers appreciate brands that mirror societal diversity, perceiving such ads as more inclusive and authentic (Langer et al., 2023). Brands that feature diverse models resonate more with

consumers from various backgrounds, enhancing their cultural relevance and fostering a connection with diverse audiences (Rebollo & García, 2022).

Research shows that brands prioritizing diversity and inclusivity are viewed more favorably by consumers, leading to stronger brand loyalty and a positive reputation (Wilton et al., 2018). Additionally, ads that promote diversity and gender equality contribute to social justice by challenging stereotypes (Kaiser et al., 2013). This not only reflects ethical brand values but also supports business growth.

Impact of Consumer-Generated Content and Diversity on Brand Perception

Luxury brands must navigate the influence of consumer-generated content on social media, as it can significantly shape brand perception (Gensler et al., 2013). Consumers may react differently to the representation of race and gender in advertising, affecting their views on a brand's inclusivity and cultural relevance (Martins et al., 2019; Dahl et al., 2009). Representation of diverse models in ads can influence consumer purchase intentions and brand attitudes (Lau & Lee, 2018; Tsawaab, 2023).

Ethnicity also affects consumer engagement with social media content, with diverse representation leading to more interaction and comments (Bozkurt et al., 2021). Social media users are more likely to engage with brand content that aligns with their values, including diversity and social responsibility initiatives (Adetunji et al., 2019; Mähnert, 2024). Brands that highlight diversity and ethical values in their content foster increased engagement and positive brand perceptions (Schivinski et al., 2019; Kim et al., 2015). This, in turn, enhances brand loyalty and consumer interaction with content that resonates with their beliefs (Schweidel & Moe, 2014).

This background lays the groundwork for investigating how brand managers can strategically leverage the impact of diversity cues on consumer sentiment in social media campaigns, particularly on the increasingly influential platform TikTok. By doing so, they can enhance brand performance while contributing to the academic discourse surrounding diversity and its effect on consumer sentiment in digital marketing.

1.1.1 Pretest

To investigate how luxury and non-luxury brands utilize diverse models in their advertisements and to identify significant differences in the prevalence of diversity cues between the two categories, a preliminary study was conducted. This pretest aimed to assess the current practices of brand managers regarding diversity in advertising.

Ads were selected from Adforum, one of the largest databases for advertising campaigns, to ensure a comprehensive analysis. The brands for this study were chosen based on Forbes' Most Powerful Brands list for 2020, which includes three non-luxury and four luxury brands relevant to the analysis. The luxury brands included are Louis Vuitton (ranked 9), Gucci (ranked 31), Hermès (ranked 32), and Chanel (ranked 52). The non-luxury brands considered are Zara (ranked 41), H&M (ranked 76), and Uniqlo (ranked 84).

Due to the availability of extensive data on the *Adforum* database, a leading platform for campaigns published in the past, the analysis focused on Louis Vuitton, the highest-ranked luxury brand with 110 campaigns, and H&M, which features 78 campaigns. This selection facilitates a robust comparison between the two categories. To enhance the clarity and relevance of the analysis, sports brands and those with inadequate campaign representation were excluded from consideration.

A comprehensive list of all available campaigns from both brands was compiled, detailing the year of publication, target country, campaign name, collaborating agency, and a link to the campaign in the Adforum database. Each campaign was hand-coded to determine whether it featured a picture (coded as 1) or not (coded as 0). For those with images, the number of faces present in the advertisements was noted. If the filetype is a photo all people present have been coded separately. Parameters hand coded as 1 represent the expected value.

20-39=1	man=1	modelbody=1	white=1
d1_age	d2_gender	d3_bodysize	d4_race

Table 1: Parameters Hand Coded in Pretest

1.1.2 Pretest Results and Implications

The pretest reveals that race and gender diversity are most prominent in video content from the past.

	d1_age	d2_gender	d3_bodysize	d4_race
Percentage Diversity Total				
Total	48%	74%	33%	51%
Louis Vuitton	30%	42%	22%	25%
H&M	18%	32%	11%	26%
Percentage Diversity Videos				
Total	62%	82%	38%	78%
Louis Vuitton	23%	21%	15%	23%
H&M	38%	62%	23%	55%
Percentage Diversity Pictures				
Total	38%	68%	29%	32%
Louis Vuitton	35%	57%	26%	26%
H&M	4%	11%	3%	6%

Table 2: Pretest Results

The preliminary analysis indicates that the percentage of diversity in advertising is comparable for both Louis Vuitton and H&M. However, despite claims from brand managers, the overall representation of diversity remains low across the board. Notably, video advertisements showcase significantly higher diversity levels compared to image-based campaigns, primarily driven by non-luxury brands.

Among the 189 advertisements analyzed, 107 were still images. The advertisements from Louis Vuitton and H&M included in the Adforum database were published between 2000 and 2023.

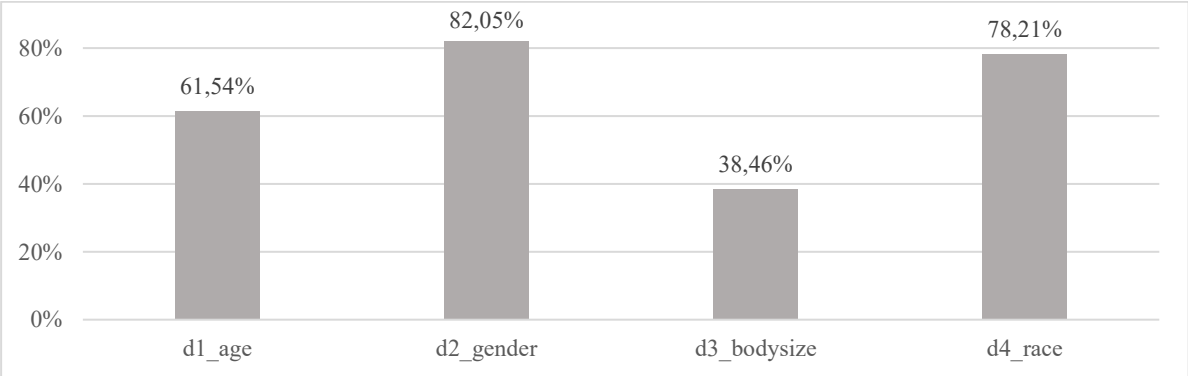


Figure 1: Diversity Cues in Video Advertisements

This pretest establishes a foundation for focusing the remainder of the research on gender and racial diversity, as these factors exhibit a higher prevalence in the analyzed advertisements. The findings reveal that both luxury and non-luxury brands have made strides in incorporating

diversity, with diversity percentages indicating that managers are increasingly recognizing its importance.

Future coding will accurately distinguish between male and female models, challenging the traditional assumption that male models serve as the default. Moreover, the study will shift its focus to TikTok, a platform centered around short-form video content, to investigate how diversity in advertisements currently influences consumer perceptions. It is to be expected, that the representation of diverse models is currently higher than it was on average between 2000 and 2023. The coding of race will also be more detailed, categorizing diversity into various ethnic groups.

1.2 Research Questions

The research questions are designed to build upon the insights from the pretest and the existing literature on brand communication, consumer engagement, and diversity in advertising. RQ1: *"How does the diversity of models in social media advertisements affect video performance?"* inquires how diversity impacts key performance metrics, such as the total number of views. This question lays the foundation for understanding the effect of diversity on not only how brand-owned content performs in terms of reach but also how the presence of diversity cues affect engagement and sentiment. Going further into depth, RQ2: *"How does the diversity of models in social media advertisements affect consumer sentiment in comments?"* will be the central focus of this study, exploring how diverse representation influences audience reactions and engagement.

Prior research suggests that consumers appreciate ads that mirror societal diversity, enhancing brand perception and relatability (Langer et al., 2023; Rebollo & García, 2022). Tafesse (2016) emphasizes that brands leverage a variety of message strategies in their social media advertisements, which can substantially influence consumer reactions and sentiment in their comments. This flexibility in advertising strategies contrasts with traditional approaches, allowing brands to connect with consumers on a deeper level. Livas et al. (2023) further illuminate this dynamic by demonstrating that diverse advertising strategies can elicit varied emotional responses, particularly among consumers who may oppose certain social causes. Their findings suggest that the alignment of advertisement diversity with consumer values is crucial for fostering positive sentiment. Moreover, Herjanto et al. (2015) explore the emotional dimensions of advertising within social networks, indicating that different emotional appeals can impact consumer sentiment. The use of diverse models that evoke a range of emotional responses may lead to diverse sentiments in comments. Chen et al. (2022) also contribute

valuable insights by analyzing how advertising value, emotional appeal, and perceived credibility shape consumer attitudes and purchase intentions, underscoring the importance of how diverse advertisements are constructed and perceived. The methodological approach taken by Areni (2021), through automated text analyses of YouTube comments, offers a framework for quantitatively assessing consumer sentiment in response to diverse advertising models. This approach can be pivotal for understanding the nuances of consumer reactions to various advertisement strategies. Given this rich body of literature, the research question seeks to investigate the intricate relationship between model diversity in social media advertisements and consumer sentiment in comments. This inquiry will provide insights into how brands can strategically leverage diversity to enhance engagement and foster positive brand perceptions. The hypothesis here is, that *advertisements featuring a higher diversity of models will generate more positive consumer sentiment and better video performance in both luxury and non-luxury comments*. This hypothesis aligns with findings regarding size diversity, that show, that including diverse models can enhance relatability, positively influencing consumer perceptions and fostering favorable sentiments towards the brand (Adil et al., 202; Lenne et al., 2023). Print advertisements featuring diverse ethnic representations can enhance consumer engagement and sentiment, for both luxury and non-luxury brands, as consumers increasingly seek representation and inclusivity in advertising (Lau & Lee, 2018). In this study interest lies in seeing if these results persist in both luxury and non-luxury brand owned content on TikTok.

The pretest findings, which show that brands choose racially diverse models in their campaigns, prompting interest in an exploration of how such diversity influences consumer sentiment. By analyzing comments, this research seeks to understand if and how diverse racial and gender representations in ads lead to positive or negative consumer reactions.

Thirdly RQ3: *"How does consumer sentiment in comments on social media advertisements vary between luxury and non-luxury brands?"* will be explored. It seems likely that consumer sentiment in response to advertisements may differ based on the brands positioning in the market. Consumer responses may vary significantly depending on the brand's market positioning. Kumar et al. (2022) highlight that luxury brands leverage social media to create exclusivity while engaging a broader audience, which is crucial for maintaining their prestige. Godey et al. (2016) support this, showing a positive relationship between social media marketing and consumer sentiment in the luxury sector. However, Creevey et al. (2021) found that consumer perceptions of luxury on social media can differ from brand intentions, indicating a need to better align strategies with audience expectations. In contrast, non-luxury brands often embrace inclusivity, with Michaelidou et al. (2022) emphasizing their use of "femvertising,"

which can foster relatability and positive engagement. Furthermore, brands prioritizing diversity and inclusivity are viewed more favorably, which can enhance brand loyalty and reputation (Wilton et al., 2018; Kaiser et al., 2013). This research question aims to delve into whether these differences in diversity practices between luxury and non-luxury brands translate into varying consumer sentiments, as expressed in social media, specifically TikTok, comments. Hypotheses therefore are, that *Consumer sentiment will differ between luxury and non-luxury brands, with non-luxury brands generating more favorable sentiment due to their focus on inclusivity and relatability*. Luxury brands may face challenges with elitist perceptions that could affect consumer sentiment (Creevey et al., 2021). Furthermore, Jiang et al. (2014) found that luxury brands tend to use models that evoke feelings of social exclusion, leading consumers to perceive a sense of rejection from these advertisements. The second hypothesis is, that *brands featuring a higher racial diversity of models will generate more positive consumer sentiment in social media comments*. This hypothesis aligns with Lenne et al. (2023) suggesing, that diverse imagery in advertising improves consumer perceptions and emotional engagement.

Research question 1 is explored in Study 1, research question 2 and research question 3 are both explored in Study 2.

1.3 Objectives and Significance of the Studies

This study investigates how diverse models affect consumers' perceptions of social media ads. It specifically attempts to investigate how different portrayals of ethnicity and gender in ads affect the opinions that customers voice in their comments. The study aims to determine the degree to which diversity in advertising influences favorable or unfavorable customer responses by examining these attitudes. This investigation will yield important new information about how inclusive advertising strategies might improve customer perception of brands and engagement. Furthermore, by using the study's findings as a guide, brands can help make sure that their advertising content matches the expectations and values of their target audience.

2 Preliminary Remarks and Literature Review

2.1 Theoretical Framework

2.1.1 Social Identity Theory

Research has shown that individuals tend to categorize themselves and others into in-groups (groups they belong to) and out-groups (groups they do not belong to). This categorization influences their perceptions and behaviors, often leading to favoritism toward members of their in-group (Korostelina, 2014). Furthermore, individuals' social identities, formed through their group memberships, play a key role in shaping how they perceive and interact with advertisements. Consumers are more likely to relate to and engage with ads that feature models representing social groups they identify with (Davis et al., 2019). This identification can directly impact their preferences, levels of engagement, and even their purchase intentions (Davis et al., 2019).

These insights can be understood through Social Identity Theory, which explains how individuals define themselves based on their group memberships. According to the theory, this group-based identity strongly influences behavior and self-concept (Tajfel & Turner, 2004). In the context of diverse models in social media advertisements, Social Identity Theory suggests that consumers may respond more favorably to ads featuring models from their in-group, as these ads reinforce their social identity (Korostelina, 2014).

In sum, Social Identity Theory implies that consumers will exhibit more positive attitudes toward advertisements that align with their social identity, demonstrating a preference for in-group representation over out-group models. This can lead to enhanced engagement and more favorable responses to diverse advertisements.

2.1.2 Representation and Diversity in Media

In the advertising realm, marketers have an ethical obligation to consider stakeholders' perspectives, leading them to create messages that better represent society and aim to influence societal norms (McDonald et al., 2020). By promoting diversity and inclusivity in advertising, brands can appeal to a broader audience, contribute to social change, and challenge stereotypes (Carrasco-Santos, 2024). Representation and diversity in media play a crucial role in shaping societal norms, influencing consumer behavior, and fostering inclusivity. Studies have emphasized the importance of accurate and humanizing representation in media to create meaningful connections with diverse audiences (Ferreyra, 2022). Research indicates that the representation of diversity in media, can empower marginalized communities, influence social

change, and challenge traditional norms (Iglesias-Sánchez et al., 2023). Additionally, incorporating diverse models in advertising, reflecting various social identities, can enhance brand engagement by resonating with consumers' sense of self and group affiliations. Social Identity Theory offers insight into how diverse models in social media ads influence consumers' perceptions. Individuals tend to respond more positively to ads that mirror their social identity or group membership, leading to increased engagement and favorable perceptions. The theory also highlights the role of social group belonging in shaping identity processes and guiding behaviors based on group norms. The representation of diversity in media, particularly in advertising, not only mirrors societal values but also drives cultural dynamics and inclusion (Rebollo & García, 2022). In conclusion, the representation of diversity in media, especially in advertising, significantly influences consumer perceptions, societal norms, and cultural dynamics. By incorporating diverse models in social media ads and ensuring accurate and humanizing representations, marketers can establish meaningful connections with diverse audiences, foster inclusivity, and drive positive social change.

2.2 Literature Review

2.2.1 Dimensions of Diversity

Luxury brands frequently evoke a sense of aesthetic pleasure and provide consumers with an escape from the ordinary. Models who communicate luxury, beauty, and exclusivity can resonate with consumers seeking a premium experience (Kim et al., 2019). Models chosen by luxury brands should align with the brand's identity, values, and target audience. The alignment between the model and the brand image is crucial in crafting a coherent brand narrative (Byun et al., 2020).

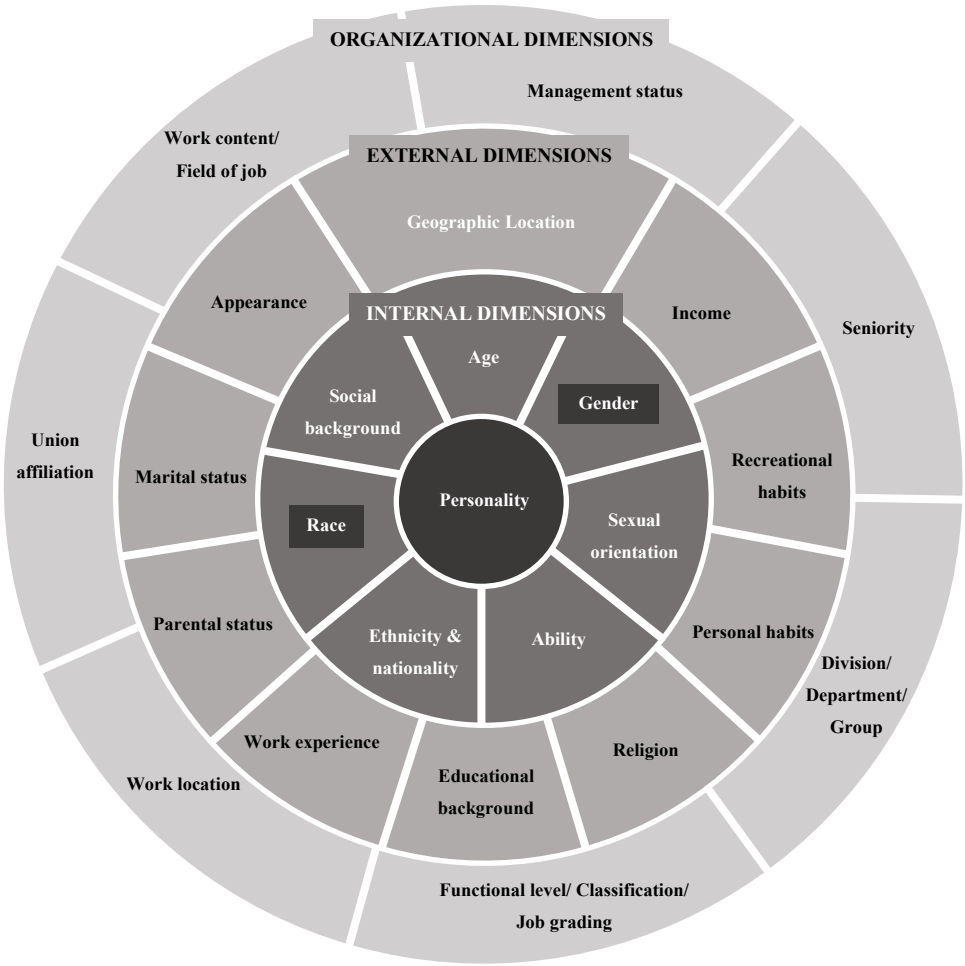


Figure 2: Dimensions of Diversity

Source: Own illustration adapted from: Charta der Vielfalt n.d., Gardenswartz & Rowe, 2008, Karay et al., 2018 & Maj 2015

Gardenswartz and Rowe (2003) introduced the "Four Layers of Diversity" model to help organizations understand and address diversity in a comprehensive way. The model has been adapted and expanded on (Charta der Vielfalt n.d., Gardenswartz & Rowe, 2008, Karay et al.,

2018 & Maj 2015) but generally consists of four layers, each representing different aspects of an individual's identity and experiences. Viewed from the outside in, these are organizational, external, and internal dimensions and, in the middle, personality.

Personality, which is the deepest layer, is made up of traits including values, communication preferences, and styles. It emphasizes how each person is different based on their personality features. It focuses on the unique qualities of individuals depending on their personality traits. Internal dimensions are aspects of diversity that are not immediately visible, such as age, race, gender, sexual orientation, physical ability and ethnicity. Internal dimensions are fundamental elements of a person's identity. External dimensions encompass elements that are more obvious and usually result from organizational and social forces. Examples include one's appearance, level of education, marital status, income, and place of residence. The Organizational Dimensions encompass factors including job role, seniority, department, and work location that are associated with a person's place in the organization. It takes into account the variety that results from a person's job title and position in the company (Charta der Vielfalt n.d., Gardenswartz & Rowe, 2003, Gardenswartz & Rowe, 2008, Karay et al., 2018 & Maj 2015).

To explore the difficulties luxury brands face in balancing their traditional exclusivity with the increasing demand for inclusivity, several dimensions of diversity are examined.

Social categorization, involves the classification of individuals into distinct groups, with superficial characteristics such as age, gender, or race serving as identifiers for the creation of subgroups (Phillips & O'Reilly, 1998). This phenomenon aligns with "social identity theory" (Tajfel, 1979), wherein perceived differences lead individuals to feel a stronger connection with those who share similar attributes. Consequently, this process gives rise to the formation of in-groups and out-groups. Notably, members of out-groups tend to be perceived as less trustworthy, honest, and competent compared to their in-group counterparts. The formation of these groups further contributes to the development of stereotypes and prejudices, leading to consequences such as impaired cooperation, communication, and an elevated potential for conflict between the groups (Phillips & O'Reilly, 1998).

2.2.1.1 Gender

The term "sex" refers to anatomy, hormones and physiology. In addition to biological sex, there is also social sex, or gender. Gender refers to the cultural, psychological and social constructs and meanings in society. Social gender is shaped by, among other things, social influences, culture, media and upbringing (Wesely, 2008: 2).

Gender is an internal dimension of diversity that cannot be controlled or regulated by oneself (Gardenswartz & Rowe, 2008: 32). In terms of differences and similarities, it can be said that at first glance a distinction can be made between women and men (Rendtorff, 2020: 125). The percentage of women in the population varies between 49 and 51 percent in the majority of countries (within one percentage point of an equal share of men and women). The sex ratios vary globally, with South and East Asian countries, like India and China, exhibiting a lower female share, while Middle Eastern nations, including Oman, the UAE, and Saudi Arabia, have a higher male share, often due to male immigration; Eastern Europe and Russia, on the other hand, show a higher female share, driven by significant sex gaps in life expectancy (Ritchie & Roser, 2024). However, gender identities are not always binary. Gender-diverse people (those who are non-cisgender) make up an estimated 0,1 to 2 percent of the population, depending on the studies' location and inclusion criteria (Goodman et al., 2019, Spizzirri, 2021, Wilson & Meyer, 2021).

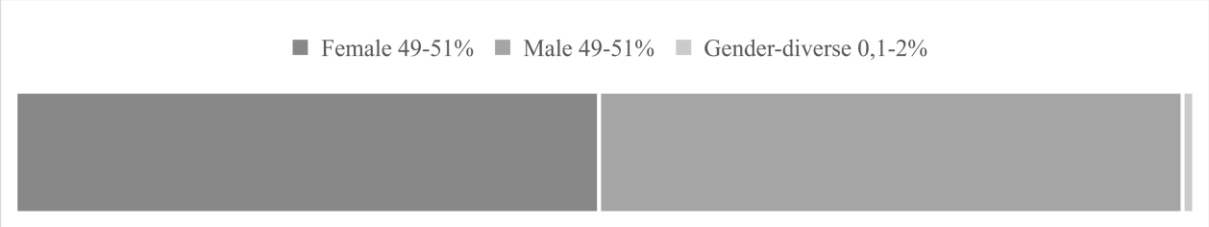


Figure 3: Distribution of Gender

Source: Own illustration based on: Goodman et al., 2019, Ritchie & Roser, 2024, Spizzirri, 2021, Wilson & Meyer, 2021

It is necessary to explicitly acknowledge the existence of non-binary, transgender, and gender non-conforming identities as well as to work to achieve fluency regarding the unique needs and experiences of this population (Fiani & Han, 2020:63ff). In terms of variability, it can be said that although biological sex is determined during pregnancy and ultimately at birth and is therefore initially unchangeable, the way it is lived out can still deviate from biological sex due to social gender. Furthermore, gender is relationship-orientated and not task-orientated (Joshi & Roh, 2009: 600). Social gender is perceptible, whereas biological gender is not in every case (Wagner & Voigt, 2007: 21). Gender fault lines are social, economic, or cultural divides that are often associated with traditional gender roles, stereotypes, and expectations. They imply the existence of tensions, inequalities, or conflicts along gender lines (Adams & Coltrane, 2005:230ff, Lips, 2016:40ff, an Knippenberg et. al, 2011, S.307-311). Leaders are often ascribed typical "male" stereotypes such as dominant, autonomous, unemotional, self-

confident, and active (Hofmeister & Hünefeld, 2010). However, board gender diversity exhibits a positive correlation with corporate social responsibility outcomes (Tichenor et al., 2022).

Gender plays a crucial role in marketing, particularly in luxury marketing, where gendered advertising strategies are often employed to target specific demographics. Research by Matthes et al. (2016) shows that gender stereotypes in television advertising are prevalent worldwide, with depictions of primary characters, voiceovers, age, associated product categories, and settings reinforcing traditional gender norms. This indicates that marketing frequently aligns with societal expectations and perceptions of masculinity and femininity.

Further studies by Nassif & Gunter (2008) and Middleton et al. (2019) reveal the gendered nature of advertising, highlighting that women are commonly portrayed in domestic roles and settings, endorsing products related to body care and household cleaning. In contrast, men are often depicted in professional roles, perpetuating traditional gender norms and stereotypes in marketing campaigns. Research by Åkestam et al. (2021) also suggests that gender stereotypes in advertising can have adverse cross-gender effects, impacting consumer perceptions and reactions. Advertisements featuring individuals in sex-typed roles can trigger stereotypic constructs, leading to stereotypic judgments and behaviors among consumers. This emphasizes the significant influence of gender portrayals in marketing on consumer attitudes and behaviors.

Luxury advertising often features models who embody a certain ideal, which can significantly impact consumers' perceptions and behaviors. For instance, Jiang et al. (2014) found that luxury brands tend to use models that evoke feelings of social exclusion, leading consumers to perceive a sense of rejection from these advertisements. Conversely, non-luxury brands are more likely to feature diverse models in their advertising, especially different body shapes and sizes (Michaelidou et al., 2022).

Luxury advertising also tends to focus on conveying exclusivity and authenticity appeals, which can influence consumers' perceptions of the brand (Seo et al., 2020). This emphasis on exclusivity may lead to portrayals of social superiority, which can be perceived as either prestige or arrogance by consumers (Sung & Phau, 2018). Furthermore, non-luxury advertising may utilize different strategies, such as femvertising, to connect with consumers on a more relatable level (Michaelidou et al., 2022). The impact of luxury advertising extends beyond visual representation; exposure to materialistic advertisements can influence consumers' perceptions of appearance and financial success. Materialistic media has been shown to affect women's body image and self-concept (Ashikali & Dittmar, 2011).

Marketing is often gendered to target specific audiences and conform to societal norms and expectations regarding gender roles. By understanding and leveraging gender stereotypes in

advertising, marketers can tailor their campaigns to resonate with consumers and achieve desired outcomes.

2.2.1.2 Race

By 2060, multiracial individuals, projected to surpass 10% of the US population, will become the fastest-growing racial group (U.S. Census Bureau, 2018). The concept of race is complex and includes many different elements, including one's own self-identification, racial appearance, classification by others, perceived classification by others, and presentation to conform to expectations (Roth, 2010). Race is an internal dimension of diversity that cannot be controlled or regulated by oneself (Gardenswartz & Rowe, 2008: 32). It has a major impact on how people think, perceive, interpret, and experience things (Oliver et al., 2017). Geographic origins, phenotypic differences, or differences in gene frequencies have all been used to classify races within science as divisions within the human species. The mid-20th century saw the emergence of the genetic conception of race, which placed an emphasis on the 99.9% genetic similarity and 0.01% real genetic differences that really exist between races (Smedley & Smedley, 2005:4). The contrast between race and ethnicity lacks a genetic foundation as well; both are social constructs for categorizing and characterizing populations. While physical traits like skin color are associated with race, ethnicity is tied to cultural expression. Despite the absence of genetic markers, these constructs significantly shape human experiences, fueling biases, discrimination, and social hierarchies. They persist in influencing societal attitudes and behaviors, leading to exclusion, discrimination, and violence, perpetuating disparities (Blakemore, 2019, Feliciano, 2016, Jablonski, 2021, Mikulak, 2011). Ethnicity is seen as more adaptable than race (Khan & Fu, 2021). The impact extends to demographics, public policy, civil rights, wealth distribution, and social stratification. Race and ethnicity profoundly influence social, personal, and cultural experiences (Blakemore, 2019, Williams et al., 2023).

Skin tone influences perceptions of racial discrimination among Black, Latinx, and White individuals, with darker-skinned Black individuals more likely to report discrimination. For Latinx individuals, skin tone and racial identity match play a significant role in how discrimination is perceived (Gonlin, 2020). Despite this growth, they exhibit higher rates of drug use, depression, and suicide compared to most other racial groups (Substance Abuse and Mental Health Services Administration, 2014; Schlabach, 2013). Unique and general discrimination, both specific to multiracial individuals and akin to that faced by racial minorities, contribute to these disparities (Brackett et al., 2006; Iijima Hall, 2004). Identity invalidation and family discrimination particularly harm their mental health (Franco et al.,

2021:1). 44 million people - about 10% of EU citizens belong to racial or ethnic minorities (Dixon-Fyle et al., 2024, Islam & Woodford, 2022). The United States are more racially diverse and are continuously becoming more racially diverse. About 40% of the country are not white (Frey, 2018, Frey, 2021, Gosh, 2020, United States Census Bureau, 2020, United States Census Bureau, 2023, United States Census Bureau, n.d.). The minority groups considered in US and EU statistics vary for historical, political and geographical reasons.

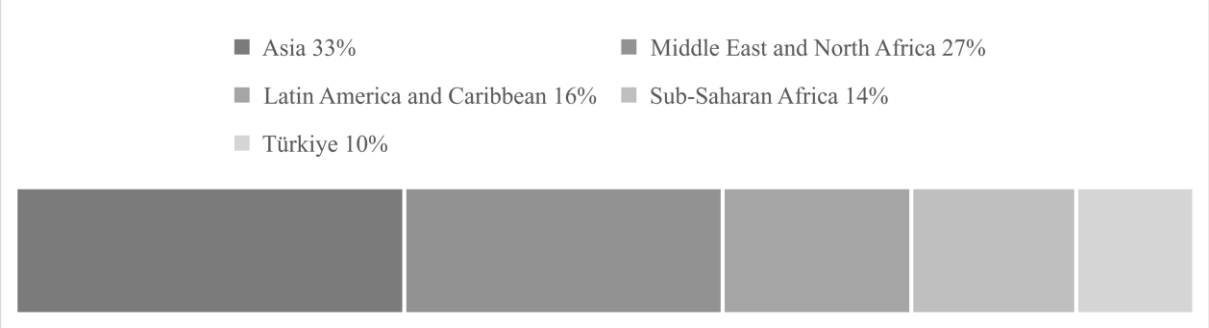


Figure 4: Minorities in the European Union

Source: Own illustration based on: Dixon-Fyle et al., 2024

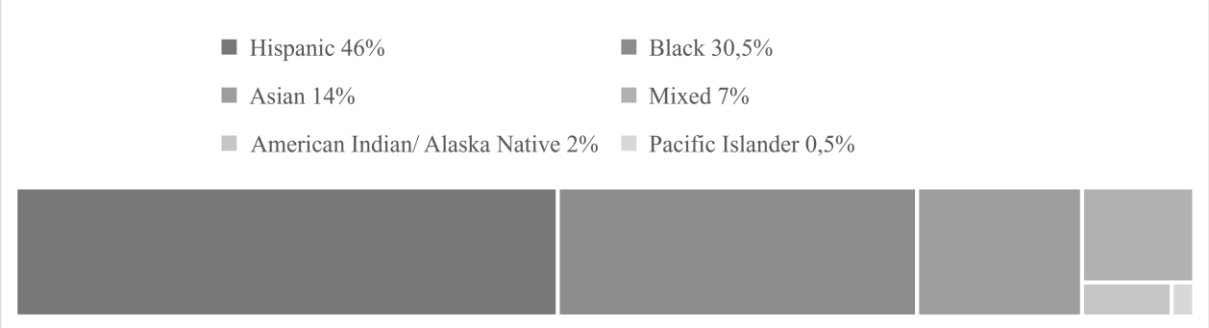


Figure 5: Minorities in the United States

Source: Own illustration based on: 2020 US Census , Gosh, 2020

Race has an impact on market segmentation, advertising tactics, and consumer behavior in marketing (Nkomo, 2021). Advertisers utilize racial themes in marketing to promote and sell products by strategically incorporating racial identities into advertising strategies and campaigns (Crockett, 2008).

By considering race as a diversity cue, marketers can strategically leverage this aspect to create more engaging and impactful advertising campaigns. Luxury brands tend to use more white models compared to non-luxury brands (Michaelidou et al., 2022). This disparity in racial diversity cues in advertisments can influence consumer perceptions and attitudes towards these brands. Luxury brands often aim to create an aspirational image associated with exclusivity and prestige. By featuring a less diverse cast in their advertising, these brands may seek to maintain

an air of exclusivity and cater to a specific demographic that perceives homogeneity as a symbol of luxury and sophistication (Azab & Clark, 2017).

Luxury brands may prioritize maintaining a consistent brand image and aesthetic. By controlling the racial diversity in their advertisements, these brands can ensure that their messaging aligns with their desired brand identity and values. Consistency in representation can help reinforce brand recognition and resonate with their target audience (Sengupta & Gorn, 2002). By maintaining a certain level of uniformity in their advertising, these brands can uphold a sense of heritage and legacy that resonates with their loyal customer base (Bartikowski et al., 2020; Wong et al., 2022). This disparity in diversity representation can impact consumer perceptions. Participants were more likely to perceive rejection by models in luxury advertisements compared to non-luxury advertisements (Jiang et al., 2014). This suggests that luxury advertising may evoke feelings of social exclusion due to its lack of diversity in representation.

Incorporating diversity in advertising brings several benefits. Consumers, especially ethnic minorities, are more aware of their race and consider it a prominent factor in their interactions (Khan et al., 2015). Therefore, incorporating race-related cues in advertising can enhance the relatability and resonance of the message with the target audience. Inclusion of diverse racial representations in advertising can enhance brand perception, increase consumer trust, and foster a sense of inclusivity among diverse audiences. Luxury brands may leverage diversity to enhance their aspirational image, while non-luxury brands may focus on community engagement and relatability. (Heath et al., 2023). Brands that prioritize diversity and inclusion are perceived more favorably, leading to increased brand credibility and positive brand associations (Wiedmann et al., 2009). By authentically representing diversity, luxury brands can stand out, connect with a broader audience, and demonstrate a commitment to equality and social responsibility (Amatulli et al., 2019). This approach can lead to increased brand loyalty, consumer trust, and positive brand associations, ultimately contributing to long-term brand success and sustainability in the market (Keller, 2009).

Luxury brands that fail to embrace racial diversity in their advertisements miss out on opportunities to enhance brand perception, increase consumer engagement, differentiate themselves in the market, and position themselves as socially responsible and inclusive brands. Leveraging diversity in marketing strategies can enable luxury brands to connect with diverse consumer segments, foster brand loyalty, and contribute to a more inclusive and culturally relevant advertising landscape. By embracing racial diversity in advertising, luxury brands can improve brand perception, increase consumer engagement, and promote inclusivity among

diverse audiences. This inclusivity can result in heightened brand loyalty, market differentiation, and broader appeal to a diverse consumer base (Keller, 2009). Featuring racial diversity in luxury brand advertising can have a positive impact on brand reputation and market positioning. Brands that prioritize diversity and inclusion are viewed more favorably by consumers, which enhances brand credibility and fosters positive brand associations (Shukla et al., 2015). By showcasing a variety of racial backgrounds in their ads, luxury brands can position themselves as socially conscious, progressive, and culturally relevant, thereby boosting brand equity and attracting a wider consumer base (Amatulli et al., 2019). Integrating racial diversity in advertising can help luxury brands distinguish themselves in a competitive landscape. By authentically representing diversity, luxury brands can stand out, connect with a broader audience, and demonstrate a commitment to equality and social responsibility (Michaelidou et al., 2022). This approach can lead to increased brand loyalty, consumer trust, and positive brand associations, ultimately contributing to long-term brand success and sustainability in the market (Baek et al., 2023).

Luxury brands that fail to embrace racial diversity in their advertisements miss out on opportunities to enhance brand perception, increase consumer engagement, differentiate themselves in the market, and position themselves as socially responsible and inclusive brands. Leveraging diversity in marketing strategies can enable luxury brands to connect with diverse consumer segments, foster brand loyalty, and contribute to a more inclusive and culturally relevant advertising landscape.

