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Less is more: Engagement with the content of social media influencers

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ABSTRACT

We draw upon theories of social media engagement to explore the factors affecting the success of the various influencer types, based on the size of their audience. We use the social media content of 8,076 influencers and employ sentiment analysis of text and facial recognition analysis of pictures in their content to examine what drives engagement. We show that the social media content of micro-influencers is more likely to be marked as favourite, while the content of other influencer types is more likely to be shared. We further show that including pictures in the content can result in higher engagement and that showing a person in the pictures also affects engagement, but the strength of this effect depends on the size of the influencer's audience. Our findings provide novel insights into the theories of social media engagement and sorely needed practical implications regarding content creation on social media platforms.

1. Introduction

Spending on social media campaigns reached $110 Billion in 2021, and almost 10 % of that was dedicated to using influencers. The use of influencers for endorsing brands on social media is a relatively nascent but rapidly growing industry (Aw & Chuah, 2021) that can bring successful outcomes. Advertisements using an influencer are almost three times more likely to generate engagement than those without one (Knoll & Matthes, 2017; Sheridan, 2020).

When a brand identifies an influencer for the target audience of a specific product that needs endorsement, the next step is to frame the social media content to generate engagement (Breves et al., 2019; Torres et al., 2019), which is the desired outcome of social media campaigns (Li et al., 2021). By social media engagement, we refer to the level of interaction and involvement that the audience has with the content, features, and activities available through the affordances of a social media platform. Prior studies have mostly focused on assessing the effectiveness of the wording of such social media content (Tan et al., 2014). For example, Li and Xie (2020) demonstrate that including a picture in social media content can positively affect engagement and that specific picture characteristics, such as high resolution, can lead to higher engagement. Prior studies have also investigated engagement in social media campaigns. For instance, Li and Xie (2020) focused on the American airline and SUV industry and called for further research in industries highly dependent on influencers for their social media campaigns. Following this line of research, others have also argued that there is a need for further research on the effectiveness of (micro-) influencers (e.g., Appel et al., 2020; Pittman & Abell, 2021; Taylor, 2020). Moreover, Marques et al. (2021) propose to further explore the types of influencers that are best for generating higher social media engagement for brands with their content, which would also be insightful for both theory and practice. To address that lacuna, therefore, in this study, we focus on the following research question:

What are the characteristics of influencers that positively affect social media engagement?

To address our research question, we employ a quantitative approach and draw upon the literature on social media engagement. In doing so, we collected a dataset that includes 8,076 self-reported micro-, meso-, macro-, as well as mega-influencers that are active on the social media platform X (formerly known as Twitter), and have at least 5,000 followers on their social media profiles; for each one of these influencers, we collected the 100 most recent social media posts on X, to test our research model and hypotheses and answer our research questions.

The findings of our study counterintuitively demonstrate that micro-influencers receive a significantly higher number of *favourites per follower* than influencers with a larger audience. However, this is not the case for *retweets*, as the social media content of micro-influencers receives significantly lower *retweets* than that of other influencer types. We also find that adding a picture along the text has a positive effect on engagement with social media content, and when a person is featured in

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the picture, more credibility is assigned to the content.

Our work expands the scope of the literature on social media engagement (e.g., Yesiloglu et al., 2021), and the characteristics of engaging with social media content (e.g., Chen et al., 2021), while it further elucidates the effect of supplementing the content with pictures on social media engagement. Additionally, while our work is in line with the extant research agenda on the topic (Kar et al., 2023; Struijk et al., 2022), it also bears implications for practice by demonstrating how social media campaigns can better use influencers and can be primarily insightful for brands that operate in market sectors highly reliant on influencers endorsements.

The rest of the paper is structured as follows. The next section discusses the literature, and hypotheses are developed. In the next section, the research methods will present how a sample is chosen and how data is collected and analysed. Subsequently, in the results section, the analysis outcome is reported, followed by a discussion of the results. Lastly, the conclusion and implications of this research are discussed, and we delineate an agenda for future research.

2. Theoretical background

The use of celebrities for product endorsement is one of the oldest advertising strategies; celebrities have been used for advertising campaigns on the radio since the early ‘30 s, and for marketing campaigns on television since the early ‘50 s. Bergkvist and Zhou (2016, p. 644) suggest that: "*celebrity endorsement is an agreement between an individual who enjoys public recognition (a celebrity) and an entity (*e.g.*, a brand) to use the celebrity for the purpose of promoting the entity*". Although the mode of communication is not explicitly mentioned, Bergkvist and Zhou (2016) note that celebrity endorsements are present in many different mediums and platforms and not only in conventional advertising channels such as television and radio (e.g., Segijn et al., 2019). Following, the success of such a strategy on the radio and television, the most recent trend is the use of celebrity endorsements on social media platforms (Bergkvist & Zhou, 2016; Felix et al., 2017; Rutter et al., 2019; Segijn et al., 2019).

The relevant literature suggests that celebrity endorsement on social media can positively affect the sales of the advertised product (Bergkvist and Zhou, 2016). For instance, Elberse and Verleun (2012) found an average increase in sales of 4 % during the endorsement periods, while Zhang et al. (2018) found a positive effect of frequent social media influencer product endorsements on sales. Moreover, Elberse and Verleun (2012) found that celebrity endorsement on social media increased stock returns by nearly 0.25 %, with a significant positive effect on stock returns also being found in other studies (e.g., Agrawal & Kamakura, 1995; Farrell et al., 2000). In addition to the financial benefits of celebrity endorsement on social media, there are further benefits for brands, such as customer relationship management, brand management, innovation management, and employee recruitment (Felix et al., 2017).

Due to the rapidly changing nature of social media platforms, however, the accompanying marketing strategies need to adapt continuously (Appel et al., 2020). Whilst the use of celebrities for marketing campaigns on social media creates exposure, it does not necessarily reach audiences with niche interests (López et al., 2017; Muñoz-Expósito et al., 2017; Park et al., 2021). A recent practice change, therefore, is the use of micro-influencers, who are not mainstream celebrities but tend to have a niche enthusiastic following on social media. Such influencers are often credible self-made online personalities, who have a talent or expertise in a specific topic and have gained a niche online audience (Khamis et al., 2017; Lin et al., 2018; Park et al., 2021). Such influencers seem to be more effective in social media advertising (Schouten et al., 2020), as their audience perceives them as more relatable and trustworthy than celebrities. Similarity and trust between influencers and their audience are, thus, essential in achieving advertising effectiveness (Schouten et al., 2020). Micro-influencers are perceived as more trustworthy and authentic, and better at generating social media content engagement (Chang et al., 2019; Park et al., 2021; Pittman & Abell, 2021).

