Exploring Audience Perceptions of Branded Content Featuring AI Influencer Lil Miquela

A Mixed-Method Analysis of YouTube and Instagram Comments

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ABSTRACT

In the rapidly evolving digital landscape, AI influencers represent a transformative development in marketing. This thesis examines Lil Miquela—one of the most prominent AI influencers—as a case study to investigate how audience interactions with her branded content on YouTube and Instagram reflect perceptions of both the AI influencer and associated brands. Through thematic analysis, sentiment analysis, and quantitative analysis, this thesis identifies key discussion topics, expression forms, and the sentiments conveyed in audience comments.

Thematic analysis reveals a broad range of topics, including influencer perception, brand perception, emotion, vibe, and commentary on comment section. Notably, Lil Miquela is perceived as both emotionally relatable and technologically alien, inviting connection while provoking unease through her content and appearance. Brand perceptions are related to not only brand value and product features but also audiences' imagination regarding product usage and brand personality. The branded collaborations with Lil Miquela have been controversial. Although the advertisements are praised by high quality, Lil Miquela was perceived to distract some audiences from core branded messaging. Some commenters directly expressed their rejection of these campaigns. Moreover, vibe descriptions span both positive and negative sentiments: descriptors such as "dream" and "futuristic" convey admiration, while terms like "disgusting" and "weird" indicate discomfort. Some commenters distanced themselves from the broader audiences, critiquing the comment section itself. Sentiment analysis confirms the predominantly positive attitudes toward both Lil Miquela and the associated brands. Quantitative analysis further reveals platform-specific patterns: Instagram comments tend to be more positive and brand-focused, whereas YouTube comments display more frequent interaction between commenters and greater emphasis on self-expression.

This thesis contributes to academic understandings by linking audience perceptions of AI influencers with those of associated brands within a shared context, while also highlighting platform-specific audience dynamics in AI-driven marketing. Practically, it provides actionable insights for marketers seeking to optimize AI influencer collaborations and leverage AI technologies for more effective and responsible campaigns.

KEYWORDS: *AI influencer, Audience Perception, Branded Content, Lil Miquela, Sentiment Analysis*

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1. Introduction

In today's digital age, artificial intelligence (AI) has been transforming marketing practices across all stages of brand communication. Throughout the brand communication process, AI enables brands, the communicators, to design engaging copy (Kavgić, 2024, p.1211) and visuals (Nesterenko & Olefirenko, 2023, p. 171) more efficiently. During the dissemination phase, AI tools help to do A/B testing in real time to adjust creative elements, such as textual content, product imagery, and banner size, thus catering to customers' preferences and habits, and enhancing advertising effectiveness (Lee & Cho, 2020, pp. 336-337). When consumers respond or make inquires, AI-powered chatbots can help brands to provide accurate information instantly, which further improves the experience for brand communication (Binlibdah, 2024, p. 1156). In addition to direct brand communication, AI has also been revolutionizing the strategic aspect, such as influencer marketing, a key approach for brand promotion on social media (Vrontis et al., 2021, p. 618).

Influencer marketing leverages social media influencers—individuals with a strong online presence—to promote brands and products (Hudders et al., 2021, pp. 27-28; Leung et al., 2022, p. 226). By collaborating with influencers, brands can reach highly targeted customer segments, amplify the impact of branded content, and enhance market positioning with greater acceptance and relevance (Leung et al., 2022, p. 248). This, in turn, fosters positive customer attitudes and behaviors, as influencer-generated content is perceived as more engaging and trustworthy than traditional brand messaging (Leung et al., 2022, p. 248). The rise of influencer marketing can be traced back to the time when social media emerged as the dominant platform for brand communication (Vrontis et al., 2021, p. 618). Over the past decade, influencer marketing has also presented significant challenges. For example, fake followers and bot-generated engagement make it difficult for brands to select the right influencers and platforms (Alipour et al., 2024, pp. 13-15). In addition, balancing brand control is crucial — excessive oversight can stifle influencer creativity and reduce audience engagement, while insufficient control may lead to brand misrepresentation, financial losses, or legal risks (Alipour et al., 2024, pp. 16-17). Moreover, influencers' personal actions and reputations directly impact brand perceptions (Alipour et al., 2024, pp. 18-19). Nowadays, virtual influencers, digital avatars designed to exhibit realistic appearances and human-like behaviors (Kim & Wang, 2024, p. 2), have introduced a new dimension to influencer marketing.

Virtual influencers encompass both CGI influencers, which are computer-generated artificial characters, and AI influencers, which are operated by artificial intelligence (Kim & Wang, 2024, p. 2). These three terms are often used interchangeably, as AI technologies and computer-generated visuals are mostly integrated (Kim & Wang, 2024, p. 2; Feng et al., 2024, p. 27; Zhang & Wei, 2021, p. 5; Moustakas et al., 2020, p.1). For clarity and consistency, this thesis uses the term "AI influencer" to refer to this concept. In general, an AI influencer does not exist in the physical word but is solely a social media

presence, managed by either backend AI or human agency (Kim & Wang, 2024, p. 2; Gerlich, 2023, p. 1). While they exhibit media personas with human-like traits (Feng et al., 2024, p. 27), AI influencers offer several advantages over human influencers. Specifically, AI influencers are often seen as more cost-effective (Thomas & Fowler, 2021, p. 12), less prone to scandals (Thomas & Fowler, 2021, p. 12), and provide brands with greater flexibility to design content that aligns with their products or services (Kim & Park, 2024, p. 1). However, AI influencers also present challenges, such as sustaining followers' interest and addressing concerns about their lack of authenticity and relatability (Moustakas et al., 2020, p. 4)

Lil Miquela, one of the most prominent AI influencers (Rana et al., 2024, p. 3), was created by the tech firm Brud (Hughes, 2023, p. 1) in 2016 (Sands et al., 2022, p. 2). As of March 31, 2025, she has amassed 2.4 million Instagram followers and 273,000 YouTube subscribers. Her communication strategy centers on showcasing her daily life to build a relatable digital persona that reflects her personality, interests, and lifestyle, rather than directly advertising products (Kim & Lee, 2024, pp. 203-208). Despite this soft-sell approach, she has partnered with brands across industries like fashion, art, and technology (Rodrigo-Martín et al., 2021, p. 86). The COVID-19 pandemic in 2020 marked a turning point, as Lil Miquela remained active while many human influencers suffered from the lockdowns and mobility restrictions (Rodrigo-Martín et al., 2021, p. 82). Her uninterrupted presence sustained audience engagement during this uncertain time when people sought normality (Rodrigo-Martín et al., 2021, p. 82). This highlights a key advantage of AI influencers — their ability to operate without physical constraints, enabling flexible content creation. This benefit is further amplified by their exemption from the financial hardship caused by frequent travel, and legal restrictions such as visa requirements; as a result, Lil Miquela can more easily project an aspirational lifestyle that further strengthens emotional bonds with followers, thereby enhancing the effectiveness of advertising (Rodrigo-Martín et al., 2021, p. 86). In addition, Lil Miquela's success is also credited to a team of experts who manage her narrative, ensuring consistency and audience appeal (Rodrigo-Martín et al., 2021, p. 79). Under this professional guidance, she frequently interacts with both virtual and real influencers, boosting her perceived realism (Rodrigo-Martín et al., 2021, p. 84) and thus deepening a sense of community among her audiences (Kim & Lee, 2024, pp. 203-208).

This thesis investigates Lil Miquela as a case study to explore AI influencer marketing, focusing on audience-expressed perceptions of both the influencer and the associated brand. Perception reflects people's understanding of a subject (Qiong, 2017, p. 18). Specifically, perceptions of AI influencer refer to how people evaluate AI influencer, which is an essential aspect of influencer marketing (Hudders et al., 2021, pp. 19-20), as these perceptions significantly influence the brand's image (Lou et al., 2023, p. 549). In parallel, brand perception refers to how people think of brands, which are influenced by marketing efforts (Mohammad et al., 2024, pp. 367-371). The brand perception can be seen as a key indicator of a

marketing strategy's effectiveness. This thesis places particular emphasis on audience-expressed perception, highlighting its publicly visible attribute (Noelle-Neumann, 1991, p. 257), which is typically observable in comments on social media. These audience-expressed perceptions are especially valuable as they reveal the publicly perceived opinion climate, which can shape underlying perceptions and people's behaviors (Hayes, Glynn, & Shanahan, 2005, p. 452). For instance, individuals may alter or suppress their personal views through "self-censorship" (Hayes, Glynn, & Shanahan, 2005, p. 452) when they realize their opinions deviate from others (Jenness, 1932, pp. 294-296), whereas some people may be motivated to voice themselves more actively in an effort to challenge or correct the perceived public consensus when it conflicts with their own beliefs (Moussaïd et al., 2013, p. 6).

This thesis focuses on YouTube and Instagram to explore audiences' perceptions. These two platforms are not only the primary channels through which Lil Miquela shares content, but they also offer complementary affordances. YouTube, as the largest online video platform, encourages more in-depth commenting and deeper engagement compared to other social media platforms, making it a valuable source for mining user-generated content (Das et al., 2019, pp. 1-2). Analyzing this unstructured textual data allows researchers to access real-time opinions, sentiments, and feedback (Das et al., 2019, pp. 1-2). In contrast, Instagram emphasizes visual content and branding (Ryhänen, 2019, p. 16), making it particularly effective for building emotional connections with audiences (Ryhänen, 2019, p. 18). Additionally, influencers' impact may vary depending on the social media platform they use (Sands et al., 2022, p. 19). As AI influencers are still emerging as a new technological phenomenon, exploring whether platforms like Instagram and YouTube are seen as supportive environments for engaging with AI influencers is helpful to promote people's acceptance of this new form of influencers (Feng et al., 2024, p. 29). Therefore, analyzing comments from both platforms offers a comparative perspective for understanding audience perceptions and platform-specific dynamics.

Building on the above, this thesis poses the following research question: *How do interactions with branded content featuring Lil Miquela on YouTube and Instagram reflect audiences' perceptions of brands and the AI influencer?* To address this, this thesis is guided by four sub-questions: (1) What key topics emerge in the comments? (2) How are these topics expressed in communication? (3) What is the sentiment expressed in audience comments? (4) How do consumer sentiments relate to the identified themes in discussions?

This study is highly relevant for both academia and practice. Firstly, while existing studies have separately examined perceptions of AI influencers—for instance, in the contexts of beauty marketing (Hidayat et al., 2024, p. 112) and luxury marketing (de Boissieu & Baudier, 2023, pp. 1169-1173)—and perceptions of brands across industries such as fashion (Si, 2024, p. 312) and banking (Alqasa, 2023, p. 176), few studies have explored how these two types of perceptions are interconnected. This study

addresses this gap by investigating the relationship between audience perceptions of AI influencer and the brands within online discourse. Secondly, previous studies have primarily relied on self-report data, collected through interviews (Crawford & Croes, 2025, pp. 14-15; Holá, 2025, pp. 39-42; de Boissieu & Baudier, 2023, pp. 1166-1167; Molin & Nordgren, 2019, pp. 11-13; West et al., 2018, pp. 323-324), surveys (Rajput & Gandhi, 2024, pp. 8-9; Feng et al., 2024, pp. 30-31; Yuan et al., 2023, p. 67; Alqasa, 2023, p. 173; Luft et al., 2024, p. 120), or experiments (Böhndel et al., 2023, p. 7; De Cicco et al., 2024, p. 4). In contrast, this thesis analyzes spontaneous data, exploring audiences' comments on branded content featuring AI influencers. This approach enables to examine audience-expressed perceptions that may not surface through more controlled methods. Thirdly, while a few studies have examined comments interacting with AI influencers on either Instagram (Hidayat et al., 2024, p. 105) or YouTube (Feng et al., 2024, p. 30) individually, this thesis considers platform-specific dynamics in audience engagement by examining both platforms, thereby offering a comparative perspective. By addressing these three gaps, this research lays a foundation for future studies examining the effectiveness of AI influencer marketing in shaping consumer perceptions and behaviors.

Practically, the findings provide valuable insights for marketers aiming to align AI influencer campaigns with brand strategies, thereby enabling more effective and responsible collaborations. As illustrated in the film *Her*, AI systems can be designed to deliver highly personalized emotional experiences, creating a persuasive sense of intimacy (Imm & Kang, 2020, p. 92). Although the movie's narrative highlights the limitations of AI in offering genuine empathy (Imm & Kang, 2020, p. 96), it reveals the vast potential of AI to foster deeper emotional connections with users. As found by Hernandez-Ortega et al. (2022, p. 732), frequent interaction with smart voice assistants can foster positive emotions, and affective relationships which resemble those among humans. Therefore, research on AI influencers holds far-reaching implications for future brand communication. In the long term, this thesis could contribute to broader discussions about AI's role in constructing digital identities and consumer culture, ultimately supporting the responsible use of AI technologies across sectors.

The following chapter discusses relevant literature organized into three sections. The first section explores people's perceptions of AI and AI's applications in marketing. The second section discusses influencer marketing and emerging AI influencers. The third section discusses brand image, highlighting how it is influenced by using AI in marketing and by influencer marketing. Given that this thesis adopts mixed methods as discussed in chapter 3, literatures discussed in next chapter mainly serve two purposes: first, they support the operationalization for the thematic analysis, suggesting potential themes that may emerge in audience comments; second, they help to develop two main hypotheses for the quantitative analysis. Specifically, public attitudes toward AI and AI's use in marketing leads to the first hypothesis

regarding overall sentiment carried by perceptions. Meanwhile, difference in platform-specific affordance leads to the second hypothesis concerning variations in audiences' interaction.

2. Theory Framework

2.1. Perception of AI and AI in marketing

Based on the Technology Adoption Model, the acceptance and continued use of new technology are primarily driven by two key perceptions: perceived usefulness and perceived ease of use (Davis, 1985, pp. 109-110). Perceived usefulness refers to the degree to which people believe a technology can improve their daily life, while perceived ease of use reflects the degree to which a technological device is perceived as effortless to use (Davis, 1985, p. 82). In the context of AI adoption in e-learning, these two factors remain especially relevant. AI enhances the learning process by providing personalized learning experience—such as tailoring study materials and methodologies to match a learner's profile, adapting to individual learning pace, and offering personalized assistance through feedback and self-evaluation (Kashive et al., 2020, pp. 10-13). These features positively shape people's perception of both usefulness and ease of use, which in turn lead to a stronger intention to continue using e-learning platforms (Kashive et al., 2020, pp.10-13). Similarly, users' acceptance of AI-based digital voice assistants is also primarily driven by perceived usefulness and perceived ease of use (Fernandes & Oliveira, 2021, pp.187-188). Notably, perceived interactivity, which involves human-like attributes of AI (Fernandes & Oliveira, 2021, p.188), further enhances perceived ease of use. Specifically, users often perceive AI voice assistants as always available, good listeners, and free from social judgment (Choi & Drumwright, 2021, p. 9). These devices are seen as comforting companions, particularly when people are feeling down (Choi & Drumwright, 2021, p. 9), fostering emotion bonding with users (Fernandes & Oliveira, 2021, pp.188-189). Therefore, AI voice assistants are perceived not only as practical tools for tasks, such as information-seeking and improving life efficiency, but also as supportive entities for social interaction and emotional companionship (Choi & Drumwright, 2021, pp. 9-10).

Perceived risk also influences the acceptance of emerging technologies (Gaskell et al. 2004, p. 186). In the context of AI, a general and growing fear is the loss of control over technology (Fast & Horvitz, 2017, p. 966). More specifically, AI-powered tools, such as service robots in the workplace, are often seen as direct threats to human employment, sparking concerns about job displacement (Meyer et al., 2020, pp. 26-27). Concerns around generative AI also persist. Despite its growing sophistication across industries, people remain wary of its potential to underperform, misleading users, violate privacy, or generate false information (Sætra, 2023, pp. 2-3). These risk perceptions could be further amplified by the public's limited understanding of AI (Chen et al., 2022, p. 133). The public generally perceives humans are more independent, creative, complex, empathetic than AI, leading to the belief that people are better suited for handling complex tasks, while AI is more appropriate for simpler ones (Chen et al., 2022, p. 133). Therefore, when users experience AI's ability to perform multiple complicated tasks seamlessly,

they may feel both impressed by its capabilities and uneasy about its power (Chen et al., 2022, p. 133). However, despite these perceived risks, the perceived benefits of AI often outweigh the risks in daily contexts. Most users recognize potential privacy trade-offs, but express low levels of concern, reasoning that they are not important enough to be hidden (Chen et al., 2022, p. 135). This cost-benefit perception may help explain why public attitudes toward AI have remained more optimistic than pessimistic over time (Fast & Horvitz, 2017, pp. 966-968).

When it comes to AI in marketing, similar perceptions persist. Consumers express negative concerns about risks related to data privacy, including fears of cyberattacks, scams, information falsification, and breaches of data confidentiality (Alhitmi et al., 2024, pp. 4-5). Despite these concerns, AI is still widely recognized for its usefulness and ease of use. From a business perspective, AI enables deeper consumer insights and more seamless engagement (Haleem et al. 2022, p. 119), which improves decision-making, enables personalized targeting, and boosts campaign efficiency (Haleem et al. 2022, p. 119; Alhitmi et al., 2024, pp. 1-2). On the consumer side, AI provides more customized experiences, delivering convenient and efficient services tailored to individual preferences (Alhitmi et al., 2024, pp. 1-2).

However, individual perceptions of AI in marketing vary widely (Kelly et al., 2023, pp. 8-10). One key factor influencing these perceptions is people's identity. For example, customers generally perceive AI-generated product ads, specifically scripts created by ChatGPT and storyboards created by Bing Image Creator, as engaging and even more appealing after knowing they were made by AI (Chaisatitkul et al., 2024, p. 142). Similarly, marketing professionals report increased interest, perceiving slight improvements in the content's quality, effectiveness, and trustworthiness after learning about their AI origin (Chaisatitkul et al., 2024, pp. 142-143). In contrast, agency professionals show decreased interest and found the content harder to understand once they knew AI was involved (Chaisatitkul et al., 2024, pp. 142-143). This group expressed greater skepticism, especially around AI's inability to capture the emotional depth of human expression—concerns likely rooted in fears of AI replacing human roles in creative industries (Chaisatitkul et al., 2024, pp. 142-143). Another factor shaping perception is prior exposure to technology. Consumers who are more tech-savvy tend to have higher risk tolerance (Moon et al., 2025, p. 15). Their desire for innovation and direct experience with emerging technologies can reduce initial fears while enhancing appreciation for AI's practical benefits (Moon et al., 2025, p. 15). All these perspectives carry distinct sentiments.