While there are strong arguments in favor of using diverse models in luxury advertising, significant concerns remain regarding brand identity, exclusivity, and market perceptions. Luxury brands, often associated with exclusivity and prestige, must carefully weigh these factors when formulating their advertising strategies. Including diverse models may inadvertently dilute this exclusivity, creating the perception that luxury is becoming more accessible and, therefore, less elite. Hennigs et al. (2013) argue that luxury brand management faces the challenge of balancing rising demand with the need to protect the uniqueness and exclusivity of luxury products. This implies that incorporating a more diverse representation might undermine the brand's perceived status. Similarly, Shukla et al. (2022) discuss the difficulties of luxury democratization, noting that consumers in developing markets are particularly sensitive to luxury brands' increased accessibility. They suggest that featuring more diverse models may decrease purchase intentions among these consumers, who equate luxury with exclusivity and status. This indicates that diverse representation could negatively affect luxury brands' appeal in certain markets. Futhermore it is important to empazise the importance

of luxury brands maintaining a distinct identity and staying ahead of consumer expectations. They argue that allowing too much consumer co-creation or adaptation to consumer preferences risks eroding a brand's identity. This further suggests that introducing diverse models might clash with traditional luxury aesthetics that brands have long relied upon (Roper et al., 2013). Additionally, Hudders & Pandelaere (2011) provide evidence that consumers with high materialistic tendencies often experience negative emotions. This could imply that luxury consumers, who are frequently driven by materialistic values, may react negatively to advertisements featuring diverse models, viewing them as less aspirational and less aligned with their personal values. Another concern is the risk of overexposure. As luxury brands grow in popularity, there is a danger of becoming too mainstream. Incorporating diverse models into advertising may contribute to this overexposure, making the brand seem less exclusive (Hennigs et al., 2013). Furthermore, the effectiveness of diverse representation in luxury advertising can vary significantly across cultural contexts - diverse models may not resonate equally across all markets. This highlights the risk of alienating core consumers who may prefer more traditional portrayals of luxury (Gupta & Kour, 2021).

The contradictions between these findings point to the need for further research into the complexities of racial diversity in luxury advertising. There is a growing need for more nuanced studies to explore how diverse representations impact various consumer segments, especially across different cultural contexts. Such research would be valuable in helping luxury brands navigate evolving consumer expectations and integrate diversity into their marketing strategies without compromising their established brand essence.

2.2.2 Social Media Advertising

Social media advertising involves placing promotional messages on social media platforms to reach target audiences and promote products or services. It has become a prevalent marketing strategy due to the widespread use of social media by individuals of diverse backgrounds and demographics. The impact of social media advertising on consumer buying intention is significant, with social media platforms serving as influential channels for delivering brand information and advertising messages (Pütter, 2017). Research shows that the use of diverse models in social media ads can significantly enhance consumer engagement and positively influence perceptions. Featuring models from various ethnicities, genders, body types, and backgrounds helps create inclusive, relatable content that resonates with a wider audience (Chiang et al., 2018). This inclusivity not only fosters emotional connections but also boosts engagement, as consumers are more likely to respond to ads that reflect their identities and

experiences. Furthermore, analyzing consumer interactions with these ads provides insights into the role of authenticity, relevance, and emotional impact in driving engagement (Chiang et al., 2018). Moreover, the role of social media advertising in shaping consumer perceptions is crucial. Studies have shown that social media campaigns that feature diverse models can influence consumer attitudes and behaviors (Arli & Dietrich, 2017). By creating ads that celebrate diversity and representation, brands can build positive associations with their target audience and differentiate themselves in a competitive market. By leveraging diverse models in ads, marketers can enhance consumer engagement, build brand trust, and ultimately drive purchase intent among a diverse range of consumers. Diversity in advertising can lead to negative consumer sentiment, particularly when the representation of diversity is perceived as inauthentic, tokenistic, or misaligned with the brand's core values (Herget & Bötzl, 2021, Lewis et al., 2008, Matthews & Dietz-Uhler, Norman & McFarlane-Alvarez 2023, 1998, Zheng, 2020).

Social media advertising plays a vital role in influencing consumer perceptions, attitudes, and behaviors, especially when diverse models are incorporated into ad campaigns. By understanding the impact of representation and diversity in media on consumer engagement, marketers can create more effective and inclusive advertising strategies that resonate with diverse audiences and drive positive brand outcomes.

2.2.3 Luxury Brands and Advertising

Luxury brands target individuals with high aspirations who seek products symbolizing status, success, and wealth (Mandal, 2021; Sharda & Bhat, 2018). This audience values exclusivity, quality, hedonism, and prestige (Truong et al., 2010). Ownership of luxury brands is seen as a way to signal wealth, status, power, and control in social settings (Sharma et al., 2021). Luxury brands strategically employ diversity cues in their marketing to create an aspirational yet inclusive image that appeals to a broader audience, differentiating them from non-luxury brands and positioning them as progressive within the market (Michaelidou et al., 2022).However, other Wu (2022) found, that Luxury brands often strategically avoid overt displays of diversity cues in their marketing materials to create a perception of exclusivity and aspiration. Luxury brands may perceive the inclusion of diversity cues as a means to differentiate themselves from non-luxury brands and establish a progressive image in the market. This approach allows luxury brands to differentiate themselves from non-luxury brands and appeal to consumers seeking a more subtle and refined brand image. Luxury brands may strategically integrate diversity cues to enhance their brand image and resonate with their target audience's values of inclusivity and

social responsibility. However, they face the challenge of balancing the rising demand for their products with the need to preserve their exclusivity and uniqueness (Hennigs et al., 2013). Traditional marketing strategies do not always apply to luxury brands due to the unique decision-making processes of consumers in the luxury market, further complicating their marketing approaches (Stegemann, 2011). Consumers perceive brands that prioritize diversity and inclusion more favorably, leading to increased brand credibility and positive brand associations (Wiedmann et al., 2009). Luxury brands exhibit distinct brand personalities, crucial in shaping consumer perceptions and preferences (Cowan, 2023).

The response to diversity in advertising among the target audience of luxury brands can vary (Ramadan et al., 2018). These perceptions impact engagement with luxury products and advertising, including views on brand loyalty, luxury status, and brand trust.

Luxury brands strategically balance inclusivity and exclusivity in their advertising to uphold their brand image. While inclusivity can broaden the brand's appeal, it may risk diluting the brand's exclusivity and perceived luxury status (Michaelidou et al., 2022; Radon, 2012). Exclusivity is often a key element of luxury brands' identity, enhancing prestige and desirability by associating with a select group (Radon, 2012; Stegemann, 2011). The perceived exclusivity of luxury brands significantly influences consumer perceptions and brand image. Brands seen as exclusive can command higher brand equity and maintain desirability (Chen & Li, 2022; Stegemann, 2011). Conversely, excessive inclusivity may harm brand image and exclusivity, affecting consumer perceptions of luxury status (Radon, 2012; Zheng et al., 2013). Emotional attachment and brand loyalty to luxury brands are shaped by perceived exclusivity and emotional appeal (Hassan et al., 2016). Previous research recommended, that luxury brands must balance creating emotional connections with consumers while maintaining an aura of exclusivity to uphold brand image and desirability (Hassan et al., 2016).

The use of thin white models may enhance the perception of exclusivity and rarity, motivating consumers to pay a premium for the associated products (Seifert et al., 2019). While inclusivity can broaden a brand's appeal and attract a more diverse consumer base, it may also risk diluting the brand's exclusivity and perceived luxury status (Cheah et al., 2022). Luxury brands often leverage exclusivity as a fundamental aspect of their identity to elevate prestige and desirability (Michaelidou et al., 2022). Therefore, an increase in inclusivity may lead to a perception of reduced exclusivity, potentially affecting the brand's luxury image. Luxury brands are highly attuned to shifts in the market and cultural landscape, as consumer consumption is underpinned by perceptions of high quality, exclusivity, and exceptional craftsmanship (Pankiw et al., 2020).

In response to increasing societal demands for diversity and inclusivity, luxury brands may leverage diverse models to position themselves as leaders in innovation and social responsibility. Inclusivity in luxury advertisements can signal a brand's commitment to social responsibility and inclusivity, resonating positively with consumers who value diversity and equality (Pankiw et al., 2020). This can lead to increased brand loyalty and positive brand perceptions among consumers who appreciate brands that embrace diversity and inclusivity. Showcasing diversity in luxury advertisements can enhance the brand's image as progressive, inclusive, and culturally sensitive, appealing to a broader audience base (Sung & Phau, 2018). Consumers may perceive brands that feature diversity positively, viewing them as more authentic, relatable, and socially conscious.

While many studies emphasize the effectiveness of diversity in luxury advertising, other studies ahow risks associted with diverse models. Some consumers may not prioritize diversity as a key factor in their purchasing decisions for luxury products (Ivanov, 2016). They may focus more on product quality, brand reputation, or design aesthetics, leading them to be indifferent to diversity messaging in luxury advertising. Consumers who do not see themselves represented in the diversity portrayed in advertisements may feel disconnected or indifferent to the brand's attempts at inclusivity (Cui, 2001). Additionally, those who view luxury brands primarily as symbols of exclusivity and status may be indifferent to diversity messaging that they perceive as detracting from the brand's elite image. Consumers who are not actively seeking brands that promote diversity or social causes may simply overlook or disregard diversity messaging in luxury advertisements (Hashim et al., 2018). If diversity is not a priority or motivating factor for these consumers, they may react indifferently to diversity-focused campaigns. It is also possible, that consumers experience the inclusion of diversity as inauthentic or tokenistic, especially if they believe brands lack genuine commitment or action (Rashid & Chattaraman, 2019). This perception of insincerity can lead to skepticism and distrust among consumers, resulting in a negative reaction to the brand's advertising efforts. T, his might be particularly true for consumers who hold traditional or conservative views may react negatively to diversity in luxury advertisements that challenge their beliefs or values (Sugiarto & Barnier, 2019). The portrayal of diverse individuals in luxury ads may be seen as controversial or inappropriate by certain segments of the audience, leading to disapproval and backlash against the brand. Additionally, consumers who associate luxury with exclusivity and a certain lifestyle may view the inclusion of diversity as diluting the brand's elite status and prestige (Yang & Mattila, 2014). The perception that luxury brands are catering to a broader, more diverse audience may diminish the brand's appeal to consumers who value exclusivity and rarity in luxury products.

Negative reactions to diversity in luxury advertisements can also stem from concerns about brand image and reputation. Consumers may worry that associating with diverse or controversial themes could tarnish the brand's identity or alienate existing loyal customers (Kashif et al., 2021). This fear of brand dilution or misalignment with core brand values can lead to a backlash against diversity-focused advertising initiatives.

Luxury brands and non-luxury brands employ distinct marketing strategies to cater to their respective target markets and achieve their brand objectives. Luxury brands often focus on creating an aura of exclusivity, prestige, and desirability, while non-luxury brands typically emphasize affordability, accessibility, and functionality in their marketing efforts. Luxury brands differentiate themselves through unique marketing strategies that emphasize brand identity, heritage, and premium pricing to maintain an aura of exclusivity and luxury Dion & Arnould (2011). These brands often prioritize creating a sense of aspiration and status among consumers, leveraging strategies that appeal to consumers' desire for luxury experiences and products that symbolize wealth and social status (MajlesiRad & Shoushtari, 2020). In contrast, non-luxury brands often prioritize product features, competitive pricing, and accessibility to attract price-conscious consumers and drive sales volume. By engaging consumers through co-creation and immersive brand experiences, luxury brands aim to build strong emotional connections and brand loyalty among their affluent clientele. These brands often focus on highlighting product benefits, value propositions, and competitive pricing to appeal to a broader consumer base and drive purchase decisions.

Luxury brands face a complex challenge in balancing inclusivity and exclusivity in their advertising strategies. While incorporating diversity can enhance brand perception, increase consumer trust, and broaden market appeal, it also risks diluting the exclusivity that defines luxury brands. Understanding the diverse preferences and values of their target audience is crucial for luxury brands to navigate these challenges successfully. By strategically leveraging diversity while maintaining their core identity, luxury brands can position themselves as socially responsible and culturally relevant, ultimately achieving long-term brand success and sustainability in the market.

Given the divergent findings, it is clear that the impact of diversity in luxury advertising is complex and not fully understood. The inconsistency in results highlights the need for further research. Investigating real-world consumer behavior is essential to better understand how inclusivity in advertising affects consumer sentiment. The studies in this thesis focus on these factors to provide a more comprehensive understanding of the balance luxury brands must strike between diversity and exclusivity.

2.2.4 Celebrities in Advertising

Utilizing celebrities in advertisements can offer several benefits to brands, contributing to increased brand awareness, enhanced brand image, and improved consumer engagement. Celebrity endorsements can significantly impact consumer perceptions and purchase behavior, making them a valuable marketing strategy for brands. Especially, luxury brands often invest in influencer partnerships, exclusive events, and limited edition releases to enhance their brand image and maintain their luxury positioning (Zha, 2023). By associating with high-profile individuals and creating scarcity through limited product offerings, luxury brands aim to reinforce their exclusivity and desirability among consumers.

Celebrity endorsements can help brands stand out in a crowded marketplace by leveraging the fame and popularity of the celebrity to attract attention and create brand awareness (Keel & Nataraajan, 2012). Consumers are more likely to remember and recognize brands that are associated with well-known personalities, leading to increased visibility and recognition.

Celebrities furthermore bring their own personality, values, and characteristics to the brands they endorse, influencing how consumers perceive the brand (Pradhan et al., 2014). Positive associations with the celebrity can transfer to the brand, enhancing its image and credibility in the eyes of consumers. This can help build trust and loyalty among consumers.

Celebrity endorsements additionally have been shown to positively impact consumers' purchase intentions and attitudes towards brands (Chan et al., 2013). Consumers may be more inclined to try or purchase products endorsed by their favorite celebrities, leading to higher sales and revenue for the brand.

Moreover celebrities can serve as effective communicators for brands, helping to deliver key brand messages and values to consumers (Tran et al., 2019). Their influence and appeal can capture consumer attention and create a strong emotional connection with the brand, driving engagement and interest. In global markets, celebrity endorsements can help mitigate cultural interferences and bridge communication gaps between brands and consumers (Akindele & Arogundade, 2022). By using celebrities with international appeal, brands can overcome cultural barriers and connect with diverse audiences effectively.

Lastly celebrity endorsements can help build brand familiarity and trust among consumers, especially when the celebrity's image aligns with the brand values and target audience (Patil, 2019). This can lead to increased brand loyalty and positive brand associations among consumers. In conclusion, leveraging celebrity endorsements in advertising can offer brands a range of benefits, including increased brand recognition, improved brand image, higher purchase intentions, effective marketing communication, cultural interference mitigation, and

enhanced brand familiarity and trust. By strategically partnering with celebrities who resonate with their target audience, brands can effectively leverage the influence and appeal of celebrities to achieve their marketing objectives and drive brand success.

2.3 Research Gap

Current research extensively explores the impact of diversity in advertising and consumer sentiment on social media platforms. Areni et al. (2021) found that automated text analyses of YouTube comments can measure consumer reactions to diversity cues, using sentiment analysis to assess consumer sentiment towards products and brands. Bozkurt et al. (2021) demonstrated how ethnicity influences consumers' intent to comment on social media posts, revealing race diversity's impact on social media interactions. Similarly, Wang et al. (2022) highlighted the relevance of machine learning by employing sentiment analysis to understand consumer attitudes toward gender or race diversity. Veletsianos et al. (2018) explored how presenter gender affects public sentiment in educational video comments, providing insights into the role of gender diversity in shaping perceptions.

In luxury brand contexts, Michaelidou et al. (2022) found significant differences between luxury and non-luxury brands in femvertising practices, particularly in how gender diversity is portrayed. Creevey et al. (2021) emphasized the importance of social media in luxury brand construction, showing that luxury brands target diverse segments. Huang et al. (2018) discovered that narrative persuasion significantly influences consumer sentiment toward luxury brands on social media. Boisvert and Ashill (2018) focused on the role of gender in evaluating luxury brand line extensions, highlighting its impact on marketing strategies. For non-luxury brands, Bozkurt et al. (2021) found that ethnicity plays a key role in comment intention on social media, providing insight into diversity's influence on non-luxury brand advertising.

While these studies offer valuable insights into diversity in advertising and consumer sentiment, several gaps remain. First, none of these studies have specifically examined the impact of gender and racial diversity on TikTok video performance for luxury and non-luxury brands. Most research focuses on platforms like YouTube, leaving a gap in how diversity cues influence video engagement on TikTok, which is crucial given its younger audience and growing influence in social media marketing. Second, there is no comprehensive analysis of consumer sentiment towards diversity in TikTok advertisements using both hand-coding and software analysis, an approach that could offer deeper insights. Third, while Michaelidou et al. (2022) compare diversity practices between luxury and non-luxury brands, they do not explore how these practices influence consumer sentiment in social media comments.

By addressing these questions, my research will provide new insights into the role of diversity in social media advertising on TikTok, which is particularly important for understanding younger generations' behaviors and preferences. This study will contribute to the fields of marketing and brand communication by offering a holistic view of how diversity influences engagement metrics and consumer sentiment on a rapidly growing platform, filling the existing gaps in the literature.

3 Methodology

Despite algorithmic biases, TikTok's democratic and inclusive potentials have made it a space where diverse voices can be heard, including discussions on race and gender (Baker, 2022). Unlike other platforms, TikTok fosters activism and empowerment among marginalized groups, allowing for direct engagement and advocacy (Vizcaíno-Verdú & Aguaded, 2022).

Unlike traditional platforms like Instagram and Facebook, which were previously used to study diversity in luxury and non-luxury brand advertisements (Michaelidou et al., 2022), TikTok's focus on short-form video content creates an interactive and dynamic environment where user-generated responses provide immediate feedback. TikTok's viral nature and high user engagement make it ideal for assessing how diversity in advertisements influences not only consumer sentiment but also the overall reach and performance of content. This makes TikTok a "better" platform for analyzing diversity cues because it reflects real-time consumer interaction, activism, and organic content spread in ways other platforms cannot offer.

Previous studies, such as those on YouTube (Puwandi et al., 2020), and traditional media (Lau & Lee, 2018; Khan et al., 2015), have shown the effectiveness of diversity cues in various contexts. However, TikTok's ability to amplify diverse voices allowing for fast past discourse uniquely position it as an ideal space to examine the role of diversity in modern advertising.

3.1 Research Objectives

This research will be conducted in two distinct but complementary studies, each designed to investigate different aspects of the impact of diversity in social media advertisements by luxury and non-luxury brands on TikTok. Due to the exploratory character of this work no hypotheses have been created.

The first study aims to examine how the presence of gender and racial diversity affects the performance of TikTok videos published by the official accounts of selected luxury and non-luxury brands. Specifically, this study will analyze the correlation between diversity cues and video performance, measured by the number of views. Aiming to understand how diversity in advertisements influences their reach in a real-world setting. Data collection will involve sourcing TikTok videos from the official accounts of selected luxury and non-luxury brands, with the key variables being the presence of gender and racial diversity in the videos and the video performance measured by view count.

The second study focuses on understanding how the presence of diversity cues in TikTok videos from these brands affects consumer sentiment in the comments section. This study aims to explore how consumers perceive and react to diverse representations in advertisements.

The objectives of these studies are twofold. In the first study, TikTok videos will be hand-coded to classify the levels of gender and racial diversity present among featured models. This data will then be analyzed to assess how varying diversity levels influence key performance metrics, such as consumer engagement and video reach, providing insights into the relationship between diversity representation and audience interaction. Secondly, Study 2 aims to analyze consumer sentiment towards diverse representations in advertisements, offering a deeper understanding of consumer perceptions and emotional responses. The methodology involves selecting a curated group of luxury and non-luxury brands based on their financial performance in the market.

This study employs a field research approach, achieving results by combining qualitative hand-coding with quantitative software analysis to comprehensively evaluate consumer sentiment. This method ensures that real-world data from social media platforms is used, providing insights that are both practical and applicable in real settings. The expected outcomes of these studies include insights into whether and how diversity cues affect the performance of social media advertisements, providing practical implications for brands and their marketing managers in terms of content strategy. Additionally, understanding consumer reactions to diversity in advertisements could inform brands on how to craft more inclusive and engaging content. By conducting these two studies, this research aims to provide a holistic view of the impact of diversity in social media advertisements on both engagement metrics and consumer sentiment, thereby offering valuable contributions to the fields of marketing and brand communication.

3.2 Data Analysis Tools

The data for the studies in this thesis was analyzed using a combination of Excel, JASP, and SPSS to ensure comprehensive statistical insights. Initially, Excel was employed for organizing and managing the data, including basic descriptive analysis to understand the overall distribution and trends of the data. For the analysis of Research Question 1, which investigates how diversity in social media advertisements affects video performance, both descriptive and linear regression analyses were conducted using SPSS. This approach helped to quantify the relationship between model diversity and video performance, measured by views. For Research Questions 2 and 3, which examine the impact of diversity on consumer sentiment and

differences between luxury and non-luxury brands respectively, linear regression analysis using JASP was used to analyze sentiment across the full dataset and hand-coded subsets. The analysis incorporated the Lexical Suite to evaluate sentiment, emotionality, and other linguistic features. To explore these relationships in more depth, multiple linear regression was employed, providing a more nuanced understanding of how diverse representation influences consumer reactions and sentiment on TikTok – this tool was utilized an all comments gathered while only the first 25 comments present on each video were fully hand coded for additional variables. By utilizing these tools, the thesis aimed to deliver robust and reliable findings, linking the diversity cues in advertisements with both video performance and consumer sentiment.

3.3 Brand Selection

A systematic approach was used to select brands for analyzing consumer sentiment in social media advertisements. The top five fashion brands were chosen based on their rankings in *Forbes' Most Valuable Brands 2020* and *Fashion United's Most Valuable Fashion Brands 2023*. The analysis targets brands that sell fashion to both adult men and women, excluding those primarily focused on sports gear or jewelry, as these categories appeal to different consumer segments. Mid-range and affordable luxury brands were also excluded to prevent variability that could obscure the specific consumer sentiments associated with purely luxury and non-luxury fashion brands. The focus is restricted to high-end luxury and non-luxury brands, ensuring a consistent and a relevant dataset allowing for clear and meaningful data. This structured and objective selection process ensures that the data is both transparent and replicable. Additionally, the selected brands must have public comment sections enabled on their most successful videos within the analyzed timeframe, as sentiment analysis depends on unrestricted access to consumer interactions. If comments are disabled or restricted, meaningful analysis becomes impossible leading to a brand being excluded from the analysis.

As of June 1, 2024, Forbes' Most Powerful Brands list includes three non-luxury and four luxury brands that are potentially relevant to this analysis. These brands and their respective rankings on the list are as follows: Louis Vuitton (LV) at rank 9, Gucci at rank 31, Hermès at rank 32, and Chanel at rank 52 are the identified luxury brands. The non-luxury brands include Zara at rank 41, H&M at rank 76, and Uniqlo at rank 84.

These brands can therefore also all be found in other prestigious rankings, most notably the top 20 of Fashion United's list of Most Valuable Fashion Brands. This list also offers additional potential brands for analysis to replace those excluded for not meeting key criteria. For example, Hermès and Chanel lack official TikTok accounts, and H&M has disabled the

comment sections on their most popular videos, limiting the ability to analyze consumer sentiment effectively.

Ranking	Brand	2023 Brand Value in USD	Selection Criteria
1	Nike	$42.5 b	Rejected; Sports attire and not general fashion brand
2	**Louis Vuitton**	**$36.4 b**	**Included – also included in *Forbes' Most Valuable Brands***
3	Chanel	$25.2 b	No official TikTok account
4	Hermes	$22.1 b	No official TikTok account
5	**Gucci**	**$18.9 b**	**Included – also included in *Forbes' Most Valuable Brands***
6	Dior	$17.6 b	Rejected; Mostly caters to women
7	Adidas	$16.1 b	Rejected; Sports attire and not general fashion brand
8	Rolex	$14.3 b	Rejected; Focus on jewelry and not general fashion
9	**Zara**	**$13.8 b**	**Included – also included in *Forbes' Most Valuable Brands***
10	H&M	$11.5 b	Rejected; Videos that fulfill further criteria have the comments turned off
11	Cartier	$11.2 b	Rejected; Focus on jewelry and not general fashion
12	**Uniqlo**	**$9.4 b**	**Included – also included in *Forbes' Most Valuable Brands***
13	**Prada**	**$5.9 b**	**Included**
14	Tiffany & Co.	$5.7 b	Rejected; Focus on jewelry and not general fashion
15	Coach	$5.5 b	Rejected; Neither clearly luxury or non-luxury branding
16	**Burberry**	**$5.2 b**	**Included**
17	Sephora	$5.1 b	Rejected; Focus on makeup/ Retailer
18	Lululemon	$5.0 b	Rejected; Sports attire and not general fashion brand
19	Moncler	$5.0 b	Rejected; Sports/ Outdoor attire and not general fashion brand
20	Patek Philippe	$4.9 b	Rejected; Focus on jewelry and not general fashion

Table 3: Breakdown of Brand Selection Rationale

As a result, the list of brands can be expanded to include two additional luxury brands, bringing the total to four luxury and two non-luxury brands that will serve as the foundation for all further research.

Brand	Link	Follower	Likes
Louis Vuitton	https://www.tiktok.com/@louisvuitton	13.400.000	92.800.000
Zara	https://www.tiktok.com/@zara	11.300.000	42.200.000
Gucci	https://www.tiktok.com/@gucci	5.000.000	53.800.000
Uniqlo	https://www.tiktok.com/@uniqloeurope	139.100	1.900.000
Prada	https://www.tiktok.com/@prada	1.500.000	16.400.000
Burberry	https://www.tiktok.com/@burberry	4.500.000	3.500.000

Table 4: TikTok Brand Metrics: Followers and Total Likes on 04.06.2024

3.4 Study 1: Analysis of Video Performance

3.4.1 Data Collection

All videos published on or before June 14, 2024, have been scraped with their view count between 3pm and 4pm using a specialized scraping tool. To ensure a sufficient sample size for analyzing the impact of diversity dimensions on content performance, the 100 most recent posts from each of the brands that suit before established criteria (Annex 1). Study 1 aims to answer RQ1: *"How does the diversity of models in social media advertisements affect video performance?"* by examining how diversity impacts the total number of views of a video as its key performance metric.

3.4.2 Variables

It is of interest to determine if diversity dimensions affect video performance, specifically the number of views, which therefore is the dependent variable here. The number of views is the outcome variable that is aimed to be understood. It represents the total number of views each video receives, serving as a measure of video performance and popularity.

The independent variables, that might influence the number of views a video receives, in this dataset are: Model: Female, Model: Male, White, Asian, Black, Other, Celebrity Focused, No Person. A video may feature multiple models, and each characteristic is coded as 1 = Yes/Present if it appears. The aim of the analysis of these independent variables, is to understand how different diversity dimensions and content characteristics impact the number of views a video receives. This will aid in identify patterns and strategies that brands can use to enhance their video performance through diverse and inclusive representation, by showing the actual performance results.

Variable	Description	Coding	Type of Variable
Number of Views	Total views received by each video (Dependent variable).	Continuous (Numeric)	Outcome Variable
Model: Female	Presence of female models in the video.	1 = Yes, 0 = No	Independent Variable
Model: Male	Presence of male models in the video.	1 = Yes, 0 = No	Independent Variable
White	Representation of white individuals in the video.	1 = Yes, 0 = No	Independent Variable
Asian	Representation of Asian individuals in the video.	1 = Yes, 0 = No	Independent Variable
Black	Representation of Black individuals in the video.	1 = Yes, 0 = No	Independent Variable
Other Ethnicity	Representation of individuals from other ethnic backgrounds.	1 = Yes, 0 = No	Independent Variable
Celebrity Focused	Indicates whether the video focuses on celebrities.	1 = Yes, 0 = No	Independent Variable
No Person	No person featured in the video.	1 = Yes, 0 = No	Independent Variable

Table 5: Variables Study 1

3.4.3 Hand Coding of Diversity Cues in Published Content

In order to examine if video views are affected by diversity cues all variables need to be hand coded (Annex 1), due to the lack of access to a software that can analyze video content for the desired diversity dimensions reliably, besides the amount of views that were able to be scraped.

Video	**Number of Views**	**Caption**	**model: female**	**model: male**	**white**	**asian**	**black**	**other**	**celebrity focused**	**no person**
Link	Viewcount	Caption	1 → yes	1 → yes	1 → yes	1 → yes	1 → yes	1 → yes	1 → yes	1 → yes
			0 → nothing	0 → nothing	0 → nothing	0 → nothing	0 → nothing	0 → nothing	0 → nothing	0 → nothing

Table 6: Breakdown of Variable Hand Coding

3.5 Study 2: Analysis of Consumer Sentiment

3.5.1 Data Collection

This study focuses on analyzing comments on TikTok posts, particularly those related to race and gender, due to the platform's extensive reach and diverse user base. In the scope of this study RQ 2 ("How does the diversity of models in social media advertisements affect consumer sentiment in comments?") and RQ 3 (How does consumer sentiment in comments on social media advertisements vary between luxury and non-luxury brands?) aim to bew answered. TikTok's large and active audience makes it a valuable source for sentiment analysis, providing insights into public perceptions of sensitive topics (Malik & Sibaroni, 2022). Its broad appeal ensures that comments reflect diverse perspectives, offering a comprehensive view of societal attitudes toward race and gender (Thelwall et al., 2010).

TikTok's interactive features such as likes, comments, and shares encourage discussions on complex issues, enabling researchers to uncover underlying biases and stereotypes (Lin, 2023). These user behaviors and sentiment expressions offer a window into the cognitive structures surrounding race and gender in online spaces (Young, 2024). Moreover, TikTok's role in shaping public discourse makes it an important platform for studying sentiment related to these issues, as it amplifies voices and sparks conversations (Nguyen et al., 2019; Pair et al., 2021).

Posts with broader reach beyond followers attract a wider array of opinions, generating diverse content for sentiment analysis (Basch et al., 2020; Southwick et al., 2021). High-viewed posts, in particular, have a greater impact on the platform and reflect trending societal sentiments, offering researchers a valuable resource to track public opinion during significant events or trends (González-Esteban, 2024; Jung, 2023). Additionally, these posts draw a variety of comments, allowing for a more nuanced understanding of audience sentiment across different

demographics (Marynak et al., 2022; Vassey et al., 2022). This approach helps identify hidden patterns and emerging trends within the TikTok community.

The timeframe for video selection for more in depth analysis was set between January 1, 2024, and June 1, 2024. Criteria for video selection include, that each selected video must show at least one human adult face. The focus of the study is on the representation and diversity of models in advertisements, and videos without human faces (e.g., purely product-focused content) do not meet this criterion. Additionally, videos featuring fashion shows were excluded, as these often feature multiple models in quick succession, making it difficult to analyze the impact of individual model diversity on consumer sentiment.

The ten videos with the highest view counts as of June 4, 2024, were selected for each brand. By focusing on the most viewed content ensures the development of a more comprehensive understanding of public opinion while minimizing the bias that may arise from analyzing content seen only by a brand's followers (Das et al., 2019). Following the same approach as a study that analyzed YouTube videos related to autonomous vehicles, that examined comments on the 15 most-viewed videos, which collectively garnered millions of views and thousands of comments, highlighting the extensive reach of such content (Das et al., 2019). Similarly, this research follows that approach by selecting the top 10 most-viewed videos, ensuring a robust dataset for analysis and enhancing the strength and cohesion of the findings. Moreover, selecting the most viewed videos allows tapping into the pulse of popular topics and trends (Laforet et al., 2022).

code	Tik Tok Link	views in M	date	comments	scrapable	model: m	model: f	diversity: y	diversity: n	hand coded
lv1	https://www.tiktok.com/@louisvuitton/video/7370313289739341089	6	18.05.24	153	113	1		1		25
lv2	https://www.tiktok.com/@louisvuitton/video/7363613366981578017	8,1	30.04.24	302	239		1	1		239
lv3	https://www.tiktok.com/@louisvuitton/video/7363553123476000033	5,9	30.04.24	243	189		1	1		25
lv4	https://www.tiktok.com/@louisvuitton/video/7363258299770277153	7,5	30.04.24	223	174		1	1		25
lv5	https://www.tiktok.com/@louisvuitton/video/7363205887076437280	5,8	30.04.24	164	150		1		1	25
lv6	https://www.tiktok.com/@louisvuitton/video/7349190861613272353	5,5	22.03.24	307	250	1			1	25

lv7	https://www.tiktok.com/@louisvuitton/video/7348778885254892832	7,3	21.03.24	439	358	1		1	1	25
lv8	https://www.tiktok.com/@louisvuitton/video/7344736494654934304	4,9	10.03.24	136	126		1		1	25
lv9	https://www.tiktok.com/@louisvuitton/video/7320238180094070048	5,2	04.01.24	1288	535	1			1	25
lv10	https://www.tiktok.com/@louisvuitton/video/7319548562415602977	5,4	02.01.24	289	201		1	1	1	25
za1	https://www.tiktok.com/@zara/video/7323189479966035232	4	12.01.24	372	297		1		1	25
za2	https://www.tiktok.com/@zara/video/7336192222238412064	4,1	18.02.24	717	495		1		1	25
za3	https://www.tiktok.com/@zara/video/7349849474753236257	3,9	24.03.24	275	217		1	1		25
za4	https://www.tiktok.com/@zara/video/7351001250294418720	3,8	31.03.24	529	419	1			1	25
za5	https://www.tiktok.com/@zara/video/7354363686300945697	3,8	07.04.24	459	399	1		1		25
za6	https://www.tiktok.com/@zara/video/7360712258713898272	3,7	22.04.24	275	182		1	1		25
za7	https://www.tiktok.com/@zara/video/7362123806279830816	3,8	28.04.24	146	126		1	1		25
za8	https://www.tiktok.com/@zara/video/7364752289585761568	4,4	05.05.24	397	311		1	1		311
za9	https://www.tiktok.com/@zara/video/7366955799651880224	4,2	09.05.24	222	138			1	1	25
za10	https://www.tiktok.com/@zara/video/7375452249331485984	3,8	01.06.24	143	130	1	1	1	1	25
un1	https://www.tiktok.com/@uniqloeurope/video/7325115043949874433	1,5	17.01.24	108	72		1		1	25
un2	https://www.tiktok.com/@uniqloeurope/video/7328323830412348680	1,1	26.01.24	215	139		1		1	25
un3	https://tiktok.com/@uniqloeurope/video/7329919545513348354	0,9	30.01.24	49	37	1			1	25
un4	https://www.tiktok.com/@uniqloeurope/video/7350977300332154130	0,68	27.03.24	190	114		1	1		25
un5	https://www.tiktok.com/@uniqloeurope/video/7350620282928844040	0,86	26.03.24	32	22		1	1		22
un6	https://www.tiktok.com/@uniqloeurope/video/7356888255926783239	1,1	12.04.24	109	91	1		1		25
un7	https://www.tiktok.com/@uniqloeurope/video/7319822348251581704	0,5	03.01.24	158	73			1	1	25
un8	https://www.tiktok.com/@uniqloeurope/video/7322189595368590610	0,2	09.01.24	42	24	1			1	24
un9	https://www.tiktok.com/@uniqloeurope/video/7332457682399513864	0,2	06.02.24	24	23		1	1		23
un10	https://www.tiktok.com/@uniqloeurope/video/7350620282928844040	0,38	26.03.24	32	23		1	1		23

gu1	https://www.tiktok.com/@gucci/video/7320184639925079329	58,9	04.01.24	963	488	1	1		1	25
gu2	https://www.tiktok.com/@gucci/video/7338919619878571297	53,2	23.02.24	1342	767		1	1		25
gu3	https://www.tiktok.com/@gucci/video/7339508990713400609	50,5	25.02.24	271	231		1	1	1	25
gu4	https://www.tiktok.com/@gucci/video/7343546300375354657	125,5	07.03.24	382	228		1		1	25
gu5	https://www.tiktok.com/@gucci/video/7343670637715574048	117	07.03.24	533	447		1	1		25
gu6	https://www.tiktok.com/@gucci/video/7347736433869884704	67,9	18.03.24	370	325	1			1	25
gu7	https://www.tiktok.com/@gucci/video/7361345673104608545	79,7	24.04.24	122	118	1	1	1	1	25
gu8	https://www.tiktok.com/@gucci/video/7363905707512466721	51,3	01.05.24	2140	620	1			1	25
gu9	https://www.tiktok.com/@gucci/video/7363156403256560928	43,8	29.04.24	4785	946	1			1	25
gu10	https://www.tiktok.com/@gucci/video/7370959939952577824	39,1	20.05.24	1086	742		1		1	25
pr1	https://www.tiktok.com/@prada/video/7348074123370827040	26,2	19.03.24	148	126		1		1	25
pr2	https://www.tiktok.com/@prada/video/7342122946229587232	43,3	03.03.24	225	187	1			1	25
pr3	https://www.tiktok.com/@prada/video/7332817885720513825	52,8	07.02.24	340	233	1	1	1	1	25
pr4	https://www.tiktok.com/@prada/video/7332536229071703329	29,2	06.02.24	152	113	1	1		1	25
pr5	https://www.tiktok.com/@prada/video/7332076457688173856	25,5	05.02.24	288	204	1			1	25
pr6	https://www.tiktok.com/@prada/video/7329523001576181024	79,6	29.01.24	157	133		1	1	1	25
pr7	https://www.tiktok.com/@prada/video/7328821948539079969	34,1	27.01.24	430	342	1			1	25
pr8	https://www.tiktok.com/@prada/video/7328761135463697696	31	27.01.24	162	141	1		1		25
pr9	https://www.tiktok.com/@prada/video/7355504935867288865	51,3	08.04.24	147	133		1		1	25
pr10	https://www.tiktok.com/@prada/video/7353622215566396705	51,8	03.04.24	642	461		1		1	25
bu1	https://www.tiktok.com/@burberry/video/7372493818538528032	3	24.05.24	107	99		1	1	1	25
bu2	https://www.tiktok.com/@burberry/video/7372493106807147809	4,3	24.05.24	422	407	1		1		25
bu3	https://www.tiktok.com/@burberry/video/7372492731316260128	2,1	24.05.24	81	75		1	1		25
bu4	https://www.tiktok.com/@burberry/video/7366643758122700064	0,731	08.05.24	237	215	1	1	1	1	25

bu5	https://www.tiktok.com/@burberry/video/7366132904612728097	0,712	07.05.24	100	81		1	1		25
bu6	https://www.tiktok.com/@burberry/video/7366116137593097505	3,7	07.05.24	865	557	1		1		25
bu7	https://www.tiktok.com/@burberry/video/7366115758977338657	1,8	07.05.24	97	80		1		1	25
bu8	https://www.tiktok.com/@burberry/video/7366115449425251616	8,9	07.05.24	1237	455	1			1	25
bu9	https://www.tiktok.com/@burberry/video/7343949738183642400	3,1	08.03.24	240	197	1			1	25

Table 7: 59 Videos Suitable for In-Depth Analysis as of 04.06.2024

The total number of comments collected was 14818, Louis Vuitton garnered 2335 comments, Zara received 2714 comments, Gucci accumulated 4912 comments, Uniqlo had 618 comments, Prada collected 2073 comments, and Burberry obtained 2166 comments.