The literature has identified four main influencer types and their characteristics (Appel et al., 2020; Khamis et al., 2017). First, *mega-influencers* have an audience of more than 1,000,000 followers on their social media profile, and they are often celebrities such as famous actors, supermodels, or high-level athletes, but also a small group of non-celebrity influencers have gathered vast numbers of followers and classify as mega-influencers. Second, *macro-influencers* have an audience between 100,000 and 1,000,000 followers on their social media profile, and often their social media activity is their primary profession, and their dependence on such an income might make them lose authenticity and trustworthiness. Third, *meso*-influencers have an audience between 50,000 and 100,000 followers on their social media profiles. Because *meso*-influencers have a sizable following and a higher engagement level than macro-influencers, such influencers are especially attractive to brands. Fourth, *micro-influencers* have an audience of around 5,000 to 50,000 followers on their social media profiles. Whilst research shows that accounts with larger audiences receive more content engagement, micro-influencers seem to defy such an observation. Such an effect could be attributed to the fact that micro-influencers do not have a very large audience and can still engage with them in an individualised way by reading and responding to their messages (Li & Xie, 2020). In the rest of this paper, we mainly focus on the differences between micro-influencers versus the other influencer types. The literature on social media influencers is mostly focused on opinion leadership (e.g., Casaló et al., 2020) and parasocial relationships (e.g., Aw & Chuah, 2021). This line of work has explored the interactions of influencers with their audience (e.g., Zhang et al., 2021), their authenticity (e.g., Audrezet et al., 2020), credibility (e.g., Sokolova & Kefi, 2020), trustworthiness (e.g., Kim & Kim, 2021), the effectiveness of the various content and engagement strategies (e.g., Lee & Theokary, 2020), and more broadly the use of influencers for social media campaigns (e.g., Carlson et al., 2020; Valsesia et al., 2020; Wang et al., 2021). Our study expands the literature on social media engagement and influencers, while further elucidating the effect on engagement of including pictures in social media content.

3. Hypotheses development

3.1. Engagement

The use of celebrities for social media advertising requires a large investment and, as such, can be unaffordable for many brands (Appel et al., 2020). For instance, a social media endorsement by Beyoncé is estimated to cost around $1,000,000. The use of micro-influencers is less costly, which makes them attractive for smaller brands. Such influencers often position themselves around a unique selling point or public identity; consequently, brands can count on the followers of micro-influencers to be interested in their niche (Khamis et al., 2017). Marques et al. (2021) found that micro-influencers receive a higher engagement with their social media content in terms of likes and comments. Concurrently, Wies et al. (2022) found that although influencers with a higher follower count reach a greater audience, their followers are less likely to engage with their content. Other studies show that the likeability of influencers increases with the size of their audience, but this does not help them to be perceived as thought leaders in their specific areas of interest (De Veirman et al., 2017). The opposite is more likely to be the case. As micro-influencers attract a more targeted audience, brands can choose the right influencer with a following that is the target audience for a specific product. According to Ray et al. (2014), social media engagement derives from self-identity verification and community identification, as consumers tend to compare themselves with advertising images (Richins, 1991). Social media engagement is defined as "a user's state of mind that warrants heightened involvement and results in a personally meaningful benefit" (Di Gangi & Wasko, 2016, p. 4) and the reason that this causes an individual to act. As the audience shares interests and identifies with the micro-influencers, thus, they are more likely to engage with their content.

According to the Media Richness Theory (MRT) (Daft & Lengel, 1986), media richness explains the use of a medium and its effectiveness. Media richness is determined by i) the number of channels used simultaneously, ii) the feedback capability, iii) the personality, and iv) the use of natural language. As micro-influencers can engage with their audience in a more personal way than influencers with more followers, micro-influencers exhibit greater richness (Dessart, 2017; Dolan et al., 2019). The more followers an influencer has, the harder it can get to engage with their audience in a personal way. Within the X platform, therefore, micro-influencers can have a higher richness than influencers with a higher number of followers, which has a positive effect on engagement (Cao et al., 2021). This leads to our first hypothesis:

H1: *Micro-influencers have higher engagement per follower than other influencer types.*

3.2. Picture in posts

Focusing further on engagement with social media content (e.g., Cyr et al., 2009), the literature portrays that including a picture in the social media content can have a positive effect and result in higher engagement with it (Li & Xie, 2020). The presence of a picture within social media content that is mostly text-based—like on X—can make the content stand out, attract more attention, and result in higher engagement (*ibid*). Additionally, the literature portrays that more obtrusive ads can be more effective because they stand out more (Bruce et al., 2017). Moreover, people assign credibility to a picture, something text-only social media content might lack (Winston, 2013), and the success of social media platforms such as Instagram can be attributed to this effect (Lee et al., 2015). Lastly, according to the MRT, visual media are richer in information, which in turn increases engagement. Therefore, our second hypothesis here is:

H2: *Including a picture within social media content has a positive effect on engagement.*

3.3. Presence of people in pictures

Another way to increase engagement with social media content might be to include human characteristics in the pictures that accompany the text. Human characteristics in advertising campaigns have been shown to generate more customer-brand interactions (Barcelos et al., 2018), while the inclusion of a picture with a human face on X increases sharing by more than 80 % compared to a picture without a face (Li & Xie, 2020). Human attributes in advertising through social media content, therefore, seem to personify the brand, bringing it closer to the consumer. Identity and credibility are found to have a positive effect on the likeability of influencers (Djafarova and Rushworth, 2017; Janssen et al., 2022). Furthermore, including a person in the picture could increase credibility even more than posting one without a person. In line with the MRT, as personal media are richer, a picture depicting people can be perceived as richer content and, thus is more engaging (Cao et al., 2021), which brings us to hypothesis 3a:

H3a: *The presence of a person in a picture positively impacts engagement.*

Prior research shows that certain narratives of social media advertising require different characteristics (Chang et al., 2019). For instance, a human representative appeals more to a social media user's self-expression. Micro-influencers allow advertising with warmer and more personal messages and are often seen as more credible than influencers with millions of followers (Appel et al., 2020; Chang et al., 2019; Parker *et al.,* 2021). Advertising with personas similar to oneself can portray to the viewer what people similar to them buy (Pollay & Mittal, 1993). Followers' similarity to and perceived attractiveness of influencers has been found to increase the effectiveness of their social media endorsements (Yuan & Lou, 2020). Credibility also plays an important role in the engagement with social media content (Winston, 2013). Consumer distrust is important in advertising because it can result in diminishing the credibility of the content (Pollay & Mittal, 1993). Human characteristics might also be more important for influencers with a small audience, like micro-influencers, who are perceived as more authentic, than influencers with a larger audience. Based on this, our hypothesis 3b is:

H3b: *The effect of the inclusion of a person in pictures that accompany social media content on engagement is higher for influencers with fewer followers.*

3.4. Text sentiment

Instances of positive news are more likely to be shared than negative ones (Soetekouw & Angelopoulos, 2024), especially when arousal is high (Berger, 2012). High arousal is characterised by a state of activation or mobilisation, whilst low arousal is characterised by deactivation or relaxation. Other studies, however, show that engagement is highest for social media content with a high positive or negative sentiment polarity (Arapakis et al., 2014). On the one hand, Yang et al. (2019) found that positive posts attract more likes on Facebook than negative ones, but negative posts get more shares. On the other hand, negative words in posts by news media accounts and members of political parties seem to increase engagement (Rathje et al., 2021). Additionally, critical posts get more likes, comments, and shares (Messing and Weisel, 2017). Negative content, thus, tends to have more impact than neutral or positive one, while a negative bias is present; adverse information and emotion can have a substantial influence (Corstjens & Umblijs, 2012). Following this line of research leads us to our fourth hypothesis:

H4: *Negative text sentiment positively affects engagement with social media content.*