Given that AI in marketing is still a relatively new phenomenon and people understanding remains limited (Chen et al., 2022, 139), this thesis specifically focuses on audience responses to branded content featuring AI influencers, using the case of Lil Miquela. The engaged audience in this context primarily consists of Lil Miquela's followers, who are generally hold more positive sentiments toward

technological innovation (Santo António & Gaidamaviciute, 2020, p. 97), and therefore, more inclined to interact with AI influencers. Moreover, consumers who perceive high utility in advertising messages are more likely to overlook potential intrusiveness or artificiality, and express positivity (Chen et al., 2022, p.139). This suggests that the effective adoption of AI in marketing may boost advertisement's appeal, thus fostering positive attitudes among audiences. Based on these insights, this study proposes the following hypotheses:

        H1a*: Audience comments express predominantly positive sentiment toward the AI influencer, Lil Miquela.*

        H1b*: Audience comments express predominantly positive sentiment toward brands featured in Lil Miquela's branded content.*

2.2. Perception of influencer and AI influencer

        The concept of influencer originates from the notion of opinion leaders (Han & Balabanis, 2024, p. 395), individuals perceived as experts in specific fields whose views can affect others' decisions (Lin, et al., 2018, p. 432). In this digital age, social media influencers, often referred to as micro-celebrities (Hudders et al., 2021, p. 31), have emerged from the early blogging culture in the late 1990s (Han & Balabanis, 2024, p. 395). These individuals engage larger audiences, partner with brands, and actively maintain their online presence on social media platforms such as Instagram and YouTube (Han & Balabanis, 2024, p. 395), aiming to boost product visibility and enhance brand recognition (Hudders et al., 2021, p. 33). Two defining characteristics of a social media influencer are reach and impact (Hudders et al., 2021, p. 31). Reach refers to the size of the influencer's audience, including both direct followers and secondary networks that extend through their followers (Hudders et al., 2021, p. 32). Impact describes their ability to affect their audiences' attitudes and purchasing behaviors (Hudders et al., 2021, p. 32). Owing to this combination of extensive reach and persuasive influence, social media influencers have become key players in digital marketing. Recent reports indicate that 90% of marketers now incorporate influencer marketing in their strategies (SocialPubli, 2020), and an equal percentage of marketing professionals consider influencers as highly effective in driving consumer engagement (Geyser, 2021). This effectiveness is further supported by consumer behaviors, with 56% of people reporting that they have made purchases based on influencers' recommendations (IZEA Insights, 2025).

        Influencers' personal characteristics are fundamental in amplifying both their reach and impact (Han & Balabanis, 2024, p. 395; Hudders et al., 2021, p. 31). For instance, influencers who demonstrate expertise by focusing on a specific niche, such as fashion or health, are more likely to establish credibility and be perceived as opinion leaders within their area of expertise (Hudders et al., 2021, p. 32). Similarly, when influencers are viewed as genuine, this perception carries over into their commercial collaborations,

enhancing the perceived authenticity of their promotional activities (Crawford & Croes, 2025, pp. 20-21). This effect is further reinforced when influencers share intimate experiences (Crawford & Croes, 2025, pp. 20-21), which enhance their perceived charisma by differentiating them from others within the same niche (Khamis et al., 2017, p. 191). To better understand influencer's characteristics, this thesis draws on source credibility theory, which posits that the persuasiveness of a message is influenced by traits of the communicator (Ohanian, 1990, p.41). In the context of influencer marketing, these traits can be categorized into two main dimensions: credibility and attractiveness (Hudders et al., 2021, pp. 43-44).

Credibility, as a broad construct, is commonly defined by three key elements: expertise, trustworthiness, and authenticity (Han & Balabanis, 2024, pp. 396-397; Hudders et al., 2021, pp. 19-20). Expertise refers to the perceived knowledge, skills, and qualifications of a source, emphasizing its competence and capabilities (Han & Balabanis, 2024, pp. 396-397). Trustworthiness encompasses perceptions of the source's honesty, fairness, and integrity (Han & Balabanis, 2024, p. 397). Authenticity refers to the extent to which an influencer is perceived as genuine, sincere, and honest (Han & Balabanis, 2024, p. 397). Together, these factors enhance the message persuasiveness and foster a sense of reliability in the source (Han & Balabanis, 2024, pp. 396-397; Hudders et al., 2021, pp. 43-44). In the context of AI influencers, establishing credibility poses distinct challenges, as they lack real-world experiences and professional qualifications (Lou et al., 2023, p. 550; Xie-Carson et al., 2023, p. 9). Consequently, audience perceptions of their expertise (Xie-Carson et al., 2023, p. 9) and trustworthiness (Molin & Nordgren, 2019, pp. 31-32) become especially significant. However, the perception of AI influencer's credibility remains contested. On one hand, skepticism exists due to their artificial nature, which often leads audiences to assume the content they share is equally inauthentic (Xie-Carson et al., 2023, p. 10). Specifically, AI influencers are frequently viewed as fake, overly perfect, or even uncanny, making them seem less authentic than human influencers (Crawford & Croes, 2025, pp. 25-26). The fact that AI influencers are typically managed by anonymous companies further leads audiences to question the motives behind their communication (Molin & Nordgren, 2019, pp. 31-32). Notably, too much branded content further weakens AI influencers' perceived trustworthiness (Molin & Nordgren, 2019, pp. 31-32). On the other hand, empirical studies reveal that audiences perceive AI influencers as similarly competent to human influencers in terms of expertise (Böhndel et al., 2023, p. 9). In some cases, AI influencers are even regarded as more authentic due to their transparency in clearly disclosing commercial affiliations—a contrast to the often ambiguous promotional intentions of human influencers (Lee et al., 2024, pp. 11-12). This positive perception may also be attributed to the professional teams managing these AI personas, who ensure frequent and consistent communication to maintain strong social presence (Molin & Nordgren, 2019, pp. 31-32).

Attractiveness, another key trait of influences, is shaped by three interconnected factors: likeability, familiarity, and similarity to the audience (Hudders et al., 2021, pp. 43-44; Han & Balabanis, 2024, p. 398). Likeability involves a positive emotional attitude toward an individual, often fostered by familiarity, which can be improved by repeated exposure, and perceived similarity, which refers to shared values, beliefs, and attitudes between influencer and their audiences (Böhndel et al., 2023, p. 6; Han & Balabanis, 2024, pp. 397-398). AI influencers' physical appearance and projected personalities in content could demonstrate these attributes. Consumers are more likely to engage with AI influencers who exhibit a humanlike appearance, which fosters trust and relatability (Molin & Nordgren, 2019, pp. 31-32; Holá, 2025, p. 22). In particular, AI influencers in the fashion field often inspire audiences by sharing their aesthetic preferences, which further strengthens emotional bonds (Holá, 2025, pp. 31-32). However, while physical appearance may initially generate likability, its impact on long-term engagement is limited (Rajput & Gandhi, 2024, p. 15). For sustained interaction, audiences prioritize influencers' content (de Boissieu & Baudier, 2023, p. 1174), which reflects influencers' actions (Stein et al., 2024, p. 3447) and personality traits, such as humor (Mirowska & Arsenyan, 2023, p. 7; Xie-Carson et al., 2023, p. 10). To improve the appeal of content, AI influencers' active social presence—through content sharing, interactions, and endorsements (Rajput & Gandhi, 2024, p. 3)—plays a crucial role, which helps to cultivate emotional closeness with followers (Rajput & Gandhi, 2024, p. 3).

Nowadays, the boundary between human and AI influencers becomes increasingly blurred (Sands et al., 2022, pp. 3-5). However, given both human-likeness and distinct artificiality, the role of similarity in shaping AI influencer attractiveness remains contested. In terms of physical resemblance, while human-like features are generally believed to enhance relatability (Han & Balabanis, 2024, pp. 397-398), an overly realistic appearance may instead provoke discomfort. According to the "uncanny valley" theory (Mori, 1970, pp. 33-35), robots that appear almost—but not fully—humans can evoke unsettling emotions or even fear. In the case of AI influencers, overly realistic visuals also lead to this uncanny perception, ultimately undermining emotional bonds with audiences (Lou et al., 2023, p. 548; Holá, 2025, p. 68; Molin & Nordgren, 2019, p. 31). Beyond appearance, similarity in personality traits and behaviors also requires careful consideration. Although qualities like warmth and responsiveness in communication (Rajput & Gandhi, 2024, p. 4) contribute to emotional closeness (Sands et al., 2022, p. 17) by fulfilling people's need for relatedness (Lee, 2023, p. 16) and reducing uncertainty in consumer-agent interactions (Holá, 2025, p. 22), these humanlike characteristics alone do not fully explain AI influencer's appeal. In fact, many audiences are initially drawn to AI influencers because of their non-human identity (Xie-Carson et al., 2023, p. 10). Their artificial nature introduces a sense of novelty and uniqueness that is central to their attractiveness. Moreover, an escapism effect has been identified: when participants know the influencer is virtual, they felt more confident in engaging with the contents, seeking an escape from

the emotional complexities of their daily lives (Mirowska & Arsenyan, 2023, pp. 6-7). The contested role of similarity in shaping AI influencer's attractiveness could be explained by the fact that, beyond content and appearance, different audiences have different psychological feelings. Therefore, this thesis argues that credibility and attractiveness, the core attributes of AI influencers, are reflected by discussions about the AI influencer's personality traits, content, physical appearance, social presence, and psychological feelings of audiences themselves.

Just as opinions on the adoption of AI in marketing vary, individuals also hold diverse perceptions of AI influencers. Firstly, personality traits, such as self-esteem and empathy, play a critical role in shaping how people perceive AI influencers (Mirowska & Arsenyan, 2023, pp. 7-8). For example, individuals with higher levels of empathy are more inclined to follow AI influencers (Mirowska & Arsenyan, 2023, p. 6). This tendency aligns with "escapism effect" discussed earlier: when people explicitly realize that an influencer provides less emotional demanding interactions, they see this influencer as a way to detach from daily life's emotional burdens (Mirowska & Arsenyan, 2023, p. 7). In this context, empathy not only improves emotional sensitivity, but also enhances the appeal of AI influencer as emotional refuges from human socializations (Mirowska &ArsArsenyan, 2023, p. 8). Secondly, culture background shapes perceptions of AI influencers (de Boissieu & Baudier, 2023, pp. 1169-1174). Regarding credibility, French people value AI influencers who can tailor their responses to individual needs, but remain more skeptical due to their perceived perfection, and over-commercialization (de Boissieu & Baudier, 2023, pp. 1169-1170). In contrast, Chinese people prioritize collective approval—trusting AI influencers with large followings and team-supported content—and view them as more transparent in their commercial intentions, particularly appreciating their constant availability (de Boissieu & Baudier, 2023, pp. 1169-1170). Regarding attractiveness, French people, driven by hedonic goals such as seeking escapism, uniqueness, and self-expression, emphasize cultural alignment in AI influencers' content (de Boissieu & Baudier, 2023, pp. 1172-1173). In contrast, Chinese people, who are motivated by both utilitarian and hedonic factors, prioritize technological compatibility, seeing AI influencers as a seamless part of digital landscape (de Boissieu & Baudier, 2023, pp. 1172-1173). Thirdly, previous experience with the metaverse shapes people's perceptions of AI influencer. The metaverse is a virtual environment where users interact with each other, digital content, and virtual agents through customizable avatars (Haikel-Elsabeh, 2023, p. 257). Those unfamiliar with the metaverse environment show greater interest in AI influencers and are more open to form connections with these digital personas, while people with prior metaverse experience are often more likely to question the trustworthiness of AI influencers (Haikel-Elsabeh, 2023, p. 267-268).

In addition, platform context may also influence how individuals perceive AI influencers. Platform-specific characteristics, particularly those affecting interactivity and communication, could

influence parasocial relationships—one-sided psychological bonds between users and influencers (Han & Balabanis, 2024, p. 397). Compared to platforms like Snapchat with its fleeting content, and LinkedIn with its professional orientation, Instagram and YouTube are more conductive to fostering a sense of intimacy with influencers (Han & Balabanis, 2024, pp. 399-400). Accordingly, this thesis focuses specifically on Instagram and YouTube. While both platforms attract users across various age groups, they differ in content format, user expectations, and interaction dynamics—all of which shape how audiences engage with influencers (Han & Balabanis, 2024, p. 399). Specifically, Instagram emphasizes esthetic appeal and aspirational lifestyles through visually engaging, short-form content, especially via features like "stories" (Han & Balabanis, 2024, p. 399), which heighten perceived authenticity by offering immediate, personal glimpses into influencers' lives (Lee & Watkins, 2016, p. 5759). In contrast, YouTube provides comprehensive information and expert reviews through long-form videos and tools like "playlists", enhancing perceived credibility through extended exposure (Han & Balabanis, 2024, p. 400). These platform-driven differences in communication shape how audiences perceive influencers (Han & Balabanis, 2024, p. 419), which could also be inferred in the context of AI influencers. As discussed in the previous section, individual's perceptions of emerging technologies such as AI are often accompanied by distinct sentiments. Therefore, this thesis proposes the following hypotheses:

> **H2a**: *The topics discussed in audience comments differ between YouTube and Instagram.*
>
> **H2b**: *The sentiments expressed in audience comments vary between YouTube and Instagram.*

2.3. Brand perception in AI influencer marketing

Branded content encompasses various brand-related formats, such as videos, stories, and brand-related online games (Waqas et al., 2021, p. 966). Unlike traditional media, branded content on social media is inherently interactive, and participatory, allowing consumers to engage by liking, commenting, sharing, and following (Waqas et al., 2021, p. 966). As brand-consumer communication helps people distinguish a brand from its competitors by evoking associations with the brand's unique attributes (Ateke & Nwulu, 2017, p. 217), individual who engage in such communication show stronger brand preference (Gómez-Rico et al., 2023, p.12723), which contributes positively to overall brand image—defined as the mental associations that consumers develop about a brand (Wijaya, 2013, p. 57). Scholars have approached brand image from two distinct perspectives: the consumer-driven and the brand-driven. From a consumer-driven approach, brand image refers to various brand-related attributes stored in consumers' mind, including situational factors (e.g., being at the beach), benefit-driven characteristics (e.g., low in fat), country of origin cues (e.g., Italian), and quality markers (e.g., the best in its category) (Romaniuk & Sharp, 2003, p. 220). Keller (2008, as cited in Lee et al., 2014, p. 6) further elaborates this through four dimensions: brand performance (e.g., reliability, durability), brand imagery (e.g., history, user profiles,

situations, personality), consumer judgments (e.g., quality, credibility), and consumer feelings (e.g., warmth, excitement). From a brand-driven approach, brand image is actively constructed through deliberate strategic efforts aimed at influencing consumer perceptions (Wijaya, 2013, pp. 62-63). This perspective defines brand image through five key elements: brand identity (tangible elements, such as logo, colors, and packaging), brand personality (human-like traits that make brand distinctive, such as friendliness, assertiveness), brand association (connection to a specific attributes or figures, e.g., Apple with innovation), brand attitude and behavior (the tone, style, and consistency of brand communication), and brand benefit and competence (the brand's ability to address consumer desires) (Wijaya, 2013, pp. 62-63). This thesis adopts a consumer-driven perspective, shifting attention from top-down brand messaging to audience-expressed perceptions emerging through interactions. Therefore, in this thesis, brand-customer communication is considered not only an influencing factor in shaping brand perceptions, but also as content reflecting consumer's perceptions.

Swani and Labrecque identified two key motivations for engagement with brands (2020, p. 289): self-presentation and brand relationship connections. Self-presentation refers to how individuals manage their own identity by selectively expressing thoughts that align with a desired self-image (Swani & Labrecque, 2020, p. 281). Brand relationship connections, in contrast, emphasize the interactive and relational nature of engagement, where users comment to maintain or strengthen their ongoing connection with a brand (Swani & Labrecque, 2020, p. 281). Notably, most social media engagement tends to be predominantly driven by one of these two motivations over the other (Swani & Labrecque, 2020, p. 289), and individuals with different motivations are likely to express in different ways (Swani & Labrecque, 2020, pp. 288-289). Building on this, this thesis also analyzes the forms of audience expression to deepen understanding of audiences' perceptions in the context of AI influencer marketing.

The adoption of AI in marketing significantly enhances customer perceptions of brands (Luft et al., 2024, p. 123; Yuan et al., 2023, p. 71; West et al., 2018, pp. 326-328). On one hand, AI strengthens a brand's ability to fulfill its promise through improved operational efficiency. As Garnett (2017, as cited in West et al., 2018, p. 325) assets, a brand needs to "do what they say they are going to do". AI contributes to this by optimizing resource use and increasing customer satisfaction (Hulme, 2017, as cited in West et al., 2018, p. 325). Its core capabilities—accuracy, problem-solving, and customization—play a critical role in consistently delivering on brand promises, thereby shaping a positive brand image (Yuan et al., 2023, p.71). More specifically, AI improves accessibility, enabling constant customer interaction (West et al., 2018, p. 328), and offers personalized, efficient, and accurate problem resolution (Alqasa, 2023, p. 176; West et al., 2018, pp. 326-328). This high-quality service delivery reinforces the brand's reliability and enhances customer satisfaction, ultimately shaping a positive brand image (Alqasa, 2023, p. 176; West et al., 2018, pp. 326-328). However, not all AI applications are equally effective. Some functions,

such as pricing algorithms, remain underdeveloped, resulting in lower perceived value (Luft et al., 2024, p. 123), suggesting that immature AI technologies may fail to improve brand image if they fall short of customer expectations. On the other hand, AI also supports branding efforts. While traditional brand personalities enhance brand preference by fostering trust, AI-generated brand personalities offer more distinct, and brand-specific traits, which are often communicated in direct and personalized ways that align closely with consumer preferences, thus enhancing purchase intention (Park & Ahn, 2024, p. 9). However, AI is not equally effective across all branding contexts. Different brands cater to different audiences, and thus the impact of AI varies depending on the consumer type. For example, utilitarian consumers, who prioritize efficiency, functionality and clear product information, find less value in interactive or anthropomorphic AI features always improved by AI (Yurova et al., 2017, p. 276). In contrast, hedonic consumers, who seek enjoyment and engagement, are more responsive to AI-driven anthropomorphic traits of brands, which can enhance their emotional connection to the brand, and thus generate more favorable brand perceptions (Yurova et al., 2017, p. 276).

Influencer marketing helps to shape brand perception. The informative value of influencer-generated content enhances a brand's perceived credibility (Liu & Zheng, 2024, p. 8), while cultural alignment and community engagement foster greater brand authenticity (Mohammad et al., 2024, p. 371). Additionally, influencers help reinforce brand personality traits, such as sincerity and competence, contributing to a more favorable brand image (Ekstam & Bjurling, 2018, p. 76). For example, when Justin Bieber is featured in a Calvin Klein campaign, audiences may associate the brand with his aspirational image (Tengblad-Kreft et al., 2017, p. 10). In the context of AI marketing, while De Cicco et al. (2024, p. 8) found no significant differences between AI and human influencer marketing in shaping brand trust, other studies suggest that AI influencers, such as Lil Miquela, can substantially boost brand recognition (Si, 2024, p. 312). Firstly, AI influencers offer a unique opportunity for brands to both capture attention and communicate brand values. Through curated virtual personas, these digital figures help convey specific brand identities and cultural narratives across platforms (Si, 2024, p. 311), driving greater visibility and consumer engagement (Jiang et al., 2024, p. 8). However, while AI influencers may initially drive brand message acceptance, this impact can fade over time (Hidayat et al., 2024, p. 108). To ensure sustained influence, brands must move beyond visual appeal of AI influencer and build deeper emotional connections with customers, for instance, by training AI influencer with more contextualized captions (Hidayat et al., 2024, p. 110). Moreover, AI influencers like Lil Miquela create immersive brand experiences that blur the lines between virtual and real, reshaping brand perceptions (Si, 2024, p. 312). Their innovative presence associates brand perception with terms like modernity, innovation, and inclusivity, thus appeals to younger audience (Si, 2024, p. 312). This, in turn, positions the brand as

forward-thinking and trendy (Lou et al., 2023, p. 549), while also enhancing consumer perceptions of product and service quality (Rana et al., 2024, p. 11).