Louis Vuitton is the most influential luxury brand, while Zara is the most powerful non-luxury brand, making them ideal for deeper analysis if required. Louis Vuitton, owned by LVMH, maintains a leading position in the luxury market by blending tradition with innovation and avoiding commoditization (Shao, 2022; Matić & Bajs, 2022; Kumagai & Nagasawa, 2015). Its global success is bolstered by collaborations and strong social media presence (Guo & Zhang, 2019; Ochkovskaya et al., 2021). Zara's success stems from its fast-fashion model, global expansion, and innovative operational strategies, establishing a strong brand identity and influencing the retail industry (Barnes & Lea-Greenwood, 2006; Liu, 2024; López & Fan, 2009).Therefore these two brands have been chosen for a more in depth analysis of comment sentiment.

All comments sentiment metrics were analyzed utilizing The Lexical Suite. Furthermore the first 25 comments of each of the 59 videos have been hand coded (unless fewer comments were able to be scraped). Therefore 1467 comments were fully hand coded. Comments that receive a higher number of likes, replies, or shares may be given more prominence to encourage further interaction and conversation within the TikTok community. Additionally, TikTok's algorithm aims to create a dynamic and interactive user experience by showcasing comments that spark discussions, elicit emotional responses, or contribute to the overall engagement of the video (Cheng & Li, 2023). By highlighting comments that resonate with users and drive meaningful interactions, TikTok can enhance the user experience and foster a sense of community on the platform. Therefore 1967 comments have been selected for hand coding. These additional comments have been collected in order to be able to explore if less popular comments differ in their sentiment from those further up in the comment section.

A total of 1,467 comments from the first 25 comments of each of the 59 videos were hand-coded (or fewer if the comments available for scraping were limited). Additionally, the most-viewed videos from both Louis Vuitton and Zara were fully hand-coded to ensure that comment sentiment did not change significantly based on the position within the comment section. TikTok's algorithm tends to highlight comments that generate more likes, replies, or shares, as these are designed to drive further interaction and foster discussions (Cheng & Li, 2023). This algorithmic feature may cause certain types of comments to appear more prominently, influencing user interactions and video engagement. To account for this, an additional 500 comments were selected, bringing the total to 1,967. This ensures that coding only a portion of comments from a wide range of videos does not significantly affect the results. By expanding the dataset, the analysis gains reliability and can more accurately reflect overall sentiment trends, regardless of how prominently specific comments are displayed in the comment section.

3.5.2 Variables

The effect of diversity cues on consumer sentiment will be assessed through a combination of hand-coding and software analysis to ensure accuracy and depth. Hand-coding will involve manually reviewing and categorizing comments, while sentiment analysis software will provide higher accuracy as well as an additional layer of sentiment categorization and identify patterns that might not be immediately evident through manual coding. The independent variables represent the factors hypothesized to potentially influence the dependent variables. These factors include demographic attributes and content characteristics, which were all hand coded: Target Group, Model: Female, Model: Male, White, Asian, Black, Other, Celebrity Focused, Brand, Luxury. A video may feature multiple models, and each characteristic is coded as 1 = Yes/Present if it appears.

The dependent variables represent the outcomes that will be analyzed. These variables cover a broad spectrum of emotional and sentiment-related categories, as well as other evaluative measures. They are: Language, Emotionality, Sentiment, Exclusivity, LGBTQ+, Gender Specific, Racial Representation, Racism, Race Activism, Fandom/Celebrity, Politics, Lexical Analysis.

The Lexical Suite was used to automatically code the comments, which were then analyzed for various textual features, such as word count, valence, extremity, emotionality, evaluative expressions, and certainty (Rocklage et al., 2018). These metrics provide valuable insights into how consumers react to content, especially when evaluating sentiment. The analysis focused specifically on valence, extremity, and emotionality to capture a more nuanced understanding

of consumer sentiment. Valence measures the overall positivity or negativity of the comments, extremity assesses the intensity of these emotions, and emotionality evaluates the depth of emotional expression in the text. These variables were treated as dependent variables, as they are influenced by the content characteristics.

Each variable was processed as follows: Valence was treated as a continuous variable representing the polarity of the sentiment, indicating whether the sentiment was positive or negative. Extremity was coded to reflect the intensity of the sentiment, with higher extremity values signifying more intense emotions. Emotionality was coded to measure the emotional tone of the comment, focusing on whether the comment contained significant emotional content or was more neutral in nature.

These dependent variables were examined in the context of independent variables such as language, gender representation, and racial diversity, to explore how different content factors influence consumer responses. The Lexical Suite provides a nuanced understanding of consumer sentiment. This approach enables a detailed analysis of how diverse representations in advertisements are perceived, allowing researchers to capture both the direction and intensity of sentiments. These variables are particularly useful in this research as they allow for the differentiation between subtle variations in sentiment and the intensity of emotional reactions. This comprehensive evaluation is essential for drawing meaningful conclusions about the impact of diversity in social media advertising, as it reveals not only the overall consumer sentiment but also the strength and emotional engagement behind these sentiments.

Variable	Description	Coding	Type of Variable
Target Group	Indicator of whether the target group is a particular demographic.	1 = Yes, 0 = No	Independent Variable
Model: Female	Presence of female models in the content.	1 = Yes, 0 = No	Independent Variable
Model: Male	Presence of male models in the content.	1 = Yes, 0 = No	Independent Variable
White	Representation of white individuals in the content.	1 = Yes, 0 = No	Independent Variable
Asian	Representation of Asian individuals in the content.	1 = Yes, 0 = No	Independent Variable
Black	Representation of Black individuals in the content.	1 = Yes, 0 = No	Independent Variable
Other	Representation of individuals from other racial or ethnic backgrounds.	1 = Yes, 0 = No	Independent Variable
Celebrity Focused	Content that is focused on celebrities.	1 = Yes, 0 = No	Independent Variable
Brand	The brand associated with the content.	Categorical	Independent Variable
Luxury	Indicator of whether the content is related to luxury brands or products.	1 = Yes, 0 = No	Independent Variable
Language	The primary language of the content and comments.	Categorical	Dependent Variable
Emotionality (Hand Coded)	A measure of how emotional a given comment is expressed.	Likert type rating scale (0 = not emotional, 5 = highly emotional)	Dependent Variable
Sentiment	The overall sentiment expressed, ranging from positive to negative.	Likert type rating scale (0 = very negative, 5 = very positive)	Dependent Variable
Exclusivity	The degree to which the content is perceived as exclusive or inclusive.	Likert type rating scale (0 = very inclusive, 5 = very exclusive)	Dependent Variable
LGBTQ+	Whether the content relates to LGBTQ+ themes or issues.	Likert type rating scale (0 = not related, 5 = highly related)	Dependent Variable
Gender Specific	Whether the content is specific to a particular gender.	Likert type rating scale (0 = not specific, 5 = highly specific)	Dependent Variable
Racial Representation	The representation of different racial groups within the content.	Likert type rating scale (0 = not represented, 5 = well represented)	Dependent Variable
Racism	Instances or discussions of racism.	Likert type rating scale (0 = not present, 5 = highly present)	Dependent Variable
Race Activism	Content related to activism around racial issues.	Likert type rating scale (0 = not present, 5 = highly present)	Dependent Variable
Fandom/Celebrity	The presence and influence of celebrity culture and fandom.	Likert type rating scale (0 = not present, 5 = highly present)	Dependent Variable
Politics	Content related to political topics or discussions.	Likert type rating scale (0 = not present, 5 = highly present)	Dependent Variable
Lexical Analysis	If the Lexical Suite was able to gather information on a comment.	1 = Yes, 0 = No	Dependent Variable
Valence	Represents the polarity of the sentiment (positive or negative).	Continuous	Dependent Variable
Extremity	Coded as the intensity of the sentiment, with higher extremity indicating more intense emotions.	Continuous	Dependent Variable
Emotionality (Lexical Suite)	Emotional tone, focusing on whether the comment contains significant emotional content or is neutral.	Continuous	Dependent Variable

Table 8: Variables Study 2

3.5.3 Sentiment Analysis of Comments

Sentiment analysis is a technique used to analyze and extract subjective information, opinions, and emotions from text data, such as online comments, reviews, and social media posts. In the scope of this thesis it will be utilized in order to be able to understand user sentiment of social media comments under videos published by brands. By applying natural language processing and machine learning algorithms, sentiment analysis can categorize text data into positive, negative, or neutral sentiments, providing insights into how users feel about a brand or product based on their expressed opinions and emotions (Pang & Lee, 2008; Bilro et al., 2021). When

examining online comments, sentiment analysis offers a valuable way to understand how users perceive and interact with a brand. By analyzing the sentiment expressed in comments, marketers can gain insights into consumer attitudes, opinions, and emotions towards the brand, products, or services. This information can help brands assess customer satisfaction, identify areas for improvement, and tailor their marketing strategies to better meet consumer needs and preferences (Song et al., 2022; Xu et al., 2019). By monitoring sentiment trends in online comments, brands can gauge the effectiveness of their diversity initiatives, identify areas of improvement, and measure the impact of their social responsibility campaigns on consumer perceptions and attitudes (Kauffmann et al., 2019; Sv et al., 2022).

Within the scope of this thesis the Lexical Suite will be utilized in ordert o be able to analyze more commets than what can be handcoded. The Lexical Suite enables sentiment analysis beyond positivity to measure not only positivity, but also the extremity, emotionality, and confidence (certainty/ valence) of people's opinions. The lexical suite serves as a valuable tool for linguistic research, language analysis, and semantic exploration, providing a rich source of lexical information, semantic connections, and linguistic insights for studying language structure, meaning, and usage in diverse contexts (The Lexical Suite, n. D). In the scope of this reseach this tool will be used in order to understand consumer sentiment better.

In 2018 three of the five creators of the Lexical Suite, Matt Rocklage, Derek Rucker and Loran Nordgren published a paper explaining the tool they created. The application aids in understand the emotional content, intensity, and positivity/negativity of individuals' expressions. The Evaluative Lexicon is a tool specifically designed to measure emotionality, extremity, and valence in language, resulting in valuable insights regarding individuals' evaluative reactions and attitudes.

Emotionality refers to the degree of emotional content or sentiment expressed in language. Words or phrases with high emotionality convey strong feelings, such as joy, anger, sadness, or excitement. Emotionality can be summed up as the emotional impact of language on readers or listeners. Emotionality in language is measured by analyzing the presence of emotional words or expressions in text. Words with high emotional content, such as "happy," "sad," "excited," or "angry," are indicators of emotionality.

Extremity measures the intensity or extremeness of an individual's evaluation or opinion. It indicates how strong or intense a sentiment is, whether positive or negative. Extreme language can convey strong preferences, beliefs, or reactions. Extremity is measured by assessing the intensity or extremeness of language used in expressing opinions or evaluations. Words or phrases that convey strong sentiments or extreme positions are considered high in extremity.

Valence refers to the positivity or negativity of language. Words or phrases with positive valence express favorable sentiments, while those with negative valence convey unfavorable or critical opinions. Thereby the overall tone or attitude expressed in text can be understood. Valence, representing the positivity or negativity of language, is measured by assessing the overall tone or sentiment conveyed in text. Positive words like "love," "joy," or "excellent" have high valence, while negative words like "hate," "sad," or "poor" have low valence. Valence ratings help quantify the emotional polarity of language and provide insights into the overall sentiment expressed in text data.

3.5.4 Hand Coding of Comments

The Lexical Suite offers comprehensive and detailed sentiment analysis data that would have not possible to hand code in the scope of this work – nevertheless it is limited to specific variables. Some additionally desired variables nevertheless needed to be hand coded in order to ensure the comprehensiveness of the data. Therefore, the target group, the gender of the model, the ethnicity of the model, if a celebrity is at the center of the content, the name of the brand and if it is a part of the luxury segment are hand coded in the dataset of the published comments. Coding the independent variables by hand was essential as there was no tool available to do so.

Furthermore, the dependent variables emotionality, sentiment and most importantly perceived exclusivity were hand coded in order to add to the richness of the sentiment data that was gathered utilizing The Lexical Suite. Human coders can better understand the nuances of language, cultural references, and sarcasm, which are challenging for automated tools to interpret accurately (Teh et al., 2018). Human coders can adapt to different contexts and understand the subtleties of sentiment expression, making them versatile and reliable in sentiment analysis tasks (Oksanen et al., 2015), and in this case able to focus on a variable that available sentiment analysis tools are not trained to analyze.

While sentiment analysis tools have their advantages in processing large volumes of data quickly, the use of human coders helps to ensure accurate, contextually appropriate, and nuanced sentiment analysis results, especially in complex and sensitive domains. Social media platforms are rich sources of diverse and unstructured data, making sentiment analysis challenging (Peng & Park, 2021). Human coders can better understand the context, tone, and subtleties of comments, especially in areas like sarcasm detection, where automated tools may struggle. Additionally, human coders can capture emotions and sentiments that automated tools

might overlook, providing a more comprehensive analysis of user opinions and attitudes (Hruska, 2020, Srnka & Koeszegi, 2007).

4 Data Analysis and Results

4.1 Study 1: Impact of Diversity on Video Performance

4.1.1 Research Question 1: Effect of Diversity on Video Performance

4.1.1.1 Descriptive Statistics

The descriptive statistics provide an overview of the dataset, including the distribution of independent variables such as model gender, ethnicity, and content characteristics. This analysis helps identify trends in representation and the prevalence of specific attributes in videos that may influence performance metrics like view count.

The frequencies for model representation, content characteristics, and other variables are summarized in the table below. These distributions highlight the proportion of videos containing specific attributes and serve as a foundation for understanding the diversity presented in the dataset.

Variable	Frequency (1)	Percentage (1)	Frequency (0)	Percentage (0)	Total
Representation of White individuals	270	45.0%	330	55.0%	600
Representation of Black individuals	141	23.5%	459	76.5%	600
Representation of Asian individuals	144	24.0%	456	76.0%	600
Representation of individuals from Other Ethnic backgrounds	58	9.7%	542	90.3%	600
Representation of at least one Non-White model	228	38.0%	372	62.0%	600
Presence of Female models	275	45.8%	325	54.2%	600
Presence of Male models	186	31.0%	414	69.0%	600
No person featured	200	33.3%	400	66.7%	600
Video focuses on celebrities	166	27.7%	434	72.3%	600

Table 9: Presence of Model Attributes

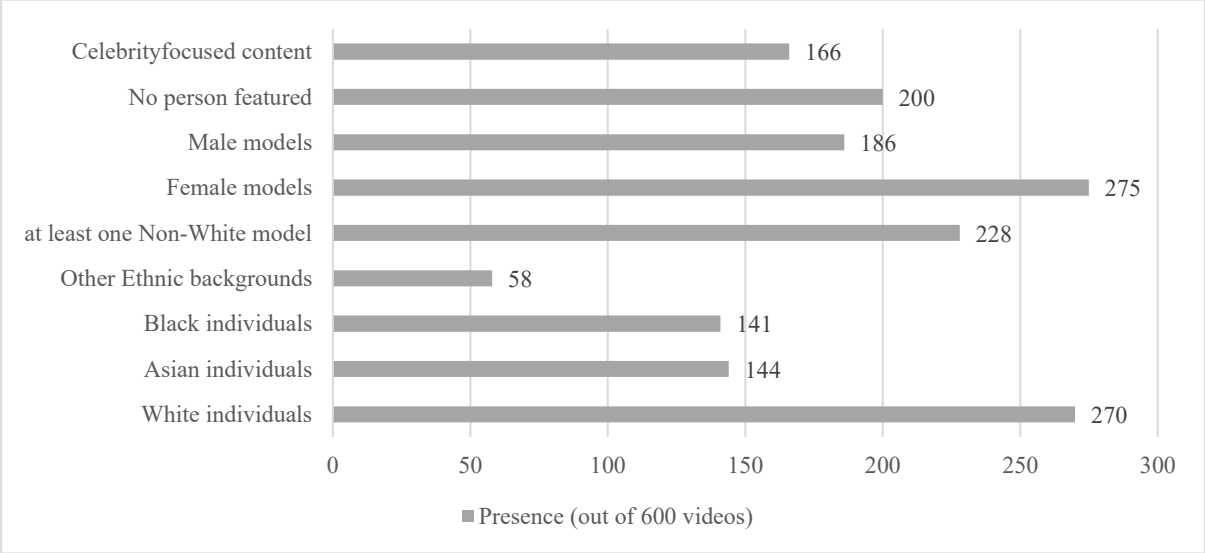


Figure 6: Presence of Model Attributes

White individuals are the most represented (45.0%), while Black (23.5%), Asian (24.0%) and other ethnicities (9.7%) are underrepresented. Videos featuring at least one non-White model make up 38.0% of the dataset.
Female models are featured in 45.8% of the videos, slightly less than male models, who appear in only 31.0%. Videos without people account for 33.3% of the sample, and only 27.7% of videos focus on celebrities. These figures suggest that a majority of videos emphasize other forms of content, such as branding or products, over celebrity influence.

4.1.1.2 Linear Regression

The following analysis investigates how diversity dimensions in TikTok videos influence video performance, specifically the logarithmized number of views (used to address the non-normal distribution of the dependent variable). This study evaluates the effects of gender, racial diversity, celebrity presence, the absence of individuals in videos, and the brand type (luxury or non-luxury). Each variable's contribution to video performance is assessed using simple linear regression, with results summarized below. As the number of views in the dataset is not normally distributed the number of views have been logarithmized.

The regression analysis examining the presence of female models in videos yielded a weak positive relationship, which was not statistically significant at the .05 level ($R = .078$, $R^2 = 0.006$, $p = 0.055$). The model explained only 0.6% of the variance in video performance (log-transformed views). The coefficient for the presence of female models ($\beta = -0.078$) indicated a slight negative association, but this effect approached significance ($p = 0.055$). This result suggests that the presence of female models might not significantly impact the logarithmized number of views, though further research with larger sample sizes could clarify this.
The regression model for male models also indicated a negligible relationship with video performance ($R = 0.013$, $R^2 = 0.000$, $p = 0.753$). The model accounted for virtually no variance in the logarithmized number of views. The unstandardized coefficient ($\beta = 0.013$, $p = 0.753$) suggests no meaningful effect of male model presence on video views. This result implies that male representation in these videos is not a significant predictor of performance.

The presence of white individuals in videos was not significantly related to video performance ($R = 0.007$, $R^2 = 0.000$, $p = 0.855$). The standardized coefficient ($\beta = 0.007$, $p = 0.855$) suggests a negligible effect. Thus, representation of white models does not appear to meaningfully influence the logarithmized number of views.

Representation of Asian models in videos also showed no significant effect on video performance ($R = .020$, $R^2 = .000$, $p = .621$). The unstandardized coefficient ($\beta = 0.020$, $p = 0.621$) indicates a minimal association. The findings suggest that including Asian models does not significantly predict view counts.

The regression analysis for Black models produced a slightly higher R value ($R = .055$), yet the effect was still not significant ($R^2 = 0.003$, $p = 0.181$). The coefficient ($\beta = 0.055$, $p = 0.181$) suggests a positive but weak and non-significant association. These findings indicate that Black model representation may not substantially affect video performance.

Videos featuring individuals from other ethnic backgrounds showed a non-significant relationship with video performance ($R = 0.068$, $R^2 = 0.005$, $p = 0.097$). The standardized coefficient ($\beta = 0.068$, $p = 0.097$) suggests a weak positive trend that is not statistically significant. Future research could explore whether this trend becomes significant in larger or more diverse datasets.

When considering videos featuring at least one non-white model, results indicated no significant relationship with video performance ($R = 0.008$, $R^2 = 0.000$, $p = 0.843$). The unstandardized coefficient ($\beta = -0.008$, $p = 0.843$) highlights an almost negligible negative association, reinforcing that racial diversity alone does not predict video performance.

The presence of celebrities in videos was also not significantly related to video performance ($R = 0.024$, $R^2 = 0.001$, $p = 0.564$). The standardized coefficient ($\beta = 0.024$, $p = 0.564$) suggests a very small positive effect that is not statistically meaningful. This finding suggests that celebrity-focused content may not automatically translate to higher view count.

For videos without any individuals, the regression model showed a weak and non-significant relationship with performance ($R = 0.027$, $R^2 = 0.001$, $p = 0.506$). The coefficient ($\beta = 0.027$, $p = 0.506$) indicates that the absence of human representation in videos does not meaningfully impact the number of views.

Luxury brand affiliation was the only variable demonstrating a statistically significant relationship with video performance. The model ($R = 0.187$, $R^2 = 0.035$, $p < 0.001$) explained 3.5% of the variance in logarithmized views. The unstandardized coefficient ($\beta = 0.187$, $p < 0.001$) indicates a positive association, with luxury brand videos performing better than non-luxury videos. This result suggests that brand prestige may play a role in driving higher engagement or visibility.

Variable	Adjusted R2	B	p	Significance
Female Models	0.004	-0.180	0.055	Weak negative effect, marginally insignificant
Male Models	-0.002	0.032	0.753	No significant effect
White Representation	-0.002	0.017	0.855	No significant effect
Asian Representation	-0.001	0.054	0.621	No significant effect
Black Representation	0.001	0.148	0.181	No significant effect
Other Ethnicities	0.003	0.263	0.097	Weak positive effect, marginally insignificant
At Least One Non-White Model	-0.002	-0.019	0.843	No significant effect
Celebrity-Focused Videos	-0.001	0.060	0.564	No significant effect
No Person Featured	-0.001	0.066	0.506	No significant effect
Luxury Brands	0.033	0.454	<0.001	Significant positive effect

Table 10: Summary Linear Regression RQ1

These results of the linear regression analyses indicate that, within the context of TikTok videos, diversity dimensions such as gender and racial representation do not significantly predict video performance when measured by logarithmized views. However, luxury branding demonstrates a significant positive effect, suggesting that brand positioning may play a more critical role than diversity in driving viewership. These findings highlight the need for further research into contextual and content-specific factors that influence social media engagement, further insights on how consumer sentiment is affected by the presence of diversity in models and wheatear sentiment in comments on social media advertisements varies between luxury and non-luxury brands will be explored in Study 2.

Furthermore a multiple linear regression was conducted which included several predictors, such as brand type (luxury or non-luxury), gender and racial diversity, celebrity focus, and the presence of individuals in the videos, to assess their influence on the number of views. The analysis revealed that the luxury brand variable was a significant positive predictor of video performance ($B=0.449$, $p<0.001$), indicating that luxury brand videos consistently attracted more views than non-luxury brand videos. This finding confirms the earlier observation that brand positioning strongly influences video performance.

In contrast, the presence of female models had a significant negative association with the number of views ($B=-0.416$, $p=0.020$). Videos featuring female models tended to receive fewer views than those without, a result that challenges expectations and suggests that the portrayal of gender in these advertisements warrants further investigation.

The presence of male models was not a significant predictor ($B=-0.190$, $p=0.255$), indicating that male representation in videos does not strongly influence viewership.

Regarding racial diversity, none of the individual racial categories (White, Asian, Black, or Other ethnic backgrounds) emerged as significant predictors, although Black representation

approached significance (B=0.396, p=0.058), suggesting a potential positive trend that could be explored further in future studies. The composite variable representing videos featuring at least one non-white model was also non-significant (B=−0.340, p=0.253).

The inclusion of celebrity-focused content did not significantly predict video performance (B=0.003B=0.003, p=0.983 p=0.983), contrary to earlier assumptions about its potential impact. Similarly, videos without any individuals featured did not significantly affect viewership (B=−0.110, p=0.554).

The findings partially address RQ1, showing that luxury branding is a critical driver of video performance, while gender representation—particularly the negative effect of female models—plays a role in influencing viewership. Suggesting, that gender representation influences consumer engagement, though the reasons behind this remain unclear.

However, the results indicate that racial diversity alone does not have a strong, standalone effect on video performance, despite a marginal trend for Black representation. Additionally, the lack of significance for celebrity focus suggests that this variable's influence may be context-dependent or confounded by other factors in the model. While luxury branding and gender representation are key factors influencing TikTok video performance, the impact of racial diversity and other content characteristics is less pronounced.

4.2 Study 2: Impact of Diversity on Consumer Sentiment

4.2.1 Research Question 2: Effect of Diversity on Consumer Sentiment

4.2.1.1 Linear Regression: Sentiment Analysis

Research Question 2 investigates how the diversity of models in social media advertisements affects consumer sentiment in comments. The average sentiment scores for variables valence (positivity or negativity of sentiment) extremity (emotional intensity) and emotionality (degree of emotional content) gathered with the Lexical Suite were chosen for this Analysis as this work is in interested on exploring the sentiment of comments overall and not that of the most positive or negative word within them. This provided several significant findings that offer insights into the nuanced effects of diversity on consumer perceptions.

Predictor	Dependent Variable	R	R^2	Adjusted R^2	RMSE	F	p-value	Coefficient	t	Direction	Significant
Diversity (all)	Valence	0.105	0.011	0.011	1.632	66.430	<.001	0.367	8.150	Positive	Yes
White	Valence	0.103	0.011	0.010	1.632	63.221	<.001	-0.342	-7.951	Negative	Yes
Asian	Valence	0.138	0.019	0.019	1.625	115.158	<.001	0.454	10.731	Positive	Yes
Black	Valence	0.052	0.003	0.003	1.639	16.321	<.001	-0.203	-4.040	Negative	Yes
Other	Valence	0.008	0.000	-0.000	1.641	0.408	0.523	0.049	0.639	Neutral	No
Diversity (all)	Extremity	0.019	0.000	0.000	0.510	2.089	0.148	-0.020	-1.445	Neutral	No
White	Extremity	0.016	0.000	0.000	0.510	1.438	0.231	0.016	1.199	Neutral	No
Asian	Extremity	0.046	0.002	0.002	0.510	12.637	<.001	-0.047	-3.555	Negative	Yes
Black	Extremity	0.028	0.001	0.001	0.510	4.519	0.034	0.033	2.126	Positive	Yes
Other	Extremity	0.010	0.000	-0.000	0.510	0.579	0.447	-0.009	-0.761	Neutral	No
Diversity (all)	Emotionality	0.085	0.007	0.007	1.305	42.831	<0.001	-0.235	-6.545	Negative	Yes
White	Emotionality	0.103	0.011	0.010	1.302	63.278	<0.001	0.273	7.955	Positive	Yes
Asian	Emotionality	0.152	0.023	0.023	1.294	140.217	<0.001	-0.398	-11.841	Negative	Yes
Black	Emotionality	0.099	0.010	0.010	1.303	58.256	<0.001	0.304	7.633	Positive	Yes
Other	Emotionality	0.048	0.002	0.002	1.308	13.509	<0.001	0.224	3.675	Positive	Yes

Table 11: Summary Linear Regression Lexical Suite Average Sentiment Score RQ2

The analysis revealed that overall diversity in advertisements had a small but statistically significant positive relationship with valence ($R^2 = 0.011$, $F = 66.430$, $p < .001$, $\beta = 0.367$). This indicates that including diverse models in social media advertisements is associated with slightly more positive consumer sentiment in comments. When examining individual racial categories, significant patterns emerged. The inclusion of white models was significantly and negatively associated with valence ($\beta = -0.342$, $t = -7.951$, $p < .001$). Advertisements prominently featuring white models tended to elicit less positive sentiment. This suggests that

audiences may expect more diversity or may react negatively to perceived lack of inclusivity. Representation of Asian models had the strongest positive effect on valence ($\beta = 0.454$, $t = 10.731$, $p < .001$). This finding highlights that Asian representation resonates positively with audiences, potentially reflecting appreciation for underrepresented groups or cultural relevance in certain market contexts.

Black representation was negatively associated with valence ($\beta = -0.203$, $t = -4.040$, $p < .001$), though the effect was smaller than for white models. This could reflect underlying biases in consumer responses or unmet expectations for authentic and meaningful representation of Black individuals in advertisements.

The presence of models from other ethnic backgrounds showed no significant effect on valence ($p = 0.523$). This neutrality may indicate that such representations are not yet salient enough to impact consumer sentiment meaningfully.

Unlike valence and extremity, emotionality focuses on whether comments are more emotionally expressive, regardless of their positivity or negativity. However, the updated analysis indicates that overall diversity had a weak but statistically significant negative effect on emotionality. Asian representation, previously reported as strongly positive, actually exhibited a negative effect ($\beta = -0.398$, $t = -11.841$, $p < .001$), suggesting that while comments were more positive overall, they were less emotionally intense. In contrast, Black representation showed a positive association with emotionality ($\beta = 0.304$, $t = 7.633$, $p < .001$), contradicting prior reports of neutrality. The presence of White models continued to show a negative impact on emotionality, while the effect of models from other ethnic backgrounds remained non-significant. The analysis found a weak but significant negative association between diversity and emotionality in consumer comments ($R^2 = 0.007$, $F = 42.831$, $p < .001$, $\beta = -0.235$). This indicates that advertisements featuring diverse models elicit slightly more emotionally expressive comments overall.

Representations of Asian models showed a significant negative effect on emotionality ($\beta = -0.398$, $t = -11.841$, $p < .001$). This suggests that Asian representation often evokes comments that are both positive and emotionally rich, highlighting its resonance with audiences.

White Models: The presence of white models was associated with a small negative effect on emotionality ($\beta = -0.116$, $t = -2.987$, $p = 0.003$). This indicates that such representations are less likely to elicit emotionally expressive responses, possibly due to lower perceived novelty or engagement.

Representation of Black models had a positive effect on emotionality ($\beta = 0.304$, $t = 7.633$, $p < .001$), indicating that their presence led to more emotionally expressive comments. This neutrality may indicate varied audience reactions that average out emotionally expressive comments. Lastly Models categorized under "Other Ethnicities" had no significant impact on emotionality ($p = 0.578$), reflecting the limited salience of these representations.

The findings suggest that diversity in advertisements modestly enhances the emotional expressiveness of consumer responses; however, Asian representation had a negative effect on emotionality, indicating that while comments were more positive overall, they were less emotionally intense. This underscores the importance of diversifying content to foster richer engagement. Positive emotional responses associated with Asian representation can be leveraged to strengthen brand affinity. Advertisements that feature underrepresented groups in culturally relevant and authentic contexts are likely to generate more emotionally charged and engaging comments.

By integrating diverse models and tailoring representation strategies, brands can not only enhance sentiment but also encourage more emotionally engaging conversations around their content. The findings furthermore suggest that diversity in social media advertisements influences consumer sentiment (valence) more than the intensity of emotional responses (extremity). The positive association between diversity and valence underscores the value of inclusive advertising strategies. However, the varying effects across racial categories highlight the importance of thoughtful representation tailored to audience expectations and cultural sensitivities.

4.2.1.2 Linear Regression: Hand-Coded Variables

The analysis of hand-coded comments offers insights into how diversity in social media advertisements influences consumer sentiment, emotionality, and perceptions of exclusivity. The findings reveal nuanced effects that vary across different diversity dimensions and racial categories.

Predictor	Dependent Variable	R	R^2	Adjusted R^2	RMSE	F	p-value	Coefficient	t	Direction	Significant
Diversity (all)	Emotionality	0.104	0.011	0.010	0.974	16.028	<.001	0.205	4.004	Positive	Yes
White	Emotionality	0.111	0.012	0.012	0.973	18.119	<.001	-0.220	-4.257	Negative	Yes

Asian	Emotionality	0.078	0.006	0.005	0.976	8.964	0.003	0.163	2.994	Positive	Yes
Black	Emotionality	0.008	0.000	-0.001	0.979	0.089	0.766	0.017	0.298	Neutral	No
Other	Emotionality	0.054	0.003	0.002	0.977	4.304	0.038	-0.147	-2.075	Negative	Yes
Diversity (all)	Sentiment	0.055	0.003	0.002	1.256	4.366	0.037	0.138	2.090	Positive	Yes
White	Sentiment	0.109	0.012	0.011	1.250	17.482	<.001	-0.278	-4.181	Negative	Yes
Asian	Sentiment	0.039	0.002	0.001	1.257	2.200	0.138	0.104	1.483	Neutral	No
Black	Sentiment	0.042	0.002	0.001	1.257	2.612	0.106	-0.115	-1.616	Neutral	No
Other	Sentiment	0.094	0.009	0.008	1.252	12.994	<.001	-0.327	-3.605	Negative	Yes
Diversity (all)	Exclusivity	0.071	0.005	-0.005	1.371	0.505	0.479	-0.447	-0.711	Neutral	No
White	Exclusivity	0.193	0.037	0.028	1.349	3.911	0.051	0.573	1.978	Positive	Marginal
Asian	Exclusivity	0.379	0.144	0.135	1.272	16.942	<.001	-1.069	-4.116	Negative	Yes
Black	Exclusivity	0.042	0.002	-0.008	1.373	0.181	0.671	-0.123	-0.425	Neutral	No
Other	Exclusivity	0.153	0.023	0.014	1.358	2.421	0.123	-0.537	-1.556	Negative	No

Table 12: Summary Linear Regression Hand Coded Variables RQ2

Diversity overall was significantly associated with emotionality ($R2=0.011$, $F=16.028$, $p<0.001$ $R2=0.011$, $F=16.028$, $p<0.001$). The positive coefficient ($\beta=0.205$, $p<0.001$) suggests that advertisements featuring diverse representations foster more emotionally expressive consumer comments. This highlights the role of diversity in engaging audiences on a deeper emotional level. However, the effects differ across racial categories. White representation had a significant negative effect on emotionality ($\beta=-0.220$, $p<0.001$), indicating that comments on advertisements featuring white models were less emotionally rich. Asian representation positively influenced emotionality ($\beta=0.163$, $p=0.003$), suggesting that such representations resonate emotionally with audiences. No significant relationship was observed for Black representation ($p=0.766$), implying a neutral impact on emotionality. Representations categorized as "Other" had a small but significant negative effect on emotionality ($\beta=-0.147$, $p=0.038$).

These findings suggest that while diversity overall enhances emotional engagement, the specific impact depends on the racial category of the models, with Asian representation being the most emotionally engaging.

The analysis revealed a modest positive relationship between diversity and sentiment ($\beta=0.138$, $p=0.037$), indicating that diverse advertisements generally evoke slightly more favorable consumer responses. However, the effects were not uniform across racial categories. White representation negatively impacted sentiment ($\beta=-0.278$, $p<.001$), reflecting less favorable consumer perceptions. However no significant effect was observed for Asian representation ($p=0.138$), indicating a neutral impact on sentiment. Similarly, Black representation did not significantly influence sentiment ($p=0.106$). Representations of "Other" ethnicities had a significant negative effect on sentiment ($\beta=-0.327$, $p<.001$).
These results highlight the mixed effects of diversity on sentiment. While diversity overall improves sentiment, specific representations, particularly white and "Other" categories, may elicit less favorable responses.

