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# Artificial intelligence-generated virtual influencer: Examining the effects of emotional display on user engagement

Joanne Yu [a,d,*], Astrid Dickinger [a], Kevin Kam Fung So [b], Roman Egger [a,c]

[a] School of Tourism and Service Management, Modul University Vienna, Am Kahlenberg 1, 1190, Wien, Austria
[b] School of Hospitality and Tourism Management, Spears School of Business, Oklahoma State University, Stillwater, OK, 74078, United States
[c] Department of Business & Tourism, Salzburg University of Applied Sciences, Urstein Süd 1, A-5412, Puch, Salzburg, Austria
[d] Faculty of International Tourism and Management, City University of Macau, Avenida Padre Tomás Pereira Taipa, Macau

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ABSTRACT

Focusing on the application of artificial intelligence, this study investigates the impact of emotional display on user engagement with computer-generated imagery influencers through the lens of the computers are social actors (CASA) framework. It breaks down emotions into individual muscle movements (i.e., facial action units). By using facial recognition based on 1,028 pictures shared by Lil Miquela, the findings disclose the significance of happiness, sadness, disgust, and surprise in triggering user engagement when promoting diverse products with visually captivating content. The findings highlight the importance of balancing the intensity of muscle movement to streamline the interplay between technology, human behaviour, and digital communication.

## 1. Introduction

The rapid advancement of artificial intelligence (AI) has enabled widespread digital transformation and given rise to avatars, content-generation AI, and computer-generated universes that promote unparalleled levels of social connectivity (Ahn et al., 2022; Miao et al., 2022). Content-generation AI systems such as ChatGPT and DALL·E2 have the capability to generate textual and pictorial content, allowing for the creation of immersive and engaging content across various industries. This revolutionization enables more immersive interactions with consumers in various industries, such as entertainment (Kim and Yoo, 2021) and retailing (Chuah and Yu, 2021). Through far-reaching and impactful non-human digital communications that simulate a more realistic experience, this transformative technology results in enhanced customer engagement (Rahman et al., 2023). Although anthropomorphic characters have been met with criticism over uneasiness and eeriness resulting from the uncanny valley effect (Lou et al., 2022; Mori, 1970), the increasing sophistication of computer graphics has begun to shift public attitudes towards humanlike characters, demonstrating that viewers may not always respond negatively. For instance, computer-generated imagery (CGI) influencers, such as Lil Miquela and Imma, are a remarkable innovation that leverages the power of AI to create digital personas that look and behave like real humans, thus pushing the boundaries of what is possible in the realm of virtual media (Drenten and Brooks, 2020).

In addition to their curated online presence, CGI influencers have the potential to express emotions in a way that avatars cannot. The use of animation and rendering techniques allows CGI influencers to mimic the subtleties of human expressions (Ahn et al., 2022). CGI influencers can consistently convey a broad spectrum of emotions, which is a feat that may prove challenging for their human counterparts to maintain. Adding on to the six basic emotions (i.e., happiness, sadness, surprise, fear, anger, and disgust) identified by Ekman (1992), a more sophisticated approach for assessing facial expressions is the examination of facial muscle movements through action units (AUs) (Ngan and Yu, 2019). Prior research has demonstrated the utility of AUs in enabling an objective deconstruction of potential facial muscle activations that lead to specific emotional expressions (Schoner-Schatz et al., 2021), such as in the context of service encounters (Ngan and Yu, 2019). This offers a more nuanced and detailed understanding of the emotions being exhibited by computer-generated imagery influencers and their impact on user engagement.

Despite the growing fascination with CGI (Lou et al., 2022), consumers' reactions to virtual influencers within the marketing context remain ambiguous with regards to emotional display (Miao et al., 2022; Mrad et al., 2022). Reflecting the paradigm of computers are social

* Corresponding author.
*E-mail addresses:* joanne.yu@modul.ac.at (J. Yu), astrid.dickinger@modul.ac.at (A. Dickinger), kevin.so@okstate.edu (K.K.F. So), roman.egger@fh-salzburg.ac.at (R. Egger).

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actors (CASA), this theory posits that humans instinctively apply interpersonal relationship principles and respond to computers in a social manner (Gambino et al., 2020; Nass et al., 1994). These responses are often elicited by social cues conveyed by computers (Nass and Brave, 2005). Emotional displays, as one type of non-verbal social cues, thus serve as a crucial element in influencing viewer reactions such as their liking and commenting behaviour on social media (Aramendia-Muneta et al., 2020). In other words, since social media engagement implicitly reflect emotional experiences (Jones and Lee, 2022), it can be assumed that the dynamics of emotional exchange lead to a higher degree of behavioural responses. Hence, the significance of facial expression of virtual agents has been underscored as a means to stimulate behaviour in marketing (Chuah and Yu, 2021; Zhang et al., 2022).

The emergence of virtual influencers on popular platforms (Mrad et al., 2022) suggests that they have successfully overcome the territory of uncanny valley for many people. From marketing perspectives, collaborating with CGI influencers provides brands with enhanced control and safety over their marketing campaigns (Drenten and Brooks, 2020; Sands et al., 2022), as evidenced by partnerships with industry leaders such as Calvin Klein, Puma, and Prada. Although the ethics of CGI influencers remains debatable, there is no denying that the computer-generated universe is the next big thing. As emphasised by recent studies, marketers are urged to prepare for next-level social, design, and creative experiences in AI (Grundner and Neuhofer, 2021) to enhance knowledge in online influencer marketing (Leung et al., 2022a). In such context, understating of how consumers react to CGI influencers is of high importance (Chuah and Yu, 2021; Lou et al., 2022) in order to encourage user engagement (Leung et al., 2022b), which (in) directly, may improve parasocial relationships on social media (Mrad et al., 2022).

Although user engagement on social media indicates the level of audience involvement with a brand or content (Cheung et al., 2022), there is limited understanding of CGI influencers in the marketing field (Drenten and Brooks, 2020; Mrad et al., 2022), in contrast to the attention given to celebrities (Djafarova and Rushworth, 2017; Hwang and Zhang, 2018). Therefore, by acknowledging the importance of emotional interaction in digital communication, this study aims to investigate emotional expressions of CGI influencers and their potential influences on user engagement to empirically unfold their behavioural impact in contemporary human-computer interactions.