3. Methods

3.1. Justification of mixed methods

Given that social phenomena are inherently context-dependent (Faber & Scheper, 2003, p. 138), it is important to use methods which can capture the contextual complexity. In this regard, qualitative research is particularly valuable, as it focuses on interpreting diverse perspectives within social settings (Kvale, 1996, p. 11, as sited in Brennen, 2021, pp. 3-4). This approach emphasizes understanding how individuals think, feel, and express themselves (Rambocas & Gama, 2013, pp. 14-15), offering greater flexibility in data collection and analysis (Brennen, 2021, p. 15), despite its subjective nature (Rambocas & Gama, 2013, pp. 14-15). In contrast, quantitative research focuses on testing relationships between variables through the analysis of large numerical datasets (Chih-Pei & Chang, 2017, p. 206). It employs statistical techniques to identify patterns between measured variables (Rambocas & Gama, 2013, pp. 14-15), with a strong emphasis on validity, reliability, and objectivity (Brennen, 2021, pp. 3-4). As each method offers distinct advantages while compensating for the other's limitations, this study adopts a mixed-methods approach. This choice is informed by the nature of the research topic, AI influencer marketing, which is a relatively new phenomenon that requires both exploratory insights and generalizable findings. Specifically, this thesis examines audience perceptions reflected in large online comments. Qualitative methods, content analysis in particular, provide in-depth insights into how individuals express their thoughts and feelings, while quantitative methods help to identify broader patterns across the dataset. The combination of these two approaches enhances analytical rigor and contributes to a more holistic understanding of AI influencer marketing.

This thesis draws on existing secondary data derived from user-generated content on social media platforms. As discussed in the introduction, it specifically examines audience perceptions conveyed through comments on YouTube and Instagram in response to branded content featuring Lil Miquela. Social media platforms offer extensive data that capture organic audience interactions (Giglietto et al., 2012, p. 155), making them valuable for investigating perceptions. By employing an unobtrusive data collection method, this thesis minimizes potential reactive effects, where individuals might alter their behavior due to the awareness of being studied (Bryman, 2016, p. 304). Moreover, this approach facilitates access to diverse perceptions that might otherwise be difficult to reach, especially those of the target audience who actively engaged with AI influencer marketing. For data analysis, the thesis adopts a computer-assisted mixed-methods approach, with thematic analysis as the primary analytical technique. Thematic analysis is not limited to categorizing data; it aims to identify contextually rich themes that uncover deeper meanings embedded in discourse (Flick, 2013, p. 7). Owing to its flexible and iterative nature, thematic analysis is well suited to integration with computational techniques (Forest & Meunier,

2005, p. 11), which are particularly effective for analyzing large volumes of digital data (Giglietto et al., 2012, p. 154).

To support thematic analysis, this thesis integrates text mining, sentiment analysis, and statistical analysis. Text mining refers to the use of computational techniques to extract meaningful patterns from textual datasets by identifying frequently occurring keywords (Levallois, 2017, p. 2), which improves the efficiency and consistency of thematic analysis (Altameemi & Altamimi, 2023, p. 4). Moreover, sentiment analysis is employed alongside text mining to assess the emotional tone expressed in audience comments. As sentiment functions as a social cue that supports emotional expression (Thelwall, 2013, p. 1), understanding affective content enhances the interpretive depth of thematic analysis. To capture this affective dimension, this thesis employs two sentiment analysis tools: ConText 2.0, the word-level analysis (Diesner, 2014, p. 1) which classifies individual words within comments as positive, negative, or neutral to capture affective tone; and SentiStrength, a text-level dual-scoring tool tailored for short texts that assigns both positive and negative sentiment values to each comment (Pang & Lee, 2008, p. 12). Finally, statistical analysis is conducted to explore relationships between identified themes, sentiment scores, and different social media platforms. This mixed method enhances analytical robustness by complementing the subjectivity of qualitative interpretation with measurable insights into how audiences perceive the AI influencer and associated brands.

3.2. Data collection and sampling

This thesis targets audience comments on branded content featuring Lil Miquela, collected from both YouTube and Instagram. To align with the research objectives, purposive sampling was applied to both platforms. As of 20 April 2025, Lil Miquela had published 72 videos on her official YouTube channel, compared to 1,367 posts on Instagram, indicating significantly higher activity on the latter platform. Given this disparity, YouTube data was sourced from both Lil Miquela's official channel and brand-owned channels. Relevant videos were identified using YouTube's search function with keywords such as "Lil Miquela" and "brand", sorted by relevance. To ensure reproducibility, the search was conducted on 20 April 2025, with the location set to the Netherlands. Videos were selected based on the following inclusion criteria: (1) the content explicitly featured branded collaborations involving Lil Miquela, evidenced by the simultaneous presence of the influencer and brand-related elements, such as product placements, brand mentions, tags, or logos, either in the video or accompanying metadata (e.g., title and description); (2) each video contained at least 50 comments to ensure sufficient data for analysis. Based on these criteria, six videos were selected (see Table 1 below for data sources). All associated comment data were extracted using the Netvizz YouTube Data Tool on 21 April 2025.

Figure 1

Screenshot of Comments under Branded Posts on Instagram
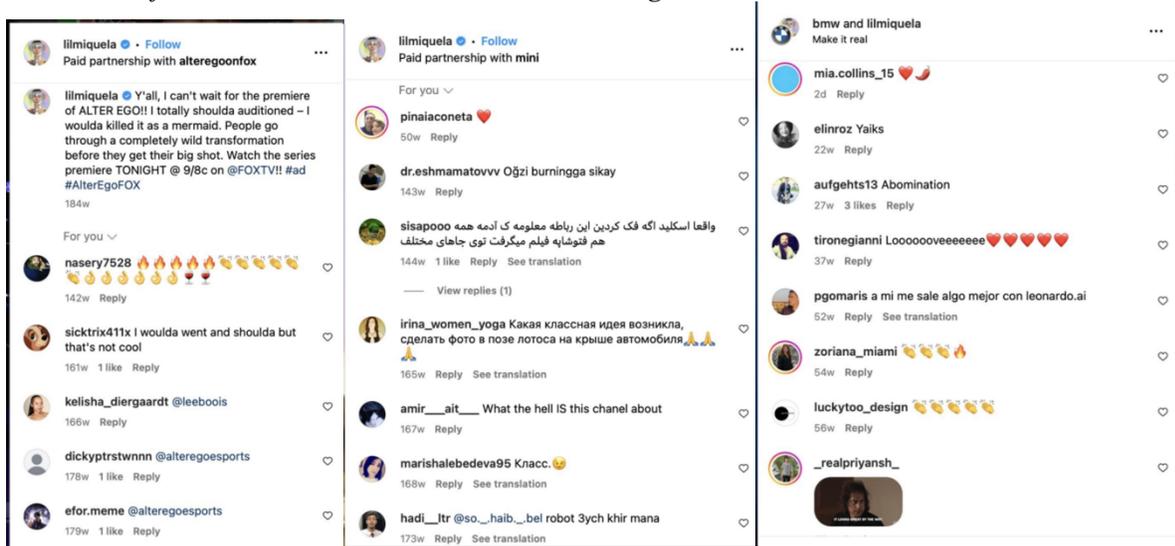
Note. Screenshot taken on 21 April 2025. Own work.

On Instagram, where Lil Miquela is considerably more active, data was collected directly from her official account. Since Instagram comments are typically shorter, more informal, and include non-textual elements such as emojis and GIFs (see Figure 1), they tend to offer less analytical depth for thematic analysis compared to YouTube comments. To compensate for this lower textual depth, a larger sample of nine branded posts were selected based on the following criteria: (1) posts were explicitly labeled as "Paid partnership with [brand]", confirming their status as official brand collaborations; and (2) posts were among the most recently published. All Instagram comments were manually collected on 21 April 2025 (see Table 1 for data sources). After data collection, a manual data cleaning process was carried out to enhance the quality of the dataset. The following types of comments were excluded: (1) comments consisting solely of emojis, non-verbal symbols, or user tags (e.g., "@username") without any accompanying textual content; (2) semantically incomplete or fragmented comments lacking interpretable meaning (e.g., isolated words or unfinished sentences); and (3) duplicate comments or clear instances of spam (e.g., repeated promotional links). In addition, all non-English comments were translated into English using Google Translate. Following this cleaning process, the final dataset comprises 1,643 usable comments, serving as a sample of all comments on branded content featuring Lil Miquela.

The ethical considerations of this study center on protecting the privacy and anonymity of commenters. Since YouTube and Instagram comments are publicly accessible, the thesis only uses publicly available data. To ensure anonymity, no personally identifiable information was recorded or

stored. Additionally, this research is conducted solely for academic purposes. The data was not used for any commercial purposes and was not shared with any third parties.

Table 1

Sampled Branded Content Featuring Lil Miquela

No.	Platform	Title	Brand Involved	Date Posted	Raw Comment Count
1	YouTube	The first-ever BMW iX2 × lil Miquela	BMW	October 10, 2023	211
2	YouTube	Miquela and Bella Hadid Get Surreal | CALVIN KLEIN	Calvin Klein	May 16, 2019	720
3	YouTube	#TeamGalaxy | Miquela	Samsung	July 16, 2019	86
4	YouTube	Go Borderless with MSI QD-OLED	MSIGaming	April 11, 2024	60
5	YouTube	Miquela and Her New BFF Soto Gang Celebrate Self Love | HEROES! | CLUB 404	tattoo studio SOFTFLEX	July 19, 2019	103
6	YouTube	Miquela Explores Magic at House of Intuition | HEROES! | CLUB 404	House of intuition	July 3, 2019	78
7	Instagram	/	Liquid I.V.	March 27, 2025	/
8	Instagram	/	Liquid I.V.	March 2, 2025	/
9	Instagram	/	Liquid I.V.	January 29, 2024	/
10	Instagram	/	CleanItUp	October 17, 2024	/
11	Instagram	/	Manychat	September 20, 2024	/
12	Instagram	/	MSIGaming	April 11, 2024	/
13	Instagram	/	BMW	October 11, 2023	/
14	Instagram	/	BMW	October 11, 2023	/
15	Instagram	/	PacSun	August 12, 2022	/

Note. Instagram posts do not include formal titles. Additionally, due to account privacy settings, raw comment counts are not available for Instagram posts.

3.3. Operationalization

This thesis focuses on audiences' interaction with branded content featuring Lil Miquela by analyzing audiences' comments. These comments are operationalized by two independent parallel dimensions, specifically expression form and comment topic. As mentioned in the theory framework, self-presentation and brand relationship connections are key motivations for people to engage with branded content, which lead to different forms of audience expression (Swani & Labrecque, 2020, p. 289). Based on this theory, this thesis operationalizes expression form through two sub-dimensions: self-expression, reflected in comments that convey personal feelings or opinions, and social interaction, which includes

actions such as debating, complimenting, or engaging with specific targets of interaction—such as brands or the influencer.

The second dimension, comment topic, reflects themes discussed by audiences. To answer the research question, this dimension is further operationalized into the AI influencer perception and brand perception. Based on the theoretical insights about AI influencers discussed earlier, credibility and attractiveness, the core attributes of AI influencer, are typically discussed around influencer's content, personality traits, appearance, and psychological feelings they evoke from audiences. Therefore, comments defined as AI influencer perception are operationalized into the following sub-categories: physical appearance, influencer content, psychological feelings, and influencer attributes. The influencer attributes category is further operationalized into two characteristics: social presence and personality traits. Given that some categories may overlap—for instance, a comment discussing influencer content may also imply influencer's personality traits—the category "influencer attributes" only refers to comments which explicitly evaluate the influencer's characteristics.

As described in the theoretical framework, brand perception is approached from a consumer-driven perspective, focusing on brand associations stored in consumers' minds (Wijaya, 2013, p. 57). These associations are operationalized through indicators such as brand activity (e.g., marketing campaigns, customer services) (Wijaya, 2013, pp. 62-63), brand imagery (e.g., brand history, user profiles, usage situations, brand personality) (Keller, 2008, as cited in Lee et al., 2014, p. 6), and brand benefits (e.g., benefit-driven characteristics, quality markers) (Romaniuk & Sharp, 2003, p. 220).

As illustrated in Figure 2 below, the operationalization is rooted in the theory framework. It serves as the initial coding frame for the thematic analysis. As new codes emerged inductively during the analysis process, the thematic coding tree presented in results (as detailed in Appendix A) is different from the initial coding frame.

Figure 2

Operationalization Framework
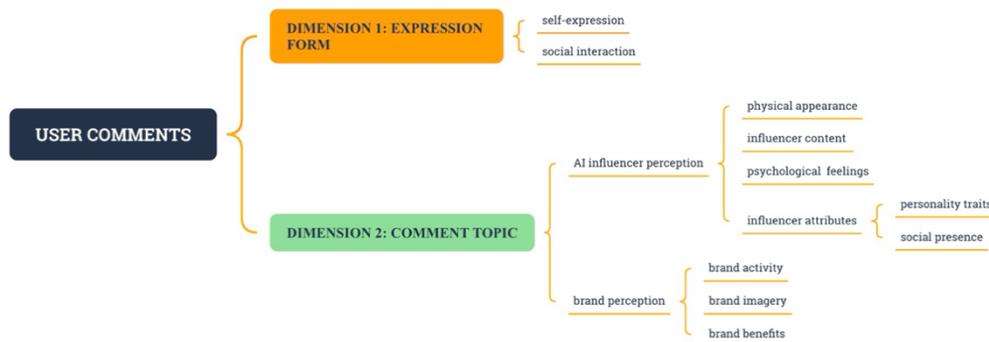
Note. The two dimensions are independent parallel categories.

3.4. Data analysis

3.4.1. Thematic analysis supported by text mining using ConText 2.0

This thesis adopts a mixed-methods approach to analyze audience comments. To address the sub-questions— (1) What topics emerge in the comments? and (2) How are these topics expressed in communication? —a thematic analysis was conducted. The coding process began with a deductive approach, guided by a predefined coding frame explained in the operationalization above. All comments were initially reviewed and coded according to predefined categories (Elo & Kyngäs, 2008, pp. 111). However, given the complexity and richness of social media discourse, it became evident that the initial code framework could not fully capture nuances in the dataset. To address this limitation, an inductive approach was subsequently employed. This involved immersing myself in the data to generate open codes, then iteratively identifying related codes, and grouping them into broader categories (Elo & Kyngäs, 2008, pp. 109-111). This inductive process enriches the deductive coding frame by including unanticipated detailed codes emerging from the dataset.

As a result, the coding process yielded four themes under the first dimension (expression form): self-expression, engagement with brands, engagement with the influencer, and interaction with other commenters. Under the second dimension (comment topic), eight themes were identified: influencer perception, brand perception, technological discussion, commentary on the comment section, emotion, vibe, references to other popular figures, and presence marking (see Appendix A for details). The majority of comments were independently coded into these two distinct dimensions. Notably, some comments' content was too ambiguous to classify, resulting in missing value in either dimension 1 or dimension 2 for the subsequent sentiment analysis performed by SentiStrength and SPSS (as discussed in next section).

Given the richness of digital data, this thesis further conducted text mining on selected meaningful categories or sub-categories which contain a substantial number of relevant comments. These include influencer physical appearance, influencer content, phycological feelings, emotion, vibe, collaboration with the influencer, and identity discussion. This analysis was conducted by ConText 2.0, a computational text mining tool that extracts frequently occurring keywords from selected segments (Diesner, 2014, p. 1). Moreover, ConText conducted a word-level sentiment analysis, categorizing identified words as positive, neutral, or negative. Since the computational outputs were relatively raw and messy, another thematic analysis was conducted on the representative words from text mining's output. Terms with relevant meanings were grouped into broader categories to improve interpretability. These categories were labeled with an asterisk "*" in Appendix A. This step further enriched the qualitative findings by highlighting the semantic focus and emotional tone within these selected categories.

3.4.2. Sentiment analysis using SentiStrength and statistic analysis

To address sub-questions (3) What is the sentiment expressed in audience comments and (4) How do consumer sentiments relate to the identified themes in discussions, this thesis employed SentiStrength, a lexical-based tool designed to evaluate sentiment in short, informal texts, such as social media comments (Nadali et al., 2016, p. 102). SentiStrength assigned two scores for each comment: a positive sentiment score ranging from +1 (neutral) to +5 (strongly positive), and a negative sentiment score ranging from -1 (neutral) to -5 (strongly negative), enabling to detect mixed emotions within a single comment (Nadali et al., 2016, p. 104). To better interpret the results, each sentiment dimension scores were offset to ensure that a net score of zero represents a truly neutral sentiment. Specifically, positive scores were recalculated by subtracting 1, and negative scores by adding 1. Based on these modified values, two additional sentiment metrics were calculated for further analysis: overall sentiment, calculated as the arithmetic sum of the adjusted positive and negative scores, and sentiment intensity, computed as the Euclidean distance between the positive and negative scores (i.e., $\sqrt{(\text{positive}^2 + \text{negative}^2)}$). These measures provided insights regarding both the direction (positive, neutral, or negative) and the strength of sentiment expressed. The sentiment analysis supports the hypothesis testing (***H1a***, ***H1b***, and ***H2b***), and the exploratory investigation which complements the findings of qualitative content analysis.

Using these sentiment measures, ANOVA tests and t-tests were performed. The first set of ANOVAs evaluated whether sentiment scores—both overall and intensity—differed significantly across themes identified through the qualitative analysis. In dimension 1 (expression form), four themes were included: (1) self-expression, (2) engagement with brands, (3) engagement with the influencer, and (4) interaction with other commenters. In dimension 2 (comment topic), eight themes were examined: (1) influencer perception, (2) brand perception, (3) technological discussion, (4) commentary on the comment section, (5) emotion, (6) vibe, (7) references to other public figures, and (8) presence marking. Moreover, subsequent ANOVA tests were conducted to compare sentiment variations of specific sub-categories. One test explored sentiment values across sub-categories within theme "influencer perception", such as influencer physical appearance, influencer content, and identity discussion. Another explored sentiment values across sub-categories within theme "brand perception", such as product features, brand value, and scene imagination. These more specific analyses provide insights into which aspects of influencer and brand perception were associated with more positive or stronger emotional responses.

To test ***H1a*** that *audience comments express predominantly positive sentiment toward the AI influencer Lil Miquela*, a one-sample t-test was conducted to compare the overall sentiment of the influencer perception category against a value of 0 (neutral). To test ***H1b*** that *audience comments express predominantly positive sentiment toward brands featured in Lil Miquela's branded content*, a one sample t-test was also conducted to compare the overall sentiment of the brand perception category against a

value of 0 (neutral). To examine **H2b**, *audience sentiment differs between platforms*, an independent samples t-test was conducted. This test compared the average overall sentiment and sentiment intensity scores between comments posted on YouTube and Instagram.