No significant relationship was found between diversity overall and perceptions of exclusivity ($p=0.479$), indicating that diversity alone does not strongly influence how exclusive advertisements are perceived. However, distinct patterns emerged across racial categories. Asian representation had a significant negative effect on exclusivity ($\beta=-1.069$, $p<.001$), suggesting that such advertisements are perceived as less exclusive. White representation on the other hand had a marginally positive effect on exclusivity ($\beta=0.573$, $p=0.051$), indicating that advertisements prominently featuring white models might reinforce perceptions of exclusivity. Neither Black Models nor Other Ethnicities showed significant effects on exclusivity ($p>0.05$).
These findings imply that perceptions of exclusivity are complex and influenced by cultural and contextual factors. While Asian representation challenges traditional notions of exclusivity, white representation marginally aligns with them.

The hand-coded analysis provides critical insights into the impact of diversity on consumer responses. The positive association between diversity and emotionality underscores the importance of inclusive advertisements in fostering richer consumer interactions. While diversity generally enhances sentiment, the varying effects across racial categories emphasize the need for thoughtful and context-sensitive representation.

There are discrepancies highlight that while automated tools like the Lexical Suite effectively capture broad trends, they may overlook context-specific nuances. Manual coding can uncover subtle negative effects or neutral responses that automated methods might misinterpret as

positive or neutral but like here suffer often from a smaller sample size. Combining both methods ensures a more comprehensive understanding of how diversity affects consumer sentiment and emotionality.
The Lexical Suite suggested a neutral or slightly positive effect on sentiment and emotionality when white models were present, whereas the hand-coded data identified strong negative effects, highlighting dissatisfaction or disengagement.
A further discrepancie is to be noted; when models of other ethnicities were present The Lexical Suite showed neutral effects, but the hand-coded data revealed clear negative effects on both sentiment and emotionality, suggesting biases or misalignments in perception.
Additionally sentiment scores gathered with The Lexical Suite show positive effects on sentiment when Asian models were present, but the hand-coded data showed no significant impact, indicating variability depending on context or dataset size. Similar discrepancies are present when black models were present; The Lexical Suite indicated a slightly negative trend, while the hand-coded data found no significant relationship, showing neutrality.

Advertisements featuring Asian models may challenge traditional perceptions of exclusivity, while white representation marginally reinforces exclusivity. This is in line with Wu (2022) having found, that Luxury brands often strategically avoid overt displays of diversity cues in their marketing materials to create a perception of exclusivity and aspiration. Luxury brands may perceive the inclusion of diversity cues as a means to differentiate themselves from non-luxury brands and establish a progressive image in the market. As well as that luxury brands face the challenge of balancing the rising demand for their products with the need to preserve their exclusivity and uniqueness (Hennigs et al., 2013).
Overall, these findings highlight the importance of strategically incorporating diversity into advertisements to enhance emotional and sentiment-based consumer engagement while being mindful of audience expectations and cultural nuances. The most notable finding of the hand coded comments is, that in line with previous research white models affect perceived exclusivity positively.

4.2.1.3 Multilinear Regression: Influence of Luxury vs. Non-Luxury Brands

In this analysis, I am investigating how the presence of different races of models in advertisements for luxury brands affects the sentiment expressed in comments, as measured by the variables valence, extremity and emotionality. This analysis aims to determine whether

there is a significant relationship between these factors and if specific combinations, such as white models in luxury brand advertisements, produce unique effects on consumer sentiment.

Using multiple linear regression, I examine three primary components: the main effect of the various races of models (whether their presence generally influences the dependent variables), the main effect of luxury brands (whether content from luxury brands affects the dependent variables overall), and the interaction effect between the presence of models of various races and luxury brand content. Multiple regression with interaction terms was chosen for comparing the effect of different races on the dependent variables and testing whether luxury modifies these effects. Interaction terms reveal if the relationship between race and valence changes depending on whether the ad is luxury or non-luxury.

Predictor	Dependent Variable	Coefficient	tt	pp	Direction	Significant
White	Valence	-0.192	-2.967	0.003	Negative	Yes
Asian	Valence	0.311	4.551	< .001	Positive	Yes
Black	Valence	-0.161	-2.531	0.011	Negative	Yes
Other Ethnicities	Valence	0.091	0.913	0.361	Neutral	No
Luxury	Valence	-0.020	-0.323	0.746	Neutral	No
White	Extremity	0.007	0.351	0.725	Neutral	No
Asian	Extremity	-0.018	-0.842	0.400	Neutral	No
Black	Extremity	0.023	1.133	0.257	Neutral	No
Other Ethnicities	Extremity	-0.027	-0.861	0.389	Neutral	No
Luxury	Extremity	-0.081	-4.252	< .001	Negative	Yes
White	Emotionality	0.084	1.627	0.104	Neutral	No
Asian	Emotionality	-0.300	-5.536	< .001	Negative	Yes
Black	Emotionality	0.158	3.127	0.002	Positive	Yes
Other Ethnicities	Emotionality	0.215	2.721	0.007	Positive	Yes
Luxury	Emotionality	-0.199	-4.114	< .001	Negative	Yes

Table 13: Summary Multi Linear Regression Interaction Lexical Suite Average Sentiment Score and Brand Type RQ2

The results provide insights into how diversity dimensions, such as racial representation, and brand positioning (luxury vs. non-luxury) combine to influence audience sentiment. The analysis revealed that racial representation significantly affects valence (positivity/negativity of sentiment), with specific patterns emerging. Firstly asian models had a positive and significant effect on valence ($\beta=0.311$, $p<0.001$), reinforcing findings from the Lexical Suite analysis that diversity—especially Asian representation—enhances positivity. This aligns with the observation that Asian representation resonates positively with audiences, reflecting cultural relevance or appreciation for underrepresented groups. White models negatively

influenced valence (β=−0.192, p=0.003), which is consistent with both the hand-coded and lexical suite findings. The negativity may reflect audience expectations for greater inclusivity or biases against perceived exclusivity conveyed by predominantly white representations. A negative effect on valence was observed regarding the presence of black models (β=−0.161, p=0.011), aligning with prior findings that black representation, while necessary for inclusivity, might evoke mixed responses due to biases or unmet expectations for meaningful representation. Luxury branding did not significantly affect valence (p=0.746). This contrasts with the notion that luxury brands strategically balance diversity cues to maintain exclusivity and aspiration (Wu, 2022).

These results support the broader pattern that diversity enhances positivity overall, particularly through Asian representation, but white and Black representations face unique challenges in meeting audience expectations.

Luxury advertisements reduced extremity (β=−0.081, p<0.001), suggesting that luxury content evokes less polarized emotional reactions. This finding aligns with the view that luxury brands aim to maintain an aspirational and controlled image, minimizing emotionally charged responses. None of the racial categories significantly influenced extremity (p>0.05), indicating that diversity does not strongly affect the intensity of sentiment. This aligns with previous findings from the Lexical Suite that extremity was not significantly affected overall, with minor nuances observed for specific categories. This suggests that while luxury branding tempers emotional intensity, diversity itself does not amplify or polarize consumer reactions, reflecting a more subdued engagement.

Asian models negatively influenced emotionality (β=−0.300, p<0.001), contrasting with findings from the hand-coded dataset, where Asian representation enhanced emotionality. This discrepancy suggests that in broader analyses, Asian representation may be seen as less emotionally engaging, possibly due to over-generalized or standardized portrayals. Black representation on the other hand positively influenced emotionality (β=0.158, p=0.002), supporting findings that Black models can evoke more emotionally expressive comments, albeit with varied valence. Furthermore other ethnicities: envoked a positive effect (β=0.215, p=0.007), suggesting that representation of diverse, non-mainstream groups fosters richer emotional responses.

A significant negative effect on emotionality (β=−0.199, p<.001) was observed, consistent with the notion that luxury brands tend to evoke more measured and less expressive responses to maintain their aspirational identity (Hennigs et al., 2013).

These findings indicate that diversity enhances emotional expressiveness for certain racial categories, but luxury branding tempers this engagement, reflecting a strategic balance between inclusivity and exclusivity.

The negative effect of white models on valence and emotionality aligns with hand-coded findings, which emphasized that white representation marginally reinforces exclusivity. However, the lack of significance for luxury branding's effect on valence contrasts with previous observations that luxury brands strategically limit overt diversity cues to maintain exclusivity. Furthermore the positive effects of Black and representation of other ethnicities on emotionality in the multilinear regression model diverge slightly from hand-coded data, where black representation was more neutral. The positive impact of Asian representation on valence aligns with the Lexical Suite's findings that Asian diversity strongly improves sentiment. However, the negative impact on emotionality contrasts with the Lexical Suite's observation that Asian representation enhances emotional richness, suggesting variability depending on dataset or context. Furthermore the neutrality of extremity in relation to racial representation supports previous findings that diversity does not strongly influence emotional intensity.

These findings provide important insights into the complex interplay of diversity and luxury branding; the consistent positive impact of Asian representation on valence highlights the value of incorporating underrepresented groups to foster favorable consumer sentiment. However, its negative impact on emotionality in broader analyses suggests the need for authentic and contextually relevant portrayals. Luxury brands must navigate the tension between exclusivity and inclusivity. The findings reinforce previous research (Wu, 2022; Hennigs et al., 2013) that luxury brands strategically temper diversity cues to maintain aspirational appeal while addressing evolving consumer expectations for representation. Additionally, the positive effects of Black and other representation on emotionality suggest opportunities for brands to foster richer audience engagement through diverse portrayals, provided they are authentic and meaningful. By strategically incorporating diversity and tailoring representation to align with audience expectations and brand identity, companies can enhance sentiment and engagement while maintaining their desired positioning. This analysis underscores the importance of understanding nuanced consumer responses to diversity in advertisements.

4.2.2 Research Question 3: Sentiment Differences Between Luxury and Non-Luxury Brands

4.2.2.1 Linear Regression: Sentiment Analysis

The relationship between luxury brand advertisements and consumer sentiment, emotional intensity, and emotional expressiveness has been widely debated in the literature, with several studies pointing to the importance of exclusivity, prestige, and the nuanced effects of diversity cues (Mandal, 2021; Sharda & Bhat, 2018; Michaelidou et al., 2022). Using Lexical Suite analysis of consumer comments on social media advertisements, this study investigates whether advertisements from luxury versus non-luxury brands generate different types of responses, specifically examining valence (positivity/negativity), extremity (emotional intensity), and emotionality (emotional expressiveness).

Predictor	Dependent Variable	Coefficient	t-value	p-value	Direction	Significant
Luxury	Valence	0.152	2.642	0.008	Positive	Yes
Luxury	Extremity	-0.093	-5.201	< 0.001	Negative	Yes
Luxury	Emotionality	-0.359	-7.845	< 0.001	Negative	Yes

Table 14: Summary Linear Regression Lexical Suite Average Sentiment Score RQ3

The analysis of valence reveals that luxury brands generate slightly more positive sentiment compared to non-luxury brands, though the effect is relatively small. The model summary indicates that luxury branding explains 0.1% of the variance in sentiment (R^2 = 0.001), which is consistent with previous findings that suggest luxury brands are primarily concerned with refined and subtle emotional connections with their target audience (Mandal, 2021; Sharda & Bhat, 2018). The ANOVA results show statistical significance (F = 6.980, p = 0.008), and the regression coefficient for luxury branding is 0.152 (p = 0.008), meaning that luxury brands evoke slightly more positive responses from consumers compared to non-luxury brands. This finding aligns with the idea that luxury brands position themselves as aspirational and prestigious, creating subtle positive emotions to appeal to their high-aspiration target market (Mandal, 2021; Truong et al., 2010). However, the magnitude of the effect is small, suggesting that brand prestige alone may not be a primary driver of sentiment in the online space. While luxury brands often employ diversity cues to balance their image of exclusivity with broader appeal (Michaelidou et al., 2022), this nuanced approach to brand identity may only slightly impact the sentiment in consumer comments. Previous research (Wu, 2022) found that luxury brands might prefer more exclusive marketing approaches, often avoiding overt displays of diversity to preserve their aspirational image. This study's findings are consistent

with that, as the positive sentiment present when looking at brand owned content by luxury brands is not particularly pronounced.

When examining emotional intensity (extremity), a more pronounced pattern emerges. The model summary shows that luxury branding accounts for only 0.5% of the variation in extremity ($R^2 = 0.005$), a modest effect, but the results are highly significant ($F = 27.055$, $p<0.001$). The regression coefficient for luxury branding is negative ($\beta = -0.093$, $p<0.001$), indicating that luxury brand ads evoke less emotional intensity than their non-luxury counterparts. This result is in line with previous research on luxury branding, which suggests that luxury brands often focus on subtlety and controlin their marketing to avoid overly emotional or extreme responses (Michaelidou et al., 2022; Hennigs et al., 2013). The negative coefficient suggests that luxury ads are less likely to provoke extreme emotional reactions, such as enthusiasm or outrage, in consumers. This finding reinforces the notion that luxury brands maintain a more refined, controlled emotional appeal, focusing on consumers who value prestige and exclusivity (Stegemann, 2011). Non-luxury brands, on the other hand, may cater to a broader audience and are more likely to generate stronger emotional reactions, as they typically aim to be more relatable and accessible to a wider range of consumers. This difference reflects the ongoing challenge that luxury brands face in balancing exclusivity with the increasing societal push for inclusivity (Radon, 2012; Michaelidou et al., 2022).

For emotionality, the analysis reveals that luxury branding is significantly associated with less emotional expressiveness in comments. The R^2 value for emotionality is 0.010, indicating that luxury branding explains just 1% of the variance in the emotional richness of comments. This effect is statistically significant ($F = 61.544$, $p < 0.001$), and the regression coefficient for luxury branding is negative ($\beta = -0.359$, $p < 0.001$). This result shows that advertisements from luxury brands tend to provoke less emotionally expressive responses compared to non-luxury brands, which often elicit more emotionally charged comments.

This aligns with previous research that found that luxury brands are associated with prestige and exclusivity (Hassan et al., 2016; Radon, 2012). Luxury advertisements typically use more subdued emotional tones to maintain their elite status and avoid over-saturation of emotions, which may undermine their refined image (Wu, 2022). Non-luxury brands, on the other hand, aim to create more engaging and relatable content to foster strong emotional connections with consumers. This aligns with the broader industry trend where non-luxury brands capitalize on inclusivity and emotional appeal to drive consumer engagement and brand loyalty (Pankiw et al., 2020). The results are furthermore in line with previous

research, which emphasizes that luxury brands must strike a delicate balance between exclusivity and emotional connection. While inclusivity and emotional appeal can broaden the market for luxury brands (Sung & Phau, 2018), excessive emotional engagement may dilute the brand's perceived prestige (Hennigs et al., 2013). Therefore, luxury brands tend to limit emotional expressiveness in their advertising to preserve their exclusive image and appeal to high-status consumers who seek products that signal wealth and control (Sharma et al., 2021).

The results of this analysis show that luxury brands tend to generate slightly more positive sentiment in consumer comments than non-luxury brands, but the impact is relatively minor. This finding is consistent with the notion that luxury brands aim to evoke positive emotions related to prestige and refinement, which resonate with a high-aspiration audience (Mandal, 2021; Sharda & Bhat, 2018). However, luxury brands tend to evoke less emotional intensity and emotional richness, which aligns with the broader strategy of exclusive marketing designed to appeal to consumers seeking status and control (Hassan et al., 2016; Stegemann, 2011).

The results highlight the challenges luxury brands face in balancing exclusivity with inclusivity. Firstly the positive relationship between luxury branding and sentiment suggests that luxury advertisements tend to evoke more positive consumer responses. However, the effect is small, indicating that sentiment may be influenced by a broader range of factors beyond just the luxury classification of the brand. Brands that wish to evoke positive sentiment may still benefit from considering additional elements such as the content of the advertisement, the cultural context, and the demographic of the audience.
Furthermore the negative relationship between luxury branding and emotional intensity suggests that luxury brands deliberately manage emotional reactions by creating more subdued and controlled advertisements. This is consistent with the image that luxury brands aim to cultivate—aspirational and exclusive. On the other hand, non-luxury brands tend to create more emotionally intense advertisements, which might resonate with a wider audience looking for more immediate emotional engagement.
Lastly the negative association between luxury branding and emotionality further reinforces the notion that luxury brands prioritize a refined and exclusive emotional tone, avoiding excessive emotional expressiveness. In contrast, non-luxury brands may use more emotionally engaging content to appeal to a broader consumer base, encouraging more emotionally charged responses.

In conclusion, while luxury branding can influence consumer sentiment and emotional engagement, the effects are relatively modest and typically result in more controlled and less emotionally expressive reactions. Non-luxury brands, by contrast, elicit more polarized and emotionally rich responses, suggesting that these brands may benefit from using content that actively engages a wider range of emotional responses from their audience. Brands, regardless of luxury status, should consider these nuances when shaping their marketing strategies to better resonate with their target consumers.

4.2.2.2 Linear Regression: Hand-Coded Variables

This study utilizing hand-coded analysis explores the impact of luxury versus non-luxury brands on emotionality, sentiment, and exclusivity in consumer comments. The models for emotionality and sentiment were statistically significant, with luxury brands influencing emotional responses. However, exclusivity did not show a significant relationship with brand type.

Predictor	Dependent Variable	Coefficient	t-value	p-value	Direction	Significant
Luxury	Emotionality	0.426	8.023	< .001	Positive	Yes
Luxury	Sentiment	0.645	9.534	< .001	Positive	Yes
Luxury	Exclusivity	-0.447	-0.711	0.479	Negative	No

Table 15: Summary Linear Regression Hand Coded Variables RQ3

The emotionality model demonstrated that luxury brand advertisements were associated with more emotionally expressive responses. The regression results revealed that luxury ads generated more emotionally rich comments than non-luxury ads ($\beta = 0.426$, $p < 0.001$). This was supported by the significant ANOVA results ($F = 64.373$, $p < 0.001$). The R^2 value of 0.042 suggests that luxury branding accounts for 4.2% of the variation in emotional expressiveness in comments. This contrasts with previous findings suggesting that luxury brands, known for their exclusivity, tend to elicit more subdued emotional responses (Michaelidou et al., 2022; Hennigs et al., 2013). The positive relationship here indicates that the luxury brand's attempt to balance exclusivity with emotional appeal may resonate more emotionally than anticipated, especially in the top comments that are seen first by users.

For sentiment (valence), the results were also significant, indicating that luxury brands generate more positive sentiment in comments compared to non-luxury brands ($\beta = 0.645$, $p < 0.001$). The R^2 value of 0.059 reflects that luxury branding explains about 5.9% of the variance in sentiment. The ANOVA results ($F = 90.894$, $p < 0.001$) highlight the robust effect of luxury branding on positive sentiment in consumer reactions. This finding is in line

with the notion that luxury brands appeal to consumers' desire for prestige and aspirational living, often eliciting more positive emotional responses (Truong et al., 2010). Compared to the minimal effect seen in valence in the Lexical Suite data, this stronger effect suggests that luxury advertisements successfully generate more positive feelings toward the brand. This leaves room for future research to explore what influences the order of comments shown to a Tik Tok user and if potentially more emotional comments and those with a more positive sentiment are shown first.

The hand-coded analysis reveals a stronger emotional and positive sentiment response to luxury brands compared to the Lexical Suite, which indicates more subdued emotionality and moderate sentiment effects. Both analyses agreed that luxury brands tend to elicit more positive sentiment, though the effect was stronger in the hand-coded analysis. This may indicate that Lexical Suite models are more conservative in measuring sentiment, while the hand-coded analysis reflects a deeper emotional connection. This highlights the potential for different methodologies to capture nuanced aspects of consumer engagement and underscores the importance of context when interpreting brand perceptions in social media environments. However, the varying results may also be influenced by the significantly smaller sample size of this dataset.

Lastly the analysis of exclusivity revealed no significant impact from luxury branding ($\beta = -0.447$, $p = 0.479$) unlike the other variables. The R^2 value was only 0.005, meaning luxury branding accounted for only 0.5% of the variance in perceptions of exclusivity. The ANOVA result ($F = 0.505$, $p = 0.479$) further confirms the lack of significant effect of luxury branding on perceived exclusivity. This finding diverges from the established notion that luxury brands, by their nature, emphasize exclusivity as a key part of their identity (Radon, 2012; Stegemann, 2011). The lack of a strong effect in this analysis might suggest that exclusivity may not be a major focus of the ads sampled or may have been overshadowed by other brand-related cues, such as prestige or aspiration.

The hand-coded analysis indicates that luxury brands tend to elicit more emotionally expressive and positive sentiment in consumer comments compared to non-luxury brands. This supports the idea that luxury advertisements evoke an emotional response, likely leveraging aspirational appeal to generate deeper connections with their audiences. However, the lack of a significant relationship with exclusivity suggests that exclusivity may not be as central to the consumer's reaction in the context of online engagement, or that consumers may experience the content or designs shown as non-exclusive – potentially consumer reactions may even be

cynical as the rise of counterfeits may lead to the broad viewer (who is not necessarily a buyer) experiencing the goods as less exclusive. Previous research has shown that the mere visibility of counterfeit luxury goods can undermine the exclusivity and prestige of authentic luxury brands, even for non-purchasing observers (Koay, 2018; Doss & Robinson, 2013).

4.2.2.3 Multilinear Regression: Influence of Celebrity-Focused Content

A series of multiple regression analyses were conducted to examine the influence of celebrity-focused advertising content, along with ethnic and diversity cues, on three dimensions of consumer responses: valence, extremity, and emotionality. Each dependent variable was modeled in two ways: one including ethnic cues (White, Asian, Black, Other) and the other including a diversity cue, with both sets of models considering celebrity-focused content.

Dependent Variable	Predictor	Coefficient	t	p	Direction	Significant
Valence	White	-0.172	-2.612	0.009	Negative	Yes
Valence	Asian	0.288	4.353	< .001	Positive	Yes
Valence	Black	-0.127	-1.876	0.061	Neutral	No
Valence	Other Ethnicities	0.101	1.014	0.311	Neutral	No
Valence	Celebrityfocused	0.083	1.492	0.136	Neutral	No
Valence	Celebrityfocused	0.250	5.428	< .001	Positive	Yes
Valence	Diversity	0.309	6.691	< .001	Positive	Yes
Extremity	White	-0.025	-1.233	0.218	Neutral	No
Extremity	Asian	-0.030	-1.462	0.144	Neutral	No
Extremity	Black	-0.007	-0.324	0.746	Neutral	No
Extremity	Other Ethnicities	-0.017	-0.562	0.574	Neutral	No
Extremity	Celebrityfocused	-0.072	-4.135	< .001	Negative	Yes
Extremity	Celebrityfocused	-0.071	-4.948	< .001	Negative	Yes
Extremity	Diversity	-0.004	-0.263	0.793	Neutral	No
Emotionality	White	0.040	0.763	0.445	Neutral	No
Emotionality	Asian	-0.355	-6.749	< .001	Negative	Yes
Emotionality	Black	0.139	2.593	0.010	Positive	Yes
Emotionality	Other Ethnicities	0.248	3.144	0.002	Positive	Yes
Emotionality	Celebrityfocused	-0.046	-1.048	0.294	Neutral	No
Emotionality	Celebrityfocused	-0.265	-7.221	< .001	Negative	Yes
Emotionality	Diversity	-0.174	-4.722	< .001	Negative	Yes

Table 16: Summary Multi Linear Regression Interaction Lexical Suite Average Sentiment Score and Celebrity Presence RQ3

For the model including ethnicities, the presence of Asian cues was positively associated with consumer valence (B = 0.288, $p < 0.001$), while White cues yielded a small but significant negative association (B = -0.172, $p = 0.009$). Although celebrity-focused content was not statistically significant in this model, results from the diversity model indicated that both

celebrity-focused ($B = 0.250$, $p < 0.001$) and diversity cues ($B = 0.309$, $p < 0.001$) significantly increased positive sentiment. These findings suggest that visible diversity and associating products with celebrities can enhance overall positive reactions to the content.

Regarding emotional extremity, the inclusion of celebrity-focused content consistently predicted lower levels of extreme emotional reactions in both the ethnic ($B = -0.072$, $p < 0.001$) and diversity ($B = -0.071$, $p < 0.001$) models. In contrast, none of the ethnic cues were significantly associated with extremity, and diversity cues also did not produce a notable effect in the second model. This pattern indicates that while featuring celebrities may boost valence, it simultaneously tempers emotionally extreme responses.

Emotionality. For emotionality, the ethnic model showed that Asian cues were associated with reduced emotional expressiveness ($B = -0.355$, $p < 0.001$), whereas Black ($B = 0.139$, $p = 0.010$) and Other ($B = 0.248$, $p = 0.002$) cues increased emotional expressiveness. However, celebrity-focused content was not significant in the ethnic model. In the diversity model, both celebrity-focused ($B = -0.265$, $p < 0.001$) and diversity ($B = -0.174$, $p < 0.001$) cues led to lower emotional expressiveness. These results suggest that, although certain ethnic cues can heighten emotional responses, the introduction of celebrity content within a more diverse context appears to moderate and diminish the intensity of these emotions.

In sum, these analyses indicate that incorporating celebrity figures and diversity cues into social media advertisements can shape how consumers respond. Celebrity-focused content and diversity cues positively influenced overall sentiment but simultaneously reduced the intensity and richness of emotions. These findings underscore the nuanced role that celebrity endorsement and diversity play in shaping consumer sentiment, highlighting that while celebrities and diverse representation may elevate the baseline positivity of responses, their presence can also temper more extreme or deeply felt emotional reactions.

5 Discussion

5.1 Summary of Key Findings

The results of Research Question 1, exploring the impact of diversity on video performance, indicates that the diversity of models in social media advertisements, specifically in TikTok videos, does not significantly influence video performance when measured by the logarithmized number of views. The analysis examined various diversity dimensions, including gender and racial representation, celebrity focus, and the presence or absence of individuals in the videos.

First, the presence of female models showed a weak, non-significant relationship with video performance ($R = 0.078$, $p = 0.055$), suggesting a slight negative association with the number of views, although this effect was marginally insignificant. Similarly, the presence of male models did not significantly affect video views ($R = 0.013$, $p = 0.753$), indicating that male representation in the videos did not have a notable impact on engagement. The analysis of racial diversity, including the representation of White, Black, Asian, and other ethnic models, revealed no significant relationships with video performance, further suggesting that racial diversity in these videos does not strongly influence view counts.

Interestingly, videos that featured at least one non-white model also showed no significant relationship with performance ($R = 0.008$, $p = 0.843$), reinforcing the idea that racial diversity alone does not appear to be a strong predictor of video performance on TikTok. The inclusion of celebrity models did not yield a significant impact on view counts either ($R = 0.024$, $p = 0.564$), suggesting that celebrity focus does not automatically lead to higher engagement in the context of these videos.

However, the luxury brand affiliation was the only variable that demonstrated a statistically significant positive effect on video performance. Videos from luxury brands ($R = 0.187$, $p < 0.001$) outperformed those from non-luxury brands, with the analysis showing that luxury branding contributed positively to higher view counts, explaining 3.5% of the variance in performance.

Further analysis using multiple linear regression confirmed that luxury branding remained a significant predictor of video performance ($B = 0.449$, $p < 0.001$), with videos from luxury brands consistently receiving more views. In contrast, the presence of female models ($B = -0.416$, $p = 0.020$) showed a negative relationship with views, suggesting that female representation might be associated with fewer views, while male models ($B = -0.190$, $p = 0.255$) and racial diversity did not significantly affect views.

The study's results indicate that diversity in social media advertisements across gender and racial dimensions does not, by itself, drive short-term video performance on TikTok. Instead, luxury brand affiliation emerged as a key factor positively influencing view counts, suggesting that brand prestige and exclusivity can overshadow diversity cues in capturing immediate viewer interest. Nevertheless, these findings do not negate the broader literature that highlights the societal importance and long-term strategic value of inclusive advertising (Carrasco-Santos, 2024; Ferreyra, 2022; Iglesias-Sánchez et al., 2023; McDonald et al., 2020). Instead, they point to a nuanced reality: while diversity may not significantly boost initial view counts, it remains an important ethical and strategic practice with potential benefits for brand equity, societal impact, and consumer identification that extend beyond the immediate metrics of social media performance.

The findings for Research Question 2 reveal that diversity in social media advertisements has a modest but positive effect on consumer valence, yet a negative effect on emotional expressiveness. Diversity overall was associated with slightly more positive consumer sentiment, but did not strongly influence extremity (emotional intensity), and surprisingly, reduced emotionality. Among racial categories, Asian representation had the strongest positive impact on valence ($\beta = 0.454$, $p < .001$), but a significant negative effect on emotionality ($\beta = -0.398$, $p < .001$), suggesting that while it increases positivity, it does not evoke stronger emotional responses. In contrast, Black representation was negatively associated with valence ($\beta = -0.203$, $p < .001$) but positively influenced emotionality ($\beta = 0.304$, $p < .001$), indicating that comments on advertisements featuring Black models tend to be more emotionally expressive. White representation had negative effects on both valence and emotionality, while models from other ethnic backgrounds had no significant impact on consumer sentiment.

These results suggest that while diversity enhances overall positivity in consumer sentiment, its impact on emotional engagement varies across racial categories. Brands should consider not just the presence of diversity but also the emotional dynamics it creates, ensuring that representations resonate authentically with audiences.

Research Question 3 explored differences in consumer sentiment between luxury and non-luxury brands. The results demonstrated that luxury brands evoke slightly more positive sentiment compared to non-luxury brands, as reflected in the small but significant positive effect on valence ($\beta = 0.152$, $p = 0.008$). Hand-coded data further supported this finding, showing a stronger positive relationship ($\beta = 0.645$, $p < .001$) and highlighting the aspirational

and refined image of luxury brands as drivers of positive consumer responses. However, the magnitude of the effect was relatively small, indicating that brand prestige alone may not be the primary determinant of sentiment.

Luxury branding was found to temper emotional intensity, as evidenced by a significant negative effect on extremity ($\beta = -0.093$, $p < .001$). This aligns with the strategic emphasis of luxury brands on maintaining a controlled and refined image, minimizing overly emotional or polarized responses. Similarly, luxury advertisements were associated with lower emotional expressiveness in comments, with the Lexical Suite analysis showing a significant negative relationship with emotionality ($\beta = -0.359$, $p < .001$). However, hand-coded data provided a contrasting perspective, indicating that luxury advertisements elicited richer emotional responses ($\beta = 0.426$, $p < .001$). This discrepancy may stem from contextual factors, such as the prominence of certain types of comments in luxury brand content, or the limitations of automated tools like the Lexical Suite in capturing nuanced emotional expressions.

The analysis of exclusivity found no significant relationship between luxury branding and consumer perceptions of exclusivity ($p > 0.05$). This contradicts the common assumption that luxury brands inherently signal exclusivity through their advertisements. The lack of a strong effect on exclusivity may suggest that consumers are influenced by additional contextual or cultural factors that extend beyond the advertisement itself.

Overall, the findings highlight that diversity in advertisements positively influences consumer sentiment, particularly through Asian representation, which resonates strongly with audiences. However, representations of White and Black models face challenges, including negative associations with valence and, in the case of Black representation, more polarized emotional reactions. For luxury brands, the results show a nuanced balance between fostering positive sentiment and maintaining a controlled emotional tone. While luxury advertisements elicit more positive sentiment compared to non-luxury ads, they tend to temper emotional intensity and expressiveness. These insights underscore the importance of tailoring representation strategies to align with audience expectations and brand identity

5.2 Theoretical Implications

This study offers several theoretical implications for understanding the role of diversity, luxury branding, and celebrity presence in social media advertising particularly on a platform like TikTok. The findings build a baseline for further explorations on how short-form video content may reshape consumers' reactions to inclusive advertising cues.

Gardenswartz and Rowe's (2003) model posits that internal dimensions—such as race and gender—fundamentally shape perceptions. While prior research often associates higher diversity with enhanced engagement, the results here suggest a more nuanced reality: racial and gender diversity did not significantly boost TikTok view counts, despite marginal or negative trends for female models and certain ethnic categories. In fast-paced social media contexts, diversity of internal dimensions of diversity alone may not instantly translate into higher quantitative metrics (e.g., views). Instead, the data reveal diversity's qualitative influence on sentiment. Showing that both the Lexical Suite and hand-coding analyses indicated that inclusive content elicits modestly more positive or emotionally rich comments. Thus, rather than driving instant "clicks," internal dimensions of diversity seem more powerful in shaping how consumers engage attitudinally, offering an important refinement to diversity theory in digital environments.

Social identity theory (Tajfel, 1979) contends that individuals align with in-groups and can distance themselves from out-groups. Our findings add complexity to this perspective in two ways. First, the marginally negative effect of predominantly White representation on consumer sentiment implies that some audiences may perceive racially homogeneous ads as exclusionary—amplifying out-group perceptions. Second, the strong positive response to Asian representation suggests that historically underrepresented groups on mainstream platforms may become in-groups for certain TikTok demographics. These nuances emphasize that in-group/out-group dynamics are fluid and platform-dependent, indicating that social media contexts can disrupt traditional identity boundaries as younger or more diverse audiences respond differently to representation cues than do those consuming traditional media.

While brand exclusivity has been theorized as a hallmark of luxury branding, the works findings show that luxury status alone significantly boosts view counts, often overshadowing demographic cues like race or gender for brands that economically perform similarly powerful. This reveals a dual mechanism: on one hand, strong brand equity sustains higher initial engagement; on the other hand, inclusive casting appears largely irrelevant to short-term performance. Nonetheless, the positive sentiment gleaned from diverse luxury ads hints that exclusivity may not necessarily conflict with inclusivity if done authentically. Hence, current exclusivity theories should be expanded to account for contexts in which representation can coexist with premium positioning, adding a novel dimension to the luxury-brand literature.

Finally, the minimal effect of celebrity-focused content on views or comment sentiment challenges the assumption, that celebrities automatically enhance consumer engagement (Keel & Nataraajan, 2012). On TikTok, the ephemeral nature of content and algorithm-driven feeds could dilute typical celebrity star power. This calls for a theoretical revision to account for platform-specific factors that mediate or weaken the traditional benefits of celebrity endorsements.

Overall, these insights demonstrate that theories of diversity, social identity, and exclusivity must be adapted to fast-evolving social media ecosystems. Rather than offering purely additive effects, diversity cues on TikTok appear to influence how consumers discuss the brand more than whether they view it. Future models should differentiate between performance metrics (views) and affective responses (sentiment), clarifying why certain platforms elevate brand prestige while moderating the impact of diversity. Moreover, cross-cultural studies and longitudinal designs could assess whether these dynamics persist over time or shift as luxury and celebrity strategies evolve. Furthermore the study underscores the importance of context-sensitive diversity strategies in branding and opens new avenues for research into how short-form video platforms reshape established advertising theories.

5.3 Practical Implications

For managers, marketers, and agencies negotiating the intricate aspects of social media advertising on sites like TikTok, these studies offers insightful information. The results highlight how crucial it is to strike a balance between sentiment, inclusion, and performance indicators in order to generate both immediate engagement and long-term brand equity. For luxury and non-luxury brands alike, understanding how diversity, exclusivity, and platform-specific nuances shape consumer behavior is crucial for crafting effective campaigns.

Firstly the necessity for marketers to refocus their attention from conventional performance metrics like view counts is one of the main implications. While diversity in advertising did not significantly influence TikTok video performance, it played a pivotal role in shaping consumer sentiment and emotional engagement. This emphasizes how crucial it is to gauge both qualitative results like emotional expressiveness and remark positivity as well as quantitative ones like views and shares. Dual key performance indicators which measure both

immediate reach and the more profound emotional ties that eventually generate brand loyalty, should be implemented by managers. Sentiment analysis systems can offer insights into how audiences see campaigns, offering opportunities for future material to be improved iteratively.

On platforms like TikTok, where attention spans are short, crafting a compelling hook remains essential for attracting viewers. However, subtle diversity cues embedded in storytelling and model selection can amplify how audiences engage with the brand after the initial viewing. This dual focus on creating attention-grabbing content while integrating inclusive representation aids both in supporting short-term engagement as well as the long-term relational impact.
The findings also underscore the critical role of authenticity in implementing diversity strategies. Tokenistic approaches can backfire, leading to skepticism or negative sentiment. For both luxury and non-luxury brands, it is essential to embed diversity authentically into the creative process. Involving diverse voices in casting, scripting, and approval phases can ensure that representation feels organic and aligns with the brand's broader narrative.

In particular, luxury brands have to balance the conflict between inclusivity and exclusivity. Because luxury branding has historically been linked to conformity and aspirational imagery, it has frequently been reluctant to embrace diversity for fear of losing its status. Nonetheless, this study shows that inclusive representation does not always have to be at odds with exclusivity when done carefully. Instead, it might promote favorable customer emotion and update the brand's image. Campaigns that showcase diverse models in upscale, aspirational settings, such prestigious events or upscale experiences, for example, can preserve the brand's premium positioning while demonstrating a dedication to diversity. Conversely, non-luxury firms can use diversity to increase emotional resonance.