By focusing on the interplay between emotional expressions and user engagement, the specific research goals contributing to the existing literature are manifold. Theoretically, in light of the CASA paradigm (Ahn et al., 2022; Nass et al., 1994), this study introduces a novel approach by quantifying facial expressions of CGI influencers using AUs and investigates their intriguing and unique influence on user engagement. On a methodological level, through the use of data mining and facial recognition algorithm, this study provides novel findings to answer the call to look beyond the status quo of AI in the foreseeable marketing ecosystems. Practically speaking, the findings provide valuable insights into the impact of emotional displays on user engagement by revealing that specific emotions exhibit optimal effectiveness within certain contextual conditions. This knowledge unlocks the full potential of collaborating with CGI influencers through strategically programming to showcase different products on social media with visually captivating content.

## 2. Literature review

### 2.1. *The emergence of CGI influencers*

The increasing sophistication of AI has enabled the fabrication of humanoid objects for use in services and marketing (Lou et al., 2022; Wirtz et al., 2018). In physical environments, examples can be seen from humanlike robots in hotels, frontline, restaurants, and airports (Wirtz et al., 2018; Yu, 2020), whereas marketers also adopt AI in the digital landscape such as avatars (Miao et al., 2022), humanoid chatbots (Spillner and Wenig, 2021), and virtual agents (Sands et al., 2022). The commonality among the aforementioned cases are their anthropomorphic attributes, which aim to humanise digital experiences when in-person interaction is absent (Araujo, 2018). However, a major criticism of robots and AI is their level of human-likeness (Yu, 2020), with many consumers finding current applications to be rather unreal, resulting in feelings of eeriness and creepiness (Söderlund, 2022). Commonly known as the uncanny valley effect, the theory refers to one's negative emotional reactions towards anthropomorphic characteristics or audio/visual simulations that closely resemble humans (Mori, 1970). Although uncanny valley is based on solid knowledge (Söderlund, 2022; Zhang et al., 2022), it does not seem to keep up with the more recent development in computer graphics (Ahn et al., 2022).

Under the umbrella of computer-mediated communication (Herring, 2019), scholars reinforced the possibility to combine different modalities to facilitate connection and enrich experiences in the digital era (Fotheringham and Wiles, 2022). One trendy and novel case is the integration of robots and graphics, leading to the development of CGI (Ahn et al., 2022; Lou et al., 2022). Over time, technologies for creating CGI have grown more sophisticated and advanced (Miao et al., 2022). Given that CGI is driving innovation in video games and movies, it appears inevitable that it will turn into future marketing practice. Recently, CGI influencers have become a relatively new phenomenon on social media (Lou et al., 2022). Similar to their human counterparts, CGI influencers have a carefully curated online presence with well-followed social media profiles and an awareness of trending topics (Baklanov, 2021). However, what sets CGI influencers apart is that they are specifically designed to look and act in a manner desired by content marketers (Drenten and Brooks, 2020). By taking on digital personalities (Mrad et al., 2022), CGI influencers have high perceived physical and social attractiveness, which consequently stimulates consumer engagement (Ahn et al., 2022).

Certainly, the compelling impact brought by CGI influencers is undeniable (Deng and Jiang, 2023). Recent research showed that CGI influencers can significantly influence consumer decision-making (Da Silva Oliveira and Chimenti, 2021), evaluation of the endorsed brands (Ahn et al., 2022), and online experiences (Mrad et al., 2022). Thus, it is valuable to re-examine the interactions between technology and humans, as well as the conflicts between reality and artifice in digital environments (Drenten and Brooks, 2020). Nevertheless, due to the infancy of computer-generated characters in marketing (Lou et al., 2022; Miao et al., 2022), knowledge of consumer experiences with CGI influencers remains limited and requires further exploration (Ahn et al., 2022).

### 2.2. *User engagement in social actor framework*

To consolidate the understanding of virtual influencers (Deng and Jiang, 2023), tracing back to the root of how humans communicate with machines showcasing social potential is necessary (Gambino et al., 2020). Grounded in human-computer interaction, the CASA paradigm operates on the premise that interactions with computers, technologies, and new media are fundamentally social and natural (Nass et al., 1994). When computers demonstrate humanlike attributes, consumers tend to anticipate that they will conform to a range of social norms (Wang, 2017), such as language use, humanlike facial features, and the ability to convey emotions (Xu et al., 2022). However, one shall keep in mind that the CASA theory does not apply to all forms of social technology (Nass and Moon, 2000). In fact, this paradigm only applies when technological artifacts exhibit adequate social cues that imply their ability to serve as a point of reference for social interaction (Gambino et al., 2020).

In light of the AI revolution, the CASA paradigm has been applied in various technology-oriented services such as chatbots, smartphones, voice assistants, and social robots (Xu et al., 2022). Previous research conducted under the CASA framework demonstrated that humanoid interfaces have the potential to enhance users' trust and performance in decision-making processes (Bass et al., 2011). Relevant studies further showed that service robots equipped with gesture-based interfaces can promote communication (Mara and Appel, 2015) and stimulate user engagement (Chuah and Yu, 2021). More recently, anthropomorphism has been reinforced as a major mechanism by which consumers respond in a social manner (Xu et al., 2022). When interpreting human social behaviours on social media, engagement is found to be the most conspicuous phenomenon (Lim et al., 2020). For instance, when virtual agents portray emotion in a theatrical manner, user engagement can be established through likes or comments (Chuah and Yu, 2021), which subsequently accelerates the connections between the audience and media figures (Lim et al., 2020).

In recent years, user engagement has emerged as a key metric for measuring the success of social media marketing campaigns (Jones and Lee, 2022). Specifically, the engagement rate can be defined as the level of interaction between users and social media content, including likes and comments (Yu and Egger, 2021). Liking behaviours are often associated with positive emotions such as happiness and excitement, whereas commenting behaviours suggest higher levels of engagement and interactivity on social media (Swani et al., 2017). In marketing, existing literature has demonstrated the positive relationship between user engagement and brand loyalty (Labrecque, 2014), trust (Da Silva Oliveira and Chimenti, 2021), and reputation (Song et al., 2020). Hence, when marketers collaborate with virtual influencers embedded with humanlike characteristics, they are engaging in social interaction with the audience in a manner that is consistent with the social nature of the CASA paradigm (Nass et al., 1994). Consequently, by understanding how humanlike factors may influence one's behaviours, businesses can create more effective and engaging social media content that resonates with their audience and encourages greater levels of engagement (Cheung et al., 2022; Fotheringham and Wiles, 2022).