3.5. Emotions in post images

As text sentiment can influence engagement with social media content, so can emotions that are portrayed through an included picture. When an influencer includes a picture with an emotional expression in social media content, this might spark an audience reaction. For instance, when someone posts a picture of a happy person, their audience may share or favourite the content. Alternatively, when a sad person is depicted in the picture, users might leave comments about compassion. The effect of emotions by visual *stimuli* is well explored in neurophysiology and psychology (Dodich et al., 2014). However, within the context of social media, much is left to explore surrounding the effect of picture emotions. Studies on the impact of picture emotions on attention and engagement show that social media content with positive picture context elicits higher intentions of clicking on and sharing the story (Keib et al., 2016). In line with these studies, Berger (2011) shows that high-arousal emotions (i.e., anxiety, amusement) lead to increased sharing compared to low-arousal ones (i.e., sadness or contentment). Similarly, Nelson-Field et al. (2013) show that high-arousal videos are shared twice as often as low-arousal videos. Following this line of work, we form our fifth hypothesis:

H5: *High arousal Emotions in images included in the social media content have a more positive effect on engagement than Low arousal ones.*

In Fig. 1, we present an overview of the variables in our study, as well as their expected effects on engagement with the content of social media influencers. In summary, we expect that i) the size of the audience of an influencer, ii) including a picture in the content, iii) including a picture with a person, as well as iv) negative text sentiment to have a positive direct effect on engagement with social media content of influencers. Whilst the size of the audience of an influencer is expected to have a positive effect on engagement with social media content, the size of the audience is also expected to negatively moderate the effect of including a picture with a person. The effect of including a picture with a person is further explored. Herein, the high-arousal emotions of the person in the picture are expected to have a more positive effect on engagement with social media content than low-arousal ones. Consequently, we expect

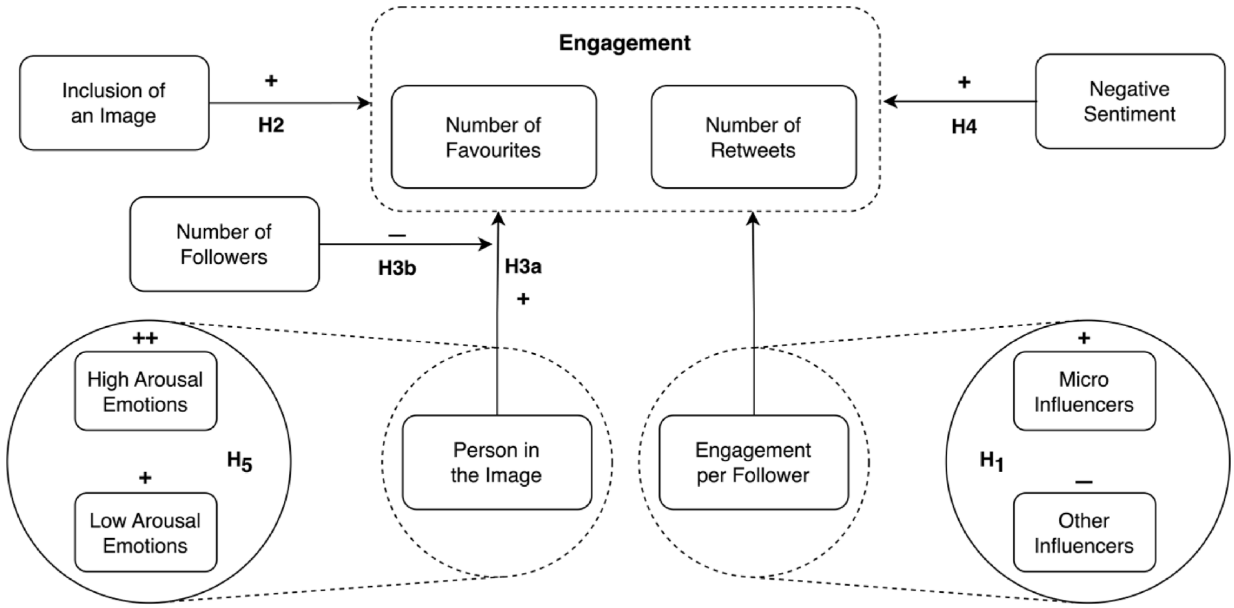

Fig. 1. Hypothesised effects on engagement with social media content.

micro-influencers to receive higher engagement with their social media content per follower than other influencer types.

4. Methodology

4.1. Data collection

The sample of our study was selected through the self-declaration of X users as "influencers" or "brand ambassadors" in their profile bio, which is a short description of themselves or their accounts (Harrigan et al., 2021). Another requirement was that their account should have at least 5,000 followers and the content of their tweets should be written in English. This enabled us to compile a list of 8,076 active influencers who self-reported themselves as "influencers" or "brand ambassadors", resulting in a non-probability sampling technique. Influencers with an audience between 5,000 and 50,000 followers are classified as *micro*; influencers with an audience between 50,000 and 100,000 followers are classified as *meso*; influencers with an audience between 100,000 and 1,000,000 followers are classified as *macro*; influencers with an audience of more than a million followers are classified as *mega*. Self-reported "influencers" or "brand ambassadors" with an audience of fewer than 5,000 followers were disregarded as they did not fit the purpose of this study. For each influencer, the 100 most recent posts on X for the period between 01–01-2021 and 04–04-2021 were collected so that not too many posts by certain influencers would skew the data, and to ensure that all the posts would be recent. Furthermore, posts were only collected if they were at least one week old at the time of collection to ensure that the number of likes and Retweets had settled and would not change too much after collection (Huang & Yeo, 2018). The data was collected through the X application programming interface (API), and the content that contained pictures was identified and downloaded separately. All the pictures were saved as the Tweet ID and were stored in a secure location to be used for facial recognition analysis. Posts that had their picture removed by the time of data collection were excluded from the analysis.

4.2. Variables

Our dependent variables (DV) signify engagement with social media content. We follow O'Brien and Toms (2008), who define such engagement as: "*a quality of user experiences with technology that is characterized by challenge, aesthetic and sensory appeal, feedback, novelty, interactivity, perceived control and time, awareness, motivation, interest, and affect*". Engagement with social media content, thus, can be measured through the interactions of followers in terms of *Number of Favourites*, and *Number of Retweets*. To test our *H1*, two DV are created to measure engagement per follower: *Number of Favourites per Follower* and *Number of Retweets per Follower*. These DV are created by dividing respectively the *Number of Favourites* and the *Number of Retweets*, by the *Number of Followers*.

Text Sentiment is our first IV. Sentiment analysis returns the scores for negative, neutral, and positive sentiment and a compound score between −1 (very negative), 0 (neutral), and 1 (very positive). The sentiment compound score is used for the sentiment variable (e.g., Georgiadou et al., 2020; Qazi et al., 2017). The *Inclusion of an Image* and the presence of a *Person in an Image* are the second and third IV (Fiore & Jin, 2003). The *Inclusion of an Image* is whether a picture is included in the post. If so, image recognition software detects if a person is present in a picture. These variables are coded into two dummy variables: *Image Without a Person* and *Image With a Person*. These are further divided into eight dummy variables of emotional expressions. Whenever a face is detected in a picture, the analysis returns scores for the emotional expressions of the detected face through a facial analysis. The picture analysis produces scores for *High Arousal Emotions*; anger, fear, surprise, happiness and disgust, and for *Low Arousal Emotions*; confusion, sadness and calmness (Lim, 2016). When multiple people are detected in a picture, the analysis returns emotion scores for each face. For each face recognised, a score of 0 to 1 is returned by the facial recognition software. Here, 0 is a 0 % chance that the face expresses that emotion and 1 is a 100 % assessment of the relative emotion. We assess an overall emotion score by coding these into dummy variables. Herein, the emotion with the highest score is coded as 1 and all the other emotions for that face are coded as 0.