Localization also plays a critical role in diversity strategies. While global audiences on TikTok often respond positively to underrepresented groups, the cultural relevance of representation varies across regions. Marketers should tailor campaigns to local contexts, where possible. Nevertheless it is unlikely that brand owned content will not be shown across borders – therefore no localized campaign should be followed through with without considering a potential impact on international audiences.
For luxury brands, the study confirms the enduring power of exclusivity in driving engagement, as luxury affiliation was one of the strongest predictors of higher video performance. However, the findings challenge the traditional assumption that exclusivity and diversity are mutually

exclusive. Thoughtfully integrating diversity into luxury campaigns can enhance emotional engagement and positive sentiment without undermining the brand's prestige. This approach requires a strategic balance: inclusive content should align with the brand's heritage and aesthetic while avoiding overexposure, which can dilute its aspirational appeal.
Moreover, luxury brands should actively monitor and analyze consumer feedback in comment sections to identify potential risks or misalignments. Real-time social listening can help managers detect negative sentiment early and adjust campaign strategies accordingly. For example, if consumers perceive a diversity campaign as inauthentic or inconsistent with the brand's values, brands can respond with clarifications or adjustments to maintain trust and credibility. It is essential to consider the current political sentiment and active controversies before publishing brand owned content in order to not risk affecting consumer sentiment negatively.

The findings also offer critical insights for brands relying on celebrity endorsements. Contrary to traditional theories, the mere presence of celebrities in TikTok ads did not significantly boost performance metrics like view counts or emotional engagement. This suggests that, on platforms like TikTok, the algorithmic and fast-scrolling nature of the feed may dilute the traditional star power effect. To maximize the impact of celebrity partnerships, brands should focus on integrating celebrities into TikTok-native formats, such as viral challenges, duets, or skits, that align with platform culture and audience expectations. Potentially it could be viable to work with platform specific influencers that often are celebrities to a niche audience in the way they would if they were not cooperating. Generally the emphasis should shift from name recognition to co-creating engaging, relatable content that resonates with a platforms specific audience.

Lastly, the study emphasizes how crucial it is to build campaigns using a test-and-refine methodology. Context, demographics, and cultural quirks can all affect how an audience reacts to different types of representation. Before launching extensive campaigns, marketers may determine which strategies work best by testing a variety of ad variations and tracking sentiment in real time. A thorough grasp of customer reactions is ensured by combining automatic sentiment analysis techniques with manual evaluation of comment sections, allowing for more sophisticated and knowledgeable decision-making.

5.4 Ethical Considerations

This research carefully addresses several ethical challenges associated with analyzing social media data and coding diversity cues in TikTok advertisements. Ethical integrity and respect for individuals' rights were central to the study design and execution.

A primary ethical concern is the use of publicly available TikTok data without explicit consent from the creators or commenters. Users do likely not anticipate that their postings or comments will be used for academic purposes, regardless of whether TikTok content is publicly available. To address this, the study adhered to ethical guidelines for internet-based research, focusing solely on publicly available data, therefore no private or restricted content was included. To protect people's privacy, comments were anonymised all throughout analysis, and results were presented in an aggregate manner to avoid being able to identify individual users.

Another ethical consideration involves the manual coding of models' appearances, especially as it was done by only one individual, particularly their gender and ethnicity, based on visual assessment. This method carries the risk of misrepresentation, as categorizations may not align with individuals' self-identified characteristics or reality. This limitation is explicitly acknowledged, eventhough efforts were made to apply consistent and systematic coding procedures to minimize bias. Nonetheless, the potential for stereotyping or reinforcing biases remains a concern.

Another major concern was the ethical treatment of hate speech and potentially harmful data in the dataset. The prevalence of harsh or discriminatory language on social media sites raises questions regarding how research approaches this type of content. Despite being marked as hate speech or containing discriminatory language, comments in this work were processed using the Lexical Suite for sentiment analysis since user reactions to brand-owned content sometimes include speech that may be legally relevant. Their material was, however, not directly covered or discussed in the study in order to prevent the spread of damaging narratives. Thereby the risk of spreading offensive content is reduced while ensuring that insights concerning sentiment trends are recorded.

In conclusion this work striving to balance the valuable insights gained from analyzing TikTok data with the need to respect individual rights and mitigate potential harm were a priority. While it is neccesary to be aware of these ethical considerations, the studies takes meaningful steps to ensure ethical compliance and responsible handling of sensitive issues.

5.5 Limitations and Future Research

This thesis presents a foundation into the impact of diversity in social media advertising on TikTok. However, several limitations must be acknowledged, alongside opportunities for future research to build on and refine these findings.

One notable limitation is the potential for bias introduced by the single-author approach. As the sole researcher, I performed all the hand coding of data, including the classification of diversity dimensions in TikTok videos and the analysis of comments. While every effort was made to maintain objectivity, bias may inadvertently influence the results. Although the research was conducted in an exploratory manner without explicit hypotheses or a preference for a specific preconceived outcome, future studies should employ multiple independent coders. Coders who are unaware of the body of previously conducted research, research objectives and potential implications. This would further reduce the risk of bias and enhance reliability. Moreover, implementing inter-rater reliability testing would ensure consistency and accuracy in coding decisions.

Another limitation arises from the hand-coding process itself. Hand coding is inherently subjective and may result in errors or inconsistencies, especially when interpreting complex or ambiguous content. Future studies should involve larger teams of coders to verify findings, cross-check classifications, and minimize individual biases. Additionally, the context and nuance of certain social media interactions, particularly those involving slang, sarcasm, or culturally specific references, may be lost or misinterpreted. Greater cultural awareness or linguistic expertise in coding teams could mitigate this issue.

The limited timeframe for conducting the initial coding and research as well as the scope of this thesis also posed constraints. This restriction prevented the full coding of all comments under analyzed TikTok posts. Instead, the study focused on a subset of comments, prioritizing those with the highest engagement (e.g., shown first). While these comments provide valuable insights, they may not fully represent the breadth of consumer sentiment, particularly less visible perspectives. Comments further down in the comment section, often overlooked due to fewer engagements, sometimes address political or socially significant themes. Analyzing these comments in future studies would offer a more nuanced and comprehensive understanding of consumer interaction as well as sentiment.

Another challenge stems from the limitations of current AI and sentiment analysis tools. The sentiment analysis employed in this study relied on a combination of hand coding and software tools, which are not yet advanced enough to fully capture the complexity of human language

and sentiment. Future research should revisit this topic as these tools evolve, enabling more precise and automated analyses which would be more consistent than human coders can be.
Finally, while this research aimed to provide meaningful insights, it was conducted by a researcher with limited experience in advanced data analysis. Future studies led by interdisciplinary teams with expertise in marketing, data science, and social psychology could enhance methodological rigor and analytical depth – thereby getting more detailed results out of the same dataset.

This thesis offers a starting point for examining diversity in TikTok advertising, but its findings should be treated as exploratory. Building on the findings of this thesis, future research could explore additional facets of how diversity and other content characteristics influence both video performance and consumer sentiment. One potential area of expansion involves analyzing the role of celebrities in brand advertisements on social media. Specifically, it would be valuable to investigate whether platform- or audience-specific celebrities, especially those with active fan communities or current relevance on platforms, boost video performance and consumer sentiment. Celebrities who resonate strongly with the platform's demographic may not only enhance video views but also foster positive engagement, as their followers are likely to amplify content through shares and comments.
Future studies might also examine how brands can strategically balance inclusion and exclusivity to appeal to both traditional luxury consumers and emerging market segments. While this thesis explored broad patterns of sentiment, future work could segment audiences more granularly by demographics, cultural context, or brand loyalty to determine how diverse representation is received across different consumer groups. For instance, are younger audiences more likely to respond positively to diverse representation, and do older demographics exhibit different sentiment trends? Are there regional differences in the perception of diversity within luxury advertisements? Answering these questions could refine marketing strategies to better meet the expectations of local and global audiences.
Moreover, long term or repeated studies could assess how consumer sentiment evolves over time, especially as societal attitudes toward diversity continue to shift. Furtermore a larger dataset of a higher variety and more specific classification of brands could also be explored.
Finally, future research should consider integrating cross-platform analyses to compare how diversity cues perform on TikTok versus other platforms like Instagram or YouTube. Given the unique demographic and algorithmic dynamics of each platform, such comparisons would shed light on whether the findings of this thesis are platform-specific or broadly applicable across

social media. By addressing these questions, future research could significantly advance the understanding of diversity in digital advertising and provide actionable insights for brands navigating an increasingly complex marketing landscape.

This thesis did not account for the current ban of TikTok in the United States as of January 19th 2025, as all research was conducted before it took effect. Additionally, future legislative changes under the Trump administration could impact the platform's algorithm if TikTok were to become accessible to U.S. users again. Given these ongoing developments, future research could explore how TikTok users in different countries respond to diversity cues differently and how content strategies might be strategically adapted accordingly. Furthermore, it would be valuable to examine how sentiment varies across different platforms, especially in light of the potential migration of U.S.-based TikTok users to Instagram Reels, YouTube Shorts, and 小红书 (Xiao Hong Shu, also known as Red Note). Brand managers must recognize that different user bases, on different platforms with different algorithms and policies, may respond differently to the same content, highlighting the need for a comparative sentiment analysis of content posted by the same creators or brands across multiple platforms. This could provide deeper insights into platform-specific audience preferences and inform more tailored content strategies.

6 Conclusion

This thesis set out to explore the impact of diversity cues in social media advertisements on consumer engagement and sentiment, with a specific focus on brand owned content on TikTok. Grounded in the increasing managerial and societal importance of diversity, equity, and inclusion practices, this research sought to address gaps in the literature by examining how ethnicity, gender, and inclusivity in advertising affect consumer perceptions and interactions. Two complementary studies were conducted to firstly investigate how diversity influences the performance of TikTok videos, measured by view count, and secondly how it shapes consumer sentiment in comment sections. The findings provide both theoretical and practical contributions, offering insights for academics and practitioners alike.

The results of this research demonstrate that diversity representation plays a significant role in shaping consumer engagement and sentiment on social media. Study 1 revealed that TikTok videos featuring diverse models, particularly in terms of ethnicity and gender, do not tend to perform better in terms of views. The only metric considered that significantly affected views was if the content stems from a luxury brand. Videos from luxury brands outperformed those from non-luxury brands, with the analysis showing that luxury branding contributed positively to higher view counts.

Study 2 further uncovered that diversity was associated with a slight increase in positive sentiment, as shown by the significant but small positive effect on valence. Among racial categories, Asian representation emerged as the most impactful, significantly improving valence ($\beta = 0.454$, $p < 0.001$) but had a negative effect on emotionality ($\beta = -0.398$, $p < 0.001$). These results suggest that audiences responded favorably to the inclusion of Asian models in terms of positivity, their presence did not evoke stronger emotional expression and may have tempered it.

Furthermore, luxury brands evoke slightly more positive sentiment compared to non-luxury brands, as reflected in the small but significant positive effect on valence. However, the magnitude of the effect was relatively small, indicating that brand prestige alone may not be the primary determinant of sentiment.

Luxury branding was found to temper emotional intensity, as evidenced by a significant negative effect on extremity. This aligns with the strategic emphasis of luxury brands on

maintaining a controlled and refined image, minimizing overly emotional or polarized responses.

This thesis underscores the role of TikTok as a dynamic platform for examining diversity's impact in real-time, given its unique algorithmic structure and interactive features. It also highlights the challenges brands face in balancing inclusivity with their traditional brand values, particularly in the luxury sector, where exclusivity remains a core component of brand identity.

While this research provides valuable insights, several limitations warrant discussion. The exploratory nature of the study, combined with the reliance on hand-coded data – especially regarding the independent variables, introduces potential biases that future research could address by involving multiple independent coders. Additionally, the scope of the dataset was constrained by time and resource limitations, with only a subset of comments analyzed in detail. Expanding the sample size to include all comments, particularly those less visible in the algorithmic hierarchy, could offer a more comprehensive view of consumer sentiment.

Further studies might examine the role of platform-specific celebrities and their influence on both video performance and consumer sentiment, especially when they resonate strongly with the target audience or have active fan communities. Finally, as AI and sentiment analysis tools continue to evolve, future work should leverage these advancements to analyze visual and textual content with greater precision, enabling deeper insights into the interplay of diverse representations and consumer behavior.

Theoretically, this thesis contributes to the growing body of literature on diversity in advertising, consumer behavior, and digital engagement by providing evidence of the tangible benefits of inclusive marketing strategies. Practically, the findings offer clear guidance for marketers and brand managers, emphasizing the importance of integrating diversity cues thoughtfully and authentically to maximize engagement and positive sentiment, while not mistaking them as a “fix all” when trying to be perceived more favorably.

Bibliography

Achenbaum WA. 1978. Old Age in the New Land: The American Experience Since 1790. Baltimore, MD: Johns Hopkins Univ. Press

Acker, J. (2006). Inequality regimes gender, class, and race in organizations. Gender & Society, 20(4), 441-464. https://doi.org/10.1177/0891243206289499

Adams, M., & Coltrane, S. (2005). Boys and men in families. Handbook on studies on men and masculinities, 230-248.

Adetunji, R., Rashid, S., & Ishak, S. (2019). The mediating effect of brand image on the relationships between social media advertising content, sales promotion content and behaviuoral intention. Journal of Research in Interactive Marketing, 13(3), 302-330. https://doi.org/10.1108/jrim-01-2018-0004

Adil, S., Abdeltawab, A. M., & Lecointre-Erickson, D. (2021). The effectiveness of model's body size in digital and print advertisements. International Journal of Marketing Studies, 13(3), 1. https://doi.org/10.5539/ijms.v13n3p1

Adil, S., Abdeltawab, A., & Lecointre-Erickson, D. (2021). The effectiveness of model's body size in digital and print advertisements. International Journal of Marketing Studies, 13(3), 1. https://doi.org/10.5539/ijms.v13n3p1

Adomaitis, A. and Saiki, D. (2019). Brand personality and sexuality levels of luxury advertisements. Journal of Fashion Marketing and Management, 23(4), 572-586. https://doi.org/10.1108/jfmm-01-2019-0004

Ahadi, S., Zhou, W., Schüssler-Fiorenza Rose, S. M., Sailani, M. R., Contrepois, K., Avina, M., ... & Snyder, M. (2020). Personal aging markers and ageotypes revealed by deep longitudinal profiling. Nature Medicine, 26(1), 83-90.

Ajitha, S. and Sivakumar, V. (2019). The moderating role of age and gender on the attitude towards new luxury fashion brands. Journal of Fashion Marketing and Management, 23(4), 440-465. https://doi.org/10.1108/jfmm-05-2018-0074

Akindele, G. and Arogundade, K. (2022). Nexus of overall cost of celebrity endorsement and market performance of alcoholic brewery products in lagos metropolis, nigeria. International Journal of Science and Management Studies (Ijsms), 21-26. https://doi.org/10.51386/25815946/ijsms-v5i3p103

Alafwan, B. (2023). Comments analysis on social media: a review. Icst Transactions on Scalable Information Systems. https://doi.org/10.4108/eetsis.3843

Ali, M., Ahmed, T., & Absar, S. (2020). Urban Youth Attitude toward Online Shopping: Evidence from Dhaka City. International Journal of Entrepreneurial Research, 2020, 33-40.

Amatulli, C., Angelis, M., & Donato, C. (2019). An investigation on the effectiveness of hedonic versus utilitarian message appeals in luxury product communication. Psychology and Marketing, 37(4), 523-534. https://doi.org/10.1002/mar.21320

Amatulli, C., Angelis, M., Pichierri, M., & Guido, G. (2018). The importance of dream in advertising: luxury versus mass market. International Journal of Marketing Studies, 10(1), 71. https://doi.org/10.5539/ijms.v10n1p71

An, D., Lee, C., Kim, J., & Youn, N. (2019). Grotesque imagery enhances the persuasiveness of luxury brand advertising. International Journal of Advertising, 39(6), 783-801. https://doi.org/10.1080/02650487.2018.1548198

Areni, C. (2021). Automated text analyses of youtube comments as field experiments for assessing consumer sentiment towards products and brands. Journal of Product & Brand Management, 31(5), 702-717. https://doi.org/10.1108/jpbm-01-2021-3341

Arli, D. and Dietrich, T. (2017). Can social media campaigns backfire? exploring consumers' attitudes and word-of-mouth toward four social media campaigns and its implications on consumer-campaign identification. Journal of Promotion Management, 23(6), 834-850. https://doi.org/10.1080/10496491.2017.1323259

Aruna, M. and Gunasundari, K. (2022). Empowering of feminine in indian advertisements. International Journal of Computer Communication and Informatics, 4(1), 11-22. https://doi.org/10.34256/ijcci2212

Ashikali, E. and Dittmar, H. (2011). The effect of priming materialism on women's responses to thin-ideal media. British Journal of Social Psychology, 51(4), 514-533. https://doi.org/10.1111/j.2044-8309.2011.02020.x

Athwal, N., Istanbulluoğlu, D., & McCormack, S. (2019). The allure of luxury brands' social media activities: a uses and gratifications perspective. Information Technology and People, 32(3), 603-626. https://doi.org/10.1108/itp-01-2018-0017

Atteveldt, W., Velden, M., & Boukes, M. (2021). The validity of sentiment analysis: comparing manual annotation, crowd-coding, dictionary approaches, and machine learning algorithms. Communication Methods and Measures, 15(2), 121-140. https://doi.org/10.1080/19312458.2020.1869198

Atwal, G. and Williams, A. (2009). Luxury brand marketing – the experience is everything!. Journal of Brand Management, 16(5-6), 338-346. https://doi.org/10.1057/bm.2008.48

Audrin, C., Ceravolo, L., Chanal, J., Brosch, T., & Sander, D. (2017). Associating a product with a luxury brand label modulates neural reward processing and favors choices in materialistic individuals. Scientific Reports, 7(1). https://doi.org/10.1038/s41598-017-16544-6

Avery, D. (2003). Reactions to diversity in recruitment advertising--are differences black and white?. Journal of Applied Psychology, 88(4), 672-679. https://doi.org/10.1037/0021-9010.88.4.672

Azab, C. and Clark, T. (2017). Speak my language or look like me? – language and ethnicity in bilingual customer service recovery. Journal of Business Research, 72, 57-68. https://doi.org/10.1016/j.jbusres.2016.11.012

Baek, T., Kim, J., Yoon, S., Choi, Y., & Taylor, C. (2023). The covid-19 threat and luxury advertising. Journal of Consumer Behaviour, 22(3), 582-596. https://doi.org/10.1002/cb.2137

Baker, J. (2022). Muscles, makeup, and femboys: analyzing tiktok's "radical" masculinities. Social Media + Society, 8(3), 205630512211260. https://doi.org/10.1177/20563051221126040

Bandyopadhyay, A. and Nallaperuma, K. (2021). Mixed feelings enhance the effectiveness of luxury advertising. Australasian Marketing Journal (Amj), 30(1), 28-34. https://doi.org/10.1177/1839334921998848

Barnes, L. and Lea-Greenwood, G. (2006). Fast fashioning the supply chain: shaping the research agenda. Journal of Fashion Marketing and Management, 10(3), 259-271. https://doi.org/10.1108/13612020610679259

Barrett AE. 2022. Centering age inequality: developing a sociology-of-age framework. Annu. Rev. Sociol. 48:213–32

Bartikowski, B., Fastoso, F., & Gierl, H. (2020). How nationalistic appeals affect foreign luxury brand reputation: a study of ambivalent effects. Journal of Business Ethics, 169(2), 261-277. https://doi.org/10.1007/s10551-020-04483-8

Basch, C., Hillyer, G., & Jaime, C. (2020). Covid-19 on tiktok: harnessing an emerging social media platform to convey important public health messages. International Journal of Adolescent Medicine and Health, 34(5), 367-369. https://doi.org/10.1515/ijamh-2020-0111

Baxter K. 2008. The Modern Age: Turn-of-the-Century American Culture and the Invention of Adolescence. Tuscaloosa: Univ. Ala. Press

Beyond the Click: Understanding the impact of views on TikTok. (2024). TikTok. https://www.tiktok.com/business/en/blog/beyond-click-attribution-views-impact-purchase?redirected=1

Billari FC, Badolato L, Hagestad GO, Liefbroer AC, Settersten RA, et al. 2021. The timing of life: topline results from round 9 of the European Social Survey. ESS Topline Results Ser. Issue 11, Eur. Soc. Surv., London

Bilro, R., Loureiro, S., & Santos, J. (2021). Masstige strategies on social media: the influence on sentiments and attitude toward the brand. International Journal of Consumer Studies, 46(4), 1113-1126. https://doi.org/10.1111/ijcs.12747

Blakemore, E. (2019). Race and ethnicity: How are they different? National Geographic. https://www.nationalgeographic.com/culture/topics/reference/race-ethnicity/.

Boisvert, J. and Ashill, N. (2018). The impact of branding strategies on horizontal and downward line extension of luxury brands. International Marketing Review, 35(6), 1033-1052. https://doi.org/10.1108/imr-10-2017-0208

Boisvert, J. and Ashill, N. (2021). The impact of gender on the evaluation of vertical line extensions of luxury brands: a cross-national study. Journal of Product & Brand Management, 31(3), 484-495. https://doi.org/10.1108/jpbm-09-2020-3119

Bossom, I. and Tabri, N. (2022). No evidence that exposure to materialistic advertisements influence appearance overvaluation and financial success overvaluation in the self-concept. Collabra Psychology, 8(1). https://doi.org/10.1525/collabra.32642

Boukes, M., Velde, B., Araujo, T., & Vliegenthart, R. (2019). What's the tone? easy doesn't do it: analyzing performance and agreement between off-the-shelf sentiment analysis tools. Communication Methods and Measures, 14(2), 83-104. https://doi.org/10.1080/19312458.2019.1671966

Bourcier-Bequaert, B., Chevalier, C., & Moal, G. (2021). The old and the beautiful: senior women's exposure to models in advertisements and the impact on their identity. Journal of Consumer Marketing, 38(4), 410-419. https://doi.org/10.1108/jcm-07-2019-3324

Boutilier, R. and Bahr, K. (2020). A natural language processing approach to social license management. Sustainability, 12(20), 8441. https://doi.org/10.3390/su12208441

Bozkurt, S., Gligor, D. M., & Babin, B. J. (2021). The role of perceived firm social media interactivity in facilitating customer engagement behaviors. European Journal of Marketing, 55(4), 995-1022.

Bozkurt, S., Gligor, D., & Hollebeek, L. (2021). Ethnicity's effect on social media-based comment intention: comparing minority and majority consumers. Psychology and Marketing, 38(11), 1895-1910. https://doi.org/10.1002/mar.21549

Bracey, G. E. (2022). The spirit of critical race theory. Sociology of Race and Ethnicity, 8(4), 503-517. https://doi.org/10.1177/23326492221114814

Brackett, K. P., Marcus, A., McKenzie, N. J., Mullins, L. C., Tang, Z., & Allen, A. M. (2006). The effects of multiracial identification on students' perceptions of racism. The Social Science Journal, 43(3), 437–444. https:// doi.org/10.1016/j.soscij.2006.04.016

Byun, S., Long, S., & Mann, M. (2020). Drivers and dynamics of brand prominence preferences among the chinese little emperors residing in the us. Journal of Fashion Marketing and Management, 24(1), 66-82. https://doi.org/10.1108/jfmm-01-2019-0007

Calasanti T, King N. 2015. Intersectionality and age. In Routledge Handbook of Cultural Gerontology, ed. J Twigg, W Martin, pp. 193–200. London: Routledge. 1st ed.

Cannon, C. and Rucker, D. (2018). The dark side of luxury: social costs of luxury consumption. Personality and Social Psychology Bulletin, 45(5), 767-779. https://doi.org/10.1177/0146167218796790

Cao, J. (2024). Enabling zaras operational innovation and value creation with artificial intelligence. Advances in Economics Management and Political Sciences, 86(1), 81-87. https://doi.org/10.54254/2754-1169/86/20240948

Carrasco-Santos, M. (2024). Evolution of men's image in fashion advertising: breaking stereotypes and embracing diversity. Journal of Theoretical and Applied Electronic Commerce Research, 19(1), 188-208. https://doi.org/10.3390/jtaer19010011

Carrigan, M. and Szmigin, I. (1999). The portrayal of older characters in magazine advertising. Journal of Marketing Practice Applied Marketing Science, 5(6/7/8), 248-261. https://doi.org/10.1108/eum0000000004577

Chan, K., Ng, Y., & Luk, E. (2013). Impact of celebrity endorsement in advertising on brand image among chinese adolescents. Young Consumers Insight and Ideas for Responsible Marketers, 14(2), 167-179. https://doi.org/10.1108/17473611311325564

Charta der Vielfalt. (n.d.). https://www.charta-der-vielfalt.de/en/

Cheah, I., Shimul, A., & Teah, M. (2022). Sustainability claim, environmental misconduct and perceived hypocrisy in luxury branding. Spanish Journal of Marketing - Esic, 27(3), 306-323. https://doi.org/10.1108/sjme-02-2022-0012

Chen, C. (2015). Advertising representations of older people in the united kingdom and taiwan. The International Journal of Aging and Human Development, 80(2), 140-183. https://doi.org/10.1177/0091415015590305

Chen, W., Ling, C., & Chen, C. (2022). What affects users to click social media ads and purchase intention? the roles of advertising value, emotional appeal and credibility. Asia Pacific Journal of Marketing and Logistics, 35(8), 1900-1916. https://doi.org/10.1108/apjml-01-2022-0084

Chen, X. and Li, Z. (2022). Investigating the consumer evaluation of the co-branding of luxury brands. International Journal of Research in Business and Social Science (2147-4478), 11(4), 01-15. https://doi.org/10.20525/ijrbs.v11i4.1808

Cheng, Z. and Li, Y. (2023). Like, comment, and share on tiktok: exploring the effect of sentiment and second-person view on the user engagement with tiktok news videos. Social Science Computer Review, 42(1), 201-223. https://doi.org/10.1177/08944393231178603

Chevalier, C. and Moal-Ulvoas, G. (2018). The use of mature models in advertisements and its contribution to the spirituality of older consumers. Journal of Consumer Marketing, 35(7), 721-732. https://doi.org/10.1108/jcm-04-2017-2175

Chiang, I., Lo, S., & Wang, L. (2018). Customer engagement behaviour in social media advertising: antecedents and consequences. Contemporary Management Research, 13(3). https://doi.org/10.7903/cmr.17673

Cosenza, W. (2024, 18. September). Diversity Fuels Creativity: How DEI is Driving Innovation in the Retail, Luxury and Tech Industries. Seramount. https://seramount.com/articles/diversity-fuels-creativity-how-dei-is-driving-innovation-in-the-retail-luxury-and-tech-industries/

Cowan, K. (2023). The influence of luxury brand personality on digital interaction evaluations: a focus on european and north american markets. International Marketing Review, 41(2), 386-410. https://doi.org/10.1108/imr-02-2022-0044

Cowan, K. and Kostyk, A. (2023). The influence of luxury brand personality on digital interaction evaluations: a focus on european and north american markets. International Marketing Review, 41(2), 386-410. https://doi.org/10.1108/imr-02-2022-0044

Creevey, D., Coughlan, J., & O'Connor, C. (2021). Social media and luxury: a systematic literature review. International Journal of Management Reviews, 24(1), 99-129. https://doi.org/10.1111/ijmr.12271

Crockett, D. (2008). Marketing blackness: How advertisers use race to sell products. Journal of consumer culture, 8(2), 245-268.

Cui, G. (2001). Marketing to ethnic minority consumers: a historical journey (1932-1997). Journal of Macromarketing, 21(1), 23-31. https://doi.org/10.1177/0276146701211003

Cunningham H. 2012. The Invention of Childhood. New York: Random House

Dahl, D. W., Sengupta, J., & Vohs, K. D. (2009). Sex in advertising: gender differences and the role of relationship commitment. Journal of Consumer Research, 36(2), 215-231. https://doi.org/10.1086/597158

Dannefer D. 2003. Cumulative advantage/disadvantage and the life course: cross-fertilizing age and social science theory. J. Gerontol. Ser. B 58(6):327–37

Das, S., Dutta, A., Lindheimer, T., Jalayer, M., & Elgart, Z. (2019). Youtube as a source of information in understanding autonomous vehicle consumers: natural language processing study. Transportation Research Record Journal of the Transportation Research Board, 2673(8), 242-253. https://doi.org/10.1177/0361198119842110

Davis, J., Love, T., & Fares, P. (2019). Collective social identity: synthesizing identity theory and social identity theory using digital data. Social Psychology Quarterly, 82(3), 254-273. https://doi.org/10.1177/0190272519851025

Dion, D. and Arnould, E. (2011). Retail luxury strategy: assembling charisma through art and magic. Journal of Retailing, 87(4), 502-520. https://doi.org/10.1016/j.jretai.2011.09.001

Dixon-Fyle, S., Giordano, M., Holt, T., Olanrewaju, T., Olufon, D., & Sancier-Sultan, S. (2024). Ethnocultural minorities in Europe: A potential triple win. In McKinsey & Company. https://www.mckinsey.com/featured-insights/europe/ethnocultural-minorities-in-europe-a-potential-triple-win

Doss, F. and Robinson, T. (2013). Luxury perceptions: luxury brand vs counterfeit for young us female consumers. Journal of Fashion Marketing and Management: An International Journal, 17(4), 424-439. https://doi.org/10.1108/jfmm-03-2013-0028

DUV. https://doi.org/10.1007/978-3-8350-9610-3

Ebrahim, R. (2021). Studying the drivers of consumer behavioural engagement with social media brand-related content. International Journal of Customer Relationship Marketing and Management, 13(1), 1-24. https://doi.org/10.4018/ijcrmm.2022010106

Eckhardt, G. M., Belk, R. W., & Wilson, J. A. (2014). The rise of inconspicuous consumption. Journal of Marketing Management, 31(7-8), 807-826. https://doi.org/10.1080/0267257x.2014.989890

Eftekhari, M., Perry, J. C., Rajabi, G., & Aslani, K. (2021). Explaining the marital adjustment process in iranian women: a grounded theory study. Journal of Research and Health, 11(2), 77-86. https://doi.org/10.32598/jrh.11.2.1706.1

Eisend, M. (2009). A meta-analysis of gender roles in advertising. Journal of the Academy of Marketing Science, 38(4), 418-440. https://doi.org/10.1007/s11747-009-0181-x

European Commission. (2020). Ageing Europe - statistics on population developments. Eurostat. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Ageing_Europe_-_statistics_on_population_developments9ce7fdbf-d7a3-47b3-9773-0ddc5ef7e997

Eurostat. (2024). Population structure and ageing. Eurostat. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Population_structure_and_ageing#Past_and_future_population_ageing_trends_in_the_EU

Fashion United. (2023). Most valuable fashion brands. FashionUnited. https://fashionunited.com/i/most-valuable-fashion-brands

Feliciano, C. (2016). Shades of race: How phenotype and observer characteristics shape racial classification. American Behavioral Scientist, 60(4), 390-419.

Ferreyra, E. (2022). Lgbtq+ representation in fictional podcast series. Literatura Ludowa, 66(2), 13-27. https://doi.org/10.12775/ll.2.2022.002

Fiani, C. N., & Han, H. J. (2020). Navigating identity: Experiences of binary and non-binary transgender and gender non-conforming (TGNC) adults. In Non-binary and Genderqueer Genders (pp. 63-76). Routledge.

Francis, J. (2022). Rescuing marketing from its colonial roots: a decolonial anti-racist agenda. Journal of Consumer Marketing, 40(5), 558-570. https://doi.org/10.1108/jcm-07-2021-4752

Franco, M., Durkee, M., & McElroy-Heltzel, S. (2021). Discrimination comes in layers: Dimensions of discrimination and mental health for multiracial people. Cultural Diversity and Ethnic Minority Psychology, 27(3), 343.

Freling, T. H. and Forbes, L. (2005). An empirical analysis of the brand personality effect. Journal of Product &Amp; Brand Management, 14(7), 404-413. https://doi.org/10.1108/10610420510633350

Frey, W. H. (2018, March 14). The US will become ‘minority white’ in 2045, Census projects. Brookings. https://www.brookings.edu/articles/the-us-will-become-minority-white-in-2045-census-projects/

Frey, W. H. (2021, August 13). New 2020 census results show increased diversity countering decade-long declines in America's white and youth populations. Brookings. https://www.brookings.edu/articles/new-2020-census-results-show-increased-diversity-countering-decade-long-declines-in-americas-white-and-youth-populations/

Gardenswartz, L. & Rowe, A. (2008). Diverse teams at work: Capitalizing on the power of diversity. Society for Human Resource Management.

Gardenswartz, L. and Rowe, A. (2003): Diverse Teams at Work. Society for Human Resource Management.

Geiger-Oneto, S., Nguyen, H., & Munch, J. (2022). An empirical investigation of regional differences in consumption behaviors in an emerging economy. Journal of Consumer Behaviour, 22(1), 27-42. https://doi.org/10.1002/cb.2120

Gensler, S., Völckner, F., Liu-Thompkins, Y., & Wiertz, C. (2013). Managing brands in the social media environment. Journal of Interactive Marketing, 27(4), 242-256. https://doi.org/10.1016/j.intmar.2013.09.004

Ghosh, I. (2020). Visualizing the U.S. population by race. Visual Capitalist. https://www.visualcapitalist.com/visualizing-u-s-population-by-race/

Ghosh, K. and Bhattacharya, S. (2022). Investigating the antecedents of luxury brand loyalty for gen z consumers in india: a pls-sem approach. Young Consumers Insight and Ideas for Responsible Marketers, 23(4), 603-626. https://doi.org/10.1108/yc-09-2021-1390

Gilleard C, Higgs P. 2002. The third age: class, cohort or generation? Ageing Soc. 22(3):369–82

Godey, B., Manthiou, A., Pederzoli, D., Rokka, J., Aiello, G., Donvito, R., … & Singh, R. (2016). Social media marketing efforts of luxury brands: influence on brand equity and consumer behavior. Journal of Business Research, 69(12), 5833-5841. https://doi.org/10.1016/j.jbusres.2016.04.181

Golub, M., Štadáni, D., & Bolek, Š. (2022). Consumers' attitudes toward social media and targeted advertising in the czech republic . Elektronički Zbornik Radova Veleučilišta U Šibeniku, 16(3-4), 59-75. https://doi.org/10.51650/ezrvs.16.3-4.3

Gonlin, V. (2020). Colorful reflections: Skin tone, reflected race, and perceived discrimination among Blacks, Latinxs, and Whites. Race and Social Problems, 12(3), 246-264.

González-Esteban, J. (2024). Intensification of hate speech, based on the conversation generated on tiktok during the escalation of the war in the middle east in 2023. Social Sciences, 13(1), 49. https://doi.org/10.3390/socsci13010049

Goodman, M., Adams, N., Corneil, T., Kreukels, B., Motmans, J., & Coleman, E. (2019). Size and distribution of transgender and gender nonconforming populations: a narrative review. Endocrinology and Metabolism Clinics, 48(2), 303-321.