### 2.3. Emotional displays in the digital landscape

As machines become more advanced and intelligent in terms of their widespread applications, there is a growing body of research that highlights the potential of AI to generate emotional connections (Huang and Rust, 2021). Echoing the CASA paradigm, the phenomenon of encountering psychological characteristics while interacting with anthropomorphic objects could trigger emotional bonds (Rincon et al., 2019). Under the assumption that in-person interaction can be extended to computer-mediated communication (McShane et al., 2021), relevant examples can be found in live streaming platforms, where the display of emotions is a powerful trigger for engagement (Lin et al., 2021) in non-human or virtual entities (Chuah and Yu, 2021). Particularly, the six core emotions (i.e., fear, disgust, anger, happiness, surprise, sadness) defined by Ekman (1992) are powerful in influencing social interactions (Landwehr et al., 2011), consumer behaviours in retail service (Pantano and Scarpi, 2022), and user engagement on social media (Chuah and Yu, 2021). For instance, display of happiness increases the level of consumer pleasure (Chuah and Yu, 2021). Expression of fear implies a sense of urgency or necessity, prompting consumers to take desired actions (Roberts and David, 2020). Sadness may evoke empathy and emotional resonance to foster emotional engagement (Taruffi et al., 2021). Yet, the portrayal of anger, if not carefully handled, may be misinterpreted (Campos et al., 2013), causing unintended offense or controversy. Likewise, surprise (Chuah and Yu, 2021) and disgust (Fischer et al., 2012) can be strategically used to intrigue consumers in the digital space. By incorporating unexpected experiences into user interfaces, marketers can generate curiosity through the display of surprise (Chuah and Yu, 2021). Additionally, highlighting unappealing elements through expressions of disgust (Fischer et al., 2012) are likely to compel users to take notice and engage with the brand message.

Since retailing and marketing consumption is upon selling emotional experiences and is affectively rich in nature (Longoni and Cian, 2022), latest research calls an urgent need to demystify the interplay between facial expression of digital agents and consumers' reactions, especially in one-to-many screen-mediated marketing contexts (Bharadwaj et al., 2022). With the help of advanced data analytics, one method for quantifying emotions, which has its roots in psychology, involves the use of the Facial Action Coding System (FACS) (Ekman and Friesen, 1978). FACS identifies visually discernible facial movements that correspond to the expression of a particular emotion (see section 3.3 for details). To date, FACS has been applied beyond psychology, and moved into the field of neuroscience, human-computer interaction (Clark et al., 2020), and digital marketing (Schoner-Schatz et al., 2021). Commonly referred to as AUs, they represent a specific action or movement of a particular muscle(s) on the face (Campos et al., 2013). For example, AU12 corresponds to the action of raising the corners of the lips, which is often associated with a smile (Ngan and Yu, 2019).

By coding the presence of specific AUs, this method provides a standardised framework for measuring facial expressions across different individuals (Campos et al., 2013). For instance, Liu et al. (2018) classified consumers' facial expression into a set of emotions using facial muscles when watching movies and trailers. Other scholars evaluated the role of emotional displays of a salesperson and reinforced that emotional cues can digitally simulate in-person interaction (Bharadwaj and Shipley, 2020). Nonetheless, while acknowledging that emotional exchange is a mutual process (Goldenberg and Gross, 2020), how emotional display of digital agents can influence consumer reactions is underexplored (Bharadwaj et al., 2022). In the context of CGI influencers, their novelty further surges an urgency to understand consumers' reactions in digital media (Ahn et al., 2022; Cheung et al., 2022; Drenten and Brooks, 2020).

## 3. Methodology

To explore the effect of emotional expression of CGI influencers on user engagement presented by images, this research employed a combination of data mining, image clustering, and emotion analysis as the primary methods. First, Lil Miquela was selected as the study context. Despite the existence of other virtual influencers, Lil Miquela appears to be the most active and humanlike on Instagram with more than 1,000 posts. In contrast, other popular CGI influencers such as Bermuda and Shudu have less than 300 posts. Since context plays a significant role in shaping consumer behaviour, context-specific research can help identify the unique aspects of a particular market and provide a basis for the development of culturally sensitive and relevant marketing strategies (Stremersch et al., 2023).

First appeared on social media in 2016, Lil Miquela has ballooned in popularity since 2018 as a cultural icon and has been embraced by the fashion, beauty, and music industries, among others. As of 2022, its Instagram account has attracted over three million followers. Primarily used as a marketing tool, Lil Miquela has been featured in product endorsements for streetwear and luxury brands such as Calvin Klein and Prada (Miao et al., 2022). Its unique style and appearance represent a new frontier in marketing and retail, where virtual influencers are becoming an asset for companies looking to engage with audiences in innovative ways. After the introduction of the selected virtual influencer, the following section outlines the methodological steps.

### 3.1. Data extraction

To identify Instagram posts published by Lil Miquela, the official account (@lilmiquela: https://www.instagram.com/lilmiquela) was used as the data source. Data extraction was conducted using the Instagram API Scraper available on Apify in February 2023. There was a total of 1,249 posts at the time of data collection. Extracted data includes post captions, number of likes and comments, post URLs, image URLs, and the type of posts (image/video). For the 372 carousels, only the first picture of each post was extracted. To ensure that facial expression of Lil

Miquela can be captured precisely, the subsequent analysis focused on static images. After the removal of video-based posts and data that were corrupt due to wrong delimiters, the final dataset contained 1,028 posts. The earliest post within this dataset dates back to June 2017, while the most recent post was shared in February 2023. Thereafter, all pictures were downloaded in Python based on image URLs.

### 3.2. Image annotation and clustering

Since Lil Miquela has partnered with several brands in different sectors, the purpose of this step is to cluster the extracted posts into different categories based on the pictorial elements. Specifically, the process of annotating images was done using Google Cloud Vision API. For each image, the entities were displayed by the most prominent image labels with a confidence level greater than 0.5 (Chen and Chen, 2017).