The Number of Followers of a user is the moderating variable and is retrieved directly from the collected X data. On top of the expectation that the *Number of Followers* has a positive effect on user engagement, we hypothesise that the *Number of Followers* of an influencer has a negative moderating effect on the effect of *Image With a Person*. The *verified Status* of an influencer is a control variable. The users of X can request to get verified. To get verified, the account of the user must be authentic, notable, and active according to the rules of X. However, since November 2022 the rules to get verified were significantly modified.

Currently, anyone with a verified phone number and a paid subscription can become verified and receive a blue checkmark except for verified organisations and government accounts, which receive a gold or grey checkmark respectively. This change became active after we collected our data, and we believe that this significantly reduces the positive effect of being a verified user.

4.3. Reliability and validity

For this study, only existing publicly available data is used, while the unit of analysis—tweets by influencers—is easily obtainable and available. Therefore, our study is reproducible and a similar study should find similar results (Hammersley, 1987). Regarding the validity of our study, the chosen sample most closely characterises actual influencers. One can argue whether users who call themselves "influencers" or "ambassadors" in their X bio are representative of the whole population of influencers. A non-probability sampling approach was chosen to acquire the largest sample possible, fitting the time and scale of this study, and ensuring internal validity by using a large sample of real-world data. Although social media platforms have much in common, every platform has unique characteristics. According to Jordan (2018), choosing whether to focus on the platform or its users is a fundamental dilemma. Social media is comprised of a wide range of technologies, offering similar and different functionalities. Not much progress has been made in researching and comparing constructs among different types of social media. Therefore, generalisability between social media platforms is often limited.

4.4. Text and Image analysis

For sentiment analysis, data pre-processing is an essential step as tweets are short and tend to be noisy, which makes them challenging for sentiment analysis models (Giachanou & Crestani, 2016). The sentiment analysis tool VADER requires only minimal data cleaning (Georgiadou et al., 2020), while it takes punctuation, capitalisation and even smileys into account when assessing the sentiment of a text (Hutto & Gilbert, 2014). Furthermore, VADER does not need any training data as it is developed as a simple rule-based natural language processing model and includes a gold standard sentiment lexicon specifically constructed to assess sentiment in social media content (Hutto & Gilbert, 2014). The output of VADER includes a positive, neutral, and negative sentiment score from 0 to 1 and combines these scores in a final, normalised combination of the three previous scores into a compound sentiment score between −1, for very negative sentiment, and 1 for very positive one (Georgiadou et al., 2020). The picture characteristics are assessed through *Rekognition,* a deep learning algorithm which provides detection of objects (e.g., a face) and can analyse facial attributes like a smile or frown. For each person in a picture, the algorithm automatically determines what emotion the face expresses and the level of confidence. If the confidence level is above 70 %, we assume that the person expresses that emotion in the picture. The algorithm can recognise the emotions of happiness, sadness, anger, confusion, disgust, surprise, calmness, and fear.

4.5. Tests and analyses

To test *H1*, the variables *Favourites per Follower* and *Retweets per Follower* are created by dividing the *Number of Favourites* and *Number of Retweets* of posts by the number of followers of the influencers. To explore whether micro-influencers have a higher user engagement per follower, the medians of the variables between the groups are compared. We report the descriptive statistics of the variables and groups in Table 2. All groups in both variables are not normally distributed and have a high skewness; we, therefore, use a Mann-Whitney *U* test instead of a *t*-test (Nachar, 2008). Levene's test showed that variances between groups are equal for the variable *Favourites per Follower* $F(1{,}260969) = 2.056$, $p = 0.152$ and for the variable *Retweets per Follower* $F(1{,}260957) = 3.299$, $p = 0.069$; therefore the assumptions for the Mann-Whitney *U* Test are met (Mann and Whitney, 1947).

We report the mean, standard deviation, and correlations of all variables in Table 1. Both the *Number of Favourites* and *Number of Retweets* are non-negative integers and show high overdispersion, as count data distributions often have. We test three regression models per DV and choose the model that has the best fit for our data. The regression models we test are i) Poisson, ii) Negative Binomial (NB) with a log link and dispersion parameter 1 (NB(1)), and iii) NB with the dispersion parameter estimated (NB(MLE)). These models pass the omnibus test; their Akaike's Information Criterion (AIC) are respectively 196853616, 3136348, and 2300684. Both the Poisson and NB(1) models show overdispersion, while the overdispersion in NB(MLE) is corrected by the model estimating the dispersion parameter. Therefore, we conclude that the NB(MLE) model best fits the data.

We estimate six NB(MLE) in total, three for each DV: *Number of Favourites* and *Number of Retweets*. For each DV we test for the direct effects of the IV among all data, and then we test for the moderating effect of the *Number of Followers* on including an *Image With a Person*. Lastly, for each DV we investigate further the effect of a person's facial expression in a picture. The data for these regressions are limited to only posts with pictures. Here the variable *Image With a Person* is split into eight facial expressions by the person or persons in the picture.

5. Findings

5.1. Direct Effects: All posts

We present the results of the direct effects of the variables *Number of Followers*, *Text Sentiment*, *Image Without a Person*, *Image With a Person,* and *Verified Status* on the IV *Number of Favourites* and *Number of Retweets* in Table 3. The NB models pass the omnibus test ($p < 0.001$) and are a significant improvement over a model without predictors. The results suggest that the *Number of Followers* positively impacts the *Number of Favourites* ($\beta = 0.000003334$, $p < 0.0001$) as well as the *Number of Retweets* ($\beta = 0.000002239$, $p < 0.0001$). Including an *Image Without a Person* positively impacts both the *Number of Favourites* ($\beta = 1.138$, $p < 0.0001$) as well as the *Number of Retweets* ($\beta = 1.298$, $p < 0.0001$), supporting *H2*.

Including an *Image With a Person* has an even greater impact on the *Number of Favourites* ($\beta = 1.348 p < 0.0001$). However, the effect of an *Image With a Person* on the *Number of Retweets* ($\beta = 1.185$, $p < 0.0001$) is less than the effect of *Image Without a Person*. These results suggest that *H3a* is supported with respect to the *Number of Favourites* but is rejected for the *Number of Retweets*, which means that the effect of an *Image With a Person* over the effect of an *Image Without a Person* is greater on the *Number of Favourites* but lower on the *Number of Retweets*. Furthermore, *Text Sentiment* negatively impacts the *Number of Favourites* ($\beta = -0.264$, $p < 0.0001$) and the *Number of Retweets* ($\beta = -0.457$, $p < 0.0001$), suggesting that social media content with negative sentiment gets a higher *Number of Favourites* and *Number of Retweets* than content with positive sentiment, supporting *H4*. Lastly, the results suggest that *Verified Status* has a positive impact on favourites ($\beta = 0.780$, $p < 0.0001$) and retweets ($\beta = 0.546$, $p < 0.0001$).