In addition, this thesis explored thematic variation in audience comments across platforms to test **H2a**, *the topics discussed in audience comments differ between YouTube and Instagram*. A series of Chi-square tests of independence were conducted. First, a test examined the relationship between dimension 1 (expression form) and platform to determine whether expression forms varied between YouTube and Instagram. Second, a test assessed whether the distribution of themes within dimension 2 (comment topic) differed between YouTube and Instagram, revealing platform-based distinctions in audience discourse. Third, a test examined the association between comment's expression form (dimension 1) and comment topic (dimension 2), exploring whether specific expression form was more likely to co-occur with particular discourse focus. Together, these analyses provide a nuanced understanding of how audiences engage with branded content featuring Lil Miquela across different social media platforms—both in terms of what they discussed and how they expressed it.

3.5. Validity and reliability

Efforts were made to enhance validity and reliability in this thesis. Validity refers to the extent to which the research corresponds to what it is intended to study, while reliability refers to the consistency of results when the same methods are used repeatedly (Riger & Sigurvinsdottir, 2016, p. 36). To improve validity in the thematic analysis, this thesis employed a systematic coding process, beginning with a theory-driven coding frame. To ensure reliability, the data were carefully reviewed multiple times, and coded into two distinct dimensions independently. All coding decisions were carefully documented, and the complete process was transparently discussed in data analysis section. For the quantitative analysis, ConText 2.0 and SentiStrength were used to analyze sentiments. The combination of these two computational tools helps improve the validity of the sentiment measurement. Moreover, as explained by Thelwall (2013, p. 6), analyzing over 1,000 text samples ensures a more reliable sentiment assessment with SentiStrength. This thesis includes a larger number of comments to support greater reliability.

However, limitations in validity and reliability cannot be ignored. First, thematic analysis inevitably involves a degree of subjectivity (Riger & Sigurvinsdottir, 2016, p. 36). As the researcher is not a native English speaker, subtle nuances in idiomatic expressions or internet language may have been overlooked or misinterpreted, potentially affecting the accuracy of categorization. As the thematic categories serve as variables for subsequent statistical analysis, any subjectivity in thematic coding could also influence the quantitative results. Second, the computational tools used for sentiment analysis have inherent limitations. The lexicon used by Context 2.0 has limited vocabulary coverage, which leads to an

incomplete identification of words carrying sentiments. Moreover, given that both Context 2.0 and SentiStrength rely on older language datasets, these automated tools may fail to analyze the complex sentiments of comments online. This could lead to biased sentiment classification or inaccurate sentiment scores for satirical or humorous tones.

4. Results

After data cleaning, a total of 1,643 comments were retained for analysis. Of these, 610 comments (37.1%) were collected from Instagram, and 1,033 comments (62.9%) were collected from YouTube (see Appendix B, Table B1). A mixed-methods approach was adopted: thematically, comments were categorized based on expression form and comment topic; quantitatively, two sentiment-related variables were computed to capture sentiments of audiences' comments. The overall sentiment score ranged from -4 (extremely negative) to +4 (extremely positive), with $M = 0.37$, $SD = 1.27$ (see Appendix B, Table B2). The sentiment intensity, which captures the emotional strength of the comment, ranged from 0 to 4.24, with $M = 1.09$, $SD = 1.02$ (see Appendix B, Table B2).

A chi-square test of independence descriptively examines the relationship between the two dimensions of comments: expression form and comment topic. Out of 1,643 total cases, 1,543 (93.9%) were valid and included in the analysis; 100 cases (6.1%) were excluded due to unclassifiable values in either the expression form or comment topic variable (see Appendix C, Table C1). The results indicate a statistically significant relationship between expression form and comment topic, $\chi 2$ (21, $N = 1543$) = 1597.69, $p < .01$ (see Appendix C, Table C2). Descriptive results reveal distinct patterns across expression forms. Comments engaging with brands were overwhelmingly related to brand perception (98.2%), while comments engaging with the influencer were primarily centered around influencer perception (88.3%) (see Appendix C, Table C3). Self-expression comments were more heterogeneous, covering influencer perception (38.1%) and emotional expression (37.7%) (see Appendix C, Table C3). In addition, comments within interaction with other commenters focused on influencer perception (73.9%), followed by technological discussions (16.5%) (see Appendix C, Table C3).

These findings demonstrate the diverse themes in people's comments. The following sections specifically discuss (1) audience perceptions of Lil Miquela (all sub-categories of **influencer perception** and relevant sentiment analysis); (2) perceptions of brands (all sub-categories of **brand perception** and relevant sentiment analysis); (3) other topics and sentiment variation (other thematic categories parallel to influencer perception and brand perception; responding *H1a* and *H1b*); and (4) platform-based differences (responding *H2a* and *H2b*).

4.1. Perception of Lil Miquela

4.1.1. Thematic analysis of influencer perception

Among the 802 comments related to perceptions of Lil Miquela, 178 comments (22.19%) explicitly addressed her content (see Table 2 in next section). Focusing on **influencer content** (see Figure 3 below), many audiences pay particular attention on *musical elements*. According to the text mining

output (see Appendix K, Table K1 for details), frequent references to music (n = 23), song (n = 30), piano (n = 3), melody (n = 1), and sound (n = 1) highlight music's central role in shaping audience engagement. In addition, *visual elements* and *narrative elements* also captured attention. *Visual elements* were identified through terms such as video (n=13), shot (n=1), picture (n=1), and album (n=3) (see Appendix K, Table K1). Narrative references, though less frequently, included kiss (n=17), storytelling (n=1), and news (n=3) (see Appendix K, Table K1). In this case, "kiss" denotes a specific plot event featured in Lil Miquela's videos. Notably, despite awareness of the content's *commercial nature*, evidenced by terms like "sponsorship" and "advertisement" (see Appendix K, Table K1), audiences expressed appreciation for Lil Miquela's creative output. Comments such as "Ok now use the sponsorship money to release new music" and "Stop distributing this advertisement please. The piano interpretation as soundtrack is simply amazing, but I cannot find information and/or how to buy it anywhere!" reflect ongoing expectations for her musical content. These responses suggest collaboration potential between Lil Miquela and the music industry. Furthermore, around **influencer content**, *sentiment elements* were identified by Context 2.0 (see Appendix K, Table K1). Audiences used predominantly positive descriptors, such as wonderful (n=3), beautiful (n=4), love (n=11), and amazing (n=6). Negative sentiment words were fewer, including fake (n=3) and miss (5). It is important to note that the term "miss" was misclassified as negative by Context 2.0. In the proper context—for example, "I miss your music so much"—this term conveys a positive emotional attachment to musical content. This misclassification reflects the limitation of computational sentiment analysis tools, which often fail to capture contextual nuances.

Aligning with previous finding that audiences prioritize AI influencers' content during sustained interactions (de Boissieu & Baudier, 2023, p. 1174), there are fewer comments focusing on Lil Miquela's **physical appearance** than those discussing her content (see Table 2 in next section). However, 18.20% (see Table 2 in next section) of comments within influencer perception focusing on Lil Miquela's **physical appearance** still suggests that appearance remains a significant point of audience interest. Regarding **physical appearance** (see Figure 3 below), audiences' attention was directed toward several aspects: *bodily features* (e.g., wrist, finger, chest, foot, tongue, face, skin, head, armpit, eye, lips, body, tooth), *cosmetics* (e.g., hairstyle, makeup), *vocal traits* (e.g., laugh, voice, tone), and *fashion choices* (e.g., tattoo, bag, pet, style, dress, clothing, outfit, shoe, vestment) (see Appendix K, Table K2 for details about terms identified through text mining). This concentrated focus on *fashion choices* could explain the strategic collaborations between Lil Miquela and fashion brands such as Calvin Klein. The *sentiment elements* identified within **physical appearance** are predominantly positive, including descriptors such as gorgeous, elegant, and amazing, though a small number of negative descriptors like scary, terrible, and spooky (see Appendix K, Table K2 for details). Interestingly, comments within **physical appearance** also carry *identity cues*. The recurring use of the word "girl" (*n* = 14) reflects a perception of feminine and

human-like qualities, while references such as avatar ($n =1$), animation ($n = 5$), and robotic ($n = 1$), with descriptors like real ($n = 13$) and fake ($n = 1$) (see Appendix K, Table K2 for details) signal a shift from aesthetics to identity. This indicates that comments on physical traits served as a starting point for broader reflections on Lil Miquela's authenticity.

Figure 3

Thematic Coding Tree of Influencer Perception
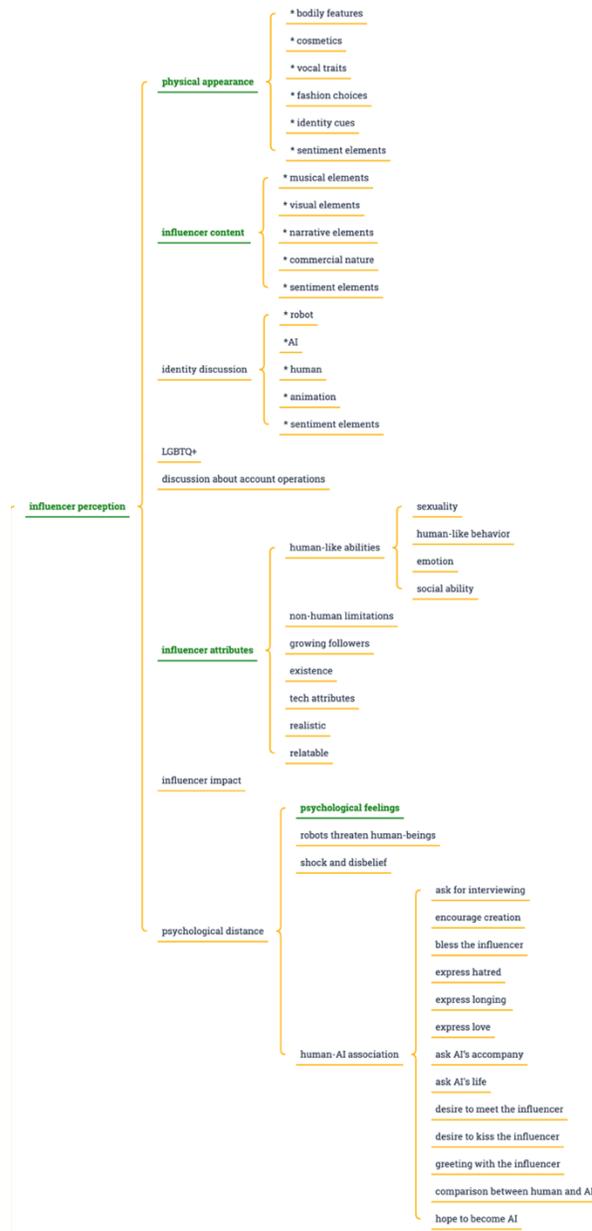
Note. This figure presents part of the complete coding tree in Appendix A. Codes in green are retained codes from the initial coding frame in operationalization. Black codes represent new categories that

emerged during the thematic analysis. Codes marked with an asterisk (*) reflect categories identified through thematic analysis of ConText 2.0 output.

Within influencer perception, 18.95% of comments fell under Lil Miquela's **identity discussion** (see Table 2 in next section). The topic promoted a high level of user-to-user engagement—75.66% of comments within **identity discussion** involving **interaction with other commenters** (category within dimension 1 expression form) (manually calculated by the author). Speculation centered on whether Lil Miquela is a robot ($n = 70$), AI character ($n = 7$), CGI model ($n = 1$), animation ($n = 13$), or digital figure ($n = 4$) (see Appendix K, Table K3 for details identified by text mining). The prominence of the term "*robot*" could be attributed to the public's greater familiarity with this concept, compared to the notion of *AI*. Conversely, a notable number of comments insisted that Lil Miquela is a *human*, exemplified by "She is not robot, she is just a human girl using her own made animation filter and playing with social media", and "That's obviously a person with a modified face". All these claims within **identity discussion** were rarely supported by clear evidence or reasoning, highlighting the ambiguity surrounding the **identity discussion**. *Sentiment elements*, such as "stress", "confusion", and "mystery" (see Appendix K, Table K3 for details identified by text mining), further highlight this uncertainty. Negative descriptors such as fake ($n = 6$), and comments like "who controls this" or demands for "the truth" suggest growing skepticism about Lil Miquela's identity, which could erode audience trust, and thus undermining the effectiveness of her marketing campaigns.

Despite ongoing debates within identity discussion, many audiences continued to engage with her as a social persona, which is reflected by comments categorized into **influencer attributes** (see Figure 3 above). Instead of focusing solely on what she is, audiences frequently turned their attention to her *existence*, specifically whether and how she exists. To counter claims denying her *existence*, comments like "She can't be air if she was fake, you wouldn't be able to see her shadow" and "How does she not exist if You're looking at her" tried to affirm her *existence* from visual and philosophical perspectives. Beyond *existence*, audiences often projected *human-like abilities* onto Lil Miquela. Commenters inquired about her *human-like behavior*, asking whether she has hobbies, eats, studies, drives, gets tattoos, or creates her own content. *Emotion* and *social ability* were also attributed to her, with people asking whether she can experience mood shifts, self-acceptance, or friendships. Notably, although Lil Miquela does not explicitly state her *sexuality*, a scene depicting her kissing another girl led audience to interpret her as lesbian. This demonstrates how audiences fill the gap in the influencer's persona through content cues. At the same time, some audiences acknowledged her *non-human limitations*, noting that she likely cannot sleep, dream, or feel hunger. This dual perception—recognizing *human-like abilities* and *non-human limitations*—reflects the deeply comparative lens through which AI influencer are understood. As

a result, some comments directly perceived Lil Miquela as *realistic* (e.g., "So realistic, shows what happens in normal life. Touches your emotions… the robot is wanting so bad to feel real, what humans feel. She wants to be more human.") and *relatable* (e.g., "Never thought this sims character's life would be so relatable"). Furthermore, some people focused on Lil Miquela's *tech attributes*, seeing her as a symbol of technological progress. The perception of Lil Miquela's attributes blends human familiarity with technological novelty could explain another perceived attribute, *growing followers*. Several audiences expressed surprise at the rapid growth of her follower base, actively noting and tracking its increase over time. This reinforces Lil Miquela's legitimacy as an influencer.

A few comments affirm Lil Miquela's **influencer impact** directly, which is often described as "inspiration". Notably, her broader impact is also reflected by discourses around **LGBTQ+** and **psychological distance**. Lil Miquela's depiction of same-sex intimacy triggered extensive discourse on **LGBTQ+**. In response to the emergence of homophobic attitudes, comments like "Yes! Miquela is a lesbian! Join the crew hon!" expressed support. Meanwhile, comments like "Just because she kisses a girl doesn't mean she's a lesbian; she can be bi or pan" suggest a more neutral stance. However, opposite voices further accused the creators of queerbaiting or leveraging LGBTQ+ imagery as a marketing strategy.

In addition, Lil Miquela's influence is evident in comments relevant to **psychological distance** (see Figure 3 above), particularly through *human-AI association*, where people project emotions, desires, and comparisons onto AI personas. Within *human-AI association*, audiences expressed emotional attachment by offering affection (e.g., *express love*, *express longing*, *bless the influencer*), or imagining social interaction (e.g., *desire to meet the influencer*, *ask AI's accompany*, or *desire to kiss the influencer*). A notable pattern in responses within *human-AI association* is implicit comparison: people often perceive Lil Miquela as leading a happier life, highlighting her access to BMW, or romantic relationships. This comparison led several commenters to *hope to become AI*, suggesting underlying feelings of inadequacy, envy, or escapist longing. Despite this psychological closeness reflected by *human-AI association*, comments that directly expressed *psychological feelings* are predominantly negative. Consistent with prior studies (Lou et al., 2023, p. 548; Holá, 2025, p. 68; Molin & Nordgren, 2019, p. 31) which point out that overly realistic presence of AI influencers leads to an uncanny perception, comments within category *psychological feelings* show that people feel scared (n=4), weird (n=6), uncanny (n=2), uncomfortable (n=3), and cringe (n=3) (see Appendix K, Table K4 for details). Such psychological unease is also manifested in expressions of *shock and disbelief*. Within category *shock and disbelief*, people questioned what they were seeing, and voiced anxiety about not being ready to accept AI influencers. More radical responses were categorized as *robots threaten human-beings*, which further interpreted AI figures like Lil Miquela as a signal of "existential crises". These comments expressed anxiety about job displacement,

which mirror broader perceived risks about AI in general (Meyer et al., 2020, pp. 26-27), as well as fears of AI rebellion and civilizational decline (e.g., "This is the new way we found in the 'how to end the planet faster' race"). These align with Chen et al.'s finding (2022, p. 133) that people feel uneasy about AI's expanding potential.

4.1.2. Statistical sentiment analysis of sub-categories within influencer perception

To empirically examine audience overall sentiment across categories within **influencer perception**, a one-way ANOVA tested eight categories: influencer content, physical appearance, identity discussion, influencer attributes, influencer impact, psychological distance, LGBTQ+, and discussion about account operations, on overall sentiments. Results reveal a significant main effect, $F(7, 794) = 6.35$, $p < .01$, partial $\eta^2 = .05$ (see Appendix G, Table G1). Post hoc Tukey tests indicated that the overall sentiment of influencer impact ($M = 2.13$, $SD = 0.64$) was significantly more positive than comments within identity discussion ($M = 0.06$, $SD = 0.87$, $p < .01$), psychological distance ($M = 0.24$, $SD = 1.40$, $p < .01$), discussion about account operations ($M = 0.23$, $SD = 0.93$, $p = .01$), LGBTQ+ ($M = 0.11$, $SD = 1.21$, $p < .01$), physical appearance ($M = 0.65$, $SD = 1.35$, $p = .02$), influencer attributes ($M = 0.45$, $SD = 1.12$, $p < .01$), and influencer content ($M = 0.56$, $SD = 1.16$, $p = .01$). Additionally, identity discussion's overall sentiment ($M = 0.06$, $SD = 0.87$) was significantly less positive than comments regarding physical appearance ($M = 0.65$, $SD = 1.35$, $p < .01$), and influencer content ($M = 0.56$, $SD = 1.16$, $p < .01$). Average sentiment scores and standard deviations for each category's overall sentiment are presented in Table 2 below, and p-values for all comparisons can be found in Appendix G, Table G2.

Table 2

Descriptive Statistic: Overall Sentiment about Categories within Influencer Perception

Sub-categories within influencer perception	Mean	Std. Deviation	N	Percent
identity discussion	0.06	0.87	152	18.95%
psychological distance	0.24	1.40	156	19.45%
discussion about account operation	0.23	0.93	13	1.62%
LGBTQ+	0.11	1.21	44	5.49%
physical appearance	0.65	1.35	146	18.20%
influencer impact	2.13	0.64	8	1.00%
influencer attributes	0.45	1.12	105	13.09%
influencer content	0.56	1.16	178	22.19%
TOTAL	0.39	1.22	802	100%

Another one-way ANOVA, which examined the sentiment intensity across these eight categories, also shows a significant main effect, $F_{(7, 794)} = 10.44$, $p < .01$, partial $\eta^2 = .08$ (see Appendix G, Table G3). Post hoc Tukey tests indicated that comments within identity discussion ($M = 0.54$, $SD = 0.87$) showed significantly less intense sentiments than those within psychological distance ($M = 1.30$, $SD = 1.01$, $p < .01$), LGBTQ+ ($M = 1.13$, $SD = 1.15$, $p = .01$), physical appearance ($M = 1.24$, $SD = 1.09$, $p < .01$), influencer impact ($M = 2.13$, $SD = 0.64$, $p < .01$), and influencer content ($M = 1.15$, $SD = 1.01$, $p < .01$). Additionally, comments within influencer impact ($M = 2.13$, $SD = 0.64$) showed significantly more intense sentiments than discussion about account ($M = 0.54$, $SD = 0.78$, $p = .01$), and influencer attributes ($M = 0.92$, $SD = 0.90$, $p = .02$). Moreover, influencer attributes ($M = 0.92$, $SD = 0.90$) were discussed with significantly lower intense sentiments than psychological distance ($M = 1.30$, $SD = 1.01$, $p = .04$). Average sentiment scores and standard deviations for each category's sentiment intensity are presented in Table 3 below, and p-values for all comparisons can be found in Appendix G, Table G4.