These labels were then combined as one document. By applying document embeddings with FastText, they were converted into numbers, where labels appearing near to one another in a vector space are with comparable connotations (Egger, 2022). Subsequently, the approach proceeded by clustering photos based on their observed labels using the Louvain algorithm. In addition to its usage in identifying communities in social networks (Nguyen et al., 2018), the Louvain algorithm is a heuristic and has recently been adopted as a technique for image classification in retailing and marketing (Ma and Palacios, 2021; Yu and Egger, 2021).

### 3.3. Detecting facial expressions in pictures

In order to unfold facial expressions conveyed by Lil Miquela, this study taxonomised facial movements by their appearance on the face based on FACS (Ekman and Friesen, 1978) using the Py-Feat package in Python. Py-Feat quantifies facial behaviour and muscle movements that correspond to a displayed emotion through AUs (Baltrusaitis et al., 2018). Table 1 lists most of the possible AUs commonly associated with a particular emotional expression (i.e., happiness, sadness, surprise, fear, disgust, anger). Notably, emotion expressions (e.g., sadness) often combine different sets of AUs (AU1 + AU4 + AU15). Additional AUs less commonly used to train models were not considered in this research.

Since some of the pictures included multiple virtual influencers, the pipeline started with the detection of the number of faces in an image. For each face, the output included the activation of AUs and corresponding emotions with the intensity ranging from 0 to 1. Overall, the data contained 598 pictures with a single face, 404 pictures with multiple faces, and 35 without any face showing in the images. In case of multiple faces, the presented AUs and emotions were averaged. Those without any face were not included in the analysis of facial expression.

**Table 1**
List of AUs and their corresponding emotions.

| Action Unit | Description | Emotion |
|---|---|---|
| AU1 | Inner Brow Raiser | Sadness, surprise, fear |
| AU2 | Outer Brow Raiser | Surprise, fear |
| AU4 | Brow Lowerer | Sadness, fear, anger |
| AU5 | Upper Lid Raiser | Surprise, fear, anger |
| AU6 | Cheek Raiser | Happiness, disgust |
| AU7 | Lid Tightener | Fear, anger |
| AU9 | Nose Wrinkler | Disgust |
| AU11 | Nasolabial Deepener | Disgust, fear |
| AU12 | Lip Corner Puller | Happiness |
| AU15 | Lip Corner Depressor | Sadness, disgust |
| AU17 | Chin Raiser | Disgust |
| AU20 | Lip Stretcher | Fear |
| AU23 | Lip Tightener | Anger |
| AU25 | Lip Part | Happiness, surprise, fear |
| AU26 | Jaw Drop | Fear, surprise |

### 3.4. Analysing emotion and user engagement

After obtaining the emotional states of the CGI influencer presented in pictures, the analysis moved on to the evaluation of user engagement using stepwise multiple regression analysis. The engagement rate was calculated based on the total number of likes and comments of a post and dividing it by the number of followers of Lil Miquela (2,897,266 as of February 2023) (Stevanovic, 2020). Yet, as assessed by visual inspection of the plots that the engagement rate and emotional intensity were strongly positively skewed, a log transformation was performed to transform all variables to approximately conform to normality. The Variance Inflation Factor showed that all values were below the recommended threshold of 5 (Menard, 2001), with the highest being 1.80. After the transformation, all other requirements for regression analysis were met. The stepwise procedures were then conducted for each of the clusters. When particular emotion(s) had been identified as the most important variable in predicting user engagement, its corresponding AUs were analysed to further reveal the effect of different intensity of facial movements.

## 4. Results

### 4.1. Image clustering and descriptive statistics

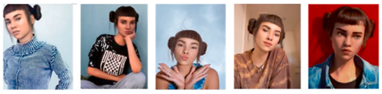
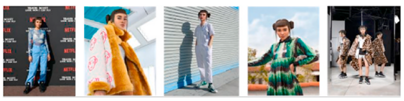
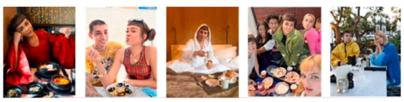
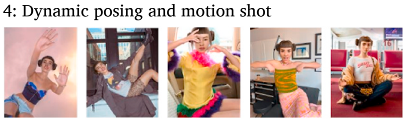
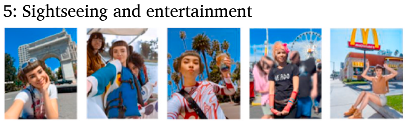
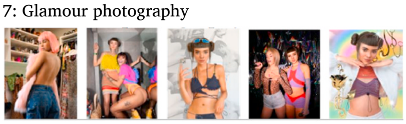
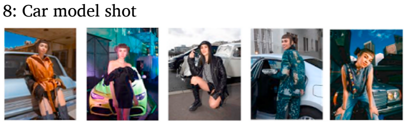
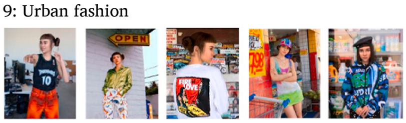
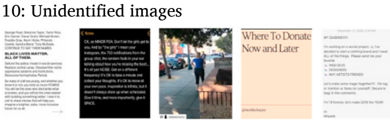
Overall, the Louvain algorithm generated 10 image clusters, which correspond to different visually captivating products in various sectors. The evaluation, ranging from −1 to 1, was conducted using network modularity in Gephi. The modularity algorithm is a method for detecting communities by looking for nodes that are more densely connected than to the rest of the network (Blondel et al., 2008). The metric was 0.737, suggesting a good clustering result. Next, to facilitate the naming process of each cluster, human visual inspection was performed on the designated pictures and image labels with higher term frequency-inverse document frequency. Table 2 provides an overview of the identified clusters and their corresponding emotional intensity embedded in pictures and the respective engagement rate. Notably, pictures categorised in cluster 10 were excluded as they are either posters or did not contain faces in the pictures.

Based on the identified topics, the results pointed towards two main topics within the fashion retail market, namely, '*fashion and branded content*' and '*urban fashion*'. These pictures are often used by influencers to promote clothing brands and showcase their style. They are typically staged and may include a mix of indoor and outdoor settings. Yet, the latter, '*urban fashion*', is particularly noteworthy as it not only showcases one's personal fashion sense, but also captures the ambiance and surroundings of a particular location, akin to street style photography. Furthermore, the analysis revealed that virtual influencers utilising '*car model shot*' as part of their content strategy have gained significant traction in the market, indicating a potential strategy to boost interest and engagement among potential consumers.