Grassi, A. and Wigley, S. (2018). Gucci inclusivity is the new exclusivity. International Journal of Costume and Fashion, 18(1), 1-11. https://doi.org/10.7233/ijcf.2018.18.1.001

Grassi, A. and Wigley, S. M. (2018). Gucci inclusivity is the new exclusivity. International Journal of Costume and Fashion, 18(1), 1-11. https://doi.org/10.7233/ijcf.2018.18.1.001

Grier, S. A., Thomas, K. D., & Johnson, G. D. (2017). Re-imagining the marketplace: addressing race in academic marketing research. Consumption Markets &Amp; Culture, 22(1), 91-100. https://doi.org/10.1080/10253866.2017.1413800

Guo, X. and Zhang, L. (2019). The marketing plan for louis vuitton's entry into the market of cambodia.. https://doi.org/10.2991/assehr.k.191221.048

Gupta, S. and Kour, P. (2021). Luxury hospitality service adoption amongst indian millennial: an analytical approach. Enlightening Tourism a Pathmaking Journal, 11(2), 360. https://doi.org/10.33776/et.v11i2.5080

Hagtvedt, H. and Patrick, V. (2009). The broad embrace of luxury: hedonic potential as a driver of brand extendibility. Journal of Consumer Psychology, 19(4), 608-618. https://doi.org/10.1016/j.jcps.2009.05.007

Haselmayer, M. and Jenny, M. (2016). Sentiment analysis of political communication: combining a dictionary approach with crowdcoding. Quality & Quantity, 51(6), 2623-2646. https://doi.org/10.1007/s11135-016-0412-4

Hashim, N. and Sajali, N. (2018). The influence factors towards mobile advertising message content on consumer purchase intention. Global Business Review, 19(5), 1187-1206. https://doi.org/10.1177/0972150918788746

Hassan, S., Ilyas, M., & Rehman, C. (2016). Corporate branding , emotional attachment and brand loyalty : the case of luxury fashion branding. Kuwait Chapter of Arabian Journal of Business and Management Review, 6(2), 43-57. https://doi.org/10.12816/0031561

Hawkins, A. and Filtness, A. (2017). Driver sleepiness on youtube: a content analysis. Accident Analysis & Prevention, 99, 459-464. https://doi.org/10.1016/j.aap.2015.11.025

Heath, A., Carlsson, M., & Agerström, J. (2023). What adds to job ads? the impact of equality and diversity information on organizational attraction in minority and majority ethnic groups. Journal of Occupational and Organizational Psychology, 96(4), 872-896. https://doi.org/10.1111/joop.12454

Hennigs, N., Wiedmann, K., Behrens, S., & Klarmann, C. (2013). Unleashing the power of luxury: antecedents of luxury brand perception and effects on luxury brand strength. Journal of Brand Management, 20(8), 705-715. https://doi.org/10.1057/bm.2013.11

Herget, A. and Bötzl, F. (2021). Sounds like respect. the impact of background music on the acceptance of gay men in audio-visual advertising. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.645533

Herjanto, H., Gaur, S., & Yap, S. (2015). Consumer emotional responses to emotional appeal advertising within an online social network context., 226-233. https://doi.org/10.1007/978-3-319-24184-5_59

Hoyer, W. D. and Brown, S. P. (1990). Effects of brand awareness on choice for a common, repeat-purchase product. Journal of Consumer Research, 17(2), 141. https://doi.org/10.1086/208544

Hruska, J. (2020). Sentiment analysis of national tourism organizations on social media.. https://doi.org/10.36689/uhk/hed/2020-01-028

Huang, R., Ha, S., & Kim, S. (2018). Narrative persuasion in social media: an empirical study of luxury brand advertising. Journal of Research in Interactive Marketing, 12(3), 274-292. https://doi.org/10.1108/jrim-07-2017-0059

Hudders, L. and Pandelaere, M. (2011). The silver lining of materialism: the impact of luxury consumption on subjective well-being. Journal of Happiness Studies, 13(3), 411-437. https://doi.org/10.1007/s10902-011-9271-9

Hughes, M., Bendoni, W., & Pehlivan, E. (2016). Storygiving as a co-creation tool for luxury brands in the age of the internet: a love story by tiffany and thousands of lovers. Journal of Product & Brand Management, 25(4), 357-364. https://doi.org/10.1108/jpbm-09-2015-0970

Hur, W., Kim, M., & Kim, H. (2014). The role of brand trust in male customers' relationship to luxury brands. Psychological Reports, 114(2), 609-624. https://doi.org/10.2466/01.07.pr0.114k15w8

Hwang, J. and Kandampully, J. (2012). The role of emotional aspects in younger consumer-brand relationships. Journal of Product & Brand Management, 21(2), 98-108. https://doi.org/10.1108/10610421211215517

Iglesias-Sánchez, P., Jambrino-Maldonado, C., Pedrosa, C., & Díaz-Tendero, R. (2023). Queervertising: an empowerment tool for the gay men and lesbian community. F1000research, 12, 295. https://doi.org/10.12688/f1000research.126882.1

Iijima Hall, C. I. (2004). Mixed-race women: One more mountain to climb. Women & Therapy, 27(1–2), 237–246. https://doi.org/10.1300/ J015v27n01_16

Islam, S., & Woodford, E. (2022, November 22). Diversity and power in the European Union. European Policy Center. Retrieved February 29, 2024, from https://www.epc.eu/content/PDF/2022/Jubilee_Papers/Jubilee_Think_Piece_Islam_Woodford.pdf

Ivanov, L. (2016). The «4cs» of cultural diversity in consumer research: a literature review and research agenda. European Journal of Management Issues, (7), 194-200. https://doi.org/10.15421/191620

Jablonski, N. G. (2021). Skin color and race. American journal of physical anthropology, 175(2), 437-447.

Jiang, M., Gao, D., Ren, H., DeWall, C., & Zhou, X. (2014). The devil wears prada: advertisements of luxury brands evoke feelings of social exclusion. Asian Journal of Social Psychology, 17(4), 245-254. https://doi.org/10.1111/ajsp.12069

Johfre, S., & Saperstein, A. (2023). The Social Construction of Age: Concepts and Measurement. Annual Review of Sociology, 49.

Jongeling, R., Sarkar, P., Datta, S., & Serebrenik, A. (2017). On negative results when using sentiment analysis tools for software engineering research. Empirical Software Engineering, 22(5), 2543-2584. https://doi.org/10.1007/s10664-016-9493-x

Jung, S. (2023). Normalization of vaping on tiktok: a mixed-methods approach using computer vision, natural language processing, and qualitative thematic analysis (preprint). Journal of Medical Internet Research. https://doi.org/10.2196/55591

Kaiser, C., Major, B., Jurcevic, I., Dover, T., Brady, L., & Shapiro, J. (2013). Presumed fair: ironic effects of organizational diversity structures.. Journal of Personality and Social Psychology, 104(3), 504-519. https://doi.org/10.1037/a0030838

Kankaanpää, A., Tolvanen, A., Bollepalli, S., Leskinen, T., Kujala, U. M., Kaprio, J., ... & Sillanpää, E. (2021). Leisure-time and occupational physical activity associates differently with epigenetic aging. Medicine and Science in Sports and Exercise, 53(3), 487.

Karay, Yassin & Hallal, H. & Stosch, Christoph. (2018). Research into finding a stable prognosis parameter for the detection of students in need of guidance - Realization of equal opportunities through a diversity-oriented study guidance. GMS Journal for Medical Education. 35.

Kashif, M., Devrani, T., Rehman, A., & Samad, S. (2021). Love is not blind: investigating a love-hate transition among luxury fashion brand consumers. Journal of Fashion Marketing and Management, 25(4), 625-643. https://doi.org/10.1108/jfmm-04-2020-0058

Kasztalska, A. (2018). Louis vuitton as an example of the old and modern in the same time luxury brand in the eyes of its clientele. Cbu International Conference Proceedings, 6, 226-230. https://doi.org/10.12955/cbup.v6.1161

Kauffmann, E., Peral, J., Gil, D., Ferrández, A., Sellers, R., & Mora, H. (2019). Managing marketing decision-making with sentiment analysis: an evaluation of the main product features using text data mining. Sustainability, 11(15), 4235. https://doi.org/10.3390/su11154235

Kautish, P., Khare, A., & Sharma, R. (2020). Influence of values, brand consciousness and behavioral intentions in predicting luxury fashion consumption. Journal of Product & Brand Management, 30(4), 513-531. https://doi.org/10.1108/jpbm-08-2019-2535

Keel, A. and Nataraajan, R. (2012). Celebrity endorsements and beyond: new avenues for celebrity branding. Psychology and Marketing, 29(9), 690-703. https://doi.org/10.1002/mar.20555

Keith J, Fry CL, Glascock AP, Ikels C, Dickerson-Putman J, et al. 1994. The Aging Experience: Diversity and Commonality Across Cultures. Thousand Oaks, CA: SAGE

Keller, K. (2009). Managing the growth tradeoff: challenges and opportunities in luxury branding. Journal of Brand Management, 16(5-6), 290-301. https://doi.org/10.1057/bm.2008.47

Khan, H., Lee, R., & Lockshin, L. (2015). Do ethnic cues improve advertising effectiveness for ethnic consumers?. Australasian Marketing Journal (Amj), 23(3), 218-226. https://doi.org/10.1016/j.ausmj.2015.07.001

Khan, Z., & Fu, Y. (2021). One label, one billion faces: Usage and consistency of racial categories in computer vision. In Proceedings of the 2021 acm conference on fairness, accountability, and transparency (pp. 587-597).

Kim, D., Spiller, L., & Hettche, M. (2015). Analyzing media types and content orientations in facebook for global brands. Journal of Research in Interactive Marketing, 9(1), 4-30. https://doi.org/10.1108/jrim-05-2014-0023

Kim, J. and Park, J. (2020). The impact of socioeconomic status on preference for sustainable luxury brands.. https://doi.org/10.21203/rs.3.rs-79790/v1

Koay, K. Y. (2018). Understanding consumers' purchase intention towards counterfeit luxury goods. Asia Pacific Journal of Marketing and Logistics, 30(2), 495-516. https://doi.org/10.1108/apjml-05-2017-0100

Kohlbacher, F., Prieler, M., & Hagiwara, S. (2013). Japan's demographic revolution? a study of advertising practitioners' views on stereotypes. Asia Pacific Business Review, 20(2), 249-268. https://doi.org/10.1080/13602381.2013.841451

Korostelina, K. (2014). Intergroup identity insults: a social identity theory perspective. Identity, 14(3), 214-229. https://doi.org/10.1080/15283488.2014.921170

Kumagai, K. and Nagasawa, S. (2015). Customer experience and determinants of consumer attitude toward luxury brands: observations in japan and china. Science Journal of Business and Management, 3(2), 24. https://doi.org/10.11648/j.sjbm.s.2015030201.13

Kumar, V., Khan, I., Fatma, M., & Singh, A. (2022). Engaging luxury brand consumers on social media. Journal of Consumer Marketing, 39(1), 121-132. https://doi.org/10.1108/jcm-10-2020-4175

Kwon, E. (2023). Materialistic consumers who need to signal their status: examination of antecedents and consequences of consumers' luxury brands engagement on social media. International Journal of Marketing Studies, 15(1), 98. https://doi.org/10.5539/ijms.v15n1p98

Laforet, P., Basch, C., & Tang, H. (2022). Understanding the content of covid-19 vaccination and pregnancy videos on youtube: an analysis of videos published at the start of the vaccine rollout. Human Vaccines & Immunotherapeutics, 18(5). https://doi.org/10.1080/21645515.2022.2066935

Langer, M., Roulin, N., & Oostrom, J. (2023). Diversity and technology—challenges for the next decade in personnel selection. International Journal of Selection and Assessment, 31(3), 355-360. https://doi.org/10.1111/ijsa.12439

Lassar, W. M., Mittal, B., & Sharma, A. (1995). Measuring customer-based brand equity. Journal of Consumer Marketing, 12(4), 11-19. https://doi.org/10.1108/07363769510095270

Lau, H. and Lee, R. (2018). Ethnic media advertising effectiveness, influences and implications. Australasian Marketing Journal (Amj), 26(3), 216-220. https://doi.org/10.1016/j.ausmj.2018.05.014

Lau, H. T. and Lee, R. (2018). Ethnic media advertising effectiveness, influences and implications. Australasian Marketing Journal, 26(3), 216-220. https://doi.org/10.1016/j.ausmj.2018.05.014

Lau, M., Ng, P., Chan, E., & Cheung, C. (2022). Examining purchase intention for luxury fashion: integrating theory of reasoned action, with affect-behavior-cognition (abc) model, identity and social identity theories. Young Consumers Insight and Ideas for Responsible Marketers, 24(1), 114-131. https://doi.org/10.1108/yc-07-2022-1557

Lee, B., Kim, B., & Han, S. (2006). The portrayal of older people in television advertisements: a cross-cultural content analysis of the united states and south korea. The International Journal of Aging and Human Development, 63(4), 279-297. https://doi.org/10.2190/ellg-jely-uccy-4l8m

Lenne, O., Mahon, C., Eggermont, S., Smits, T., Hevey, D., & Vandenbosch, L. (2023). Intercultural insights on the impact of different non-idealized models on men's body image and advertising perceptions. Journal of Health Psychology, 28(10), 913-928. https://doi.org/10.1177/13591053231152012

Lewis, I., Watson, B., & White, K. (2008). An examination of message-relevant affect in road safety messages: should road safety advertisements aim to make us feel good or bad?. Transportation Research Part F Traffic Psychology and Behaviour, 11(6), 403-417. https://doi.org/10.1016/j.trf.2008.03.003

Li, Y. (2021). How should zara optimize its marketing strategies to cater to the needs of new generations – gen z and millennials.. https://doi.org/10.2991/aebmr.k.210917.048

Liaukonytė, J., Teixeira, T. S., & Wilbur, K. C. (2015). Television advertising and online shopping. Marketing Science, 34(3), 311-330. https://doi.org/10.1287/mksc.2014.0899

Lin, H. (2023). Applying means-end chains theory to understanding psychological cognitive structure of online video sharing platforms: a study of user behavior in tiktok. Journal of Consumer Behaviour, 23(3), 1158-1174. https://doi.org/10.1002/cb.2268

Lips, H. M. (2016). A new psychology of women: Gender, culture, and ethnicity. Waveland Press.

Liu, S. (2024). Analyzing the strategic impact of zara's branding strategies on consumer engagement and market position. SHS Web of Conferences, 185, 03018. https://doi.org/10.1051/shsconf/202418503018

Livas, C., Theofanidis, F., & Karali, N. (2023). Consumer sentiment toward international activist advertising. Innovative Marketing, 19(2), 250-260. https://doi.org/10.21511/im.19(2).2023.20

Lucka, N., Caldieraro, F., & Zanini, M. (2021). The influence of gender stereotyping and issue advocacy on consumer sentiment. Marketing Intelligence & Planning, 39(6), 777-791. https://doi.org/10.1108/mip-11-2020-0469

López, C. and Fan, Y. (2009). Internationalisation of the spanish fashion brand zara. Journal of Fashion Marketing and Management, 13(2), 279-296. https://doi.org/10.1108/13612020910957770

Maj, Jolanta. (2015). Diversity management's stakeholders and stakeholders management. Proceedings of the 9th International Management Conference. 9. 780-793.

MajlesiRad, Z. and Shoushtari, A. (2020). Analysis of the impact of social network sites and ewom marketing, considering the reinforcing dimensions of the concept of luxury, on tendency toward luxury brand. Future Business Journal, 6(1). https://doi.org/10.1186/s43093-020-00025-w

Makarem, S. and Jae, H. (2015). Consumer boycott behavior: an exploratory analysis of twitter feeds. Journal of Consumer Affairs, 50(1), 193-223. https://doi.org/10.1111/joca.12080

Makhitha, K. (2021). Black consumers perceptions towards luxury brands in south africa. International Journal of Research in Business and Social Science (2147-4478), 10(4), 28-36. https://doi.org/10.20525/ijrbs.v10i4.1135

Malik, R. and Sibaroni, Y. (2022). Multi-aspect sentiment analysis of tiktok application usage using fastext feature expansion and cnn method. Journal of Computer System and Informatics (Josyc), 3(4), 277-285. https://doi.org/10.47065/josyc.v3i4.2033

Mandal, P. (2021). Achieving business excellence for luxury brands. International Journal of Business Strategy and Automation, 2(4), 1-14. https://doi.org/10.4018/ijbsa.287108

Marmot M. 2004. Status Syndrome: How Your Social Standing Directly Affects Your Health. London: Bloomsbury

Martins, J., Costa, C. B. d., Oliveira, T., Gonçalves, R., & Branco, F. (2019). How smartphone advertising influences consumers' purchase intention. Journal of Business Research, 94, 378-387. https://doi.org/10.1016/j.jbusres.2017.12.047

Marynak, K., Robichaud, M., Puryear, T., Kennedy, R., & Moran, M. (2022). #nicotineaddiction on tiktok: a quantitative content analysis of top-viewed posts. Tobacco Induced Diseases, 20(August), 1-9. https://doi.org/10.18332/tid/151868

Matić, L. and Bajs, I. (2022). Specificity and development of distribution strategies of luxury fashion brands. Textile & Leather Review, 5, 540-563. https://doi.org/10.31881/tlr.2022.69

Matthews, D. and Dietz-Uhler, B. (1998). The black-sheep effect: how positive and negative advertisements affect voters' perceptions of the sponsor of the advertisement1. Journal of Applied Social Psychology, 28(20), 1903-1915. https://doi.org/10.1111/j.1559-1816.1998.tb01352.x

Maung, H. H. (2021). What's my age again? Age categories as interactive kinds. History and Philosophy of the Life Sciences, 43(1), 36.

McDonald, R., Laverie, D., & Manis, K. (2020). The interplay between advertising and society: an historical analysis. Journal of Macromarketing, 41(4), 585-609. https://doi.org/10.1177/0276146720964324

Meijani, M., Rousta, A., & Jamshidi, D. (2023). Is brand addiction important to persuade islamic consumers in order to repurchase luxury products?. South Asian Journal of Marketing, 4(2), 93-109. https://doi.org/10.1108/sajm-12-2022-0078

Michaelidou, N., Siamagka, N., Hatzithomas, L., & Chaput, L. (2022). Femvertising practices on social media: a comparison of luxury and non-luxury brands. Journal of Product & Brand Management, 31(8), 1285-1300. https://doi.org/10.1108/jpbm-09-2020-3074

Mikulak, M. L. (2011). The symbolic power of color: Constructions of race, skin-color, and identity in Brazil. Humanity & Society, 35(1-2), 62-99.

Montes, A. (2021). Gender stereotyping and retro-sexism in advertising discourse from a postfeminist perspective. Feminismo/S, (38), 177. https://doi.org/10.14198/fem.2021.38.07

Most valuable fashion brands. (o. D.). FashionUnited. https://fashionunited.com/i/most-valuable-fashion-brands

Moursi, A. (2024, 27. Mai). How to Get More Views on TikTok (2024). Hopper HQ. https://www.hopperhq.com/blog/how-to-get-more-views-on-tiktok/#:~:text=On%20TikTok%2C%20a%20view%20is,you%20watch%20your%20own%20video

Murgia, A., Tourani, P., Adams, B., & Ortu, M. (2014). Do developers feel emotions? an exploratory analysis of emotions in software artifacts.. https://doi.org/10.1145/2597073.2597086

Murugesan, S. (2023). Sentiment analysis of celebrity-endorsed advertisements. IMS. https://doi.org/10.1177/0976030x231163380

Mähnert, L. (2024). Brand heritage on twitter: a text-mining stereotype content perspective. Journal of Product & Brand Management, 33(3), 370-384. https://doi.org/10.1108/jpbm-07-2023-4612

Neugarten BL. 1974. Age groups in American society and the rise of the young-old. Ann. Am. Acad. Political Soc. Sci. 415(1):187–98

Nguyen, T., Criss, S., Allen, A., Glymour, M., Phan, L., Trevino, R., … & Nguyen, Q. (2019). Pride, love, and twitter rants: combining machine learning and qualitative techniques to

understand what our tweets reveal about race in the us. International Journal of Environmental Research and Public Health, 16(10), 1766. https://doi.org/10.3390/ijerph16101766

Nkomo, S. M. (2021). Reflections on the continuing denial of the centrality of “race” in management and organization studies. Equality, Diversity and Inclusion: An International Journal, 40(2), 212-224. https://doi.org/10.1108/edi-01-2021-0011

Norman, M. and McFarlane-Alvarez, S. (2023). Beyond colorblindness in advertising education: multiculturalism and advertising pedagogy since the 2020 racial reckoning. Journal of Advertising Education, 27(2), 91-100. https://doi.org/10.1177/10980482231174885

Oc, Y., Plangger, K., Sands, S., Campbell, C., & Pitt, L. (2023). Luxury is what you say: analyzing electronic word-of-mouth marketing of luxury products using artificial intelligence and machine learning. Psychology and Marketing, 40(9), 1704-1719. https://doi.org/10.1002/mar.21831

Ochkovskaya, M., Mkhitaryan, S., Indichekova, E., & Puig, V. (2021). Influence of collaborations with visual art on luxury brand identity: pilot study. Vestnik of Saint Petersburg University Management, 20(1), 3-29. https://doi.org/10.21638/11701/spbu08.2021.101

Oeppen, J. and Jamal, A. (2014). Collaborating for success: managerial perspectives on co-branding strategies in the fashion industry. Journal of Marketing Management, 30(9-10), 925-948. https://doi.org/10.1080/0267257x.2014.934905

Oksanen, A., García, D., Sirola, A., Näsi, M., Kaakinen, M., Keipi, T., … & Räsänen, P. (2015). Pro-anorexia and anti-pro-anorexia videos on youtube: sentiment analysis of user responses. Journal of Medical Internet Research, 17(11), e256. https://doi.org/10.2196/jmir.5007

Oliver, M., Datta, S., & Baldwin, D. R. (2017). Wellness among african-american and caucasian students attending a predominantly white institution. Journal of Health Psychology, 24(12), 1637-1645. https://doi.org/10.1177/1359105317694484

Owotomo, O., & Walley, S. (2022). The youth e-cigarette epidemic: updates and review of devices, epidemiology and regulation. Current problems in pediatric and adolescent health care, 52(6), 101200.

Pair, E., Vicas, N., Weber, A., Meausoone, V., Zou, J., & Njuguna, A. (2021). Quantification of gender bias and sentiment toward political leaders over 20 years of kenyan news

using natural language processing. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.712646

Pan, P. and Zhang, H. (2023). Research on social media advertising persuasion based on the elaboration likelihood model. SHS Web of Conferences, 154, 03024. https://doi.org/10.1051/shsconf/202315403024

Pang, B. and Lee, L. (2008). Opinion mining and sentiment analysis. Foundations and Trends® in Information Retrieval, 2(1–2), 1-135. https://doi.org/10.1561/1500000011

Pankiw, S., Phillips, B., & Williams, D. (2020). Luxury brands' use of csr and femvertising: the case of jewelry advertising. Qualitative Market Research an International Journal, 24(3), 302-325. https://doi.org/10.1108/qmr-05-2020-0061

Park, H., Rabolt, N., & Jeon, K. (2008). Purchasing global luxury brands among young korean consumers. Journal of Fashion Marketing and Management, 12(2), 244-259. https://doi.org/10.1108/13612020810874917

Patil, P. (2019). A study on celebrity endorsed promotional video advertisements with reference to jewelers. International Journal of Advanced Scientific Research and Management, 4(4). https://doi.org/10.36282/ijasrm/4.4.2019.1436

Peluso, A., Pino, G., Amatulli, C., & Guido, G. (2017). Luxury advertising and recognizable artworks. European Journal of Marketing, 51(11/12), 2192-2206. https://doi.org/10.1108/ejm-09-2016-0496

Peng, W. and Park, D. (2021). Generate adjective sentiment dictionary for social media sentiment analysis using constrained nonnegative matrix factorization. Proceedings of the International Aaai Conference on Web and Social Media, 5(1), 273-280. https://doi.org/10.1609/icwsm.v5i1.14090

Pfundmair, M., Graupmann, V., Du, H., Frey, D., & Aydin, N. (2014). Suddenly included: cultural differences in experiencing re-inclusion. International Journal of Psychology, 50(2), 85-92. https://doi.org/10.1002/ijop.12082

Phillips, K., & O'Reilly. (1998). Demography and Diversity in Organizations: A Review of 40 Years of Research. JAI Press.

Pierce, J., Sargent, J., Portnoy, D., White, M., Noble, M., Kealey, S., … & Hyland, A. (2018). Association between receptivity to tobacco advertising and progression to tobacco use in youth and young adults in the path study. Jama Pediatrics, 172(5), 444. https://doi.org/10.1001/jamapediatrics.2017.5756

Poole, S. M., Grier, S. A., Thomas, K. D., Sobande, F., Ekpo, A. E., Torres, L. T., … & Henderson, G. R. (2020). Operationalizing critical race theory in the marketplace.

Journal of Public Policy &Amp; Marketing, 40(2), 126-142. https://doi.org/10.1177/0743915620964114

Pozharliev, R., Verbeke, W., Angelis, M., Bos, R., & Peverini, P. (2021). Consumer self-reported and testosterone responses to advertising of luxury goods in social context. Italian Journal of Marketing, 2021(1-2), 103-127. https://doi.org/10.1007/s43039-021-00023-y

Pradhan, D., Israel, D., & Sethi, D. (2014). Celebrity endorsement: how celebrity–brand–user personality congruence affects brand attitude and purchase intention. Journal of Marketing Communications, 22(5), 456-473. https://doi.org/10.1080/13527266.2014.914561

Prieler, M., Ivanov, A., & Hagiwara, S. (2016). The representation of older people in east asian television advertisements. The International Journal of Aging and Human Development, 85(1), 67-89. https://doi.org/10.1177/0091415016677972

Prieler, M., Kohlbacher, F., Hagiwara, S., & Arima, A. (2014). The representation of older people in television advertisements and social change: the case of japan. Ageing and Society, 35(4), 865-887. https://doi.org/10.1017/s0144686x1400004x

Puwandi, P., De, G., & Brasali, N. (2020). The factors affecting consumer response towards online video advertisement: youtube as a platform. International Journal of Multicultural and Multireligious Understanding, 7(2), 375. https://doi.org/10.18415/ijmmu.v7i2.1396

Pütter, M. (2017). The impact of social media on consumer buying intention. Journal of International Business Research and Marketing, 3(1), 7-13. https://doi.org/10.18775/jibrm.1849-8558.2015.31.3001

Qin, Y. (2020). Fostering brand–consumer interactions in social media: the role of social media uses and gratifications. Journal of Research in Interactive Marketing, 14(3), 337-354. https://doi.org/10.1108/jrim-08-2019-0138

Radon, A. (2012). Unintended brand endorsers' impact on luxury brand image. International Journal of Marketing Studies, 4(1). https://doi.org/10.5539/ijms.v4n1p108

Ramadan, Z., Farah, M., & Dukenjian, A. (2018). Typology of social media followers: the case of luxury brands. Marketing Intelligence & Planning, 36(5), 558-571. https://doi.org/10.1108/mip-01-2018-0039

Rambocas, M. and Pacheco, B. (2018). Online sentiment analysis in marketing research: a review. Journal of Research in Interactive Marketing, 12(2), 146-163. https://doi.org/10.1108/jrim-05-2017-0030

Rao, Q. and Ko, E. (2021). Impulsive purchasing and luxury brand loyalty in wechat mini program. Asia Pacific Journal of Marketing and Logistics, 33(10), 2054-2071. https://doi.org/10.1108/apjml-08-2020-0621

Rashid, S. and Chattaraman, V. (2019). Do consumers react differently to sweatshop allegations on luxury and non-luxury brands? a brand entitativity-based account. Journal of Fashion Marketing and Management, 23(1), 138-155. https://doi.org/10.1108/jfmm-12-2017-0139

Rebollo, J. and García, N. (2022). The representation of phenotypic diversity in audiovisual advertising in spain: professional perspectives and implications for the cultural dynamics of inclusion. Anàlisi, (Extra), 131-148. https://doi.org/10.5565/rev/analisi.3401

Ren, Y. and Yuan, Z. (2022). Marketing strategy and consumer psychology.. https://doi.org/10.2991/assehr.k.220105.021

Rendtorff, B., Mahs, C. & Warmuth, A. D. (2020). Geschlechterverwirrungen. Campus Verlag.

Rennes, J., & Throssell, K. (2019). Unpacking Age as a Category: Chronological Age, Life Stage, and Bodily Aging in Age-Based Prejudice. Revue Française de Sociologie (English Edition), 60(2), 1–25. https://www.jstor.org/stable/48740416

Results from the 2013 national survey on drug use and health: Summary of national findings (NSDUH Series H-48, HHS Publication No. (SMA) 14-4863). Substance Abuse and Mental Health Services Administration.

Ritchie, H., & Roser, M. (2024). Gender ratio. Our World in Data. https://ourworldindata.org/gender-ratio

Robinson, T., Gustafson, B., & Popovich, M. (2008). Perceptions of negative stereotypes of older people in magazine advertisements: comparing the perceptions of older adults and college students. Ageing and Society, 28(2), 233-251. https://doi.org/10.1017/s0144686x07006605

Rocklage, M. D., Rucker, D. D., & Nordgren, L. F. (2018). The Evaluative Lexicon 2.0: The measurement of emotionality, extremity, and valence in language. Behavior research methods, 50, 1327-1344. https://doi.org/10.3758/s13428-017-0975-6

Roper, S., Caruana, R., Medway, D., & Murphy, P. (2013). Constructing luxury brands: exploring the role of consumer discourse. European Journal of Marketing, 47(3/4), 375-400. https://doi.org/10.1108/03090561311297382

Roth, W. D. (2010). Racial mismatch: the divergence between form and function in data for monitoring racial discrimination of hispanics*. Social Science Quarterly, 91(5), 1288-1311. https://doi.org/10.1111/j.1540-6237.2010.00732.x

Rubaca, U. (2023). Readiness to manage more diversity and inclusion to gain competitive advantage in changing landscape of the workplace. The Changing Landscape of Workplace and Workforce. https://doi.org/10.5772/intechopen.1003122

Rumapea, A., Tumbuan, W., & Tielung, M. (2022). The influence of brand luxury, brand awareness, and perceived quality on purchase intention of iphone in manado. Jurnal Emba Jurnal Riset Ekonomi Manajemen Bisnis Dan Akuntansi, 10(3), 215. https://doi.org/10.35794/emba.v10i3.41961

Räsänen, J. (2021, April 1). Does the distinction between biological and chronological age support legal age change? Bioethics. https://bioethics.hms.harvard.edu/journal/legal-age-change

Schivinski, B., Muntinga, D., Pontes, H., & Łukasik, P. (2019). Influencing cobras: the effects of brand equity on the consumer's propensity to engage with brand-related content on social media. Journal of Strategic Marketing, 29(1), 1-23. https://doi.org/10.1080/0965254x.2019.1572641

Schlabach, S. (2013). The importance of family, race, and gender for multiracial adolescent well-being. Family Relations: An Interdisciplinary Journal of Applied Family Studies, 62(1), 154–174. https://doi.org/10 .1111/j.1741-3729.2012.00758.x

Schweidel, D. and Moe, W. (2014). Listening in on social media: a joint model of sentiment and venue format choice. Journal of Marketing Research, 51(4), 387-402. https://doi.org/10.1509/jmr.12.0424

Seifert, C., Cui, T., & Chattaraman, V. (2019). Can brands deviate from their brand aesthetic? brand luxury status as a moderator. Journal of Fashion Marketing and Management, 23(2), 176-192. https://doi.org/10.1108/jfmm-05-2018-0072

Sengupta, J. and Gorn, G. (2002). Absence makes the mind grow sharper: effects of element omission on subsequent recall. Journal of Marketing Research, 39(2), 186-201. https://doi.org/10.1509/jmkr.39.2.186.19082

Seo, Y., Buchanan-Oliver, M., & Cruz, A. (2015). Luxury brand markets as confluences of multiple cultural beliefs. International Marketing Review, 32(2), 141-159. https://doi.org/10.1108/imr-04-2013-0081

Seo, Y., Ko, D., & Kim, J. (2019). It is all in the mind(set)! matching mindsets and luxury tourism. Journal of Travel Research, 60(1), 184-196. https://doi.org/10.1177/0047287519888280

Seo, Y., Sung, B., & Fang, Z. (2020). Authenticity and exclusivity appeals in luxury advertising: the role of promotion and prevention pride. European Journal of Marketing, 54(6), 1305-1323. https://doi.org/10.1108/ejm-10-2018-0690

Shabbir, H., Hyman, M. R., & Kostyk, A. (2023). Guest editorial: challenging the coloniality of raced markets. Journal of Consumer Marketing, 40(5), 549-557. https://doi.org/10.1108/jcm-05-2023-6027

Shao, X. (2022). A study on the utilization of fan economy by luxury brands in chinese market—taking louis vuitton as an example. BCP Business & Management, 20, 216-220. https://doi.org/10.54691/bcpbm.v20i.947

Sharda, N. and Bhat, A. (2018). Austerity to materialism and brand consciousness: luxury consumption in india. Journal of Fashion Marketing and Management, 22(2), 223-239. https://doi.org/10.1108/jfmm-03-2017-0025

Sharma, P., Pradhan, S., & Srivastava, A. (2021). Understanding the luxury purchase intentions of young consumers: a qualitative analysis. Asia-Pacific Journal of Business Administration, 13(4), 452-476. https://doi.org/10.1108/apjba-01-2021-0019

Shukla, P. (2008). Conspicuous consumption among middle age consumers: psychological and brand antecedents. Journal of Product & Brand Management, 17(1), 25-36. https://doi.org/10.1108/10610420810856495

Shukla, P., Rosendo-Ríos, V., Trott, S., Lyu, J., & Khalifa, D. (2022). Managing the challenge of luxury democratization: a multicountry analysis. Journal of International Marketing, 30(4), 44-59. https://doi.org/10.1177/1069031x221126925

Shukla, P., Singh, J., & Banerjee, M. (2015). They are not all same: variations in asian consumers' value perceptions of luxury brands. Marketing Letters, 26(3), 265-278. https://doi.org/10.1007/s11002-015-9358-x

Silver CB. 2003. Gendered identities in old age: toward (de)gendering? J. Aging Stud. 17(4):379–97

Smedley, A., & Smedley, B. D. (2005). Race as biology is fiction, racism as a social problem is real: Anthropological and historical perspectives on the social construction of race. American psychologist, 60(1), 16.

Smith, L. and Foxcroft, D. (2009). The effect of alcohol advertising, marketing and portrayal on drinking behaviour in young people: systematic review of prospective cohort studies. BMC Public Health, 9(1). https://doi.org/10.1186/1471-2458-9-51

So, J., Parsons, A., & Yap, S. (2013). Corporate branding, emotional attachment and brand loyalty: the case of luxury fashion branding. Journal of Fashion Marketing and Management, 17(4), 403-423. https://doi.org/10.1108/jfmm-03-2013-0032

Song, C., Zheng, L., & Shan, X. (2022). An analysis of public opinions regarding internet-famous food: a 2016–2019 case study on dianping. British Food Journal, 124(12), 4462-4476. https://doi.org/10.1108/bfj-05-2021-0510

Sood, S., & Moody, H. R. (2020). Age Branding. The Aging Consumer: Perspectives from Psychology and Marketing, 200.

Southwick, L., Guntuku, S., Klinger, E., Seltzer, E., McCalpin, H., & Merchant, R. (2021). Characterizing covid-19 content posted to tiktok: public sentiment and response during the first phase of the covid-19 pandemic. Journal of Adolescent Health, 69(2), 234-241. https://doi.org/10.1016/j.jadohealth.2021.05.010

Souza, E. M. d. (2019). Intersections between race and class: a postcolonial analysis and implications for organizational leaders. BAR - Brazilian Administration Review, 16(1). https://doi.org/10.1590/1807-7692bar2019180062

Spizzirri, G., Eufrásio, R., Lima, M. C. P., de Carvalho Nunes, H. R., Kreukels, B. P., Steensma, T. D., & Abdo, C. H. N. (2021). Proportion of people identified as transgender and non-binary gender in Brazil. Scientific reports, 11(1), 2240.

Srnka, K. J., & Koeszegi, S. T. (2007). From words to numbers: how to transform qualitative data into meaningful quantitative results. Schmalenbach Business Review, 59, 29-57.

Stegemann, N. (2011). Unique brand extension challenges for luxury brands. Journal of Business & Economics Research (Jber), 4(10). https://doi.org/10.19030/jber.v4i10.2704

Stegemann, N. (2011). Unique brand extension challenges for luxury brands. Journal of Business &Amp; Economics Research (JBER), 4(10). https://doi.org/10.19030/jber.v4i10.2704

Substance Abuse and Mental Health Services Administration. (2014).

Sugiarto, C. and Barnier, V. (2019). Are religious customers skeptical toward sexually appealing advertising?. Qualitative Market Research an International Journal, 22(5), 669-686. https://doi.org/10.1108/qmr-09-2018-0111

Sun, M. (2024). The impact of social media on consumer sentiment. SHS Web of Conferences, 188, 03006. https://doi.org/10.1051/shsconf/202418803006

Sung, B. and Phau, I. (2018). When pride meets envy: is social superiority portrayal in luxury advertising perceived as prestige or arrogance?. Psychology and Marketing, 36(2), 113-119. https://doi.org/10.1002/mar.21162

Sung, B., & Phau, I. (2018, July). Applying biometric methods to understand luxury CONSUMERS'EMOTIONAL responses. In Global Marketing Conference (pp. 696-696).

Sung, B., Butcher, L., & Easton, J. (2021). Elevating food perceptions through luxury verbal cues: an eye-tracking and electrodermal activity experiment. Australasian Marketing Journal (Amj), 31(1), 25-35. https://doi.org/10.1177/18393349211028676

Sung, B., Butcher, L., & Easton, J. (2021). Elevating food perceptions through luxury verbal cues: an eye-tracking and electrodermal activity experiment. Australasian Marketing Journal, 31(1), 25-35. https://doi.org/10.1177/18393349211028676

Sv, P., Lorenzo, J., Ittamalla, R., Dhama, K., Chakraborty, C., Kumar, D., … & Mohan, T. (2022). Twitter-based sentiment analysis and topic modeling of social media posts using natural language processing, to understand people's perspectives regarding covid-19 booster vaccine shots in india: crucial to expanding vaccination coverage. Vaccines, 10(11), 1929. https://doi.org/10.3390/vaccines10111929

Tafesse, W. (2016). An experiential model of consumer engagement in social media. Journal of Product & Brand Management, 25(5), 424-434. https://doi.org/10.1108/jpbm-05-2015-0879

Tajfel H., T. J. (1979). The Social Identity Theory of Intergroup Behavior.