Table 3

Descriptive Statistic: Sentiment Intensity about Categories within Influencer Perception

Sub-categories within influencer perception	Mean	Std. Deviation	N
identity discussion	0.54	0.87	152
psychological distance	1.30	1.01	156
discussion about account operation	0.54	0.78	13
LGBTQ+	1.13	1.15	44
physical appearance	1.24	1.09	146
influencer impact	2.13	0.64	8
influencer attributes	0.92	0.90	105
influencer content	1.15	1.01	178
TOTAL	1.05	1.03	802

These two quantitative analyses empirically confirmed that audience comments across categories within **influencer perception** exhibited significantly different sentiment valence and intensity, supporting the emotional patterns identified in the qualitative findings discussed in last section. First, comments within *influencer impact* (those directly affirming Lil Miquela's impact) were the most positive and emotionally intense, with lowest standard deviation reflecting strong consensus. This aligns with qualitative findings above that Lil Miquela is broadly perceived as an "inspiration" by followers. Second, comments within *identity discussion* showed lower overall sentiment and sentiment intensity, indicating more surface-level engagement. This supports the previous observation that identity-related discussions

tend to lack justification or interactive dialogue. Third, in this sample, categories such as *psychological distance* and *LGBTQ+* exhibited wide variability in overall sentiment and sentiment intensity, as indicated by their standard deviations. These topics are probably shaped by individual differences in response to broader societal tensions. For example, as discussed in the theory framework, while some people fear losing control over emerging AI technologies (Fast & Horvitz, 2017, pp. 966-968), others who prioritize AI's benefits over its potential risks remain more optimistic (Chen et al., 2022, p. 135). In summary, people's perceptions of Lil Miquela are complex and multifaceted. While influencer content and physical appearance are largely discussed positively, her identity remained ambiguous and contested. Audiences' responses further reveal a psychological tension—she is perceived as both relatable and eerily artificial, reflecting a fluctuating sense of closeness and discomfort. Moreover, Lil Miquela's impact transcends entertainment, provoking sociocultural discussions and psychological engagement among audiences.

4.2. Brand perception

4.2.1. Thematic analysis of brand perception

Compared to the 802 comments (48.81% of all comments) that focused on Lil Miquela's perception (see Table 2 in last section; percentage calculated by the author), 360 comments (21.91%) were categorized as **brand perception** (see Table 4 in next section; percentage calculated by the author). This indicates that while Lil Miquela remains a focal point of audience interest, her campaigns still promoted discussions about associated brands. This section discusses sub-categories within **brand perception** (see Figure 4 below).

Notably, although the dataset includes comments for social media content regarding 11 different brands, only three—BMW, Calvin Klein, and Samsung—were explicitly mentioned by name in comments. These comments categorized as **brand name** suggest a higher degree of brand salience and awareness. A likely explanation lies in their global reach and premium market positioning, distinguishing them from more localized brands (e.g., Tattoo Studio SOFTFLEX) and mass-market brands (e.g., CleanltUp). Another influencing factor may be how actively these brands engage with audiences in comment section. Within comments categorized as **customer service**, BMW actively responded to customer inquiries and complaints. Such active engagement may contribute to higher brand visibility, as reflected by comments within **brand name**.

In addition to mentioning brand name, comments also discussed more specific characteristics about brands. First, comments within **brand value** express perceived brand values implicitly. For example, one audience member described BMW as "Sport, comfort, aggressive, classy", and one audience responded CleanItUp's environmental consciousness "Great Message, we only have one Earth!

#savetheplanet". Second, **product features** also attracted substantial attention. This was especially evident in discussions around BMW, where people frequently evaluated BMW's *visual design* (e.g., design of shape, grille, color, and rear) and *technological features* (e.g., BMW's move toward electric vehicle technology).

Figure 4

Thematic Coding Tree of Brand Perception
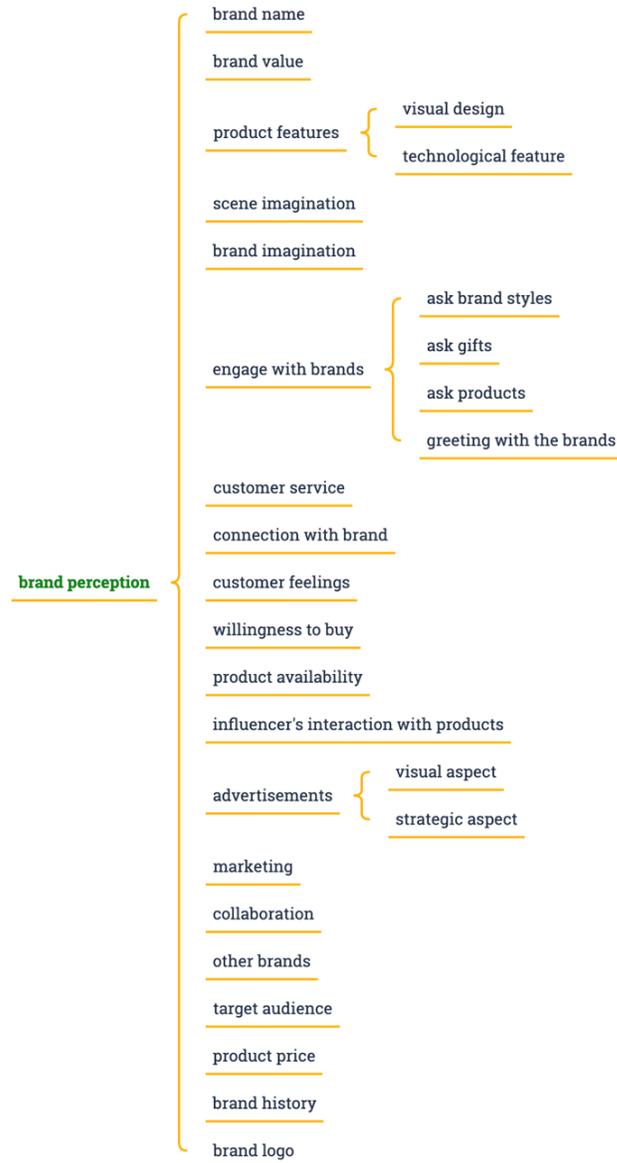
Note. This figure presents part of the complete coding tree in Appendix A. Codes in green are retained codes from the initial coding frame in operationalization. Black codes represent new categories that emerged during the thematic analysis.

Additionally, comments within **scene imagination** and **brand imagination** suggest that Lil Miquela's involvement in branded content prompted audiences to associate her content with the brands. Specifically, comments within **scene imagination** suggest that the storytelling conveyed by Lil Miquela's visual imagery fosters audience imagination about product usage scenarios, as exemplified by "I'm gonna travel to Grand Canyon with it" and "I want to have a nice car for my wife and me". Moreover, comments within **brand imagination** reflect how audiences project Lil Miquela's image onto the associated brands. For example, the comment "we love a gay icon for Calvin Klein" explicitly links the brand to LGBTQ+ inclusivity. This aligns with Tengblad-Kreft et al.'s finding (2017, p. 10) that audiences often associate the brand with influencers' image.

Beyond imagination, comments within **engage with brands** reflect more direct connection between customers and brands. Within this category, audiences *asked brand styles, ask gifts*, *ask products*, and *greetings with the brands*. Moreover, comments categorized as **connection with brand** reflect a deeper emotional connection, as illustrated by comments describing BMW as a "dream car". In addition, comments within **customer feelings** predominantly conveyed positive tones, exemplified by words such as "Classy & Cool", "power", "beautiful", and "amazing". These comments all indicate favorable brand perceptions under branded content featuring Lil Miquela. Such affection is also reflected by more direct expressions categorized as **willingness to buy**. Within this category, comments like "yall as soon as I turn 18 will flies to LA to get a soto gang tatto i swear" reveals audiences' strong interest even in Tattoo Studio SOFTFLEX, a relatively localized brand in the dataset.

However, the use of Lil Miquela in branded content also prompted skepticism and critical reflection among some audiences, which are reflected by comments categorized as **influencer's interaction with products**, and **advertisements**. Comments discussing **influencer's interaction with products** described this scene as unrealistic, exemplified by comments such as "Omg wtf is this thing?? Sis kissed her Samsung Galaxy" and "A robot talking about glowing skin, ridiculous". These criticisms became more pronounced among comments within **advertisements** where audiences evaluated the advertisement from visual and strategical perspectives. Specifically, although people acknowledged the strong appeal of the advertisements from *visual aspect*, as reflected in comments like "I haven't seen such a beautiful commercial in years.", this appreciation did not change into support for the advertisements from *strategic aspect*. For instance, one comment stated, "The car does not attract me, but very good masterpiece of ads. Thanks". This suggests that, for some people, the advertisements failed to help brands foster a deeper connection with audiences.

Consequently, some comments, categorized as **marketing**, questioned the strategic value of using AI influencers. Within this category, comments such as "They programmed an AI to queer bate and get us to buy Calvin Klein? I'm confused" and "What point is this supposed to get across? Even if it was a real

person, how does bella kissing them have anything to do with Calvin Klein???" doubted the relevance of AI influencers and visual stimulation in marketing. These comments suggest that AI influencers and visual stimulation could serve as distractions that diluted the campaigns' focus. Additionally, comments within the **marketing** category also criticized the lack of clarity in targeting, as exemplified by "Professional execution. But... what is the target audience here? Are they trying to sell a car to AI generated characters? Maybe making sure they are on the right side for when the machines take over? Let's cram AI generated images into everything because we can and it is so 'innovative'...".

In addition, this growing negative perceptions are reflected by comments about **collaboration** between brands and AI influencers. Among comments categorized as **collaboration**, responses ranged from calls for more traditional campaigns (e.g., "Just show us the car and not the vr girl") to outright rejections (e.g., "Disgraceful to see BMW using AI in a commercial. This video needs to be deleted" and "Stop advertising homosexuality!"). These reactions highlight the contested nature of AI influencer marketing. Reflecting on both the positive and negative responses, it becomes evident that acceptance of AI influencer marketing varies considerably among individuals. Similar to the individual differences in acceptance of AI (Kelly et al., 2023, pp. 8-10) and AI influencers (Mirowska & Arsenyan, 2023, pp. 7-8; de Boissieu & Baudier, 2023, pp. 1169-1174; Haikel-Elsabeh, 2023, p. 267-268), the findings reveal different audience responses to campaigns featuring AI Influencer. Focusing on positive comments, especially those within **scene imagination** and **brand imagination** categories, this thesis finds that human-centered storytelling helps build broader trust and create lasting resonance, especially when marketing efforts employ cutting-edge technologies that are unfamiliar to the general public.

4.2.2. Statistical sentiment analysis of sub-categories within brand perception

To empirically examine whether audience sentiment varies across different sub-categories within **brand perception**, a one-way ANOVA was conducted with 21 sub-categories as the independent variable. These subcategories include availability, brand history, brand imagination, brand logo, brand name, brand value, engagement with brand, collaboration, marketing, influencer's interaction with products, price, customer service, target audience, scene imagination, willingness to buy, product features, customer direct feelings, advertisements, connection with brands, other brands, customer attitudes to campaigns. Overall sentiment served as the dependent variable. The analysis reveals no significant main effect of these subcategories on overall sentiments, $F_{(20, 339)} = 0.57$, $p = .93$, partial $\eta^2 = .03$ (see Appendix H, Table H2). Average sentiment scores and standard deviations for each category's overall sentiment are presented in Appendix H, Table H1.

Table 4

Descriptive Statistic: Sentiment Intensity about Categories within Brand Perception

Sub-categories within brand perception	Mean	Std. Deviation	N
availability	1.10	1.29	10
brand history	1.83	0.58	2
brand imagination	1.12	1.58	2
brand logo	2.00	/	1
brand name	0.17	0.58	12
brand value	1.07	1.10	15
engage with brands	1.09	1.22	11
collaboration	1.37	1.04	101
marketing	1.05	0.88	9
influencer's interaction with products	2.12	0.17	2
price	0.48	0.68	5
customer service	0.97	1.03	6
target audience	0.00	/	1
scene imagination	1.45	1.02	7
willingness to buy	0.68	0.91	33
product features	1.40	1.10	76
customer feeling	1.47	1.15	37
advertisements	1.29	0.98	18
connection with brands	1.11	0.93	9
other brands	0.00	/	1
customer attitudes	0.50	0.71	2
TOTAL	1.21	1.07	360

A second one-way ANOVA was performed to examine the effect of these sub-categories on sentiment intensity—the strength of emotional expression regardless of direction. The analysis shows a significant main effect, $F(20, 339) = 1.90$, $p = .01$, partial $\eta^2 = .10$ (see Appendix H, Table H3). These results suggest that while these comments' overall sentiment did not significantly differ across topics, the sentiment intensity of response did vary. However, due to the small sample size in some subcategories (fewer than two comments), post hoc comparisons were not conducted to avoid violating assumptions necessary for valid inference. Nevertheless, the samples' statistics provide meaningful insights (see Table 4 above). Among all sub-categories, comments discussing **influencer's interactions with products** exhibit the highest sentiment intensity ($M = 2.12$, $SD = 0.17$). Other subcategories with relatively high sentiment intensity include **brand history** ($M = 1.83$, $SD = 0.58$), **customer feeling** ($M = 1.47$, $SD =$

1.15), and **scene imagination** (*M* = 1.45, *SD* = 1.02). These findings suggest that audience showed more intense sentiments when focusing on visual storytelling depicted by Lil Miquela's campaigns. In contrast, more factual themes such as **brand name** (*M* = 0.17, *SD* = 0.58) and **price** (*M* = 0.48, *SD* = 0.68) showed lower emotional intensity.

A limitation worth noting is the uneven representations of brands across the dataset. Although the campaigns involved 11 brands from diverse industries, audience engagement with brands was highly skewed. For example, BMW received substantial attention in comments, while other brands, such as Manychat, were mentioned infrequently or not at all. This uneven distribution precludes meaningful brand-specific comparisons and limits the generalizability of findings across different sectors.

Overall, while Lil Miquela effectively attracted attention and enhanced brand visibility—particularly for high-profile brands such as BMW, Calvin Klein, and Samsung—her presence also introduced notable tensions. While some audiences praised the advertisements for their high visual appeal, which may contribute to audiences' imaginations regarding brands, the artificiality of AI influencers prompted critical reflections among other audiences. Therefore, this thesis highlights the importance of complementing innovative AI influencer marketing with human-centered storytelling. Such efforts are crucial for improving audience relatability in marketing contexts.

4.3. Niche discourse topics and sentiment variation

4.3.1. Vibe, emotion, technological discussion, and other comment topics

In addition to influencer perception and brand perception, other **comment topics** (dimension 1) were identified within the comment section. One prominent category is **vibe**, where commenters employed evaluative descriptors without explicitly referencing any specific object (see Figure 5 below). The majority of these comment carried *positive descriptors*, including terms like "amazing" (n=4), "great" (n=2), "dream" (n=2), "nice" (n=2), and "futuristic" (n=2), while a minority of comments used *negative descriptors* like "disgusting" (n=2) and "weird" (n=2) (see Appendix K, Table K5 for details identified by text mining). Similarly, some comments featuring brief, spontaneous emotional reactions without explicit referents were categorized as **emotion**. These comments express a range of **emotion**, from *admiration* (e.g., "love" (n=27), "amazing" (n=9), "wow" (n=7)), to *surprise* (e.g., "omg" (n=7), "wtf" (n=17)), *aversion* (e.g., "gross" (n=2), "bad" (n=2)) and *confusion* (e.g., "confuse" (n=2)) (see Appendix K, Table K6 for details identified by text mining).

Comments categorized as **technological discussion** could explain the prevalence of terms such as "dream" and "futuristic" within **vibe**, along with *surprise* and *admiration* tones within **emotion**. Within **technological discussion**, comments center around more elaborate discussions on technological

development. For instance, some people conveyed excitement for *AI development* (e.g., "Embracing the fusion of technology and identity! At inTruth, we're exploring how AI can enhance self-awareness and authenticity. Your journey is inspiring, Miquela!"), and *AI influencer's creation* ("Tech level: 100%. Mind-blown level: totally"). Additionally, many comments discussed *technical aspects of AI influencer's content creation* (e.g., "What AI software was used to create her?"). These reactions support previous studies that people exhibited curiosity regarding mechanisms behind AI influencers (Xie-Carson et al., 2023, p. 10).

Conversely, the presence of descriptors such as "disgusting" and "weird" within category **vibe** can be explained by the "uncanny valley" effect, wherein hyper-realistic AI representations provoke discomfort (Lou et al., 2023, p. 548; Holá, 2025, p. 68; Molin & Nordgren, 2019, p. 31). The negative perception is also reflected by comments categorized as **commentary on comment section**. Within **commentary on comment section**, a minority of commenters distanced themselves from the broader audience, expressing skepticism about the authenticity of the conversation. For instance, one remarked, "this whole comment section is AI generated too", while one sarcastically questioned, "How is your conversation with software? Are you talking with your microwave also?". These responses suggest a perceived loss of authenticity and a growing distrust not only toward the AI influencer but also toward fellow commenters—who are suspected of being bots or overly enthusiastic AI advocates.

Figure 5

Thematic Coding Tree of Emotion, Vibe, Technological discussion, Commentary on Comment Section
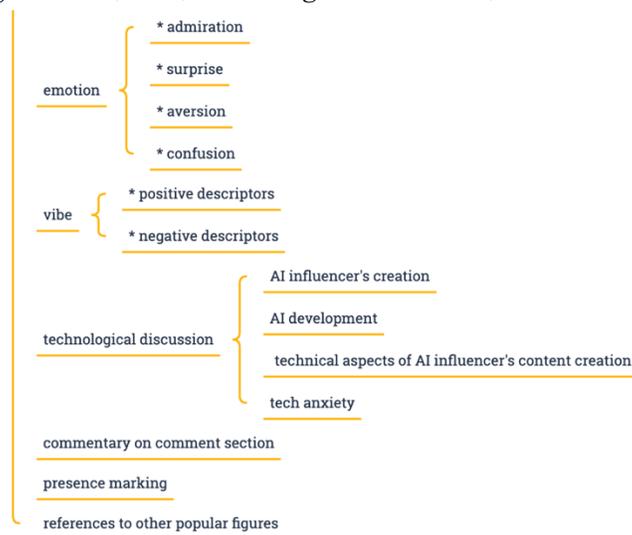
Note. This figure presents part of the complete coding tree in Appendix A. Codes in green are retained codes from the initial coding frame in operationalization. This section presents only the black codes,

which represents new categories that emerged during the thematic analysis. Codes marked with an asterisk (*) reflect categories identified through thematic analysis of ConText 2.0 output.