5.2. Moderating Effect: All posts

We tested whether the *Number of Followers* can moderate the effect of an *Image With a Person* in regard to engagement with the social media content, and we present the results in Table 4. We find that this interaction effect has a negative impact on both favourites ($\beta = -0.0000006840$, $p < 0.0001$) and retweets ($\beta = -0.0000005200$, $p < 0.0001$), and demonstrates that the effect of including an *Image With a Person* decreases with the increase of the *Number of Followers*, suggesting that the *H3b* is also supported.

Table 1
Mean, Standard deviation and Correlations of Variables.

Variables	M	SD	1	2	3	4	5	6
1. Favourites	97.68	2279.687						
2. Retweets	12.92	269.139	0.921***					
3. Followers	72174.08	571621.089	0.067***	0.041***				
4. Verified (dummy)	0.2404	0.42732	0.034***	0.018***	0.141***			
5. Picture no person (dummy)	0.1224	0.32780	0.004*	0.007**	−0.009***	−0.041***		
6. Picture with person (dummy)	0.10	0.305	0.032***	0.019***	0.029***	0.082***	−0.127**	
7. Sentiment Compound	0.298626	0.457613	0.178	−0.003	0.024***	0.053***	0.043***	0.061***

*** Significant at the 0.001 level (2-tailed).
** Significant at the 0.01 level (2-tailed).
* Significant at the 0.05 level (2-tailed).

Table 2
Descriptive Statistics Favourites per Follower and Retweets per Follower Micro-Influencer vs Other Influencer Types.

	Mean		SD		Median		Skewness	
Influencer Type	**Micro**	**Other**	**Micro**	**Other**	**Micro**	**Other**	**Micro**	**Other**
Favourites per Follower	0.00312	0.00176	0.212	0.134	0.000157	0.000078	298.648	49.651
Retweets per Follower	0.000545	0.000243	0.0379	0.00236	0.000000	0.000007	305.262	81.259

5.3. Direct Effects: Pictures only

To explore the effect of including emotional expressions in pictures, we conducted two tests using only posts with pictures. For these tests, the variable *Image With a Person* is split into eight emotional expressions of the faces detected in the picture. We present the results in Table 5. We find that *Fear (HAE)* ($\beta = 0.168$, $p = 0.009$), *Sad (LAE)* ($\beta = 0.229$, $p < 0.0001$), *Surprised (HAE)* ($\beta = 0.497$, $p < 0.0001$), *Calm (LAE)* ($\beta = 0.168$, $p < 0.0001$) and *Happy (HAE)* ($\beta = 0.215$, $p < 0.0001$) have a positive effect on the *Number of Favourites* compared to an *Image Without a Person*. We also find that *Disgusted (HAE)* (β = -0.345, $p = 0.013$) has a negative effect on the *Number of Favourites* compared to an *Image Without a Person*. We find no evidence that *Angry (HAE)* ($\beta = 0.119$, $p = 0.061$) and *Confused (LAE)* ($\beta = 0.116$, $p = 0.133$) have an effect on the *Number of Favourites*. We find that only *Sad (LAE)* ($\beta = 0.369$, $p < 0.0001$) has a positive effect on the *Number of Retweets* compared to including an *Image Without a Person*. Emotions that have a negative effect are *Confused* (LAE) (β = -0.210, $p = 0.018$), *Fear* (HAE) (β = -0.232, $p = 0.002$), and *Happy* (HAE) (β = -0.196, $p < 0.0001$). Emotions that have no significant effect on the *Number of Retweets* are *Surprised* (HAE) (β = -0.010, $p = 0.907$), and *Calm* (LAE) (β = -0.007, $p = 0.761$).

5.4. Group differences

To explore whether micro-influencers receive more engagement per follower on their social media content, two Mann-Whitney U tests were conducted to test the *Number of Favourites per Follower* and the *Number of Retweets per Follower*. The *Number of Favourites* is higher for micro-influencers (Mdn = 0.000157) compared to other influencer types (Mdn = 0.000078). This difference is statistically significant $U(N_{\text{micro-influencer}} = 260556, N_{\text{other-influencer}} = 51680) = 6{,}434{,}588{,}962.5$, Z = -16.05, $p < 0.001$. The effect size was calculated using Wilcoxon *r* (as Z statistic divided by the square root of the sample size), resulting in a value of $r = 0.029$, which is considered a small effect. The *Number of Retweets per Follower* is lower for micro-influencers (Mdn = 0.0000000) compared to other influencer types (Mdn = 0.000007). This difference is also statistically significant $U(N_{\text{micro-influencer}} = 260{,}556, N_{\text{other-influencer}} = 51{,}680) = 5{,}766{,}460{,}549.0$, Z = -59.75, $p < 001$. The effect size was calculated using Wilcoxon *r*, resulting in a value of $r = 0.110$, which is considered a small effect. These findings suggest that *H1* is only partially supported; micro-influencers had a higher *Number of Favourites per Follower* but did not have a higher *Number of Retweets per Follower* on their social media content.

In Figs. 2 and 3, we give a depiction of each IV effect on the DV. Specifically, Fig. 2 shows the results of the test using all the social media content, while Fig. 3 shows the effects of the emotional expressions from the test using only the content with pictures. In Fig. 3, the effects of the variables *Text Sentiment*, *Verified Status*, and *Number of Followers* are omitted to simplify the figure. Table 6 gives a summary of the hypotheses' status.

6. Discussion

6.1. Key findings

We find that micro-influencers get a significantly higher *Number of Favourites per Follower* on their social media content compared to influencers with more followers. This is in line with Marques et al. (2021), who found that micro-influencers are better at generating likes, comments, and shares. However, contrary to Marques et al. (2021), we find that this is not the case for Retweets, since the median *Number of Retweets per Follower* on social media content by micro-influencers is significantly lower compared to other influencer types. This result contradicted our initial exploratory analysis of the dataset as the mean Retweets of micro-influencers were higher than those of other influencer types. A closer look into the data explained such a discrepancy. We found that certain social media content by influencers with a low number of followers had a very large number of Retweets; these outliers could have been posts that had gone viral, gathering a much higher-than-expected *Number of Retweets*. These findings partially support *H1*. Therefore, while the large audience of other types of influencers can present a higher chance for a post to go viral and be extensively Retweeted, the content of micro-influencers seems to receive more intimate engagement from their audience.

In line with Xie *et al.* (2020) and Suh et al. (2010), we find that the *Number of Followers* of an influencer positively influences engagement with their social media content. We find that the number of followers had a positive effect on the *Number of Favourites* and the *Number of Retweets*. The effect of *Number of Followers* was small per follower, but for influencers with many followers, this could amount to a sizable increase in user engagement. Such a finding does not contradict the finding of *H1* as in this regard we are focused on the total *Number of Favourites* instead of the *Number of Favourites per Follower.*

Moreover, we find that adding a picture has a positive effect on engagement with social media content. Regarding favourites, this effect is even greater when the picture features a person. Several effects

Table 3
NB(MLE) Regression Direct Effects: All Posts.