Tajfel, H. and Turner, J. (2004). The social identity theory of intergroup behavior., 276-293. https://doi.org/10.4324/9780203505984-16

Teh, P., Ooi, P., Chan, N., & Chuah, Y. (2018). A comparative study of the effectiveness of sentiment tools and human coding in sarcasm detection. Journal of Systems and Information Technology, 20(3), 358-374. https://doi.org/10.1108/jsit-12-2017-0120

The lexical suite. (n. D.). https://www.lexicalsuite.com/

The World's Most Valuable Brands. (2020). Forbes. https://www.forbes.com/powerful-brands/list/;#tab:rank

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. Journal of the American Society for Information Science and Technology, 61(12), 2544-2558. https://doi.org/10.1002/asi.21416

Tichenor, J., Green, A., West, J., & Croom, R. (2022). Moving beyond the business case for female leaders: A longitudinal panel study of the impact of female leadership on corporate social responsibility. Business and Society Review, 127(3), 639-661.

Tilley, L., & Shilliam, R. (2018). Raced markets: An introduction. New political economy, 23(5), 534-543.

Tran, G., Yazdanparast, A., & Strutton, D. (2019). Investigating the marketing impact of consumers' connectedness to celebrity endorsers. Psychology and Marketing, 36(10), 923-935. https://doi.org/10.1002/mar.21245

Truong, Y., McColl, R., & Kitchen, P. (2010). Uncovering the relationships between aspirations and luxury brand preference. Journal of Product & Brand Management, 19(5), 346-355. https://doi.org/10.1108/10610421011068586

Tsawaab, A. H. (2023). The impact of body positivity in fashion advertising on customer perceptions and purchase intentions. International Journal of Multidisciplinary: Applied Business and Education Research, 4(8), 2769-2784. https://doi.org/10.11594/ijmaber.04.08.10

U.S. Census Bureau. (2018). Demographic turning points for the United States. Population projections from 2020 to 2060. https://www.census .gov/content/dam/Census/ibrary/publications/2018/demo/P25_1144.pdfl

United States Census Bureau. (2020). 2020 Census Results. Census.gov. https://www.census.gov/programs-surveys/decennial-census/decade/2020/2020-census-results.html

United States Census Bureau. (2023, October 11). Racial and ethnic diversity in the United States: 2010 census and 2020 census. Census.gov. https://www.census.gov/library/visualizations/interactive/racial-and-ethnic-diversity-in-the-united-states-2010-and-2020-census.html

United States Census Bureau. (n.d.). U.S. Census Bureau QuickFacts: United States. Census Bureau QuickFacts. https://www.census.gov/quickfacts/fact/table/US/PST045221

Utrata J. 2011. Youth privilege: doing age and gender in Russia's single-mother families. Gend. Soc. 25(5):616–41

Van Knippenberg, D., Dawson, J. F., West, M. A., & Homan, A. C. (2011). Diversity faultlines, shared objectives, and top management team performance. human relations, 64(3), (S.307-336).

Vassey, J., Donaldson, S., Dormanesh, B., & Allem, J. (2022). Themes in tiktok videos featuring little cigars and cigarillos: content analysis. Journal of Medical Internet Research, 24(11), e42441. https://doi.org/10.2196/42441

Veerman, L., Beeck, E., Barendregt, J., & Mackenbach, J. (2009). By how much would limiting tv food advertising reduce childhood obesity?. European Journal of Public Health, 19(4), 365-369. https://doi.org/10.1093/eurpub/ckp039

Veletsianos, G., Kimmons, R., Larsen, R., Dousay, T., & Lowenthal, P. (2018). Public comment sentiment on educational videos: understanding the effects of presenter gender, video format, threading, and moderation on youtube ted talk comments. Plos One, 13(6), e0197331. https://doi.org/10.1371/journal.pone.0197331

Veloutsou, C., Christodoulides, G., & Guzmán, F. (2021). Charting research on international luxury marketing: where are we now and where should we go next?. International Marketing Review, 39(2), 371-394. https://doi.org/10.1108/imr-04-2021-0154

Vigneron, F. and Johnson, L. (2004). Measuring perceptions of brand luxury. Journal of Brand Management, 11(6), 484-506. https://doi.org/10.1057/palgrave.bm.2540194

Vizcaíno-Verdú, A. and Aguaded, I. (2022). #thisismechallenge and music for empowerment of marginalized groups on tiktok. Media and Communication, 10(1). https://doi.org/10.17645/mac.v10i1.4715

Voorveld, H. A. M., Noort, G. v., Muntinga, D. G., & Bronner, F. (2018). Engagement with social media and social media advertising: the differentiating role of platform type. Journal of Advertising, 47(1), 38-54. https://doi.org/10.1080/00913367.2017.1405754

Wagner, D. & Voigt, B.F. (2007). Diversity-Management als Leitbild von Personalpolitik.

Wang, J., Shu, T., Zhao, W., & Zhou, J. (2022). Research on chinese consumers' attitudes analysis of big-data driven price discrimination based on machine learning. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.803212

Wesely Sabine (2008). Diversity und Chancengleichheit in der Wirtschaft. Gender, Fachhochschule Hannover, University of applied Scienes and Arts. Letzter Aufruf 25.11.2020 von https://serwiss.bib.hs-hannover.de/frontdoor/deliver/index/docId/954/file/sw-09-08.pdf.

Wiedmann, K., Hennigs, N., & Siebels, A. (2009). Value-based segmentation of luxury consumption behavior. Psychology and Marketing, 26(7), 625-651. https://doi.org/10.1002/mar.20292

Wilcox, K., Kim, H., & Sen, S. (2009). Why do consumers buy counterfeit luxury brands?. Journal of Marketing Research, 46(2), 247-259. https://doi.org/10.1509/jmkr.46.2.247

Williams, A. D., Aronson, K. M., Chavous, T. M., Cooke, D. Y., Glover, C. S., Hoggard, L. S., ... & Neblett Jr, E. W. (2023). Standing on the shoulders of a giant: The legacy of Robert M. Sellers. American Psychologist, 78(4), 441.

Wilson, B. D., & Meyer, I. H. (2021). Nonbinary LGBTQ adults in the United States.

Wilton, L., Sanchez, D., Unzueta, M., Kaiser, C., & Caluori, N. (2018). In good company: when gender diversity boosts a company's reputation. Psychology of Women Quarterly, 43(1), 59-72. https://doi.org/10.1177/0361684318800264

Wong, C., Kirby, T., Rink, F., & Ryan, M. (2022). Intersectional invisibility in women's diversity interventions. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.791572

Workman, J. and Lee, S. (2021). Adaptation and extension of a human charisma scale to measure non-luxury product brand charisma. Australasian Marketing Journal (Amj), 29(4), 277-287. https://doi.org/10.1177/1839334921999498

World Bank Open Data. (n.d.). World Bank Open Data. https://data.worldbank.org/indicator/SP.POP.1564.TO?locations=EU

Xu, G., Meng, Y., Qiu, X., Yu, Z., & Wu, X. (2019). Sentiment analysis of comment texts based on bilstm. Ieee Access, 7, 51522-51532. https://doi.org/10.1109/access.2019.2909919

Yadav, A. (2023). Sentiment analysis using twitter data. International Journal for Research in Applied Science and Engineering Technology, 11(5), 5833-5837. https://doi.org/10.22214/ijraset.2023.52899

Yang, W. and Mattila, A. (2014). Do affluent customers care when luxury brands go mass?. International Journal of Contemporary Hospitality Management, 26(4), 526-543. https://doi.org/10.1108/ijchm-03-2013-0124

Young, J. (2024). Cider: context-sensitive polarity measurement for short-form text. Plos One, 19(4), e0299490. https://doi.org/10.1371/journal.pone.0299490

Zha, T. (2023). Social media marketing for luxury brands: parasocial interactions and empowerment for enhanced loyalty and willingness to pay a premium. Marketing Intelligence & Planning, 41(8), 1138-1161. https://doi.org/10.1108/mip-05-2023-0192

Zhang, Y., Harwood, J., Williams, A., Ylänne-McEwen, V., Wadleigh, P., & Thimm, C. (2006). The portrayal of older adults in advertising. Journal of Language and Social Psychology, 25(3), 264-282. https://doi.org/10.1177/0261927x06289479

Zhang, Z. (2023). Research on the influence of brands on consumer purchasing behavior. Advances in Economics, Business and Management Research, 146-153. https://doi.org/10.2991/978-94-6463-098-5_18

Zheng, J., Shen, B., Chow, P., & Chiu, C. (2013). The impact of the strategic advertising on luxury fashion brands with social influences. Mathematical Problems in Engineering, 2013, 1-16. https://doi.org/10.1155/2013/534605

Zheng, M. (2020). When and why negative emotional appeals work in advertising: a review of research. Open Journal of Social Sciences, 08(03), 7-16. https://doi.org/10.4236/jss.2020.83002

List of Annexes

Annex 1: Study 1 Number of Views XXXVII
Annex 2: Study 1 Frequencies LI
Annex 3: Study 1 Linear Regression Female Models LIII
Annex 4: Study 1 Linear Regression Male Models LIII
Annex 5: Study 1 Linear Regression White Models LIV
Annex 6: Study 1 Linear Regression Asian Models LV
Annex 7: Study 1 Linear Regression Black Models LV
Annex 8: Study 1 Linear Regression Models with Other Ethnic Backgrounds LVI
Annex 9: Study 1 Linear Regression Presence of Diverse Models LVII
Annex 10: Study 1 Linear Regression Presence of Celebrity LVIII
Annex 11: Study 1 Linear Regression Presence of no Person LVIII
Annex 12: Study 1 Multi Linear Regression Diversity Cues LIX
Annex 13: Study 2 Valence - Linear Regression White Models LX
Annex 14: Study 2 Valence - Linear Regression Asian Models LX
Annex 15: Study 2 Valence - Linear Regression Black Models LXI
Annex 16: Study 2 Valence - Linear Regression Models with Other Ethnic Backgrounds LXI
Annex 17: Study 2 Valence - Linear Regression Presence of Diverse Models LXII
Annex 18: Study 2 Extremity - Linear Regression White Models LXIII
Annex 19: Study 2 Extremity - Linear Regression Asian Models LXIII
Annex 20: Study 2 Extremity - Linear Regression Black Models LXIV
Annex 21: Study 2 Extremity - Linear Regression Models with Other Ethnic Backgrounds LXV
Annex 22: Study 2 Extremity - Linear Regression Presence of Diverse Models LXV
Annex 23: Study 2 Emotionality - Linear Regression White Models LXVI
Annex 24: Study 2 Emotionality - Linear Regression Asian Models LXVII
Annex 25: Study 2 Emotionality - Linear Regression Black Models LXVII
Annex 26: Study 2 Emotionality - Linear Regression Models with Other Ethnic Backgrounds LXVIII
Annex 27: Study 2 Emotionality - Linear Regression Presence of Diverse Models LXVIII
Annex 28: Study 2 Emotionality Hand Coded - Linear Regression White Models ... LXIX
Annex 29: Study 2 Emotionality Hand Coded - Linear Regression Asian Models LXIX

Annex 30: Study 2 Emotionality Hand Coded - Linear Regression Black Models.....LXX
Annex 31: Study 2 Emotionality Hand Coded - Linear Regression Models with Other Ethnic Backgrounds.....LXX
Annex 32: Study 2 Emotionality Hand Coded - Linear Regression Presence of Diverse Models LXXII
Annex 33: Study 2 Sentiment - Linear Regression White Models..... LXXII
Annex 34: Study 2 Sentiment - Linear Regression Asian Models LXXIII
Annex 35: Study 2 Sentiment - Linear Regression Black Models LXXIV
Annex 36: Study 2 Sentiment - Linear Regression Models with Other Ethnic Backgrounds LXXIV
Annex 37: Study 2 Sentiment - Linear Regression Presence of Diverse Models.....LXXV
Annex 38: Study 2 Exclusivity - Linear Regression White Models LXXVI
Annex 39: Study 2 Exclusivity - Linear Regression Asian Models..... LXXVI
Annex 40: Study 2 Exclusivity - Linear Regression Black Models.....LXXVII
Annex 41: Study 2 Exclusivity - Linear Regression Models with Other Ethnic Backgrounds LXXVIII
Annex 42: Study 2 Exclusivity - Linear Regression Presence of Diverse Models LXXVIII
Annex 43: Study 2 Valence - Multi Linear Regression Brand Type LXXIX
Annex 44: Study 2 Extremity - Multi Linear Regression Brand Type LXXXI
Annex 45: Study 2 Emotionality - Multi Linear Regression Brand Type.....LXXXII
Annex 46: Study 3 Valence - Linear Regression Brand Type..... LXXXIV
Annex 47: Study 3 Extremity - Linear Regression Brand Type LXXXIV
Annex 48: Study 3 Emotionality - Linear Regression Brand Type LXXXV
Annex 49: Study 3 Emotionality Hand Coded - Linear Regression Brand Type ..LXXXV
Annex 50: Study 3 Sentiment - Linear Regression Brand Type LXXXVI
Annex 51: Study 3 Exclusivity - Linear Regression Brand Type LXXXVII
Annex 52: Study 3 Valence - Multi Linear Regression Celebrity Presence.....LXXXVII
Annex 53: Study 3 Extremity - Multi Linear Regression Celebrity Presence... LXXXVIII
Annex 54: Study 3 Emotionality - Multi Linear Regression Celebrity Presence XC

Annex

Annex 1: Study 1 Number of Views

Source: Author's own, information gathered from TikTok (14.06.2024 3-4pm)

Brand	Number of Views	model: female	model: male	white	asian	black	other	celebrity focused	no person
LV	77300	1	1	1	0	1	0	0	0
LV	44300	1	1	1	0	0	0	0	0
LV	97200	0	0	0	0	0	0	0	1
LV	53700	0	0	0	0	0	0	0	1
LV	28700	0	0	0	0	0	0	0	1
LV	482200	1	0	1	0	0	0	0	0
LV	4300000	1	0	0	1	0	0	0	0
LV	137200	1	0	0	0	1	0	0	0
LV	1300000	1	0	0	0	1	0	0	0
LV	41200	0	1	1	0	1	0	0	0
LV	14500	0	1	1	1	1	1	0	0
LV	15000	0	1	1	1	1	1	0	0
LV	79700	0	1	0	0	1	0	0	0
LV	568500	0	1	0	0	1	0	1	0
LV	618200	0	1	0	0	1	0	1	0
LV	572200	0	1	0	0	1	0	1	0
LV	5000000	1	0	1	1	1	1	0	0
LV	2000000	1	0	1	1	0	1	1	0
LV	4100000	1	0	1	0	0	0	1	0
LV	2500000	1	0	0	0	0	1	1	0
LV	4800000	1	0	1	1	1	1	0	0
LV	3900000	1	1	1	1	1	1	1	0
LV	4800000	1	1	1	1	1	1	0	0
LV	5000000	1	1	1	1	1	1	0	0
LV	4600000	1	0	1	0	0	0	1	0
LV	4600000	1	0	1	0	0	0	1	0
LV	4400000	1	0	1	0	1	0	0	0
LV	4900000	1	1	1	1	1	1	0	0
LV	4400000	0	1	1	0	0	0	1	0
LV	8100000	1	0	0	1	0	0	1	0
LV	6300000	1	0	1	1	1	1	0	0
LV	6200000	1	0	1	1	1	1	0	0
LV	6800000	1	0	1	1	1	1	0	0
LV	81800	0	0	0	0	0	0	0	1
LV	189500	1	0	1	0	0	0	0	0
LV	80300	0	0	0	0	0	0	0	1

LV	1300000	0	0	0	0	0	0	0	1
LV	42200	1	0	1	0	0	0	1	0
LV	29400	0	1	0	1	0	0	1	0
LV	698500	0	1	1	0	0	0	1	0
LV	6000000	1	1	1	0	0	0	1	0
LV	32300	1	0	0	1	0	0	0	0
LV	20100	1	0	0	1	1	0	0	0
LV	30500	1	0	1	0	0	0	0	0
LV	26400	1	0	1	1	1	1	0	0
LV	28900	1	0	1	0	0	0	1	0
LV	25100	1	0	1	0	0	0	1	0
LV	23600	1	1	1	0	0	0	1	0
LV	16500	1	0	1	0	0	0	1	0
LV	52000	1	0	1	0	0	0	0	0
LV	19300	1	0	0	0	1	1	0	0
LV	44100	1	0	1	0	0	0	0	0
LV	22600	1	0	1	0	0	0	0	0
LV	23200	0	0	0	0	0	0	0	1
LV	43600	1	1	1	0	0	0	0	0
LV	82500	1	1	1	0	0	0	0	0
LV	25300	1	1	0	1	0	0	0	0
LV	8100000	1	0	1	0	0	0	0	0
LV	5900000	1	0	1	0	0	0	0	0
LV	7500000	1	0	1	0	0	0	0	0
LV	5800000	1	0	0	0	1	0	0	0
LV	31500	0	1	1	1	0	0	0	0
LV	29000	0	1	1	0	1	0	0	0
LV	22700	0	1	0	1	0	0	0	0
LV	22500	0	1	1	0	0	0	1	0
LV	19000	0	1	1	0	0	0	1	0
LV	50200	1	0	0	1	0	0	1	0
LV	206600	1	0	0	1	0	0	1	0
LV	26500	1	0	1	0	0	0	1	0
LV	23500	1	0	1	0	0	0	1	0
LV	26700	1	0	1	0	0	0	1	0
LV	32400	0	1	0	1	0	0	1	0
LV	21200	1	0	0	1	0	0	0	0
LV	37900	1	0	1	1	1	1	0	0
LV	19300	1	0	1	1	1	0	0	0
LV	42300	1	0	0	1	0	0	1	0
LV	23600	1	1	1	1	1	1	1	0
LV	26000	1	0	0	1	0	0	1	0

LV	19600	1	0	0	1	0	0	1	0
LV	20200	1	1	0	1	0	0	1	0
LV	70500	0	1	0	1	0	0	1	0
LV	26900	1	0	1	1	1	0	0	0
LV	20400	1	0	0	0	0	0	0	0
LV	16900	1	0	1	1	1	1	0	0
LV	17600	1	0	0	1	0	0	1	0
LV	16300	1	0	0	1	0	0	1	0
LV	32700	1	0	0	1	0	0	1	0
LV	14500	1	0	1	1	1	1	0	0
LV	22100	0	1	1	0	0	0	1	0
LV	23400	1	0	1	1	1	1	0	0
LV	99200	0	0	0	0	0	0	0	1
LV	32400	1	0	0	1	0	0	1	0
LV	86400	0	0	0	0	0	0	0	1
LV	49500	0	0	0	0	0	0	0	1
LV	60500	1	0	0	1	0	0	0	0
LV	28600	1	0	1	1	0	0	0	0
LV	26200	1	0	1	1	0	0	0	0
LV	37500	0	1	0	0	1	0	1	0
LV	26100	0	1	0	0	1	0	1	0
LV	37800	0	1	0	1	0	0	0	0
ZA	1200000	0	1	1	0	0	0	0	0
ZA	3500000	1	1	1	1	0	0	0	0
ZA	3200000	1	0	0	0	0	1	0	0
ZA	3400000	0	1	1	0	1	0	0	1
ZA	3000000	0	1	0	1	0	0	0	0
ZA	2300000	1	1	1	0	0	0	0	0
ZA	2900000	0	1	1	1	0	1	0	0
ZA	3200000	1	1	1	1	1	1	0	0
ZA	3800000	0	1	1	0	0	0	0	0
ZA	2700000	0	0	0	0	0	0	0	1
ZA	3000000	0	0	0	0	0	0	0	1
ZA	3400000	1	1	1	0	1	0	0	0
ZA	3300000	0	0	0	0	0	0	0	1
ZA	3300000	0	1	0	0	1	0	1	0
ZA	4200000	0	1	1	0	0	0	0	1
ZA	3000000	0	1	0	0	1	0	0	0
ZA	3900000	1	0	0	0	1	0	0	0
ZA	4200000	1	0	0	0	1	0	0	0
ZA	3800000	1	0	0	1	0	0	0	0
ZA	4500000	1	0	1	0	0	0	0	0

ZA	3100000	0	0	0	0	0	0	0	1
ZA	3800000	1	0	1	0	0	0	0	0
ZA	2700000	0	1	1	0	0	0	0	0
ZA	3700000	1	0	1	0	0	0	0	0
ZA	4600000	0	0	0	0	0	0	0	1
ZA	2100000	0	1	1	0	0	0	1	0
ZA	3800000	0	1	1	0	0	0	1	0
ZA	3800000	0	1	0	0	1	0	0	0
ZA	2700000	0	1	1	0	0	0	0	0
ZA	3900000	1	0	1	0	0	0	0	0
ZA	3100000	1	0	1	0	0	0	0	0
ZA	2800000	0	1	0	0	1	0	0	0
ZA	3500000	1	0	1	0	0	0	0	0
ZA	3800000	1	1	1	1	1	0	0	0
ZA	3700000	1	0	0	1	0	0	0	0
ZA	3000000	0	1	1	0	0	0	0	0
ZA	2600000	1	0	1	0	0	0	0	0
ZA	3100000	0	1	1	0	0	0	1	0
ZA	2100000	0	1	1	0	0	0	1	0
ZA	1800000	1	0	1	0	0	0	0	0
ZA	2600000	0	0	0	0	0	0	0	1
ZA	2100000	0	0	0	0	0	0	0	1
ZA	4100000	1	0	0	0	1	0	0	0
ZA	2500000	0	1	1	0	0	0	1	0
ZA	3800000	0	0	0	0	0	0	0	1
ZA	2100000	0	1	1	0	0	0	1	0
ZA	3300000	0	0	0	0	0	0	0	1
ZA	3600000	1	0	1	0	0	0	0	0
ZA	2900000	0	1	1	0	0	0	0	0
ZA	3100000	1	0	1	0	1	0	0	0
ZA	3700000	1	0	1	0	0	0	0	0
ZA	4000000	0	0	0	0	0	0	1	0
ZA	4000000	1	0	0	1	0	0	1	0
ZA	3300000	0	0	0	0	0	0	1	0
ZA	3500000	0	0	0	0	0	0	1	0
ZA	3000000	0	0	0	0	0	0	1	0
ZA	5100000	0	0	0	0	0	0	1	0
ZA	3300000	1	0	1	0	0	0	0	0
ZA	2500000	1	0	1	0	0	0	0	0
ZA	3400000	1	0	1	0	0	0	0	0
ZA	2700000	1	0	1	0	0	0	0	0
ZA	2400000	0	0	0	0	0	0	1	0

ZA	5500000	0	0	0	0	0	0	1	0
ZA	5400000	1	0	1	0	0	0	0	0
ZA	4000000	0	1	1	0	0	0	0	0
ZA	4500000	1	0	1	0	0	0	0	0
ZA	3800000	1	0	1	0	0	0	0	0
ZA	4000000	0	1	1	0	0	0	0	0
ZA	3000000	0	0	0	0	0	0	1	0
ZA	4500000	1	0	0	0	0	1	0	0
ZA	3400000	0	1	1	0	0	0	0	0
ZA	3700000	1	0	0	0	1	0	0	0
ZA	4800000	0	0	0	0	0	0	0	1
ZA	3600000	0	0	0	0	0	0	0	1
ZA	4200000	1	0	1	0	0	0	0	0
ZA	3500000	1	0	1	0	0	0	0	0
ZA	3900000	0	0	0	0	0	0	0	1
ZA	5500000	0	0	0	0	0	0	0	1
ZA	4000000	1	0	1	0	0	0	0	0
ZA	4500000	0	0	0	0	0	0	0	1
ZA	3900000	0	0	0	0	0	0	0	1
ZA	3800000	1	1	1	1	0	0	0	0
ZA	5600000	0	0	0	0	0	0	0	1
ZA	5900000	1	0	1	0	1	0	0	0
ZA	4600000	0	0	0	0	0	0	0	1
ZA	3600000	0	0	0	0	0	0	0	1
ZA	4100000	1	0	1	1	0	0	0	0
ZA	4500000	0	0	0	0	0	0	0	1
ZA	4200000	0	0	0	0	0	0	0	1
ZA	3000000	1	1	1	0	1	0	0	0
ZA	3000000	1	1	1	1	1	1	0	0
ZA	3300000	1	0	1	0	0	0	0	0
ZA	4300000	1	1	0	0	1	0	0	1
ZA	3600000	1	0	1	0	0	0	0	0
ZA	5200000	0	0	0	0	0	0	0	1
ZA	4700000	1	1	1	1	1	1	0	0
ZA	3700000	0	0	0	0	0	0	0	1
ZA	4600000	0	0	0	0	0	0	0	1
ZA	4100000	0	0	0	0	0	0	0	1
ZA	7300000	0	0	0	0	0	0	0	1
GU	13600	0	1	0	0	1	0	0	0
GU	10200	0	1	1	0	1	0	0	0
GU	766400	1	1	1	1	1	1	0	0
GU	14400000	0	0	0	0	0	0	0	1

GU	11600000	0	0	0	0	0	0	1	1
GU	260000	1	0	0	1	0	0	1	0
GU	34100000	1	0	0	1	0	0	1	0
GU	10100000	1	0	0	1	0	0	1	0
GU	4700000	1	0	0	1	0	0	1	0
GU	205600	1	0	1	1	0	1	1	0
GU	39100000	1	0	0	1	0	0	1	0
GU	1800000	1	0	1	1	1	1	0	0
GU	33700	1	1	1	1	1	0	1	0
GU	12100000	1	0	1	0	0	0	0	0
GU	82100	1	1	1	0	0	0	1	0
GU	12900000	1	0	0	0	0	1	0	0
GU	31300	1	1	1	0	0	0	1	0
GU	232500	0	1	0	1	0	0	1	0
GU	10600000	1	0	1	0	1	0	0	0
GU	21400000	1	0	1	0	0	0	0	0
GU	72400	1	0	0	0	1	0	0	0
GU	21100	1	0	1	0	0	0	1	0
GU	33100	1	0	1	0	0	0	1	0
GU	30400000	1	0	1	0	0	0	0	0
GU	34700000	1	0	0	1	0	0	1	0
GU	31500000	1	0	1	0	0	0	0	0
GU	30300000	1	0	1	1	1	1	0	0
GU	8400000	0	0	0	0	0	0	0	1
GU	13800000	1	0	1	0	0	0	1	0
GU	19500000	0	1	1	0	0	0	1	0
GU	60000	1	0	0	1	0	0	1	0
GU	51300000	0	1	0	1	0	0	1	0
GU	45800000	0	1	0	1	0	0	1	0
GU	52600	0	1	0	1	0	0	1	0
GU	96100000	0	1	1	0	0	0	0	0
GU	65800	1	0	0	1	0	0	1	0
GU	407900	0	0	0	0	0	0	0	0
GU	75600	1	0	1	0	0	0	1	0
GU	584700	0	0	0	0	0	0	0	1
GU	32900000	1	1	1	1	1	1	0	0
GU	1300000	1	0	1	0	0	0	0	0
GU	46100	1	0	1	1	1	0	0	0
GU	331200	1	0	0	1	0	0	1	0
GU	5300000	0	0	0	0	0	0	0	1
GU	13600000	0	1	0	0	1	0	0	0
GU	67900000	0	1	0	0	1	0	0	0

GU	62400000	0	0	0	0	0	0	0	1
GU	13500000	0	0	0	0	0	0	0	1
GU	13100000	1	1	1	0	0	0	0	0
GU	16000000	0	1	1	0	0	0	0	1
GU	12500000	0	1	1	0	0	0	1	0
GU	99400	1	0	1	0	0	0	1	0
GU	227600	1	0	0	1	0	0	0	0
GU	22800000	1	0	1	0	0	0	1	0
GU	117000000	1	0	1	0	0	0	1	0
GU	125500000	0	0	0	0	0	0	0	1
GU	53400	0	0	0	0	0	0	0	1
GU	58300	1	0	1	0	0	0	1	0
GU	10200000	1	0	1	0	1	0	0	0
GU	128900	1	0	1	0	0	0	1	0
GU	92200	1	1	1	1	1	1	1	0
GU	16400000	1	0	0	1	0	0	0	0
GU	30000000	1	0	1	1	1	0	0	0
GU	126800	1	0	1	0	0	0	1	0
GU	50500000	1	0	1	1	1	1	0	0
GU	114200	1	0	0	1	0	0	1	0
GU	26700000	1	0	1	0	0	0	0	0
GU	66300	1	1	1	1	1	0	1	0
GU	42100000	1	0	1	1	1	1	0	0
GU	3600000	1	0	0	1	0	0	1	0
GU	21300000	1	0	1	1	1	1	0	0
GU	23700000	1	0	1	1	1	1	0	0
GU	72700	1	0	1	0	0	0	1	0
GU	53200000	1	0	1	1	1	1	0	0
GU	288300	1	0	0	1	0	0	1	0
GU	61200	1	0	1	0	0	0	1	0
GU	46900	1	0	0	0	1	0	1	0
GU	67600	0	1	1	0	0	0	1	0
GU	118200	1	0	1	0	0	0	1	0
GU	417300	0	0	0	0	0	0	0	1
GU	494300	0	0	0	0	0	0	0	1
GU	66800	1	0	1	0	0	0	1	0
GU	102800	1	0	1	0	0	0	1	0
GU	60200	0	1	1	0	0	0	1	0
GU	33200000	1	0	1	0	0	0	1	0
GU	86800	1	0	1	0	0	0	1	0
GU	158800	0	1	0	1	0	0	1	0
GU	3600000	0	1	1	1	1	1	1	0

GU	220200	0	1	0	1	0	0	1	0
GU	8000000	0	1	1	1	1	1	0	0
GU	467200	0	1	0	0	1	0	1	0
GU	59400000	1	1	1	1	1	1	0	0
GU	1400000	1	1	1	1	1	1	0	0
GU	20200000	0	1	1	1	1	1	0	0
GU	37900000	0	0	0	0	0	0	0	1
GU	32900000	1	1	1	1	1	1	0	0
GU	29800000	0	1	1	1	1	1	0	0
GU	22100000	0	1	0	1	0	0	1	0
GU	121500	1	0	1	0	0	0	1	0
GU	58900000	1	0	0	1	0	0	1	0
UN	408100	1	0	1	0	0	0	0	0
UN	119200	0	0	0	0	0	0	0	1
UN	710000	0	0	0	0	0	0	0	1
UN	2100	0	0	0	0	0	0	0	1
UN	27900	0	1	0	0	1	0	0	0
UN	4603	1	0	1	0	0	0	0	0
UN	31400	1	0	1	0	0	0	0	0
UN	24700	1	0	1	0	0	0	0	0
UN	9302	1	0	1	0	0	0	0	0
UN	19100	1	0	1	0	0	0	0	0
UN	18300	1	1	1	0	0	0	0	0
UN	17800	1	1	0	0	1	0	0	0
UN	17900	1	0	1	0	0	0	0	0
UN	27400	0	0	0	0	0	0	0	1
UN	16900	0	0	0	0	0	0	0	1
UN	15200	0	0	0	0	0	0	0	1
UN	32900	0	0	0	0	0	0	0	1
UN	13600	0	0	0	0	0	0	0	1
UN	316100	1	0	0	0	1	0	0	1
UN	17500	1	0	0	1	0	0	0	0
UN	38000	1	1	1	1	1	1	0	0
UN	17000	0	0	0	0	0	0	0	1
UN	73200	0	0	0	0	0	0	0	1
UN	128300	0	0	0	0	0	0	0	1
UN	23700	0	0	0	0	0	0	0	1
UN	28500	0	1	0	0	0	1	0	0
UN	2500000	0	0	0	0	0	0	0	1
UN	19700	0	1	0	0	0	1	0	0
UN	27800	0	0	0	0	0	0	0	1
UN	40900	0	1	1	0	0	0	0	0

UN	22300	0	1	0	1	0	0	0	0
UN	31400	0	1	0	1	0	0	0	0
UN	15400	1	1	0	0	1	0	0	0
UN	46500	0	0	0	0	0	0	0	1
UN	36700	0	0	0	0	0	0	0	1
UN	38000	1	1	1	0	1	0	0	0
UN	17000	1	1	1	0	1	0	0	0
UN	73200	0	0	0	0	0	0	0	1
UN	128300	1	0	1	0	0	0	0	1
UN	23700	0	0	0	0	0	0	0	1
UN	28500	0	0	0	0	0	0	0	0
UN	2500000	0	0	0	0	0	0	0	0
UN	19700	0	0	0	0	0	0	0	0
UN	19500	1	1	1	0	1	0	0	0
UN	91500	1	1	1	0	1	0	0	0
UN	410700	0	0	0	0	0	0	0	1
UN	45700	1	0	1	0	0	0	0	1
UN	1400000	0	0	0	0	0	0	0	1
UN	135700	1	0	1	0	0	0	0	0
UN	32700	0	0	0	0	0	0	0	1
UN	21200	1	0	1	0	0	0	0	0
UN	34000	1	1	1	1	0	0	0	0
UN	28600	0	0	0	0	0	0	0	0
UN	276900	1	0	0	0	1	0	0	0
UN	303200	0	0	0	0	0	0	0	1
UN	20300	1	1	1	0	1	0	0	0
UN	37800	0	0	0	0	0	0	0	1
UN	41600	0	1	1	0	0	0	0	0
UN	95400	0	0	0	0	0	0	0	1
UN	299500	0	0	0	0	0	0	0	1
UN	35200	1	1	1	0	0	0	0	1
UN	21200	0	0	0	0	0	0	0	1
UN	29000	0	0	0	0	0	0	0	1
UN	27600	0	1	1	0	0	0	0	0
UN	1200000	0	0	0	0	0	0	0	1
UN	37000	0	0	0	0	0	0	0	1
UN	195900	0	0	0	0	0	0	0	1
UN	20100	0	0	0	0	0	0	0	1
UN	109500	0	0	0	0	0	0	0	1
UN	48500	1	1	0	0	1	0	0	1
UN	23400	0	0	1	0	0	0	0	1
UN	15800	0	0	0	0	0	0	0	1

UN	108400	1	0	1	0	0	0	0	0
UN	1400000	0	0	0	0	0	0	0	1
UN	40500	0	0	0	0	0	0	0	1
UN	36600	0	0	0	0	0	0	0	1
UN	953800	0	0	0	0	0	0	0	1
UN	33900	0	1	1	0	0	0	0	1
UN	682800	0	0	0	0	0	0	0	0
UN	704500	1	0	1	0	0	0	0	0
UN	383100	0	0	0	0	0	0	0	1
UN	39900	0	0	0	0	0	0	0	1
UN	180600	1	0	1	0	0	0	0	0
UN	73200	0	0	0	0	0	0	0	1
UN	68400	1	0	0	0	1	0	0	0
UN	22800	0	1	1	0	0	0	0	1
UN	122200	0	0	0	0	0	0	0	1
UN	27300	1	0	1	0	0	0	0	0
UN	1700000	0	0	0	0	0	0	0	1
UN	202900	1	0	1	0	0	0	0	0
UN	54300	0	1	0	0	1	0	0	0
UN	44500	1	0	1	0	0	1	0	1
UN	121000	1	0	1	0	0	0	0	1
UN	35800	0	0	0	0	0	0	0	1
UN	380300	0	1	0	0	1	0	0	1
UN	42100	0	0	0	0	0	0	0	1
UN	22900	0	0	0	0	0	0	0	1
UN	139800	1	0	1	0	0	0	0	0
UN	23400	0	1	1	0	0	0	0	0
UN	25100	0	1	0	0	1	0	0	0
PR	1200	1	0	0	0	1	0	0	0
PR	1623	1	0	0	0	1	0	0	0
PR	9038	1	0	1	0	0	0	0	0
PR	436	1	0	0	1	0	0	0	0
PR	68400	0	0	0	0	0	0	0	1
PR	278800	1	0	1	0	0	0	0	0
PR	85400	1	0	1	0	0	0	0	0
PR	392300	1	0	1	0	0	0	0	0
PR	115900	0	1	1	0	0	0	0	0
PR	1600000	0	0	0	0	0	0	0	1
PR	1700000	0	1	0	1	0	0	0	0
PR	2500000	0	1	1	0	0	0	0	0
PR	638800	0	0	0	0	0	0	0	1
PR	1500000	0	1	1	0	0	0	1	0