Another stream of pictures are more hedonic in nature, such as '*gastronomy and dining experience*', '*social events and gatherings*', and '*sightseeing and entertainment*'. Gastronomic phots are often taken in social settings such as restaurants, cafes, or homes to feature the food and social experiences. Similarly, images capturing social events often include multiple individuals to document and share the experience with others, accompanied by captions or hashtags that emphasize the social aspect of the gathering, such as 'brunch with friends' or 'dinner party vibes'. Tourism-related pictures are often taken while visiting tourist destinations or landmarks to convey their enjoyment of the experience.

Not surprisingly, several image clusters feature the influencer itself such as '*self-portrait*', '*dynamic posing and motion shot*', and '*glamour photography*'. Particularly, '*self-portrait*' is often associated with promotion of accessories as most pictures focus on different parts of the face, including hair, skin, forehead, and nose (based on the detected image labels). Likewise, pictures clustered as '*dynamic posing and motion shot*'

**Table 2**
Summary of visually captivating products and embedded emotions in diverse sectors.

| Cluster | n | EN | FR | DG | AG | HN | SP | SN |
|---|---|---|---|---|---|---|---|---|
| 1: Self-portrait  | 182 | −1.70 (0.31) | −2.16 (0.91) | −2.96 (1.03) | −1.95 (0.82) | −1.99 (1.03) | −1.91 (0.99) | −1.13 (0.69) |
| 2: Fashion and branded content  | 149 | −1.69 (0.20) | −2.33 (0.79) | −3.00 (1.01) | −1.57 (0.73) | −1.95 (0.94) | −1.96 (1.00) | −1.10 (0.63) |
| 3: Gastronomy and dining experience  | 127 | −1.80 (0.28) | −2.02 (0.89) | −2.77 (0.90) | −1.61 (0.80) | −1.45 (0.93) | −1.54 (0.87) | −1.16 (0.72) |
| 4: Dynamic posing and motion shot  | 126 | −1.62 (0.21) | −2.12 (0.84) | −2.94 (0.81) | −1.55 (0.74) | −1.75 (1.02) | −1.83 (0.87) | −1.07 (0.7) |
| 5: Sightseeing and entertainment  | 116 | −1.65 (0.17) | −2.33 (0.9) | −2.86 (1.00) | −1.56 (0.88) | −1.46 (1.08) | −1.88 (0.97) | −1.24 (0.78) |
| 6: Social events and gatherings  | 103 | −1.68 (0.26) | −2.12 (0.77) | −2.70 (0.78) | −1.62 (0.75) | −1.12 (0.92) | −1.54 (0.77) | −1.24 (0.71) |
| 7: Glamour photography  | 79 | −1.66 (0.26) | −2.16 (0.76) | −3.02 (0.98) | −1.63 (0.88) | −1.66 (0.98) | −1.79 (0.97) | −1.23 (0.74) |
| 8: Car model shot  | 52 | −1.67 (0.19) | −2.22 (0.91) | −2.68 (0.90) | −1.67 (0.82) | −1.53 (1.21) | −1.68 (0.96) | −1.29 (0.78) |
| 9: Urban fashion  | 51 | −1.74 (0.21) | −2.27 (0.85) | −2.79 (0.94) | −1.47 (0.64) | −1.55 (0.95) | −1.70 (0.97) | −1.06 (0.62) |
| 10: Unidentified images  | 35 | Not applicable | | | | | | |

*Note*: EN = Engagement rate (log); FR=Fear (log); DG = Disgust (log); AG = Anger (log); HN=Happiness (log); SP=Surprise (log); SN=Sadness (log).

focus on the influencer itself, but are mostly full shots. The findings revealed that they are taken with an artistic/creative approach to capturing motion or physical activities in various settings, such as in a gym, outdoors, or during an event. Conversely, different from fashion photography, a glamour shoot is not about the clothes, but physical beauty and charm.

### *4.2. Emotional analysis on visually captivating products in diverse sectors*

A Pearson's correlation was run to provide an overview of the relationship between AUs and emotional expressions (Fig. 1). Fig. 1 serves to offer a general understanding of the association between the intensity of AUs and their corresponding emotions (Table 1). Notably, the six emotions mentioned in the analysis are the aggregated muscle movements listed in Table 1 above. Overall, the findings are mostly in line with the characteristics of human emotions. For instance, there is a significant and strong positive relationship between happiness and AU6 ($r = .739$, $p < .001$), AU12 ($r = .751$, $p < .001$), and AU25 ($r = .371$, $p < .001$). Likewise, AUs related to surprise also demonstrated a significant and positive relationship; namely AU1 ($r = .225$, $p < .001$), AU2 ($r = .155$, $p < .001$), AU25 ($r = .215$, $p < .001$), and AU26 ($r = .283$, $p < .001$). However, since individuals portray emotions differently, the intensity of AUs varies and some may not be observed for the same expression. This variability is also reflected in the findings, where not all AUs displayed a significant relationship. An example can be seen from disgust. Although AU6 ($r = .111$, $p < .001$), AU9 ($r = .124$, $p < .001$), AU11 ($r = .069$, $p = .031$), and AU17 ($r = -0.105$, $p = .001$), had a significant relationship, AU15 ($r = -0.029$, $p = .369$) which is also related to disgust did not.