Effect	Estimate		SE		95 % CI				p	
					LL		UL			
	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets
Intercept	3.339	1.684	0.0061	0.0086	3.327	1.667	3.351	1.701	0<.0001	0<.0001
Number of Followers	$3.266 \cdot 10^{-6}$	$2.239 \cdot 10^{-6}$	$3.7785 \cdot 10^{-8}$	$4.6973 \cdot 10^{-8}$	$3.192 \cdot 10^{-6}$	$2.147 \cdot 10^{-6}$	$3.341 \cdot 10^{-6}$	$2.331 \cdot 10^{-6}$	0<.0001	0<.0001
Sentiment	−0.264	−0.457	0.0088	0.0121	−0.281	−0.480	−0.247	−0.433	0<.0001	0<.0001
Image without a person	1.138	1.298	0.0124	0.0175	1.114	1.263	1.163	1.332	0<.0001	0<.0001
Image with a Person	1.348	1.185	0.0135	0.0190	1.321	1.148	1.374	1.223	0<.0001	0<.0001
Verified Status	0.780	0.546	0.0103	0.0145	0.760	0.518	0.800	0.575	0<.0001	0<.0001

Note: N = 312236, Dispersion Parameter Favourites = 5.378, Dispersion Parameter Retweets = 10.662.

Table 4
NB(MLE) Regression Moderating Effect of Number of Followers: All Posts.

Effect	Estimate		SE		95 % CI				p	
					LL		UL			
	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets
Intercept	3.331	1.678	0.0062	0.0086	3.318	1.765	3.343	1.799	0<.0001	0<.0001
Number of Followers	$3.396 \cdot 10^{-6}$	$2.330 \cdot 10^{-6}$	$4.2188 \cdot 10^{-8}$	$5.2207 \cdot 10^{-8}$	$3.291 \cdot 10^{-6}$	$2.228 \cdot 10^{-6}$	$3.479 \cdot 10^{-6}$	$2.433 \cdot 10^{-6}$	0<.0001	0<.0001
Sentiment	−0.267	−0.458	0.0088	0.0121	−0.284	−0.482	−0.249	−0.435	0<.0001	0<.0001
Image without a person	1.140	1.299	0.0124	0.0175	1.116	1.265	1.164	1.333	0<.0001	0<.0001
Image with a Person	1.416	1.238	0.0163	0.0224	1.384	1.194	1.448	1.282	0<.0001	0<.0001
Verified Status	0.779	0.546	0.0103	0.0145	0.758	0.518	0.799	0.574	0<.0001	0<.0001
Number of Followers x Image with a Person	$-6.840 \cdot 10^{-7}$	$-5.200 \cdot 10^{-7}$	$8.7835 \cdot 10^{-8}$	$1.1273 \cdot 10^{-7}$	$-8.561 \cdot 10^{-7}$	$-7.409 \cdot 10^{-7}$	$-5.118 \cdot 10^{-7}$	$-2.990 \cdot 10^{-7}$	0<.0001	0<.0001

Note: N = 312236, Dispersion Parameter Favourites = 5.377, Dispersion Parameter Retweets = 10.660.

Table 5
NB(MLE) Regression Direct Effects: Posts with Images.

Effect	Estimate		SE		95 % CI				p	
					LL		UL			
	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets	Favourites	Retweets
Intercept	4.490	3.011	0.0123	0.0138	4.466	2.984	4.514	3.038	0<.0001	0<.0001
Number of Followers	$3.338{\cdot}10^{-6}$	$2.168{\cdot}10^{-6}$	$6.4962{\cdot}10^{-8}$	$6.8161{\cdot}10^{-8}$	$3.151{\cdot}10^{-6}$	$2.034{\cdot}10^{-6}$	$3.406{\cdot}10^{-6}$	$2.301{\cdot}10^{-6}$	0<.0001	0<.0001
Sentiment	−0.166	−0.389	0.0172	0.0187	−0.180	−0.426	−0.113	−0.353	0<.0001	0<.0001
Verified Status	0.402	0.216	0.0188	0.0217	0.380	0.173	0.454	0.258	0<.0001	0<.0001
Angry (HAE)	0.119	−0.190	0.0636	0.0731	−0.006	−0.333	0.244	−0.046	0.061	0.009
Confused (LAE)	0.116	−0.210	0.0770	0.0887	−0.035	−0.384	0.267	−0.036	0.133	0.018
Fear (HAE)	0.168	−0.232	0.0643	0.0740	0.042	−0.377	0.294	−0.087	0.009	0.002
Sad (LAE)	0.229	0.369	0.0453	0.0521	0.140	0.267	0.317	0.471	0<.0001	0<.0001
Surprised (HAE)	0.497	−0.010	0.0711	0.0816	0.358	−0.170	0.637	0.150	0<.0001	0.907
Calm (LAE)	0.314	−0.007	0.0193	0.0223	0.276	−0.050	0.352	0.037	0<.0001	0.761
Happy (HAE)	0.215	−0.196	0.0238	0.0275	0.168	−0.250	0.261	−0.142	0<.0001	0<.0001
Disgusted (HAE)	−0.345	−0.531	0.1384	0.1596	−0.616	−0.843	−0.073	−0.218	0.013	0.001

Note: N = 76913, Dispersion Parameter Favourites = 4.464, Dispersion Parameter Retweets = 5.869.

explain these findings. The positive effect of the mere presence of a picture, even without a person in it, is said to grab more attention than text-only posts (Li & Xie, 2020). Furthermore, credibility is assigned to pictures, cause although they can be manipulated to show a more riveting portrayal of the truth (Winston, 2013), they are harder to manipulate than text-only posts (Hameleers et al., 2020). The effect of credibility could also be essential in understanding why including a picture with a person has an even greater effect on engagement with social media content than a picture without a person.

Regarding retweets, the effect is slightly less positive for those pictures featuring a person compared to those without one. Furthermore, when a person is featured in the picture, more credibility is assigned to the social media content, potentially when the influencers themselves are displayed in the picture. We did not, however, investigate whether the person in the picture was the influencers themselves, as this was beyond the scope of our study.

Whilst the *Number of Followers* and the presence of an *Image With a Person* positively impact engagement with the social media content, we find that the *Number of Followers* negatively moderates the effect of an *Image With a Person* on engagement. This effect is found when looking at both the *Number of Favourites,* and the *Number of Retweets*. This could be attributed to micro-influencers being perceived as warmer, more authentic, and more credible and is also in line with MRT as the social media content of micro-influencers can be richer than other influencer types and the number of followers could diminish the ability to respond in a personal manner and provide feedback to their followers (Appel et al., 2020; Daft & Lengel, 1986; Winston, 2013). Furthermore, the followers of mega-influencers might lack feelings of closeness to the influencer, limiting the effect of an *Image With a Person.* Moreover, negative *Text Sentiment* impacts engagement with the social media content more than positive *Text Sentiment.* Our findings are in contrast with Berger, 2012, who state that positive news is more likely to be shared on social media. However, our findings are in line with Corstjens *et al.* (2012) as well as Yang et al. (2019), who theorised that negative posts in a social media setting have a more significant impact on cognition due to the negative bias effect.

To explore the effect of the various emotions on engagement with social media content that includes images, two tests were conducted using only posts with images. Looking at the effects on the *Number of Favourites*, contrary to expectations, *High Arousal Emotions* did not have a more positive effect than *Low Arousal Emotions*, apart from *surprised*, which scored highest amongst all emotions. Contrary to previous studies, *calm* was ranked second highest. Furthermore, *disgust* was found to have a negative effect on the *Number of Favourites* compared to posting an *Image Without a Person*. Regarding the effects of emotions on the *Number of Retweets*, it was also found that *H5* is not supported.