4.3.2. Sentiment patterns across comment topics

To further explore all the comment topics (dimension 2), a one-way ANOVA was conducted with comment topics as the independent variable and overall sentiment scores as the dependent variable. The eight thematic categories included: **influencer perception**, **brand perception**, **technological discussion**, **commentary on the comment section**, **emotion**, **vibe**, **references to other popular figures**, and **presence marking**. Results reveal no significant effect of comment topic on overall sentiment valence, $F(7, 1539) = 1.25$, $p = .28$, partial $\eta^2 = .01$ (see Appendix J, Table J1). This suggests that average overall sentiment scores did not differ significantly across top-level thematic categories for dimension 2. Despite this, descriptive statistics provide additional insights that support earlier qualitative observations (see Table 5 below). Specifically, comments categorized as **commentary on comment section** demonstrated a negative mean of overall sentiment ($M = -0.33$, $SD = 1.75$), reflecting audience skepticism. In contrast, comments within **vibe** exhibited the most positive overall sentiment ($M = 0.84$), though the highest variability ($SD = 1.53$) indicates big difference in audience responses' overall sentiment.

Table 5

Descriptive Statistic: Overall Sentiment about Categories within Comment Topic (Dimension 2)

Sub-categories within comment topic	Mean	Std. Deviation	N
influencer perception	0.39	1.22	804
brand perception	0.38	1.34	362
commentary on comment section	-0.33	1.75	6
emotion	0.33	1.46	209
references to other popular figures	0.31	0.66	29
presence marking	0.50	1.00	4
vibe	0.84	1.53	38
technological discussion	0.55	1.10	95
TOTAL	0.40	1.28	1547

Additionally, comments within **influencer perception** ($M = 0.39$, $SD = 1.22$) and **brand perception** ($M = 0.38$, $SD = 1.34$) tended to be positive (see Table 5 above). Another two one-sample t-test further tested whether there was a difference between these two categories' overall sentiment and 0

(neutral). The overall sentiment of categories within influencer perception was significantly higher than 0, $t(803) = 9.10$, $p < .01$ (see Table 6 below). The overall sentiment of categories within brand perception was significantly higher than 0, $t(361) = 5.44$, $p < .01$ (see Table 7 below). These results support **H1a** and **H1b**, which posited that audience comments express predominantly positive sentiments toward the AI influencer Lil Miquela and brands she featured.

Table 6

One-Sample T-Test for Overall Sentiment of Influencer Perception

	t	df	Sig (2-tailed)	Mean Difference	95% confidence interval of the difference	
					Lower	Upper
overall sentiment	9.10	803	.00	.39	.31	.48

Table 7

One-Sample T-Test for Overall Sentiment of Brand Perception

	t	df	Sig (2-tailed)	Mean Difference	95% confidence interval of the difference	
					Lower	Upper
overall sentiment	5.44	361	.00	.39	.25	.52

Furthermore, a second one-way ANOVA examined the effect of comment topics on sentiment intensity. This analysis revealed a significant main effect, $F(7, 1539) = 4.53$, $p < .01$, partial $\eta^2 = .02$ (see Appendix J, Table J2), suggesting that the sentiment intensity of audience comments varied by comment topics. A Tukey HSD post-hoc test showed that comments within **references to other popular figures** ($M = 0.50$, $SD = 0.59$) were significantly lower in emotional intensity than those within **brand perception** ($M = 1.22$, $SD = 1.07$, $p = .01$), **emotion** ($M = 1.23$, $SD = 0.96$, $p = .01$), and **vibe** ($M = 1.50$, $SD = 1.00$, $p < .01$) (see Appendix J, Table J3 for p-value; see Table 8 below for descriptive statistics). Mentions of public figures, such as others AI influencers or celebrities like Millie Bobby, often lacked elaboration or strong emotional content. By contrast, although the post-hoc test does not show other statistically significant differences, comments within **commentary on comment section** ($M = 1.73$, $SD = 1.26$) exhibited comparatively high levels of emotional intensity.

Table 8

Descriptive Statistic: Sentiment Intensity about Categories within Comment Topic (Dimension 2)

Sub-categories within comment topic	Mean	Std. Deviation	N
influencer perception	1.05	1.03	804
brand perception	1.22	1.07	362
commentary on comment section	1.73	1.26	6
emotion	1.23	0.96	209
references to other popular figures	0.50	0.59	29
presence marking	0.50	1.00	4
vibe	1.50	1.00	38
technological discussion	0.94	0.96	95
TOTAL	1.11	1.03	1547

4.4. Platform-based difference: sentiment, expression form, and comment topics

4.4.1. Sentiment difference between YouTube and Instagram

To explore the differences in audience sentiment between YouTube and Instagram, two independent samples t-tests were conducted. The first t-test compared overall sentiment between the two platforms. Results reveal that comments on Instagram ($M = 0.55$, $SD = 1.35$) were significantly more positive than those on YouTube ($M = 0.27$, $SD = 1.21$), $t(1165) = -4.26$, $p < .01$ (see Appendix D, Table D1 and Table D2). A second t-test examined sentiment intensity across platforms. Results show that Instagram comments ($M = 1.21$, $SD = 1.03$) exhibited significantly higher sentiment intensity compared to YouTube ($M = 1.02$, $SD = 1.02$), $t(1269) = -3.64$, $p < .01$ (see Appendix D, Table D3 and Table D4). These findings support **H2b**, which posits that the sentiments expressed in comments differ between YouTube and Instagram.

Several possible explanations may account for these differences. First, Lil Miquela tends to update content more frequently on Instagram, which could increase audience familiarity and engagement on this platform, thereby contributing to more positive sentiment. Second, the Instagram dataset comprises comments from more recent campaigns, potentially reflecting an evolving audience perception of AI influencers. This aligns with findings by Kim and Park (2024, p. 8), who observed increasing positive attitudes toward AI influencer advertising.

4.4.2. Difference in expression form between YouTube and Instagram

To further explore the reasons for platform-based sentiment differences, a chi-square test of independence was performed to evaluate the relationship between **expression form** (dimension 1) and

platform. Of the 1643 total cases, 1639 (99.8%) were valid and included in the analysis; 4 cases (0.2%) were excluded due to unclassifiable values in the expression form variable (see Appendix E, Table E1). The results indicate a statistically significant relationship between platform and expression form, $\chi2(3, N = 1639) = 232.39$, $p < .01$ (see Appendix E, Table E2). Descriptive results show distinct expression patterns across platforms (see Appendix E, Table E3). On YouTube, 42.8% of comments within **interaction with other commenters**, followed by **self-expression** (32.9%). In contrast, Instagram comments were more likely to be categorized into **engage with the influencer** (31.3%), followed by **self-expression** (29.3%) and **engage with brands** (26.9%).

To assess the impact of expression form on sentiment, a one-way ANOVA was conducted with expression form as the independent variable (**engage with brands**, **engage with the influencer**, **self-expression**, and **interaction with other commentors**), and overall sentiments as the dependent variable. The analysis reveals a significant main effect, $F(3, 1635) = 12.73$, $p < .01$, partial $\eta^2 = .02$ (see Appendix I, Table I1). Post hoc comparisons using Tukey HSD test indicated that comments within **engage with the influencer** ($M = 0.69$, $SD = 1.18$) were significantly more positive than those within **engage with brands** ($M = 0.41$, $SD = 1.32$, $p = .03$), **interaction with other commenters** ($M = 0.15$, $SD = 1.03$, $p < .01$), and **self-expression** ($M = 0.37$, $SD = 1.46$, $p < .01$). Additionally, comments within **interaction with other commenters** ($M = 0.15$, $SD = 1.03$) were significantly less positive than those within **engage with brands** ($M = 0.41$, $SD = 1.32$, $p = .03$), and self-expression ($M = 0.37$, $SD = 1.46$, $p = .02$). Average sentiment scores and standard deviations for each category's overall sentiment are presented in Table 9 below, and p-values for all comparisons can be found in Appendix I, Table I2.

Table 9

Descriptive Statistic: Overall Sentiment about Categories within Expression Form (Dimension 1)

Sub-categories within expression form	Mean	Std. Deviation	N
engage with brands	0.41	1.32	275
engage with the influencer	0.69	1.18	328
self-expression	0.37	1.46	518
interaction with other commenters	0.15	1.03	518
TOTAL	0.37	1.27	1639

A separate one-way ANOVA was performed to test the effect of expression form on sentiment intensity. The analysis demonstrates a significant main effect, $F(3, 1635) = 24.53$, $p < .01$, partial $\eta^2 = .04$ (see Appendix I, Table I3). Post hoc analyses reveal that comments within **interaction with other commenters** ($M = 0.79$, $SD = 0.97$) showed significantly lower emotional intensity than comments within

self-expression ($M = 1.31$, $SD = 1.02$, $p < .01$), **engage with brands** ($M = 1.18$, $SD = 1.09$, $p < .01$), and **engage with the influencer** ($M = 1.12$, $SD = 0.97$, $p < .01$). Furthermore, comments categorized as **self-expression** ($M = 1.31$, $SD = 1.02$) exhibited significantly higher emotional intensity than those within **engage with the influencer** ($M = 1.12$, $SD = 0.97$, $p = .04$). Average sentiment scores and standard deviations for each category's sentiment intensity are presented in Table 10 below, and p-values for all comparisons can be found in Appendix I, Table I4.

Table 10

Descriptive Statistic: Sentiment Intensity about Categories within Expression Form (Dimension 1)

Sub-categories within expression form	Mean	Std. Deviation	N
engage with brands	1.18	1.09	275
engage with the influencer	1.12	0.97	328
self-expression	1.31	1.02	518
interaction with other commenters	0.79	0.97	518
TOTAL	1.09	1.02	1639

These results suggest that expression form is closely related to both overall sentiment and sentiment intensity. Specifically, comments within **engage with the influencer** showed more positive sentiment, reflecting possible para-social relationships toward Lil Miquela. **Interaction with other commenters** related to less positive sentiment and lower emotional intensity, possibly because 16.5% of comments within **Interaction with other commenters** centered around **technological discussion** (theme for dimension 2) (see Appendix C, Table C3) involving less affective expression. **Self-expression** tended to show higher emotional intensity, possibly because 37.7% of comments within **self-expression** were categorized as **emotion** (theme for dimension 2) (see Appendix C, Table C3) involving emotional disclosure. These patterns help to further explain the platform-based differences in sentiment. Since Instagram is characterized by a higher proportion of engagement with the influencer, it may elicit more positive and intense emotional responses. In contrast, people predominantly chatted with other commenters on YouTube, which is characterized by low overall sentiment and emotional intensity.

4.4.3. Difference in comment topics between YouTube and Instagram

Additionally, a chi-square test of independence was performed to evaluate the relationship between comment topic (dimension 2) and platform. Of the 1643 total cases, 1547 (94.2%) were valid and included in the analysis; 96 cases (5.8%) were excluded due to unclassifiable values in the comment topic variable (see Appendix F, Table F1). The results indicated a statistically significant relationship

between comment topic and platform, $\chi2(7, N = 1547) = 82.75, p < .01$ (see Appendix F, Table F2). Descriptive results reveal that while both platforms predominantly featured comments about **influencer perception** (YouTube: 54.6%; Instagram: 47.8%), notable differences emerged in other topic categories. In particular, comments within **brand perception** were substantially more frequent on Instagram (33.3%) than on YouTube (17.3%), whereas comments within **emotion** was more common on YouTube (15.3%) than on Instagram (10.6%) (see Appendix F, Table F3). These findings support H2a, which posits that topics discussed in comments differ between YouTube and Instagram.

5. Conclusion

5.1. Summary of findings

This thesis aims to answer how audience interactions with branded content featuring the AI influencer Lil Miquela on YouTube and Instagram reflect perceptions of both the AI influencer and the associated brands. The findings reveal that audience responses to Lil Miquela's branded contents are multifaceted. For dimension 1 (expression form), the initial categorization in the operationalization phase, specifically **self-expression** and social interaction, was further refined during the thematic analysis. The **self-expression** category remained unchanged, and the social interaction theme was subdivided based on the target of interaction: **engage with brands**, **engage with the influencer**, **interaction with other commenters**. For dimension 2 (comment topic), the initial themes of **influencer perception** and **brand perception** were retained, while new themes such as **emotion** and **technological discussion** emerged during the analysis. Within **influencer perception**, the categories in operationalization—*physical appearance*, *influencer content*, and *influencer attributes*—remained unchanged, but their subcategories were further improved through thematic analysis and text mining. Notably, the initial category *psychological feelings* in operationalization was included in a broader category of *psychological distance*, which captures both direct *psychological feelings* expressions and implicit expressions such as *human–AI association* (reflecting how audiences relate to or interact with AI influencers). Additionally, initial categories within **brand perception** were not retained, which changed into more specific categories. For example, categories like *advertisement*, *collaboration*, and *customer service* reflect different aspects of the original category "brand activity" in operationalization. Similarly, through categories like *scene imagination* and *brand value*, the initial category "brand imagery" is represented. In addition, brand benefit was replaced by *product features*, as relevant comments described both positive and negative characteristics of brands' products.

Although sentiment did not differ significantly across comment topic (dimension 2), data revealed predominantly positive sentiment toward both Lil Miquela and the brands featured in her content. These results support *H1a*, which posits that comments reflect predominantly positive sentiment toward the AI influencer Lil Miquela, and *H1b*, which posits that comments reflect predominantly positive sentiment toward associated brands. Additionally, despite *negative descriptors* used by comments within **vibe**, most comments expressed *admiration* and *surprise* within general **emotion**. Moreover, some audiences expressed skepticism not only toward Lil Miquela and the featured brands, but also directed their doubt at fellow commenters, reflecting a growing distrust. These layered discussions reflect AI influencer marketing's potential and its contested nature.

Within **influencer perception**, Lil Miquela is simultaneously perceived as emotionally *relatable* and technologically alien—a robot who shows *realistic* human-like life while also provoking unease among some audiences. Audiences showed interest in *musical*, *visual*, and *narrative elements* within *influencer content*, which aligns with de Boissieu and Baudier's finding (2023, p. 1174) that audiences prioritize AI influencers' content during sustained interactions. In addition, audiences paid particular attention to her *physical appearance*, including *bodily features*, *cosmetics*, *vocal traits*, and *fashion choices*. This supports Holá's finding (2025, pp. 31-32) that AI influencer's physical appeal amplifies their potential for brand collaborations, particularly within the fashion industry. However, her hyperreal presence also leaded to *identity discussion*. While most audiences recognize her as a *robot*, a minority explicitly identified her as an *AI*. This *identity discussion* remained superficial, rarely involving critical or fact-based inquiry, which is also reflected by the relatively lower overall sentiment and emotional intensity of these comments. Despite this uncertainty, many people interact with Lil Miquela as a social being, which could attribute to her *human-like abilities*, such as *human-like behavior*, *emotion*, and *social ability*. Typically, her depiction of same-sex intimacy leads audiences to perceive her as a lesbian and also sparks discussions around *LGBTQ+*. Such social dynamic elicits various evaluations: while some people perceive her *relatable* or inspirational, which reinforce Rajput and Gandhi's finding (2024, p. 3) that AI influencers' active social presence help cultivate emotional closeness with followers, others expressed discomfort by comments within *psychological feelings*. Such psychological discomfort may attribute to implicit comparisons between her artificial perfection and real human's imperfection, or broader anxieties about technology which is similar to people's perceived risks of AI in general (Alhitmi et al., 2024, pp. 4-5).

Comments also revealed nuanced **brand perception**. Many commenters responded positively to *brand value* and *product features* (e.g., *visual design* and *technological features*). Some people associated Lil Miquela's content or image with product usage scenarios and brand image, as reflected in categories of *scene imagination* and *brand imagination*. This aligns with Ekstam and Bjurling's finding (2018, p. 76) that influencers help reinforce brand traits. However, discussions within *advertisements* prompted critical reflection, especially when Lil Miquela's presence was perceived to distract from core branded messaging. Therefore, some comments within *collaborations* directly expressed rejection of AI influencers. Notably, while sub-categories within **brand perception** did not show significant differences in overall sentiment, the sentiment intensity varied significantly across these categories. In samples, comments involving personal resonance, such as *influencer-product interactions*, and *scene imagination*, exhibited higher sentiment intensity.

Comparative platform analysis further enriches these findings. Comments on Instagram exhibited significantly more positive sentiment than those on YouTube. A possible explanation is that Instagram

users are more familiar with Lil Miquela. Another explanation is that the campaigns analyzed on Instagram were released more recently. Moreover, expression form (dimension 1) and comment topic (dimension 2) differed significantly between platforms. On YouTube, audience primarily involved **interactions with other commenters**, followed by **self-expression**. In contrast, Instagram audiences were more likely to **engage with the influencer**. This aligns with Lee and Watkins's (2016, p. 5759) finding that Instagram's affordances enable audiences to feel more connected to influencers' personal lives. Regarding comment topics, although discussions around **influencer perception** remained dominant on both platforms, comments within **brand perception** were more prevalent on Instagram, whereas comments within **emotion** were more commonly observed on YouTube. These differences support both *H2a* and *H2b*, confirming that platform-specific differences are reflected in both the sentiments expressed and the topics discussed by audiences. Rooted in the context of AI influencers, these findings respond to Han and Balabanis's insights (2024, p. 399) that YouTube and Instagram's different content formats and interaction dynamics shape how audiences engage with influencers.

5.2. Implications

This thesis offers several theoretical contributions to the understanding of AI influencers. First, it examines audience perceptions of both the AI influencer and the brands featured within a shared campaign context, and highlights platform-specific differences in audience interactions. It supports previous finding that physical appearance (Molin & Nordgren, 2019, pp. 31-32) and content (de Boissieu & Baudier, 2023, p. 1174) are central for Lil Miquela to convey attractiveness and connect with audiences. It illustrates how audiences project their imagination onto brands based on the AI influencer's content and image, responding to Si's (2024, p. 312) argument that AI influencers like Lil Miquela create immersive brand experiences that blur the lines between virtual and real. It demonstrates how sentiment and thematic focus among comments differ between YouTube and Instagram, thereby extending Han and Balabanis's finding (2024, p. 419) that platform-driven differences in communication and relationship-building shape audiences' perceptions of influencers to the context of AI influencers. These findings provide an empirical foundation for examining the effects of AI influencer in marketing, which may be mediated by platform-specific factors.

Second, this thesis reveals divergent perceptions and distinct sentiments toward the AI influencer and the associated brands. While many commenters described Lil Miquela as relatable and socially engaging, others expressed discomfort and unease. These negative reactions, on the one hand, support previous findings (Lou et al., 2023, p. 548; Holá, 2025, p. 68; Molin & Nordgren, 2019, p. 31) which highlight the relevance of the uncanny valley effect in the context of AI influencers; on the other hand, they support Chen et al.'s finding (2022, p. 133) that people feel uneasy about AI's expanding potential,

reflecting broader perceived risks about AI in general (Meyer et al., 2020, pp. 26-27). Additionally, different perceptions reflect individual difference in responses to AI influencers, thus supporting previous findings (Mirowska & Arsenyan, 2023, pp. 7-8; de Boissieu & Baudier, 2023, pp. 1169-1170; Haikel-Elsabeh, 2023, p. 267-268). This opens opportunities for further research into the socio-psychological mechanisms that shape audience engagement with AI figures.