Thereafter, a backward stepwise regression analysis was applied to differentiate the contribution of emotional variables in each cluster. All models contained six emotions as the predictors at the outset. The

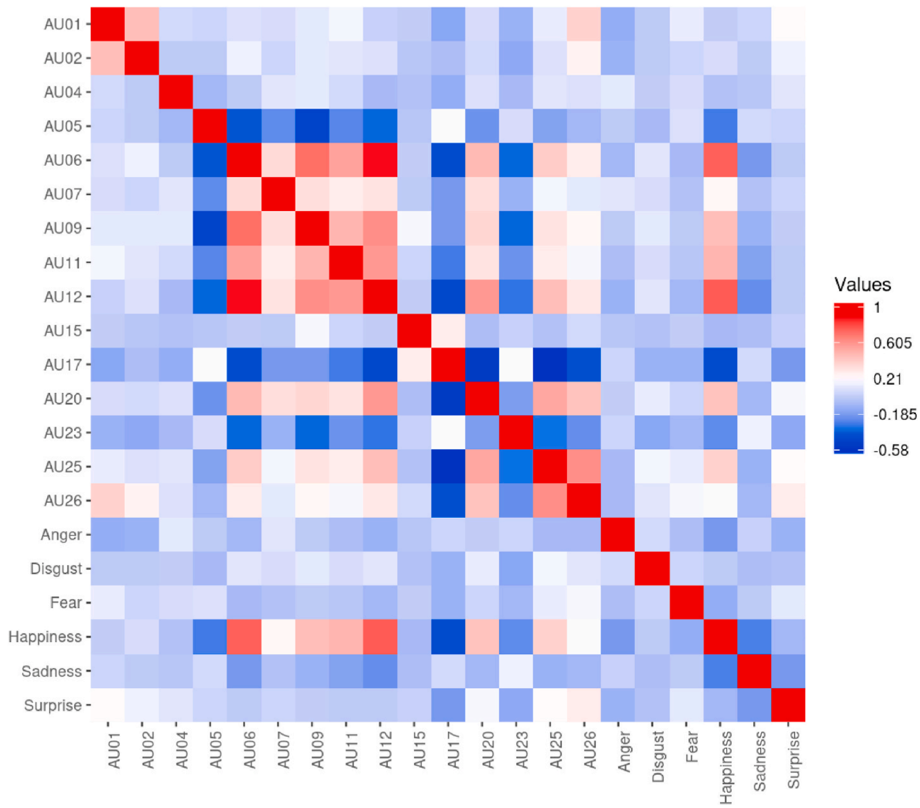



**Fig. 1.** Correlation between AUs and emotions.

significance level for variable entry and exit was 0.05. At each step, variables having the lowest correlation with user engagement were removed until no additional variables met the exclusion criteria. The final models were left with one emotional variable in each cluster, with $R^2$ of 0.32 for cluster 1, 0.34 for cluster 2, 0.64 for cluster 4, 0.36 for cluster 5, 0.42 for cluster 7, and 0.51 for cluster 9. The regression equations were significant ($F_{\text{cluster 1}}$ [1, 180] = 3.979, $p$ = .048; $F_{\text{cluster 2}}$ [1, 147] = 5.123, $p$ = .025; $F_{\text{cluster 4}}$ [1, 124] = 8.531, $p$ = .004; $F_{\text{cluster 5}}$ [1, 114] = 4.296, $p$ = .040; $F_{\text{cluster 7}}$ [1, 77] = 9.543, $p$ = .003; $F_{\text{cluster 9}}$ [1, 49] = 5.671, $p$ = .021).

Specifically, for both cluster 1 ($\beta$ = -.044, $p$ = .048) and cluster 5 ($\beta$ = .031, $p$ = .040), happiness was the strongest predictor. For cluster 2 ($\beta$ = -.057, $p < .001$) and cluster 7 ($\beta$ = -.118, $p$ = .003), sadness was found to be the most influential one. Disgust contributed significantly to the model for cluster 4 ($\beta$ = .065, $p$ = .004), whereas surprise was found to be the strongest predictor for cluster 9 ($\beta$ = .069, $p$ = .021). Yet, despite the variability in emotional expression, the findings indicated that none of the emotional variables met the criterion for clusters 8, 3, and 6, resulting in zero steps for these clusters. This outcome is particularly notable for clusters related to the social aspect of Lil Miquela, and may be attributed to the presence of multiple digital avatars in these photographs. As a result, these clusters were excluded from further analysis.

### 4.3. *Analysis of AUs and user engagement: A deeper level of emotional display*

After identifying the emotional variables present in each cluster, the analysis proceeded to a more detailed examination of facial muscle movements based on the visually captivating products that Lil Miquela is promoting (Table 3). As emotional expressions typically involve the activation of multiple AUs, multiple regression was conducted to explore how variations in AU intensity relate to changes in user engagement. Starting from happiness (AU6, 12, and 25), the results indicated that the models were significant for both cluster 1 ($F$(3, 178) = .631, $p$ = .023, $R^2$ = .21) and cluster 5 ($F$(3, 112) = .229, $p$ = .031, $R^2$ = .16). Interestingly, the findings disclosed that AU6 had a significant but negative relationship for cluster 1 ($\beta$ = -.380, $p$ = .017), while AU12 had a significant and positive relationship for cluster 5 ($\beta$ = .017, $p$ = .023) with the

**Table 3**
Estimation results of regression analysis.

| | AU1 | AU2 | AU4 | AU5 | AU6 | AU9 | AU11 | AU12 | AU15 | AU17 | AU25 | AU26 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Happiness** | | | | | | | | | | | | |
| C1 | – | – | – | – | −.380* | – | – | .297 | – | – | .005 | – |
| C5 | – | – | – | – | .042 | – | – | .017* | – | – | .030 | – |
| **Sadness** | | | | | | | | | | | | |
| C2 | −.334* | – | −.086 | – | – | – | – | – | .175 | – | – | – |
| C7 | −.351 | – | −.166 | – | – | – | – | – | .100 | – | – | – |
| **Disgust** | | | | | | | | | | | | |
| C4 | – | – | – | – | .230 | −.129* | −.010 | – | – | .159 | – | – |
| **Surprise** | | | | | | | | | | | | |
| C9 | −.607* | 1.096* | – | −.514 | – | – | – | – | – | – | .002 | −.026 |

*Note*: C = cluster; $^*p < .05$.

engagement rate. As for sadness (AU1, 4, and 15), the results presented a significant model for cluster 2 ($F(3, 145) = 2.661$, $p = .050$, $R^2 = .33$), with AU1 having a negative and significant relationship ($\beta = -.334$, $p = .030$). However, the model for cluster 7 was not statistically significant ($F(3, 75) = .527$, $p = .748$, $R^2 = .29$).