Contrary to Berger (2011), who finds that *High Arousal Emotions* increase sharing and that sadness decreases sharing, we find that expressing sadness within social media content was the only emotion that had a positive effect on the *Number of Retweets* compared to posting an *Image Without a Person*. Furthermore, a happy face in a picture decreased the *Number of Retweets* on a post, and disgust decreased the *Number of Retweets* even more. Even though we find no support for *H5*, splitting the variable *Image With a Person* into the emotional expressions of the person in the picture has given valuable insights into the effects surrounding engagement with social media content. It also provides insights into why including a person in a picture has a more positive effect on the *Number of Favourites*, and why this is not the case for the *Number of Retweets*. Regarding the effect on the *Number of Favourites*, the emotions of *fear*, *sadness*, *surprise*, *calmness*, and *happiness* have a positive effect, with only *disgust* having a significant adverse effect compared to posting an *Image Without a Person*. Whilst looking at the effect on the *Number of Retweets*, we find that only expressing sadness has a positive effect, while other emotions have negative or non-significant effects. The positive effect of *sad* emotions is in line with earlier research. For instance, Ibrahim et al. (2008) found that sadness sparks more

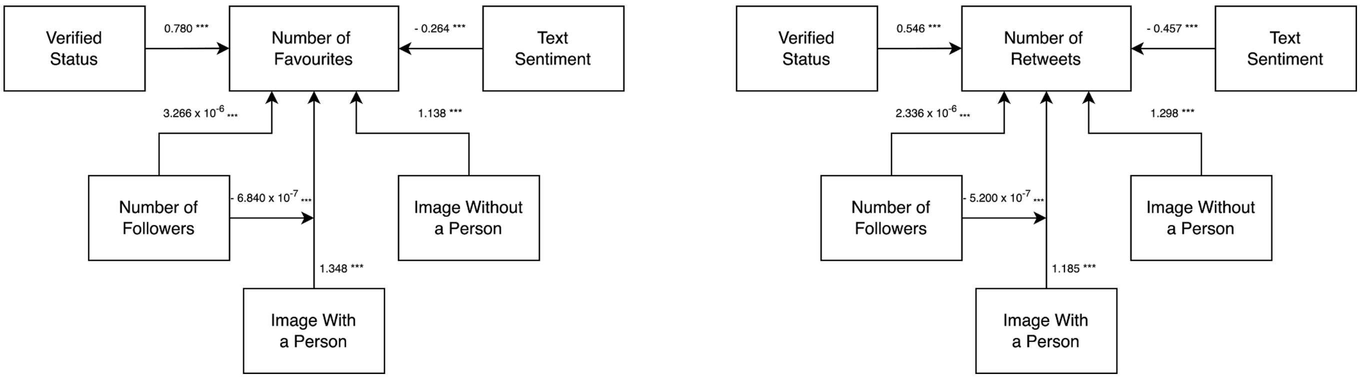

Fig. 2. Effects of regressions using all posts *** Significant at the 0.0001 level ** Significant at the 0.001 level * Significant at the 0.05 level.

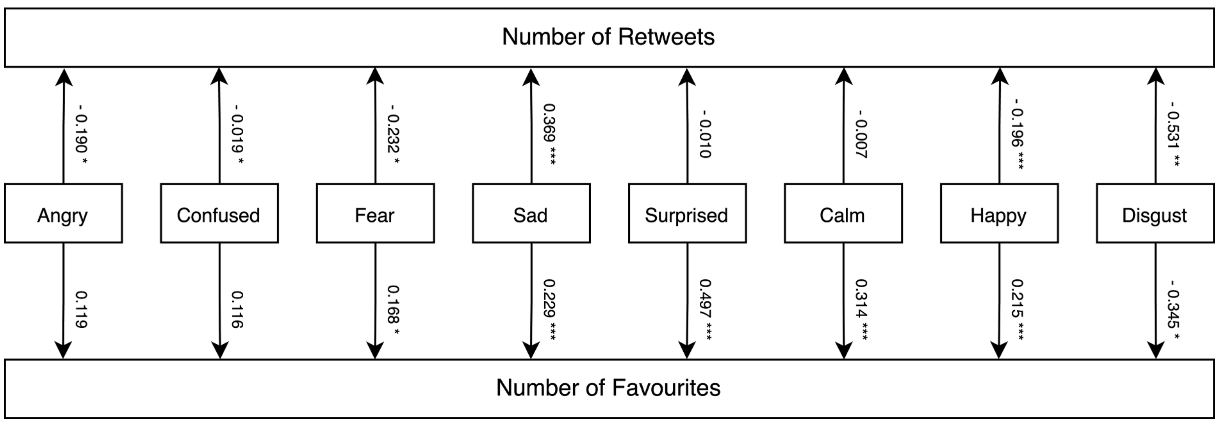

Fig. 3. Effects of regressions only on posts with images *** Significant at the 0.0001 level ** Significant at the 0.001 level * Significant at the 0.05 level.

Table 6
Summary of Hypotheses.

#	Hypothesis	Favourites	Retweets
H1	Micro-influencers have higher engagement per follower than other influencer types.	Supported	Rejected
H2	Including an image in social media content has a positive effect on engagement.	Supported	Rejected
H3a	The presence of a person in an image positively impacts engagement.	Supported	Supported
H3b	The effect of inclusion of a person in images that accompany social media content on engagement is higher for influencers with fewer followers.	Supported	Supported
H4	Negative text sentiment positively affects engagement with the social media content.	Supported	Supported
H5	High Arousal Emotions in images included in the social media content have a more positive effect on engagement than Low Arousal ones.	Rejected	Rejected

discussion and sharing as a coping mechanism. Followers may be touched by a post that raises sadness and want to share it with others. Engagement with social media content, though, depends on the emotion expressed in a picture, as well as on the context of the picture provided by the text. A sad post could have a deeper message, and the content could be more meaningful than posts expressing other emotions. Thus, future research can analyse the fit between the emotion and the text of a post.

A clue into why many emotional expressions have a lower effect on the *Number of Retweets* than on the *Number of Favourites* compared to no person in the picture could lie in what is posted when no person or emotion is in the picture. The picture could contain a landscape but also have text containing information. According to Tan et al. (2014), informativeness in a message leads to increased sharing. However, in this study, pictures are not further split into groups other than containing a person and what emotion that person expresses. Future research could try to examine and identify additional characteristics in pictures that affect the sharing behaviour.

6.2. Theoretical implications

Our work expands the literature on what drives engagement with social media content. We find that micro-influencers receive more favourites per follower, which opens avenues for future research to investigate why the followers of micro-influencers are more likely to favourite their social media content but not more likely to retweet such content. Feeling trustworthiness or similarity might be an important factor in why social media users engage with micro-influencers; we recommend, thus, to further study this in a more experimental setting.

We also contribute to the MRT, which is usually applied to determine the communication effectiveness of a medium (Daft & Lengel, 1986). Our work shows that MRT could also be applied to individual or groups of influencers with their audiences. We invite future research to determine the effects of each characteristic of the MRT on engagement.