Third, this thesis reveals audiences' tendency to project human-like qualities to the AI influencer, and implicit comparisons between Lil Miquela's artificial perfection and the real human imperfection. These strong anthropomorphic projections onto AI and the psychological comparisons between AI and humans are unexplored in current literature, presenting an open opportunity for future research. Understanding this psychological dynamic could help to better understand the impact of AI influencer in AI-human interaction.

Practically, this thesis provides actionable insights for marketers exploring the use of AI in marketing. First, audience perceptions of Lil Miquela suggest opportunities for strategic collaborations. Audiences anticipate content updates, especially musical releases, and actively engage with her visual aesthetics. This suggests that AI influencers like Lil Miquela have significant potential to collaborate with brands in music and fashion industries. Second, the observed platform-specific difference, such as the higher level of brand engagement on Instagram, suggest that marketers should consider platform affordances and user cultures before implementing marketing efforts. Given the more positive sentiment of comments on Instagram, AI-assisted campaigns are more suitable for Instagram than YouTube.

Third, the thesis reveals both positive potential and possible risks of AI influencer marketing. Lil Miquela's content and image could foster audiences' imagination around brands, but they also draw criticism for potentially distracting audiences from core brand messaging and evoking technology-related anxiety. This tension suggests that human-centered storytelling may help mitigate negative perceptions brought by technological novelty, thus improving emotional resonance with target audiences. Finally, the findings reveal the potential of AI influencers to participate in broader societal discourses. Lil Miquela, through her depiction as a lesbian, led to discussion around LGBTQ+ issues. Such identity representation extends the role of AI influencer beyond commercial value and suggests their potential to shape conversations on broader societal topics.

5.3. Limitations and recommendations

Several limitations of this thesis should be acknowledged. First, due to limited data, the comparison analysis was restricted. For qualitative analysis, while brands such as BMW, Calvin Klein, and Samsung received relatively high engagement, others like Manychat and PacSun had very few relevant comments. Such uneven distribution of brands mentions in comments limited the possibility to

compare brand perceptions across different brands or industries. For quantitative analysis, although the dataset comprises 1,643 audience comments, some thematic categories identified during analysis contained a limited number of cases. This restricted meaningful statistical comparisons of sentiment values across thematic categories using SPSS. Low expected cell counts in the contingency tables further impacted the robustness of these comparisons.

Second, this thesis focuses solely on Lil Miquela, and analyzed only publicly expressed audience perceptions through social media comments, which limits the generalizability of the findings. Although Lil Miquela is a popular AI influencer, relying on a single case makes it difficult to extend the conclusions to AI influencers more broadly. Moreover, while publicly expressed comments provide valuable insights, it is difficult to explore the underlying motivations, reasons, or contextual influences behind the sentiments expressed using such secondary data. This limited the thesis to offer psychological explanations in depth.

Third, the understanding of comments' expression form in the context of influencer marketing remains basic and underdeveloped. While this thesis develops the dimension of expression form, which is initially based on two key motivations for engaging with brands identified by Swani and Labrecque (2020, p. 289) and further developed based on the target of interaction, it does not explore other communicative features such as tone, linguistic strategies (e.g., emoji use), and syntactic structure. Future research could consider these elements to develop a more systematic framework for analyzing expression forms of comments which interact with branded content featuring influencers.

Building on the limitations of this thesis, future research should broaden the research subjects and employ a multi-method approach to gain deeper insights about AI influencer marketing. First, given that more and more AI influencers emerge on TikTok, X, and other metaverse-based environments, future studies should explore more AI influencers with different designs, audience bases, and content strategies on different media platforms. Moreover, different media's affordance may foster different user culture, thus leading to different levels of acceptance of AI influencer. The relationship among platforms' features, user culture, and people's acceptance of AI influencers remains to be further explored. Second, different brands' customers have different expectations, which possibly influence their acceptance of AI influencers. Future research could focus on a specific brand or industry, and use surveys to better examine the effects of AI influencer in marketing. Such studies could provide a foundation for comparative research on the role of AI influencers across diverse market contexts. Third, people's psychological projections onto AI influencers warrant further exploration. Qualitative methods such as in-depth interviews and focus groups could help explain individual differences in perception and sentiment toward branded content featuring AI influencers.

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Appendix A

Thematic Coding Tree

DIMENSION 1: EXPRESSION FORM
- self-expression
- engage with brands
- engage with the influencer
- interaction with other commenters

USER COMMENTS

influencer perception
- physical appearance
  - * bodily features
  - * cosmetics
  - * vocal traits
  - * fashion choices
  - * identity cues
  - * sentiment elements
- influencer content
  - * musical elements
  - * visual elements
  - * narrative elements
  - * commercial nature
  - * sentiment elements
- identity discussion
  - * robot
  - *AI
  - * human
  - * animation
  - * sentiment elements
- LGBTQ+
- discussion about account operations
- influencer attributes
  - human-like abilities
    - sexuality
    - human-like behavior
    - emotion
    - social ability
  - non-human limitations
  - growing followers
  - existence
  - tech attributes
  - realistic
  - relatable
- influencer impact
- psychological distance
  - psychological feelings
  - robots threaten human-beings
  - shock and disbelief
  - human-AI association
    - ask for interviewing
    - encourage creation
    - bless the influencer
    - express hatred
    - express longing
    - express love
    - ask AI's accompany
    - ask AI's life
    - desire to meet the influencer
    - desire to kiss the influencer
    - greeting with the influencer
    - comparison between human and AI
    - hope to become AI

DIMENSION 2: COMMENT TOPIC

brand perception
- brand name
- brand value
- product features
  - visual design
  - technological feature
- scene imagination
- brand imagination
- engage with brands
  - ask brand styles
  - ask gifts
  - ask products
  - greeting with the brands
- customer service
- connection with brand
- customer feelings
- willingness to buy
- product availability
- influencer's interaction with products
- advertisements
  - visual aspect
  - strategic aspect
- marketing
- collaboration
- other brands
- target audience
- product price
- brand history
- brand logo
- emotion
  - * admiration
  - * surprise
  - * aversion
  - * confusion
- vibe
  - * positive descriptors
  - * negative descriptors
- technological discussion
  - AI influencer's creation
  - AI development
  - technical aspects of AI influencer's content creation
  - tech anxiety
- commentary on comment section
- presence marking
- references to other popular figures

Note. Codes in green are retained codes from the initial coding frame in operationalization. Black codes represent new categories that emerged during the thematic analysis. Codes marked with an asterisk (*) reflect categories identified through thematic analysis of ConText 2.0 output.

Appendix B
Descriptive Statistics

Table B1

Descriptive Statistics: Frequency of Comments from YouTube and Instagram

	Frequency	Percent	Valid percent	Cumulative percent
YouTube	1033	62.9%	62.9%	62.9%
Instagram	610	37.1%	37.1%	100.0%
Total	1643	100.0%	100.0%	

Table B2

Descriptive Statistics: Overall Sentiment and Sentiment Intensity

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
Overall sentiment	1643	8	-4	4	0.37	1.27	1.61
Sentiment intensity	1643	4.24	0	4.24	1.09	1.02	1.05
Valid N	1643						

Appendix C
Chi-Square Test of Independence Between Expression Form and Comment Topic

This appendix presents the results of the Chi-square test of independence conducted to examine the relationship between expression form and comment topic. The analysis includes the Case Processing Summary, Chi-Square Tests, and Crosstabulation.

Table C1

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
expression form * comment topic	1543	93.9%	100	6.1%	1643	100%

Table C2

*Chi-Square Tests: Expression Form * Comment Topic*

	Value	df	Asymptotic significance (2-sided)
Pearson Chi-Square	1597.69	21	.00
Likelihood Ratio	1507.91	21	.00
Linear-by-Linear Association	34.70	1	.00
N of Valid Cases	1543		

Table C3

*Expression Form * Comment Topic Crosstabulation*

			expression form				
			engage with brands	engage with the influencer	self-expression	interaction with other commenters	Total
comment topic	influencer perception	Count	2	280	196	322	800
		% within expressionway	0.7%	88.3%	38.1%	73.9%	51.8%
	brand perception	Count	270	11	72	9	362
		% within expressionway	98.2%	3.5%	14.0%	2.1%	23.5%
	commentary on comment section	Count	0	1	2	3	6
		% within expressionway	0.0%	0.3%	0.4%	0.7%	0.4%
	emotion	Count	0	8	194	7	209
		% within expressionway	0.0%	2.5%	37.7%	1.6%	13.5%
	references to other popular figures	Count	1	1	7	20	29
		% within expressionway	0.4%	0.3%	1.4%	4.6%	1.9%
	presence marking	Count	0	3	1	0	4
		% within expressionway	0.0%	0.9%	0.2%	0.0%	0.3%
	vibe	Count	2	5	28	3	38
		% within expressionway	0.7%	1.6%	5.4%	0.7%	2.5%
	technological discussion	Count	0	8	15	72	95
		% within expressionway	0.0%	2.5%	2.9%	16.5%	6.2%
Total		Count	275	317	515	436	1543
		% within expressionway	100.0%	100.0%	100.0%	100.0%	100.0%

Independent Samples T-Tests for Sentiment Between YouTube and Instagram

This appendix presents the results of two independent samples t-tests conducted to examine differences in overall sentiment and sentiment intensity between comments on YouTube and Instagram.

Table D1

Descriptive Statistics: Overall Sentiment on YouTube and Instagram

	platform	N	Mean	Std. Deviation	Std. Error Mean
Overall Sentiment	YouTube	1033	0.27	1.21	0.04
	Instagram	610	0.55	1.35	0.06

Table D2

Independent Samples Test: Overall Sentiment between YouTube and Instagram

		Levene's test for equality of variances		T-test for equality of means				95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. Error Difference	lower	upper
Overall sentiment	Equal variances assumed	26.79	.00	-4.39	1641	.00	-0.28	0.06	-0.41	-0.16
	Equal variances not assumed			-4.26	1164.75	.00	-0.28	0.07	-0.41	-0.15

Table D3

Descriptive Statistics: Sentiment Intensity on YouTube and Instagram

	platform	N	Mean	Std. Deviation	Std. Error Mean
Sentiment Intensity	YouTube	1033	1.02	1.02	0.03
	Instagram	610	1.21	1.03	0.04

Table D4

Independent Samples Test: Overall Sentiment between YouTube and Instagram

		Levene's test for equality of variances		T-test for equality of means				95% confidence interval of the difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. Error Difference	lower	upper
Sentiment intensity	Equal variances assumed	4.14	.04	-3.65	1641	.00	-0.19	0.05	-0.29	-0.09
	Equal variances not assumed			-3.64	1268.95	.00	-0.19	0.05	-0.29	-0.09

Chi-Square Test of Independence Between Platform and Expression Form (Dimension 1)

       This appendix presents the results of the Chi-square test of independence conducted to examine the relationship between platform and expression form. The analysis includes the Case Processing Summary, Chi-Square Tests, and Crosstabulation.

Table E1

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
platform * expression form	1639	99.8%	4	0.2%	1643	100%

Table E2

*Chi-Square Tests: Platform * Expression Form*

	Value	df	Asymptotic significance (2-sided)
Pearson Chi-Square	232.39	3	.00
Likelihood Ratio	243.96	3	.00
Linear-by-Linear Association	215.90	1	.00
N of Valid Cases	1639		

Table E3

*Platform * Expression Form Crosstabulation*

			expressionform				
			engage with brands	engage with the influencer	self–expression	interaction with other commenters	Total
platform	YouTube	Count	112	138	340	442	1032
		% within platform	10.9%	13.4%	32.9%	42.8%	100.0%
	Instagram	Count	163	190	178	76	607
		% within platform	26.9%	31.3%	29.3%	12.5%	100.0%
Total		Count	275	328	518	518	1639
		% within platform	16.8%	20.0%	31.6%	31.6%	100.0%

Appendix F
Chi-Square Test of Independence Between Platform and Comment Topic (Dimension 2)

This appendix presents the results of the Chi-square test of independence conducted to examine the relationship between platform and comment topic. The analysis includes the Case Processing Summary, Chi-Square Tests, and Crosstabulation.

Table F1

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
platform * comment topic	1547	94.2%	96	5.8%	1643	100%

Table F2

*Chi-Square Tests: Platform * Comment Topic*

	Value	df	Asymptotic significance (2-sided)
Pearson Chi-Square	82.75	7	.00
Likelihood Ratio	87.55	7	.00
Linear-by-Linear Association	4.80	1	.03
N of Valid Cases	1547		

Table F3

*Platform * Comment Topic Crosstabulation*

			influencer perceptions	brand perceptions	commentary on comment section	emotion	references to other popular figures	presence marking	vibe	technological discussion	Total
platform	YouTube	Count	521	165	5	146	28	1	16	73	955
		% within platform	54.6%	17.3%	0.5%	15.3%	2.9%	0.1%	1.7%	7.6%	100.0%
	Instagram	Count	283	197	1	63	1	3	22	22	592
		% within platform	47.8%	33.3%	0.2%	10.6%	0.2%	0.5%	3.7%	3.7%	100.0%
Total		Count	804	362	6	209	29	4	38	95	1547
		% within platform	52.0%	23.4%	0.4%	13.5%	1.9%	0.3%	2.5%	6.1%	100.0%

Appendix G

One-Way ANOVA Tests for Subcategories within Influencer Perception

This appendix presents the results of two one-way ANOVA analyses conducted to examine differences in overall sentiment and sentiment intensity across sub-categories within influencer perception. In addition to Descriptive Statistics (as presented in the main body), each analysis includes Tests of Between-Subjects Effects, and Tukey HSD Multiple Comparisons.

Table G1

Test of Between-Subjects Effects for Overall Sentiment

Dependent Variable: overallsentiment

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	63.27[a]	7.00	9.04	6.35	2.79E−7	.05
Intercept	75.67	1.00	75.67	53.18	7.38E−13	.06
influencersubcate	63.27	7.00	9.04	6.35	2.79E−7	.05
Error	1129.79	794.00	1.42			
Total	1316.00	802.00				
Corrected Total	1193.06	801.00				

a. R Squared = .053 (Adjusted R Squared = .045)

Table G2

Tukey's HSD Post Hoc Test for Overall Sentiment

Dependent Variable: overallsentiment
Tukey HSD

(I) influencersubcate	(J) influencersubcate	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
identity discussion	psychological distance	−.18	.14	.88	−.60	.23
	discussion about account operation	−.17	.34	1.00	−1.22	.88
	LGBTQ+	−.05	.20	1.00	−.68	.57
	physical appearance	−.59*	.14	.00	−1.01	−.17
	influencer impact	−2.07*	.43	.00	−3.38	−.75
	influencer attributes	−.39	.15	.17	−.85	.07
	influencer content	−.50*	.13	.00	−.90	−.10
psychological distance	identity discussion	.18	.14	.88	−.23	.60
	discussion about account operation	.01	.34	1.00	−1.03	1.06
	LGBTQ+	.13	.20	1.00	−.49	.75
	physical appearance	−.41	.14	.06	−.82	.01
	influencer impact	−1.88*	.43	.00	−3.20	−.57
	influencer attributes	−.20	.15	.88	−.66	.25
	influencer content	−.32	.13	.23	−.72	.08
discussion about account operation	identity discussion	.17	.34	1.00	−.88	1.22
	psychological distance	−.01	.34	1.00	−1.06	1.03
	LGBTQ+	.12	.38	1.00	−1.03	1.26
	physical appearance	−.42	.35	.93	−1.47	.63
	influencer impact	−1.89*	.54	.01	−3.52	−.27
	influencer attributes	−.22	.35	1.00	−1.28	.85
	influencer content	−.33	.34	.98	−1.37	.71
LGBTQ+	identity discussion	.05	.20	1.00	−.57	.68
	psychological distance	−.13	.20	1.00	−.75	.49
	discussion about account operation	−.12	.38	1.00	−1.26	1.03
	physical appearance	−.54	.21	.15	−1.16	.09
	influencer impact	−2.01*	.46	.00	−3.40	−.62
	influencer attributes	−.33	.21	.77	−.99	.32
	influencer content	−.45	.20	.33	−1.06	.16
physical appearance	identity discussion	.59*	.14	.00	.17	1.01
	psychological distance	.41	.14	.06	−.01	.82
	discussion about account operation	.42	.35	.93	−.63	1.47
	LGBTQ+	.54	.21	.15	−.09	1.16
	influencer impact	−1.47*	.43	.02	−2.79	−.16
	influencer attributes	.20	.15	.89	−.26	.67
	influencer content	.09	.13	1.00	−.32	.49
influencer impact	identity discussion	2.07*	.43	.00	.75	3.38
	psychological distance	1.88*	.43	.00	.57	3.20
	discussion about account operation	1.89*	.54	.01	.27	3.52
	LGBTQ+	2.01*	.46	.00	.62	3.40
	physical appearance	1.47*	.43	.02	.16	2.79
	influencer attributes	1.68*	.44	.00	.35	3.01
	influencer content	1.56*	.43	.01	.25	2.87
influencer attributes	identity discussion	.39	.15	.17	−.07	.85
	psychological distance	.20	.15	.88	−.25	.66
	discussion about account operation	.22	.35	1.00	−.85	1.28
	LGBTQ+	.33	.21	.77	−.32	.99
	physical appearance	−.20	.15	.89	−.67	.26
	influencer impact	−1.68*	.44	.00	−3.01	−.35
	influencer content	−.11	.15	.99	−.56	.33
influencer content	identity discussion	.50*	.13	.00	.10	.90
	psychological distance	.32	.13	.23	−.08	.72
	discussion about account operation	.33	.34	.98	−.71	1.37
	LGBTQ+	.45	.20	.33	−.16	1.06
	physical appearance	−.09	.13	1.00	−.49	.32
	influencer impact	−1.56*	.43	.01	−2.87	−.25
	influencer attributes	.11	.15	.99	−.33	.56

Based on observed means.
 The error term is Mean Square(Error) = 1.423.