Turning to cluster 4, where the expression of disgust (AU6, 9, 11, 17) was found to be the most influential variable to user engagement. The analysis further demonstrated a significant model ($F(4, 121) = 1.571$, $p = .047$, $R^2 = .21$), where AU9 was found to have a significant and negative relationship ($\beta$=-.129, $p = .002$). Lastly, for cluster 9, the results indicated a significant model for the combination of AUs (AU1, 2, 5, 25, 26) related to surprise ($F(5, 45) = 1.253$, $p = .003$, $R^2 = .35$). Notably, AU1 had a significant but negative relationship to user engagement ($\beta = -.607$, $p = .008$), whereas AU2 had a positive one ($\beta = 1.096$, $p = .048$).

## 5. Discussion

The emergence of CGI influencers in recent years has brought a new dimension to the landscape of social media (Lou et al., 2022). In line with the findings of this study, their popularity has led to collaborations with several brands (Sands et al., 2022), including those in the retail, tourism, and gastronomy industries, amongst others. However, in addition to the expected image clusters such as fashion-related topics (Mrad et al., 2022), this study demonstrated the capacity of virtual influencers to engage online users on a more personal level, appealing to their sense of lifestyle and values, and fostering deeper connections with their audience. This is where emotional expressions come into play (Gambino et al., 2020). Potentially, the emotional connection between virtual influencers and online users facilitates parasocial relationship (Deng and Jiang, 2023) and stimulate user engagement (Ahn et al., 2022). Overall, this study revealed the expression of happiness, sadness, disgust, and surprise to be influential in the design of CGI influencers for different contexts and settings.

First, in line with the state-of-the-art knowledge, anthropomorphic attributes lead to both positive and negative impact in human-AI interaction (Baek et al., 2022). Although intuition may suggest that smiles signal positive social intentions (Beattie et al., 2020), scholars have referred the expression to be rather eerie due to the uncanny valley effect (Baek et al., 2022; Söderlund, 2022). As suggested by the study's findings, happiness does not always lead to positive reactions. Yet, the findings indicated that the impact of emotional expressions on user engagement may vary depending on the context, and that negative reactions do not always hold true for CGI influencers (Ahn et al., 2022). For instance, in pictures related to hedonic experiences (e.g., travel and sightseeing), expressing moments of pleasure appears to encourage user engagement, whereas in self-portrait photography, which is often used in promoting accessories, smiling was found to have an adverse effect.

Interestingly, by looking at a more sophisticated level of facial movements, the analysis revealed a striking similarity to existing knowledge in psychology, with AU6 and AU12 emerging as the most influential facial muscles in delivering positive emotions (Gunnery et al., 2013). It is worth noting that although AU6, which triggers crow's feet wrinkles, is often seen as a reliable signal of an authentic smile (Ngan and Yu, 2019), interestingly, the findings suggested that its activation actually led to a decrease in user engagement in the case of self-portrait pictures. One potential explanation could be that the muscle movements of CGI influencers are still not fully seamless (Lou et al., 2022), and as a result, viewers may be more likely to associate the authenticity of an expression with the region around the eyes (Grandey et al., 2005). This may be particularly true in close-up shots posted on social media, where the eyes are a prominent feature of the image. Indeed, in cases where there are imperfections in the CGI influencer's expression, the activation of AU6 may indeed be a critical factor that discourages engagement from users. However, AU12, which is associated with the display of a social smile and often involves the showing of teeth (Gunnery et al., 2013), was found to be a salient factor in increasing engagement in pictures related to travel and sightseeing where happiness is expressed. Existing research has shown that people are more likely to perceive a person as happy and approachable when they smile with teeth because it creates a more open and inviting facial expression (Ngan and Yu, 2019), which can foster feelings of connection and positivity. This highlights the importance of considering the context in which facial expressions are being used (Bharadwaj et al., 2022), and tailoring them accordingly to maximise their impact on user engagement.

Turning to the impact of expressing sadness, the findings highlighted '*fashion and branded content*' and '*glamour photography*' to avoid involving its respective AUs. For instance, using AU1 in pictures related to fashion content may not always be desirable because it is associated with the lowering of the eyebrows and the wrinkling of the forehead (Ekman and Friesen, 1978; Goh et al., 2020). This facial expression can create a sense of seriousness, concern or tension, which may be incongruent with the desired mood (e.g., confidence, relaxation) or image of the content (e.g., aspirational lifestyle). Likewise, this study suggested that preventing the virtual influencers from expressing sadness may improve user engagement particularly for glamour photography. Potentially, this type of pictures stereotypically conveys an alluring or seductive impression (Rose et al., 2012), wearing revealing clothing, or displaying other aspects of their physical appearance in a way that is intended to be aesthetically pleasing. Hence, as with fashion photography, overly expressive facial features may detract from the overall aesthetic or composition of the image.

With regards to surprise that plays a significant role in pictures related to urban fashion, the findings are aligned with existing knowledge, where surprise can evoke a sense of novelty and energy (Skavronskaya et al., 2020). Since urban fashion is often associated with creativity, individuality, and being on the cutting edge of trends (Gentina and Kratzer, 2020), expression of surprise can reinforce these associations by creating a sense of excitement and interest among viewers. However, it is interesting to note that there is a negative relationship between user engagement and the activation of AU1 in such contexts. Due to the association of AU1 with sadness (Goh et al., 2020), the findings reinforced the importance of balancing facial muscles of surprise to avoid confusion and maintain the desired behavioural reactions from the viewers.

Finally, disgust is a powerful and intense emotion that can create a sense of tension or conflict (Slaby and Scheve, 2019). In the context of dynamic posing and motion shot photography, its use may create a sense of contrast and intensity, drawing viewers' attention and leaving a lasting impression (Henderson, 2003). This can be especially effective in capturing the attention of viewers who are scrolling through their feeds and looking for visually striking content. However, it is important to note that activating AU9, which is associated with the wrinkling of the nose and the upper lip (Ekman and Friesen, 1978), may have a negative effect on the overall aesthetic of the image. While it can convey a sense of disgust, it can also create a distorted or unflattering facial expression (Fischer et al., 2012) that detracts from the desired effect of the photograph. The activation of AU9 may also be perceived as being overly expressive or contrived, which can undermine the authenticity of the image.