Concerning the effect of personal characteristics in pictures included in social media content, our findings both support and challenge existing research. Whilst our findings are in line with prior literature on the positive effect of personal characteristics on the *Number of Favourites* (Barcelos et al., 2018), our results are in contrast to Li and Xie (2020), who found that including a person in the picture increases sharing. However, to increase robustness, we explore more in-depth what emotional expressions affect engagement with social media content and demonstrate that certain emotions have a significant effect on both the *Number of Favourites* and the *Number of Retweets*. For instance, whilst including a person in the picture has a slightly lower effect on the *Number of Retweets* than posting a mere picture. Our findings show that individual emotional expressions have distinct effects. We find that expressing sadness does indeed get more retweets. This shows that the emotional expression of the people in pictures on social media needs to be considered in future research. Moreover, in this study, only posts from X are analysed (e.g., del Mar Galvez-Rodriguez et al., 2016). It would be beneficial to further examine whether the effects of the picture characteristics are also present in social media platforms that are predominantly picture-based, such as Instagram.

Furthermore, the fact that many emotional expressions in the pictures have a positive effect on the *Number of Favourites*, but a negative effect on the *Number of Retweets* suggests that various factors may impact favourites in a different way than retweets and these variables should be further studied independently. Future research should, thus, further explore the various factors that social media users tend to consider when engaging with such content. Our work has a clear focus on the extant Information Systems research agenda (e.g., Struijk et al., 2022) and its theoretical implications can go beyond the topic of engagement in social media (Li et al., 2021; Wies et al., 2023). For instance, our findings can be extended to work-related social media (Bulgurcu et al., 2018; Chen et al., 2021), as well as on digital platforms and online communities (Angelopoulos & Merali, 2015, Angelopoulos & Merali, 2017) and be further enhanced through a gamification lens (e.g., Alexiou et al., 2022) to inform established understandings of the engagement with online content and open new avenues for future research on the topic.

6.3. Practical implications

Our study also provides novel practical implications for social media managers as well as social media influencers. For the former, our results show that using several micro-influencers instead of influencers with more followers can be a legitimate social media strategy. Instead of using a single celebrity or mega-influencer, multiple micro-influencers can be used to reach a similar audience size when aiming for favourites whilst only slightly losing shares. The strategy of using micro-influencers is being increasingly adopted by various brands that find such influencers more trustworthy, and their followers are interested in the topics they post about, which makes it easier to target specific audiences (Khamis et al., 2017). For social media managers and influencers, our work provides insights into how engagement with social media content can be maximised, but also, what influencers should avoid such content. Our results show that pictures bring more engagement with social media content, and further evidence is found that several facial expressions increase engagement even more. However, expressing disgust in pictures is not recommended. Thirdly, it is recommended to take the number of followers an influencer has into account when forming a social media campaign (e.g., Araujo & Kollat, 2018). Our findings demonstrate that having a person in a picture is more important to influencers with fewer followers than those with more followers. Influencers and marketers, thus, can assess the richness of their social media content, as well as the medium they use as richness increases engagement. In practice, this would require them to provide feedback to followers, create content with personal messages and easy-to-understand language, and post visual content to increase richness and ensure effective communication with their audience.

6.4. Limitations and future research

Although we followed a structured and thorough research design, there are limitations that we need to acknowledge. Our study is among the first that focuses on the effects of engagement with social media content on a large sample of influencers. To get access to an extensive list of influencers, a convenience sampling technique was used. Consequently, only posts by self-reported influencers on X were analysed. We call for future research to resolve such a limitation by either taking the definition of an influencer more literally so that anyone who has a following is seen as an influencer instead of only researching people who actively strive to be influencers or by creating a list of influencers of all sizes that is most closely representative of the population of influencers. This, however, requires extensive knowledge about influencers and can be prone to biases. Second, we aimed to find what influencer type is best for social media advertising, but we did not study actual endorsements by these influencers. All posts by the selected influencers were analysed, and no distinction was made between regular posts and those that are advertisements. We, thus, call for future research to address such a shortcoming by comparing the effects found in regular non-advertising posts to advertisements by the same influencers. Our third limitation is that only social media content from X was used. Whilst this was in line with our research intentions—study the effect of pictures in a text-based social media platform—various social media platforms have many things in common, but also distinct affordances, making it difficult to generalise the findings from one platform to another. Jordan (2018) provides instructions on how to safeguard validity and reliability in multi-platform social media research. In line with this, we call for future studies to be carried out examining specific influencers who are active across multiple platforms. Fourth, our choice to only study social media content written in English could also be seen as a limitation for our study, but concurrently it opens avenues for further research. For instance, future studies could replicate and extend our work by exploring the topic in other languages and comparing their results on a cultural level with the findings of our work. Fifth, regarding the definition we follow here for the various types of influencers based on the size of their audience, some might argue that this may be context-dependent. Although by their very nature social media transcend spatial boundaries (Li et al., 2021), and unless focusing on a specific context this should not necessarily be a limitation for our study, future research could further explore this by identifying context-dependent characteristics of the various types of influencers based on the size of their audience. Sixth, we do not explore whether the persons in the pictures were the influencers themselves; we encourage future research to compare the effects of adding a picture of the influencer versus one with a person who is not the influencer. Finally, we have not accounted for how many bots follow each influencer in our dataset, and how many of the retweets and favourites in the content we use in our study could be possibly coming by bots. We would, thus, encourage future research to work on developing tools for the better identification of bots on social media and to extend our work by attending to this issue.

7. CONCLUSION

In the current day and age, anyone who aspires to, and has a talent or interest, can become an influencer on social media. Brands seem to pick up on using influencers with fewer followers as they seem more authentic and trustworthy to their followers—however, the knowledge surrounding the use of micro-influencers for online endorsements is limited. We explored whether micro-influencers create more engagement per follower than other influencer types, and what content characteristics influence such engagement. Our results show significant differences in engagement with the social media content between micro-influencers and those of other types, while we find evidence of other factors that impact engagement, such as the emotional expression in pictures, which have not been mentioned in the previous studies.

We find that the followers of micro-influencers are more likely to favourite social media content, whilst the followers of other influencer types are more likely to share it. Thus, it can be argued that using multiple micro-influencers instead of a mega or macro one is a valid alternative, especially when favourites are the desired outcome. Moreover, we demonstrate that the number of followers, including a picture, as well as having a verified profile, have a positive effect on engagement. Furthermore, our findings show that when including a person in a picture, the number of likes further increases but not the number of shares over posting a picture without a person. Posting a picture with a person, however, is negatively moderated by the number of followers, meaning that the effect of including a picture is more substantial for micro-influencers. Lastly, we show that regarding favourites, expressing sadness, calmness, happiness, surprise, or fear has a positive effect. Concerning retweets, expressing sadness has a positive effect, and expressing fear, confusion, or happiness has a negative effect. Our findings also show that expressing disgust has a negative effect on both favourites and retweets. Our findings provide novel insight into engagement with social media content and open avenues for future research on the topic. As social media platforms are ever-changing, future research needs to monitor how they transform, as well as their effects on strategies and their effectiveness.

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CRediT authorship contribution statement

Jesse van der Harst: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Formal analysis, Data curation. **Spyros Angelopoulos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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