PR	6200000	0	1	0	0	1	0	1	0
PR	2200000	0	1	1	0	0	0	1	0
PR	2100000	1	0	1	0	0	0	0	0
PR	2100000	1	0	1	0	1	0	1	0
PR	5800000	1	1	1	1	1	0	0	0
PR	12100000	1	1	1	1	1	0	0	0
PR	1500000	1	1	1	1	1	0	0	0
PR	14800000	1	1	1	1	1	0	0	0
PR	39700000	1	1	1	1	1	0	0	0
PR	22600000	1	1	1	1	1	0	0	0
PR	51300000	1	0	1	0	0	0	1	0
PR	51800000	1	0	1	0	0	0	1	0
PR	26200000	1	1	1	1	1	0	0	0
PR	36000	1	0	1	0	0	0	0	0
PR	14500000	0	1	0	0	1	0	0	0
PR	23800000	1	0	1	0	0	0	0	0
PR	35800	1	0	1	0	0	0	0	0
PR	19500000	1	0	0	1	0	0	0	0
PR	16000000	0	1	0	0	1	0	0	0
PR	3500000	0	1	0	0	1	0	1	0
PR	8500000	1	1	1	1	1	1	1	0
PR	4000000	1	1	1	1	1	1	0	0
PR	43300000	0	1	1	0	0	0	1	0
PR	18900000	0	1	0	0	1	0	1	0
PR	16200000	0	1	1	0	0	0	0	0
PR	12800000	0	1	0	0	1	0	1	0
PR	8300000	0	1	1	0	0	0	1	0
PR	5400000	1	0	1	1	1	0	0	0
PR	6500000	1	0	1	1	1	0	0	0
PR	5900000	1	0	1	1	1	0	0	0
PR	6700000	1	0	1	0	0	0	1	0
PR	6400000	1	0	1	0	0	0	1	0
PR	7000000	1	0	1	0	0	0	1	0
PR	6100000	1	0	1	0	1	0	0	0
PR	7800000	1	0	0	1	0	0	1	0
PR	10900000	1	0	0	0	1	0	1	0
PR	9100000	1	0	0	1	0	0	1	0
PR	8000000	1	0	0	0	1	0	1	0
PR	7300000	0	0	0	0	0	0	0	1
PR	41800000	0	0	0	0	0	0	0	1
PR	31100000	0	0	0	0	0	0	0	1
PR	28200	1	0	0	1	0	0	0	0

PR	63100000	0	0	0	0	0	0	0	1
PR	44000	0	0	0	0	0	0	0	1
PR	26100	0	0	0	0	0	0	0	1
PR	25300	0	1	0	1	0	0	0	0
PR	52800000	0	1	1	0	0	0	0	0
PR	29200000	1	0	1	0	0	0	0	0
PR	25500000	0	1	1	0	0	0	1	0
PR	34200	0	0	0	0	0	0	0	1
PR	37200	0	0	0	0	0	0	0	1
PR	79600000	1	0	0	0	1	0	0	0
PR	23300	1	0	1	0	0	0	0	0
PR	20800000	1	0	1	0	0	0	0	0
PR	34100000	0	1	1	0	0	0	1	0
PR	31000000	0	1	0	0	1	0	1	0
PR	21800	0	0	0	0	0	0	0	1
PR	25700	0	0	0	0	0	0	0	1
PR	25400	0	0	0	0	0	0	0	1
PR	5300000	0	1	1	0	1	0	0	0
PR	5400000	0	1	1	1	1	0	0	0
PR	5600000	0	1	1	1	1	0	0	0
PR	7300000	0	1	0	0	0	0	1	0
PR	7000000	0	1	1	0	0	0	1	0
PR	8400000	0	1	0	0	1	0	1	0
PR	6100000	0	1	0	1	0	0	1	0
PR	6200000	0	1	1	0	0	0	1	0
PR	7400000	0	1	1	0	1	0	0	0
PR	5600000	0	0	0	0	0	0	0	1
PR	33300000	0	0	0	0	0	0	0	1
PR	35900000	1	0	1	0	0	0	0	0
PR	15800000	1	0	0	1	0	0	0	0
PR	15000000	0	1	0	0	1	0	0	0
PR	69300	0	0	0	0	0	0	0	1
PR	44200	0	1	0	1	0	0	1	0
PR	40300	0	1	1	0	0	0	1	0
PR	28400	1	0	1	0	0	0	1	0
PR	3200000	1	0	0	0	1	0	0	0
PR	36400000	0	1	0	0	1	0	0	0
PR	43600000	1	0	1	1	1	0	0	0
PR	33000000	0	1	1	0	0	0	0	0
PR	136200000	0	1	0	1	0	0	0	0
PR	92400	0	0	0	0	0	0	0	1
PR	91000	0	0	0	0	0	0	0	1

PR	153900000	1	0	0	1	0	0	1	0
PR	118200000	0	1	0	1	0	0	1	0
BU	4769	0	0	0	0	0	0	0	1
BU	2100000	0	1	0	0	1	0	1	0
BU	4500000	0	0	1	0	0	0	1	0
BU	2400000	1	1	1	1	1	1	0	0
BU	2400000	0	0	0	0	0	0	0	1
BU	3000000	1	0	0	0	0	1	1	0
BU	4300000	0	1	0	1	0	0	1	0
BU	2100000	1	0	0	1	0	0	1	0
BU	2700000	0	0	0	0	0	0	0	1
BU	731400	0	1	1	0	0	0	1	0
BU	713100	1	0	0	0	1	0	1	0
BU	3700000	0	1	0	1	0	0	1	0
BU	1800000	1	0	1	0	0	0	1	0
BU	8900000	0	1	1	0	0	0	1	0
BU	11600000	0	0	0	0	0	0	1	1
BU	2700000	0	0	0	0	0	0	1	1
BU	2100000	0	1	0	0	1	0	1	0
BU	1800000	1	0	1	0	0	0	1	0
BU	8900000	0	1	1	0	0	0	1	0
BU	11600000	0	0	0	0	0	0	1	1
BU	2700000	0	0	0	0	0	0	1	1
BU	2100000	0	0	0	0	0	0	1	1
BU	10200000	0	0	0	0	0	0	1	1
BU	8400000	0	0	0	0	0	0	1	1
BU	15900000	0	0	0	0	0	0	1	1
BU	3100000	0	1	1	0	0	0	1	0
BU	12600000	0	0	0	0	0	0	0	1
BU	7600000	1	1	1	1	1	1	0	0
BU	9400000	1	1	1	1	0	0	1	0
BU	13300000	1	0	1	0	0	0	0	0
BU	14600000	1	1	1	1	0	0	0	0
BU	2800000	1	1	1	1	1	1	0	0
BU	2200000	0	0	0	0	0	0	0	1
BU	9800000	0	0	0	0	0	0	0	1
BU	8200000	0	0	0	0	0	0	0	1
BU	10400000	0	0	0	0	0	0	0	1
BU	15100000	0	0	0	0	0	0	0	1
BU	5100000	0	0	0	0	0	0	0	1
BU	4300000	0	0	0	0	0	0	0	1
BU	24300000	0	0	0	0	0	0	0	1

BU	10200000	0	0	0	0	0	0	0	1
BU	12300000	0	0	0	0	0	0	0	1
BU	15100000	0	0	0	0	0	0	0	1
BU	24300000	0	0	0	0	0	0	0	1
BU	12300000	0	0	0	0	0	0	0	1
BU	21200000	0	0	0	0	0	0	0	1
BU	17200000	0	0	0	0	0	0	0	1
BU	41500000	0	0	0	0	0	0	0	1
BU	12300000	0	0	0	0	0	0	0	1
BU	7300000	0	0	0	0	0	0	0	1
BU	19900000	0	0	0	0	0	0	0	1
BU	3500000	0	0	0	0	0	0	0	1
BU	3700000	0	0	0	0	0	0	0	1
BU	5000000	0	0	0	0	0	0	0	1
BU	3800000	0	0	0	0	0	0	0	1
BU	2200000	0	0	0	0	0	0	0	1
BU	7600000	0	0	0	0	0	0	0	1
BU	4200000	0	0	0	0	0	0	0	1
BU	6200000	0	0	0	0	0	0	0	1
BU	803600	0	1	0	0	0	1	1	0
BU	6000000	0	0	0	0	0	0	0	1
BU	5200000	0	0	0	0	0	0	0	1
BU	8300000	0	0	0	0	0	0	0	1
BU	14000000	0	0	0	0	0	0	0	1
BU	8600000	0	0	0	0	0	0	0	1
BU	14800000	0	0	0	0	0	0	0	1
BU	5400000	1	0	1	0	0	0	1	0
BU	11700000	0	0	0	0	0	0	0	1
BU	7000000	0	0	0	0	0	0	0	1
BU	7000000	0	0	0	0	0	0	0	1
BU	7900000	0	0	0	0	0	0	0	1
BU	11100000	1	0	1	0	0	0	1	0
BU	6900000	0	0	0	0	0	0	0	1
BU	2400000	1	1	1	1	1	1	0	0
BU	6700000	0	0	0	0	0	0	0	1
BU	2800000	0	0	0	0	0	0	0	1
BU	7500000	0	0	0	0	0	0	0	1
BU	6100000	0	0	0	0	0	0	0	1
BU	7000000	0	0	0	0	0	0	0	1
BU	6300000	0	0	0	0	0	0	0	1
BU	5000000	0	0	0	0	0	0	0	1
BU	5300000	0	0	0	0	0	0	0	1

BU	1600000	0	0	0	0	0	0	0	1
BU	1500000	0	0	0	0	0	0	0	1
BU	1000000	0	0	0	0	0	0	0	1
BU	1100000	0	0	0	0	0	0	0	1
BU	1300000	0	0	0	0	0	0	0	1
BU	20500000	0	0	0	0	0	0	0	1
BU	2200000	0	0	0	0	0	0	0	1
BU	4000000	0	0	0	0	0	0	0	1
BU	20900000	0	0	0	0	0	0	0	1
BU	2100000	0	0	0	0	0	0	0	1
BU	3800000	1	0	1	0	0	0	0	0
BU	2500000	0	0	0	0	0	0	0	1
BU	2600000	0	0	0	0	0	0	0	1
BU	16800000	0	0	0	0	0	0	0	1
BU	19600000	0	0	0	0	0	0	0	1
BU	963800	0	0	0	0	0	0	0	1
BU	3200000	1	1	1	1	1	1	0	0
BU	7000000	0	0	0	0	0	0	0	1

Annex 2: Study 1 Frequencies

Source: Author's own

Representation of White individuals in the video.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	330	55.0	55.0	55.0
	1	270	45.0	45.0	100.0
	Total	600	100.0	100.0	

Representation of Black individuals in the video.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	459	76.5	76.5	76.5
	1	141	23.5	23.5	100.0
	Total	600	100.0	100.0	

Representation of Asian individuals in the video.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	456	76.0	76.0	76.0
	1	144	24.0	24.0	100.0
	Total	600	100.0	100.0	

Representation of individuals from other ethnic backgrounds.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	542	90.3	90.3	90.3
	1	58	9.7	9.7	100.0
	Total	600	100.0	100.0	

Representation of at least one non white model.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	372	62.0	62.0	62.0
	1	228	38.0	38.0	100.0
	Total	600	100.0	100.0	

Presence of female models in the video.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	325	54.2	54.2	54.2
	1	275	45.8	45.8	100.0
	Total	600	100.0	100.0	

Presence of male models in the video.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	414	69.0	69.0	69.0
	1	186	31.0	31.0	100.0
	Total	600	100.0	100.0	

No person featured in the video.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	400	66.7	66.7	66.7
	1	200	33.3	33.3	100.0
	Total	600	100.0	100.0	

Indicates whether the video focuses on celebrities.					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	434	72.3	72.3	72.3
	1	166	27.7	27.7	100.0
	Total	600	100.0	100.0	

Annex 3: Study 1 Linear Regression Female Models

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.078[a]	.006	.004	1.14424
a. Predictors: (Constant), Presence of female models in the video.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	4.833	1	4.833	3.691	.055[b]
	Residual	782.948	598	1.309		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Presence of female models in the video.						

Coefficients[a]						
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	
	B		Std. Error	Beta		
1	(Constant)		6.045	.063	95.248	<.001
	Presence of female models in the video.		-.180	.094	-.078	-1.921	.055
a. Dependent Variable: NumberofViews_log						

Annex 4: Study 1 Linear Regression Male Models

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.013[a]	.000	-.002	1.14767
a. Predictors: (Constant), Presence of male models in the video.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	.131	1	.131	.099	.753[b]
	Residual	787.650	598	1.317		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Presence of male models in the video.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.953	.056		105.541	<.001
	Presence of male models in the video.	.032	.101	.013	.315	.753
a. Dependent Variable: NumberofViews_log						

Annex 5: Study 1 Linear Regression White Models

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.007[a]	.000	-.002	1.14773
a. Predictors: (Constant), Representation of white individuals in the video.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	.044	1	.044	.034	.855[b]
	Residual	787.737	598	1.317		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Representation of white individuals in the video.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.955	.063		94.256	<.001
	Representation of white individuals in the video.	.017	.094	.007	.183	.855
a. Dependent Variable: NumberofViews_log						

Annex 6: Study 1 Linear Regression Asian Models

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.020[a]	.000	-.001	1.14753
a. Predictors: (Constant), Representation of Asian individuals in the video.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	.322	1	.322	.244	.621[b]
	Residual	787.459	598	1.317		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Representation of Asian individuals in the video.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.950	.054		110.721	<.001
	Representation of Asian individuals in the video.	.054	.110	.020	.494	.621
a. Dependent Variable: NumberofViews_log						

Annex 7: Study 1 Linear Regression Black Models

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.055[a]	.003	.001	1.14604
a. Predictors: (Constant), Representation of Black individuals in the video.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	2.358	1	2.358	1.795	.181[b]
	Residual	785.423	598	1.313		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Representation of Black individuals in the video.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.928	.053		110.822	<.001
	Representation of Black individuals in the video.	.148	.110	.055	1.340	.181
a. Dependent Variable: NumberofViews_log						

Annex 8: Study 1 Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.068[a]	.005	.003	1.14512
a. Predictors: (Constant), Representation of individuals from other ethnic backgrounds.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	3.629	1	3.629	2.767	.097[b]
	Residual	784.152	598	1.311		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Representation of individuals from other ethnic backgrounds.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.937	.049		120.713	<.001
	Representation of individuals from other ethnic backgrounds.	.263	.158	.068	1.664	.097
a. Dependent Variable: NumberofViews_log						

Annex 9: Study 1 Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.008[a]	.000	-.002	1.14773
a. Predictors: (Constant), Representation of at least one non white model.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	.052	1	.052	.039	.843[b]
	Residual	787.729	598	1.317		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Representation of at least one non white model.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.970	.060		100.328	<.001
	Representation of at least one non white model.	-.019	.097	-.008	-.198	.843
a. Dependent Variable: NumberofViews_log						

Annex 10: Study 1 Linear Regression Presence of Celebrity

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.024[a]	.001	-.001	1.14744
a. Predictors: (Constant), Indicates whether the video focuses on celebrities.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	.438	1	.438	.333	.564[b]
	Residual	787.343	598	1.317		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), Indicates whether the video focuses on celebrities.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.946	.055		107.958	<.001
	Indicates whether the video focuses on celebrities.	.060	.105	.024	.577	.564
a. Dependent Variable: NumberofViews_log						

Annex 11: Study 1 Linear Regression Presence of no Person

Source: Author's own

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.027[a]	.001	-.001	1.14734
a. Predictors: (Constant), No person featured in the video.				

ANOVA[a]						
Model	Sum of Squares	df	Mean Square	F	Sig.	
1	Regression	.582	1	.582	.442	.506[b]
	Residual	787.199	598	1.316		
	Total	787.781	599			
a. Dependent Variable: NumberofViews_log						
b. Predictors: (Constant), No person featured in the video.						

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.941	.057		103.560	<.001
	No person featured in the video.	.066	.099	.027	.665	.506
a. Dependent Variable: NumberofViews_log						

Annex 12: Study 1 Multi Linear Regression Diversity Cues

Source: Author's own

Coefficients[a]						
Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta			
1	(Constant)	5.876	.190		30.885	<.001
	Indicates whether a video is from a luxury brand	.449	.107	.185	4.189	<.001
	Presence of female models in the video.	-.416	.178	-.181	-2.338	.020
	Presence of male models in the video.	-.190	.167	-.077	-1.140	.255
	Representation of white individuals in the video.	.103	.188	.045	.550	.583
	Representation of Asian individuals in the video.	.188	.199	.070	.946	.344
	Representation of Black individuals in the video.	.396	.209	.146	1.897	.058
	Representation of individuals from other ethnic backgrounds.	.187	.194	.048	.965	.335
	Representation of at least one non white model.	-.340	.297	-.144	-1.145	.253
	Indicates whether the video focuses on celebrities.	.003	.125	.001	.021	.983
	No person featured in the video.	-.110	.187	-.045	-.591	.554
a. Dependent Variable: NumberofViews_log						

Annex 13: Study 2 Valence - Linear Regression White Models

Source: Author's own

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.103	0.011	0.010	1.632

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	168.450	1	168.450	63.221	< .001
	Residual	15784.211	5924	2.664		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.396	0.028		266.188	< .001
	white (1)	-0.342	0.043		-7.951	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 14: Study 2 Valence - Linear Regression Asian Models

Source: Author's own

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.138	0.019	0.019	1.625

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	304.195	1	304.195	115.158	< .001
	Residual	15648.467	5924	2.642		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.036	0.029		240.457	< .001
	asian (1)	0.454	0.042		10.731	< .001

Coefficients

Model	Unstandardized	Standard Error	Standardized[a]	t	p

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 15: Study 2 Valence - Linear Regression Black Models

Source: Author's own

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.052	0.003	0.003	1.639

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	43.830	1	43.830	16.321	< .001
	Residual	15908.831	5924	2.685		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.301	0.024		299.875	< .001
	black (1)	-0.203	0.050		-4.040	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 16: Study 2 Valence - Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.008	0.000	-0.000	1.641

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	1.099	1	1.099	0.408	0.523
	Residual	15951.562	5924	2.693		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.249	0.022		325.366	< .001
	other (1)	0.049	0.077		0.639	0.523

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 17: Study 2 Valence - Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.105	0.011	0.011	1.632

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	176.905	1	176.905	66.430	< .001
	Residual	15775.757	5924	2.663		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.009	0.037		190.526	< .001
	diversity (1)	0.367	0.045		8.150	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 18: Study 2 Extremity - Linear Regression White Models

Source: Author's own

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.016	0.000	0.000	0.510

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.374	1	0.374	1.438	0.231
	Residual	1540.948	5924	0.260		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.178	0.009		365.995	< .001
	white (1)	0.016	0.013		1.199	0.231

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 19: Study 2 Extremity - Linear Regression Asian Models

Source: Author's own

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.046	0.002	0.002	0.510

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	3.281	1	3.281	12.637	< .001
	Residual	1538.041	5924	0.260		
	Total	1541.322	5925			

ANOVA

Model		Sum of Squares	df	Mean Square	F	p

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.207	0.009		349.565	< .001
	asian (1)	-0.047	0.013		-3.555	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 20: Study 2 Extremity - Linear Regression Black Models

Source: Author's own

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.028	0.001	0.001	0.510

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	1.175	1	1.175	4.519	0.034
	Residual	1540.147	5924	0.260		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.176	0.008		419.291	< .001
	black (1)	0.033	0.016		2.126	0.034

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 21: Study 2 Extremity - Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.010	0.000	-0.000	0.510

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.151	1	0.151	0.579	0.447
	Residual	1541.171	5924	0.260		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.186	0.007		460.001	< .001
	other (1)	-0.018	0.024		-0.761	0.447

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 22: Study 2 Extremity - Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.019	0.000	0.000	0.510

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.543	1	0.543	2.089	0.148
	Residual	1540.778	5924	0.260		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.198	0.011		278.167	< .001

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
	diversity (1)	-0.020	0.014		-1.445	0.148

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 23: Study 2 Emotionality - Linear Regression White Models

Source: Author's own

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.103	0.011	0.010	1.302

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	107.315	1	107.315	63.278	< .001
	Residual	10046.713	5924	1.696		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.379	0.022		242.667	< .001
	white (1)	0.273	0.034		7.955	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 24: Study 2 Emotionality - Linear Regression Asian Models

Source: Author's own

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.152	0.023	0.023	1.294

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	234.782	1	234.782	140.217	< .001
	Residual	9919.245	5924	1.674		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.684	0.023		243.998	< .001
	asian (1)	-0.398	0.034		-11.841	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 25: Study 2 Emotionality - Linear Regression Black Models

Source: Author's own

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.099	0.010	0.010	1.303

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	98.882	1	98.882	58.256	< .001
	Residual	10055.146	5924	1.697		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.422	0.019		280.093	< .001
	black (1)	0.304	0.040		7.633	< .001

Coefficients

Model	Unstandardized	Standard Error	Standardized[a]	t	p

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 26: Study 2 Emotionality - Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.048	0.002	0.002	1.308

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	23.102	1	23.102	13.509	< .001
	Residual	10130.925	5924	1.710		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.474	0.018		308.308	< .001
	other (1)	0.224	0.061		3.675	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 27: Study 2 Emotionality - Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.085	0.007	0.007	1.305

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	72.888	1	72.888	42.831	< .001
	Residual	10081.140	5924	1.702		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.651	0.029		192.163	< .001
	diversity (1)	-0.235	0.036		-6.545	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 28: Study 2 Emotionality Hand Coded - Linear Regression White Models

Source: Author's own

Model Summary - emotionality

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.979
H_1	0.111	0.012	0.012	0.973

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	17.149	1	17.149	18.119	< .001
	Residual	1381.818	1460	0.946		
	Total	1398.966	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.995	0.026		156.112	< .001
H_1	(Intercept)	4.125	0.040		103.779	< .001
	white (1)	-0.220	0.052		-4.257	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 29: Study 2 Emotionality Hand Coded - Linear Regression Asian Models

Source: Author's own

Model Summary - emotionality

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.979
H_1	0.078	0.006	0.005	0.976

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	8.537	1	8.537	8.964	0.003
	Residual	1390.429	1460	0.952		

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
	Total	1398.966	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.995	0.026		156.112	< .001
H_1	(Intercept)	3.942	0.031		127.045	< .001
	asian (1)	0.163	0.055		2.994	0.003

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 30: Study 2 Emotionality Hand Coded - Linear Regression Black Models

Source: Author's own

Model Summary - emotionality

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.979
H_1	0.008	0.000	-0.001	0.979

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.085	1	0.085	0.089	0.766
	Residual	1398.881	1460	0.958		
	Total	1398.966	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.995	0.026		156.112	< .001
H_1	(Intercept)	3.990	0.031		129.805	< .001
	black (1)	0.017	0.056		0.298	0.766

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 31: Study 2 Emotionality Hand Coded - Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary - emotionality

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.979
H_1	0.054	0.003	0.002	0.977

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	4.112	1	4.112	4.304	0.038
	Residual	1394.855	1460	0.955		
	Total	1398.966	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.995	0.026		156.112	< .001
H_1	(Intercept)	4.018	0.028		144.630	< .001
	other (1)	-0.147	0.071		-2.075	0.038

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 32: Study 2 Emotionality Hand Coded - Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary - emotionality

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.979
H_1	0.104	0.011	0.010	0.974

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	15.192	1	15.192	16.028	< .001
	Residual	1383.775	1460	0.948		
	Total	1398.966	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.995	0.026		156.112	< .001
H_1	(Intercept)	3.880	0.038		100.816	< .001
	diversity (1)	0.205	0.051		4.004	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 33: Study 2 Sentiment - Linear Regression White Models

Source: Author's own

Model Summary - sentiment

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.258
H_1	0.109	0.012	0.011	1.250

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	27.337	1	27.337	17.482	< .001
	Residual	2283.029	1460	1.564		
	Total	2310.367	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.752	0.033		114.095	< .001
H_1	(Intercept)	3.917	0.051		76.654	< .001
	white (1)	-0.278	0.067		-4.181	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 34: Study 2 Sentiment - Linear Regression Asian Models

Source: Author's own

Model Summary - sentiment

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.258
H_1	0.039	0.002	0.001	1.257

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	3.475	1	3.475	2.200	0.138
	Residual	2306.891	1460	1.580		
	Total	2310.367	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.752	0.033		114.095	< .001
H_1	(Intercept)	3.719	0.040		92.987	< .001
	asian (1)	0.104	0.070		1.483	0.138

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 35: Study 2 Sentiment - Linear Regression Black Models

Source: Author's own

Model Summary - sentiment

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.258
H_1	0.042	0.002	0.001	1.257

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	4.125	1	4.125	2.612	0.106
	Residual	2306.241	1460	1.580		
	Total	2310.367	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.752	0.033		114.095	< .001
H_1	(Intercept)	3.788	0.039		95.920	< .001
	black (1)	-0.115	0.071		-1.616	0.106

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 36: Study 2 Sentiment - Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary - sentiment

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.258
H_1	0.094	0.009	0.008	1.252

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	20.380	1	20.380	12.994	< .001
	Residual	2289.986	1460	1.568		
	Total	2310.367	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.752	0.033		114.095	< .001
H_1	(Intercept)	3.803	0.036		106.793	< .001
	other (1)	-0.327	0.091		-3.605	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 37: Study 2 Sentiment - Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary - sentiment

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.258
H_1	0.055	0.003	0.002	1.256

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	6.889	1	6.889	4.366	0.037
	Residual	2303.478	1460	1.578		
	Total	2310.367	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.752	0.033		114.095	< .001
H_1	(Intercept)	3.674	0.050		73.949	< .001
	diversity (1)	0.138	0.066		2.090	0.037

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 38: Study 2 Exclusivity - Linear Regression White Models

Source: Author's own

Model Summary - exclusivity

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.368
H_1	0.193	0.037	0.028	1.349

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	7.116	1	7.116	3.911	0.051
	Residual	183.739	101	1.819		
	Total	190.854	102			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	4.175	0.135		30.974	< .001
H_1	(Intercept)	3.774	0.242		15.580	< .001
	white (1)	0.573	0.290		1.978	0.051

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 39: Study 2 Exclusivity - Linear Regression Asian Models

Source: Author's own

Model Summary - exclusivity

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.368
H_1	0.379	0.144	0.135	1.272

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	27.416	1	27.416	16.942	< .001
	Residual	163.438	101	1.618		
	Total	190.854	102			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	4.175	0.135		30.974	< .001
H_1	(Intercept)	4.569	0.158		28.959	< .001
	asian (1)	-1.069	0.260		-4.116	< .001

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 40: Study 2 Exclusivity - Linear Regression Black Models

Source: Author's own

Model Summary - exclusivity

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.368
H_1	0.042	0.002	-0.008	1.373

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.341	1	0.341	0.181	0.671
	Residual	190.513	101	1.886		
	Total	190.854	102			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	4.175	0.135		30.974	< .001
H_1	(Intercept)	4.214	0.164		25.673	< .001
	black (1)	-0.123	0.290		-0.425	0.671

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 41: Study 2 Exclusivity - Linear Regression Models with Other Ethnic Backgrounds

Source: Author's own

Model Summary - exclusivity

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.368
H_1	0.153	0.023	0.014	1.358

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	4.468	1	4.468	2.421	0.123
	Residual	186.387	101	1.845		
	Total	190.854	102			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	4.175	0.135		30.974	< .001
H_1	(Intercept)	4.274	0.148		28.834	< .001
	other (1)	-0.537	0.345		-1.556	0.123

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 42: Study 2 Exclusivity - Linear Regression Presence of Diverse Models

Source: Author's own

Model Summary - exclusivity

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.368
H_1	0.071	0.005	-0.005	1.371

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.950	1	0.950	0.505	0.479
	Residual	189.904	101	1.880		
	Total	190.854	102			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	4.175	0.135		30.974	< .001
H_1	(Intercept)	4.600	0.613		7.501	< .001
	luxury (1)	-0.447	0.629		-0.711	0.479

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 43: Study 2 Valence - Multi Linear Regression Brand Type

Source: Author's own

Ethnicities & Luxury

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.145	0.021	0.020	1.624

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	337.537	5	67.507	25.593	< .001
	Residual	15615.124	5920	2.638		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.232	0.073		98.615	< .001
	white (1)	-0.192	0.065		-2.967	0.003
	asian (1)	0.311	0.068		4.551	< .001
	black (1)	-0.161	0.064		-2.531	0.011
	other (1)	0.091	0.100		0.913	0.361
	luxury (1)	-0.020	0.061		-0.323	0.746

[a] Standardized coefficients can only be computed for continuous predictors.

Diversity & Luxury

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.108	0.012	0.011	1.632

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	185.523	2	92.762	34.846	< .001
	Residual	15767.138	5923	2.662		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	6.927	0.058		119.011	< .001
	luxury (1)	0.104	0.058		1.799	0.072
	diversity (1)	0.358	0.045		7.915	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 44: Study 2 Extremity - Multi Linear Regression Brand Type

Source: Author's own

Ethnicities & Luxury

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.074	0.006	0.005	0.509

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	8.549	5	1.710	6.603	< .001
	Residual	1532.773	5920	0.259		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.255	0.023		141.664	< .001
	luxury (1)	-0.081	0.019		-4.252	< .001
	asian (1)	-0.018	0.021		-0.842	0.400
	white (1)	0.007	0.020		0.351	0.725
	black (1)	0.023	0.020		1.133	0.257
	other (1)	-0.027	0.031		-0.861	0.389

[a] Standardized coefficients can only be computed for continuous predictors.

Diversity & Luxury

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.068	0.005	0.004	0.509

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	7.217	2	3.609	13.933	< .001
	Residual	1534.104	5923	0.259		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.269	0.018		180.060	< .001
	diversity (1)	-0.013	0.014		-0.901	0.368
	luxury (1)	-0.091	0.018		-5.076	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 45: Study 2 Emotionality - Multi Linear Regression Brand Type

Source: Author's own

Ethnicities & Luxury

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.183	0.034	0.033	1.288

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	340.499	5	68.100	41.081	< .001
	Residual	9813.529	5920	1.658		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.713	0.058		98.273	< .001
	luxury (1)	-0.199	0.048		-4.114	< .001
	asian (1)	-0.300	0.054		-5.536	< .001
	white (1)	0.084	0.051		1.627	0.104
	black (1)	0.158	0.050		3.127	0.002
	other (1)	0.215	0.079		2.721	0.007

[a] Standardized coefficients can only be computed for continuous predictors.

Diversity & Luxury

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.126	0.016	0.015	1.299

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	160.562	2	80.281	47.582	< .001
	Residual	9993.466	5923	1.687		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.910	0.046		127.526	< .001
	diversity (1)	-0.208	0.036		-5.769	< .001
	luxury (1)	-0.331	0.046		-7.209	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 46: Study 3 Valence - Linear Regression Brand Type

Source: Author's own

Linear Regression

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.034	0.001	0.001	1.640

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	18.773	1	18.773	6.980	0.008
	Residual	15933.888	5924	2.690		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.126	0.053		134.976	< .001
	luxury (1)	0.152	0.058		2.642	0.008

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 47: Study 3 Extremity - Linear Regression Brand Type

Source: Author's own

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.067	0.005	0.004	0.509

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	7.007	1	7.007	27.055	< .001
	Residual	1534.314	5924	0.259		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.262	0.016		199.126	< .001

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
	luxury (1)	-0.093	0.018		-5.201	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 48: Study 3 Emotionality - Linear Regression Brand Type

Source: Author's own

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.101	0.010	0.010	1.302

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	104.404	1	104.404	61.544	< .001
	Residual	10049.623	5924	1.696		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.794	0.042		138.199	< .001
	luxury (1)	-0.359	0.046		-7.845	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 49: Study 3 Emotionality Hand Coded - Linear Regression Brand Type

Source: Author's own

Model Summary - emotionality

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.979
H_1	0.205	0.042	0.042	0.958

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	59.077	1	59.077	64.373	< .001
	Residual	1339.889	1460	0.918		
	Total	1398.966	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.995	0.026		156.112	< .001
H_1	(Intercept)	3.712	0.043		85.677	< .001
	luxury (1)	0.426	0.053		8.023	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 50: Study 3 Sentiment - Linear Regression Brand Type

Source: Author's own

Model Summary - sentiment

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.258
H_1	0.242	0.059	0.058	1.221

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	135.405	1	135.405	90.894	< .001
	Residual	2174.961	1460	1.490		
	Total	2310.367	1461			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.752	0.033		114.095	< .001
H_1	(Intercept)	3.323	0.055		60.207	< .001
	luxury (1)	0.645	0.068		9.534	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 51: Study 3 Exclusivity - Linear Regression Brand Type

Source: Author's own

Model Summary - exclusivity

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.368
H_1	0.071	0.005	-0.005	1.371

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	0.950	1	0.950	0.505	0.479
	Residual	189.904	101	1.880		
	Total	190.854	102			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	4.175	0.135		30.974	< .001
H_1	(Intercept)	4.600	0.613		7.501	< .001
	luxury (1)	-0.447	0.629		-0.711	0.479

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 52: Study 3 Valence - Multi Linear Regression Celebrity Presence

Source: Author's own

Ethnicities & Luxury

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.147	0.022	0.021	1.624

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	343.130	5	68.626	26.027	< .001
	Residual	15609.532	5920	2.637		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	7.153	0.076		93.696	< .001
	white (1)	-0.172	0.066		-2.612	0.009
	asian (1)	0.288	0.066		4.353	< .001
	black (1)	-0.127	0.068		-1.876	0.061
	other (1)	0.101	0.099		1.014	0.311
	celebrityfocused (1)	0.083	0.056		1.492	0.136

[a] Standardized coefficients can only be computed for continuous predictors.

Diversity & Luxury

Model Summary - valence_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.641
H_1	0.126	0.016	0.016	1.628

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	254.993	2	127.497	48.107	< .001
	Residual	15697.668	5923	2.650		
	Total	15952.662	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	7.254	0.021		340.301	< .001
H_1	(Intercept)	6.881	0.044		157.971	< .001
	celebrityfocused (1)	0.250	0.046		5.428	< .001
	diversity (1)	0.309	0.046		6.691	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 53: Study 3 Extremity - Multi Linear Regression Celebrity Presence

Source: Author's own

Ethnicities & Luxury

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.073	0.005	0.005	0.509

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	8.294	5	1.659	6.406	< .001
	Residual	1533.028	5920	0.259		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.260	0.024		136.271	< .001
	asian (1)	-0.030	0.021		-1.462	0.144
	white (1)	-0.025	0.021		-1.233	0.218
	black (1)	-0.007	0.021		-0.324	0.746
	other (1)	-0.017	0.031		-0.562	0.574
	celebrityfocused (1)	-0.072	0.017		-4.135	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Diversity & Luxury

Model Summary - extremity_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	0.510
H_1	0.067	0.004	0.004	0.509

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	6.886	2	3.443	13.290	< .001
	Residual	1534.436	5923	0.259		
	Total	1541.322	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	3.184	0.007		480.602	< .001
H_1	(Intercept)	3.234	0.014		237.474	< .001
	celebrityfocused (1)	-0.071	0.014		-4.948	< .001
	diversity (1)	-0.004	0.014		-0.263	0.793

[a] Standardized coefficients can only be computed for continuous predictors.

Annex 54: Study 3 Emotionality - Multi Linear Regression Celebrity Presence

Source: Author's own

Ethnicities & Luxury

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.176	0.031	0.030	1.289

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	314.267	5	62.853	37.815	< .001
	Residual	9839.761	5920	1.662		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.624	0.061		92.778	< .001
	asian (1)	-0.355	0.053		-6.749	< .001
	white (1)	0.040	0.052		0.763	0.445
	black (1)	0.139	0.054		2.593	0.010
	other (1)	0.248	0.079		3.144	0.002
	celebrityfocused (1)	-0.046	0.044		-1.048	0.294

[a] Standardized coefficients can only be computed for continuous predictors.

Diversity & Luxury

Model Summary - emotionality_avg

Model	R	R^2	Adjusted R^2	RMSE
H_0	0.000	0.000	0.000	1.309
H_1	0.126	0.016	0.016	1.299

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	160.854	2	80.427	47.670	< .001
	Residual	9993.173	5923	1.687		
	Total	10154.028	5925			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized[a]	t	p
H_0	(Intercept)	5.493	0.017		323.037	< .001
H_1	(Intercept)	5.786	0.035		166.477	< .001
	celebrityfocused (1)	-0.265	0.037		-7.221	< .001
	diversity (1)	-0.174	0.037		-4.722	< .001

[a] Standardized coefficients can only be computed for continuous predictors.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work ChatGPT (4.0 and o1), Grammarly as well as the paraphrasing tool QuillBot were used in order to edit text. ChatGPT was used to translate TikTok comments into English. Scite Assistant and Connected Papers were utilized in the search for related literature. The AI based translating tool Deepl has been used to translate between German and English. After using these tools and services, I reviewed and edited the content as needed and take full responsibility for the content of this thesis.