## 6. Conclusion

### *6.1. Theoretical contribution*

By exploring how CGI influencers can effectively communicate emotions to their audience, this research provides valuable insights into the interplay between technology, human behaviour, and marketing strategies. As CGI influencers blur the line between reality and fiction, this study reinforces the theoretical lens of the CASA paradigm (Ahn et al., 2022; Nass et al., 1994) that is pivotal to the connections between the audience and media figures (Chen, 2016). Different from the traditional CASA paradigm that concentrates on the connection between humans and agents (Arsenyan and Mirowska, 2021; Gambino et al., 2020), the underpinning logic of CASA allows mutual communication at an emotional level for CGI influencers and the public (Mrad et al., 2022), laying a solid foundation for sentimental and experiential communication of virtual agents. By analysing their facial expressions, this study reinforces the assumption that optimising emotional experiences in computer-mediated communication serves as a fundamental factor in influencing viewers' reactions in marketing (Chuah and Yu, 2021; Grundner and Neuhofer, 2021).

Besides the commonly studied positive emotions (e.g., happiness) (Baek et al., 2022; Campos et al., 2013), this research uncovers the effectiveness of specific emotions such as surprise, sadness, and disgust in distinct situational contexts. Specifically, it contributes to the understanding of AI surprise by examining the nuanced variations in different intensities of AUs (Chuah and Yu, 2021). Additionally, it reveals insights into less commonly observed expressions on social media, such as sadness and disgust. By analysing facial muscle movements, the research delves into the subtle changes within specific muscles that are associated with each emotion. Besides focusing solely on the overall intensity of emotions (Bharadwaj et al., 2022; Lin et al., 2021), this approach provides a deeper understanding of the intricacies involved in emotional expression.

Meanwhile, as CGI influencers are ultimately digital creations, this research adds original knowledge to the uncanny valley theory (Arsenyan and Mirowska, 2021). By identifying features of CGI influencers that lead to positive/negative user engagement, the findings contribute to the understanding of how to avoid the uncanny valley effect through appealing and effective design. Hence, the findings advance knowledge of the design of future robotic systems that are intended to interact with humans, answering the call to uncover the characteristics of digital images that make businesses more compelling in social media (Li et al., 2023). Given that computer-generated entities do not exist in the physical world, understanding their emotional expressions can enable individuals to form deeper connections (Miao et al., 2022) and cultivate personal intimacy in the realm of human-to-virtual-agent interactions (Hwang and Zhang, 2018). Recognising the core themes and corresponding expressive displays enhances the ability to interpret and respond to emotions in digital interpersonal interactions when promoting different products in various market sectors.

### 6.2. Practical implications

The importance of emotional expression of CGI influencers in influencing user engagement on social media cannot be overstated. Emotions play a crucial role in human decision-making, and the same is true for social media users. Overall, this research offers guidelines for AI-generated content design. Companies interested in utilising AI-generated content for marketing purposes can develop an emotion computing system to assess the alignment between the digital person's emotions and the marketing context. That is, the findings of this research allow companies to enhance their marketing effectiveness by providing insights into how digital marketing strategies can be optimised to improve user engagement.

For instance, the use of close-up photos by retailers can effectively highlight the details of accessories. However, when using CGI influencers to promote these items with self-portrait pictures, it is important to avoid the expression of happiness and pay close attention to the intensity of AU6. On the other hand, the findings implied that happiness is effective to promote hedonic experiences (e.g., travel activities). In this scenario, designers can strategically leverage the activation of AU12 to enhance user engagement. However, it is crucial to balance the intensity of AU1 with other relevant AUs for the expression of sadness and surprise in fashion-related pictures. For example, although presenting surprise is effective for pictures related to urban fashion, the intensity of AU1 should be minimised as people easily refer AU1 to the expression of sadness. In fact, to maintain congruence with the desired mood (e.g., confidence, relaxation) or the aspirational lifestyle portrayed in fashion content, it is generally advised to avoid displaying sadness. This is because the facial expressions associated with sadness, such as lowered eyebrows and a wrinkled forehead, tend to convey seriousness, concern, or tension. Nonetheless, when sharing dynamic posing and motion shots, marketers may consider incorporating the expression of disgust to create a sense of contrast and intensity. For example, in a retail campaign featuring a new collection of edgy clothes, marketers can incorporate slight elements of disgust in the influencer's facial expressions through subtle cues such as a slightly wrinkled nose or a hint of a sneer. By carefully balancing the intensity of AU9, marketers can achieve the desired effect without crossing the line into an unflattering or overly exaggerated facial expression.

Notably, since consumers are often savvy and can easily detect when retailers use emotional manipulation to push a product, it is essential that brands work with experienced marketing professionals and animators who can create a compelling and authentic emotional expression. Altogether, emotional expression is a critical component of the success of CGI influencers in social media marketing. As the use of CGI influencers continues to grow, it will be interesting to see how brands and social media users continue to interact with them on an emotional level.

### 6.3. Limitations and recommendations

This research is not without its limitations. Primarily, while the value of context-specific research has been highlighted (Stremersch et al., 2023), future studies are encouraged to continue exploring the future development of CGI influencers when available so as to increase the generalisability of the findings. However, although Lil Miquela is one of the most active and humanlike influencers, it is still uncertain whether the current techniques enable her to express the full range of human emotions and to what degree her facial muscle movements resemble those of humans. Moreover, readers should keep in mind that emotions and facial expressions are not the only factors influencing user engagement rate on Instagram. Although this study additionally performed image clustering to enhance the robustness of the results, other implicit components such as the influencer's personality may also have impact on users' reactions. Likewise, despite that Instagram is a visual-centered platform, scholars are recommended to uncover the synergy of post captions and pictures on the engagement rate. Notably, this study took the number of likes and comments as a proxy of user engagement, yet whether they represent the actual level of engagement remains unknown. Thus, considering experimental methods or incorporating biometrics (e.g., eye tracking) to evaluate the internal states of viewers or the amount of time spent engaging with the content could be beneficial. Finally, as there is a strong link between emotion and culture, future studies should take into account cultural differences when interpreting facial expressions, particularly when analysing more CGI influencers in the future. Acknowledging these limitations, it is advisable for future studies to include laboratory experiments to observe whether users exhibit higher or lower engagement behaviours under controlled conditions.

## Declaration of Competing interest

None.

## Data availability

Data will be made available on request.

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