 *. The mean difference is significant at the 0

Table G3

Test of Between-Subjects Effects for Sentiment Intensity

Dependent Variable: intensity

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	71.35[a]	7.00	10.19	10.44	1.41E−12	.08
Intercept	307.90	1.00	307.90	315.23	1.20E−59	.28
influencersubcate	71.35	7.00	10.19	10.44	1.41E−12	.08
Error	775.52	794.00	.98			
Total	1728.00	802.00				
Corrected Total	846.87	801.00				

a. R Squared = .084 (Adjusted R Squared = .076)

Table G4

Tukey's HSD Post Hoc Test for Sentiment Intensity

Dependent Variable: intensity
Tukey HSD

(I) influencersubcate	(J) influencersubcate	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
identity discussion	psychological distance	−.77*	.11	.00	−1.11	−.42
	discussion about account operation	.00	.29	1.00	−.87	.87
	LGBTQ+	−.59*	.17	.01	−1.10	−.08
	physical appearance	−.70*	.11	.00	−1.05	−.35
	influencer impact	−1.59*	.36	.00	−2.68	−.50
	influencer attributes	−.38	.13	.05	−.76	.00
	influencer content	−.61*	.11	.00	−.94	−.28
psychological distance	identity discussion	.77*	.11	.00	.42	1.11
	discussion about account operation	.77	.29	.13	−.10	1.63
	LGBTQ+	.17	.17	.97	−.34	.69
	physical appearance	.07	.11	1.00	−.28	.41
	influencer impact	−.82	.36	.30	−1.91	.27
	influencer attributes	.38*	.12	.04	.01	.76
	influencer content	.15	.11	.84	−.17	.48
discussion about account operation	identity discussion	.00	.29	1.00	−.87	.87
	psychological distance	−.77	.29	.13	−1.63	.10
	LGBTQ+	−.59	.31	.56	−1.54	.36
	physical appearance	−.70	.29	.22	−1.57	.17
	influencer impact	−1.59*	.44	.01	−2.94	−.24
	influencer attributes	−.38	.29	.89	−1.26	.50
	influencer content	−.61	.28	.38	−1.47	.25
LGBTQ+	identity discussion	.59*	.17	.01	.08	1.10
	psychological distance	−.17	.17	.97	−.69	.34
	discussion about account operation	.59	.31	.56	−.36	1.54
	physical appearance	−.11	.17	1.00	−.62	.41
	influencer impact	−1.00	.38	.15	−2.15	.16
	influencer attributes	.21	.18	.94	−.33	.75
	influencer content	−.02	.17	1.00	−.53	.49
physical appearance	identity discussion	.70*	.11	.00	.35	1.05
	psychological distance	−.07	.11	1.00	−.41	.28
	discussion about account operation	.70	.29	.22	−.17	1.57
	LGBTQ+	.11	.17	1.00	−.41	.62
	influencer impact	−.89	.36	.21	−1.98	.20
	influencer attributes	.32	.13	.19	−.07	.70
	influencer content	.09	.11	.99	−.25	.42
influencer impact	identity discussion	1.59*	.36	.00	.50	2.68
	psychological distance	.82	.36	.30	−.27	1.91
	discussion about account operation	1.59*	.44	.01	.24	2.94
	LGBTQ+	1.00	.38	.15	−.16	2.15
	physical appearance	.89	.36	.21	−.20	1.98
	influencer attributes	1.21*	.36	.02	.10	2.31
	influencer content	.98	.36	.11	−.11	2.06
influencer attributes	identity discussion	.38	.13	.05	.00	.76
	psychological distance	−.38*	.12	.04	−.76	−.01
	discussion about account operation	.38	.29	.89	−.50	1.26
	LGBTQ+	−.21	.18	.94	−.75	.33
	physical appearance	−.32	.13	.19	−.70	.07
	influencer impact	−1.21*	.36	.02	−2.31	−.10
	influencer content	−.23	.12	.56	−.60	.14
influencer content	identity discussion	.61*	.11	.00	.28	.94
	psychological distance	−.15	.11	.84	−.48	.17
	discussion about account operation	.61	.28	.38	−.25	1.47
	LGBTQ+	.02	.17	1.00	−.49	.53
	physical appearance	−.09	.11	.99	−.42	.25
	influencer impact	−.98	.36	.11	−2.06	.11
	influencer attributes	.23	.12	.56	−.14	.60

Based on observed means.
 The error term is Mean Square(Error) = .977.

 *. The mean difference is significant at the 0

This appendix presents the results of two one-way ANOVA analyses conducted to examine differences in overall sentiment and sentiment intensity across sub-categories within brand perception. Due to insufficient sample sizes in some subcategories, certain comparisons could not be performed. Moreover, the descriptive statistics for sentiment intensity is presented in the main body.

Table H1

Descriptive Statistic: Overall Sentiment about Categories within Brand Perception

Sub-categories within brand perception	Mean	Std. Deviation	N
availability	-0.10	1.73	10
brand history	0.50	0.71	2
brand imagination	0.50	0.71	2
brand logo	2.00	/	1
brand name	0.17	0.58	12
brand value	0.27	1.16	15
engage with brands	0.55	1.57	11
collaboration	0.22	1.49	101
marketing	0.67	1.12	9
influencer's interaction with products	0.50	2.12	2
price	0.20	0.45	5
customer service	0.17	0.75	6
target audience	0.00	/	1
scene imagination	0.71	1.38	7
willingness to buy	0.36	0.96	33
product features	0.33	1.46	76
customer feeling	0.62	1.46	37
advertisements	0.78	1.31	18
connection with brands	1.11	0.93	9
other brands	0.00	/	1
customer attitudes	0.50	0.71	2
TOTAL	0.38	1.34	360

Table H2

Test of Between-Subjects Effects for Overall Sentiment

Dependent Variable: overallsentiment

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	21.01[a]	20.00	1.05	.57	.93	.03
Intercept	16.26	1.00	16.26	8.78	.00	.03
brandsubcate	21.01	20.00	1.05	.57	.93	.03
Error	627.61	339.00	1.85			
Total	700.00	360.00				
Corrected Total	648.62	359.00				

a. R Squared = .032 (Adjusted R Squared = −.025)

Table H3

Test of Between-Subjects Effects for Sentiment Intensity

Dependent Variable: intensity

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	41.57[a]	20.00	2.08	1.90	.01	.10
Intercept	79.80	1.00	79.80	73.08	4.32E−16	.18
brandsubcate	41.57	20.00	2.08	1.90	.01	.10
Error	370.14	339.00	1.09			
Total	942.00	360.00				
Corrected Total	411.71	359.00				

a. R Squared = .101 (Adjusted R Squared = .048)

This appendix presents the results of two one-way ANOVA analyses conducted to examine differences in overall sentiment and sentiment intensity across various expression forms (dimension 1). The descriptive statistics is presented in the main body.

Table I1

Test of Between-Subjects Effects for Overall Sentiment

Dependent Variable: overallsentiment

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	60.31^a	3.00	20.10	12.73	3.18E−8	.02
Intercept	248.96	1.00	248.96	157.64	1.38E−34	.09
expressionform	60.31	3.00	20.10	12.73	3.18E−8	.02
Error	2582.15	1635.00	1.58			
Total	2868.00	1639.00				
Corrected Total	2642.46	1638.00				

a. R Squared = .023 (Adjusted R Squared = .021)

Table I2

Tukey's HSD Post Hoc Test for Overall Sentiment

Dependent Variable: overallsentiment
Tukey HSD

(I) expressionform	(J) expressionform	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
engage with brands	self–expression	.04	.09	.97	−.20	.28
	engage with the influencer	−.28*	.10	.03	−.55	−.02
	interaction with other commenters	.26*	.09	.03	.02	.51
engage with the influencer	engage with brands	.28*	.10	.03	.02	.55
	self–expression	.32*	.09	.00	.09	.55
	interaction with other commenters	.55*	.09	.00	.32	.77
self–expression	engage with brands	−.04	.09	.97	−.28	.20
	engage with the influencer	−.32*	.09	.00	−.55	−.09
	interaction with other commenters	.22*	.08	.02	.02	.42
interaction with other commenters	engage with brands	−.26*	.09	.03	−.51	−.02
	self–expression	−.22*	.08	.02	−.42	−.02
	engage with the influencer	−.55*	.09	.00	−.77	−.32

Based on observed means.
 The error term is Mean Square(Error) = 1.579.

*. The mean difference is significant at the

Table I3

Test of Between-Subjects Effects for Sentiment Intensity

Dependent Variable: intensity

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	74.09[a]	3.00	24.70	24.53	1.58E−15	.04
Intercept	1839.51	1.00	1839.51	1827.29	1.13E−268	.53
expressionform	74.09	3.00	24.70	24.53	1.58E−15	.04
Error	1645.93	1635.00	1.01			
Total	3656.00	1639.00				
Corrected Total	1720.03	1638.00				

a. R Squared = .043 (Adjusted R Squared = .041)

Table I4

Tukey's HSD Post Hoc Test for Sentiment Intensity

Dependent Variable: intensity
Tukey HSD

(I) expressionform	(J) expressionform	Mean Difference (I−J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
engage with brands	engage with the influencer	.06	.08	.87	−.15	.27
	self−expression	−.13	.07	.32	−.32	.07
	interaction with other commenters	.39[*]	.07	.00	.20	.58
engage with the influencer	engage with brands	−.06	.08	.87	−.27	.15
	self−expression	−.19[*]	.07	.04	−.37	−.01
	interaction with other commenters	.33[*]	.07	.00	.15	.51
self−expression	engage with brands	.13	.07	.32	−.07	.32
	engage with the influencer	.19[*]	.07	.04	.01	.37
	interaction with other commenters	.52[*]	.06	.00	.36	.68
interaction with other commenters	engage with brands	−.39[*]	.07	.00	−.58	−.20
	engage with the influencer	−.33[*]	.07	.00	−.51	−.15
	self−expression	−.52[*]	.06	.00	−.68	−.36

Based on observed means.
 The error term is Mean Square(Error) = 1.007.

*. The mean difference is significant at the

Appendix J
One-Way ANOVA Tests for Comment Topic (Dimension 2)

This appendix presents the results of two one-way ANOVA analyses conducted to examine differences in overall sentiment and sentiment intensity across various comment topics (dimension 2). The descriptive statistics are presented in the main body.

Table J1

Test of Between-Subjects Effects for Overall Sentiment

Dependent Variable: overallsentiment

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	14.29^a	7.00	2.04	1.25	.27	.01
Intercept	17.73	1.00	17.73	10.82	.00	.01
comment topics	14.29	7.00	2.04	1.25	.27	.01
Error	2522.22	1539.00	1.64			
Total	2781.00	1547.00				
Corrected Total	2536.51	1546.00				

a. R Squared = .006 (Adjusted R Squared = .001)

Table J2

Test of Between-Subjects Effects for Sentiment Intensity

Dependent Variable: intensity

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	32.90^a	7.00	4.70	4.53	5.14E−5	.02
Intercept	150.79	1.00	150.79	145.39	4.68E−32	.09
comment topics	32.90	7.00	4.70	4.53	5.14E−5	.02
Error	1596.16	1539.00	1.04			
Total	3525.00	1547.00				
Corrected Total	1629.06	1546.00				

a. R Squared = .020 (Adjusted R Squared = .016)

Table J3

Tukey's HSD Post Hoc Test for Sentiment Intensity

Dependent Variable: intensity
Tukey HSD

(I) comment topics	(J) comment topics	Mean Difference (I–J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
influencer perception	brand perception	−.17	.06	.17	−.36	.03
	commentary on comment section	−.68	.42	.73	−1.95	.58
	emotion	−.18	.08	.33	−.42	.06
	references to other popular figures	.55	.19	.08	−.03	1.14
	presence marking	.55	.51	.96	−1.00	2.10
	vibe	−.45	.17	.14	−.96	.07
	technological discussion	.11	.11	.97	−.23	.45
brand perception	influencer perception	.17	.06	.17	−.03	.36
	commentary on comment section	−.52	.42	.92	−1.79	.75
	emotion	−.01	.09	1.00	−.28	.26
	references to other popular figures	.72*	.20	.01	.12	1.31
	presence marking	.72	.51	.86	−.84	2.27
	vibe	−.28	.17	.74	−.81	.25
	technological discussion	.28	.12	.27	−.08	.63
commentary on comment section	influencer perception	.68	.42	.73	−.58	1.95
	brand perception	.52	.42	.92	−.75	1.79
	emotion	.51	.42	.93	−.77	1.79
	references to other popular figures	1.24	.46	.12	−.15	2.62
	presence marking	1.23	.66	.57	−.76	3.23
	vibe	.24	.45	1.00	−1.12	1.60
	technological discussion	.79	.43	.58	−.51	2.10
emotion	influencer perception	.18	.08	.33	−.06	.42
	brand perception	.01	.09	1.00	−.26	.28
	commentary on comment section	−.51	.42	.93	−1.79	.77
	references to other popular figures	.73*	.20	.01	.12	1.34
	presence marking	.73	.51	.85	−.83	2.29
	vibe	−.27	.18	.81	−.81	.28
	technological discussion	.29	.13	.31	−.10	.67
references to other popular figures	influencer perception	−.55	.19	.08	−1.14	.03
	brand perception	−.72*	.20	.01	−1.31	−.12
	commentary on comment section	−1.24	.46	.12	−2.62	.15
	emotion	−.73*	.20	.01	−1.34	−.12
	presence marking	.00	.54	1.00	−1.65	1.65
	vibe	−1.00*	.25	.00	−1.76	−.24
	technological discussion	−.44	.22	.45	−1.10	.21
presence marking	influencer perception	−.55	.51	.96	−2.10	1.00
	brand perception	−.72	.51	.86	−2.27	.84
	commentary on comment section	−1.23	.66	.57	−3.23	.76
	emotion	−.73	.51	.85	−2.29	.83
	references to other popular figures	.00	.54	1.00	−1.65	1.65
	vibe	−1.00	.54	.58	−2.62	.63
	technological discussion	−.44	.52	.99	−2.02	1.14
vibe	influencer perception	.45	.17	.14	−.07	.96
	brand perception	.28	.17	.74	−.25	.81
	commentary on comment section	−.24	.45	1.00	−1.60	1.12
	emotion	.27	.18	.81	−.28	.81
	references to other popular figures	1.00*	.25	.00	.24	1.76
	presence marking	1.00	.54	.58	−.63	2.62
	technological discussion	.56	.20	.08	−.04	1.15
technological discussion	influencer perception	−.11	.11	.97	−.45	.23
	brand perception	−.28	.12	.27	−.63	.08
	commentary on comment section	−.79	.43	.58	−2.10	.51
	emotion	−.29	.13	.31	−.67	.10
	references to other popular figures	.44	.22	.45	−.21	1.10
	presence marking	.44	.52	.99	−1.14	2.02
	vibe	−.56	.20	.08	−1.15	.04

Based on observed means.
 The error term is Mean Square(Error) = 1.037.

Appendix K
Representative Results from Text Mining

Due to the large volume of output generated by the Context 2.0, this appendix presents only representative examples that support key findings. Additionally, because of limitations in the software's database, sentiment analysis could not be performed for all extracted terms.

Table K1

Text Mining Terms and Sentiment Analysis Results for Comments within Influencer Content

Term	Sentiment	Frequency
music	/	23
melody	/	1
picture	/	1
piano	/	3
shot	/	1
video	/	13
album	/	3
art	/	7
song	/	30
kiss	positive	17
storytelling	/	1
news	/	3
sound	/	1
sponsorship	/	1
advertisement	/	1
wonderful	positive	3
beautiful	positive	4
love	positive	11
amazing	positive	6
miss	negative	5
fake	negative	3

Table K2

Text Mining Terms and Sentiment Analysis Results for Comments within Physical Appearance

Term	Sentiment	Frequency
wrist	/	1
finger	/	1
chest	/	1
foot	/	1
tongue	/	2
face	/	5
skin	/	4
head	/	2
armpit	/	1
eye	/	1
lips	/	1
body	/	2
tooth	/	4
hairstyle	/	1
makeup	/	3
laugh	negative	1
voice	/	1
tone	/	2
tattoo	/	10
bag	/	1
pet	/	1
style	/	1
dress	/	1
clothing	/	1
outfit	/	1
shoe	/	2
vestment	/	1

girl	/	14
avatar	/	1
animation	/	5
robotic	/	1
real	positive	13
realistic	positive	5
fake	negative	1
gorgeous	positive	2
elegant	positive	1
hot	positive	4
amazing	positive	3
adorable	positive	2
awesome	positive	1
beautiful	positive	1
cool	positive	1
powerful	positive	1
stunning	positive	1
scary	negative	6
terrible	negative	1
weird	negative	2
dirty	negative	1
spooky	negative	1
mess	negative	1
disorder	negative	1

Table K3

Text Mining Terms and Sentiment Analysis Results for Comments within Identity Discussion

Term	Sentiment	Frequency
robot	/	70
AI	/	7
CGI model	/	1
animation	/	13
digital figure	/	4
stress	negative	1
confusion	negative	1
mystery	negative	1
fake	negative	6

Table K4

Text Mining Terms and Sentiment Analysis Results for Comments within Psychological Feelings

Term	Sentiment	Frequency
scared	negative	4
weird	negative	6
uncanny	/	2
uncomfortable	negative	3
cringe	/	3

Table K5

Text Mining Terms and Sentiment Analysis Results for Comments within Vibe

Term	Sentiment	Frequency
amazing	positive	4
great	positive	2
dream	positive	2
nice	positive	2
futuristic	/	2
disguising	/	2
weird	negative	2

Table K6

Text Mining Terms and Sentiment Analysis Results for Comments within Emotion

Term	Sentiment	Frequency
love	positive	27
amazing	positive	9
wow	/	7
omg	/	7
wtf	/	17
gross	negative	2
bad	negative	2
confuse	negative	2

Appendix L
Declaration Page: Use of Generative AI Tools in Thesis

Tool Used: ChatGPT by OpenAI

Purpose: The tool was used to correct grammar mistakes.

Prompts Used:

1. "Tell me all grammar errors in the following paragraphs."

2. "Any sentence have grammar mistakes?"

Student Information
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Student ID: 673971
Course Name: Master Thesis CM5000
Supervisor Name: Ju-Sung (Jay) Lee
Date: 26 June

Declaration:

Acknowledgment of Generative AI Tools
I acknowledge that I am aware of the existence and functionality of generative artificial intelligence (AI) tools, which are capable of producing content such as text, images, and other creative works autonomously.

GenAI use would include, but not limited to:

-   Generated content (e.g., ChatGPT, Quillbot) limited strictly to content that is not assessed (e.g., thesis title).
-   Writing improvements, including grammar and spelling corrections (e.g., Grammarly)
-   Language translation (e.g., DeepL), without generative AI alterations/improvements.
-   Research task assistance (e.g., finding survey scales, qualitative coding verification, debugging code)
-   Using GenAI as a search engine tool to find academic articles or books (e.g.,

☒ I declare that I have used generative AI tools, specifically ChatGPT, in the process of creating parts or components of my thesis. The purpose of using these tools was to aid in generating content or assisting with specific aspects of thesis work.

Extent of AI Usage

☒ I confirm that while I utilized generative AI tools to aid in content creation, the majority of the intellectual effort, creative input, and decision-making involved in completing the thesis were undertaken by me. <u>I have enclosed the prompts/logging of the GenAI tool use in an appendix.</u>

Ethical and Academic Integrity

☒ I understand the ethical implications and academic integrity concerns related to the use of AI tools in coursework. I assure that the AI-generated content was used responsibly, and any content derived from these tools has been appropriately cited and attributed according to the guidelines provided by the instructor and the course. I have taken necessary steps to distinguish between my original work and the AI-generated contributions. Any direct quotations, paraphrased content, or other forms of AI-generated material have been properly referenced in accordance with academic conventions.

By signing this declaration, I affirm that this declaration is accurate and truthful. I take full responsibility for the integrity of my assignment and am prepared to discuss and explain the role of generative AI tools in my creative process if required by the instructor or the Examination Board. I further affirm that I have used generative AI tools in accordance with ethical standards and academic integrity expectations.

Signature: *Yuting Lu*
Date of Signature: 26 June 2025

☐ I declare that I have NOT used any generative AI tools and that the assignment concerned is my original work.

Signature: [digital signature]
Date of Signature: [Date of Submission]