ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/375027636

Driving Engagement with Virtual Influencer Content –Integrating Computer Vision, Text Analysis and Manual Coding

Conference Paper · December 2023

CITATIONS
0

READS
145

3 authors, including:



Kevin Schwehm
University of Wuerzburg
4 PUBLICATIONS **1** CITATION
SEE PROFILE



Steven Schwehm
University of Wuerzburg
6 PUBLICATIONS **0** CITATIONS
SEE PROFILE

All content following this page was uploaded by Kevin Schwehm on 27 October 2023.

The user has requested enhancement of the downloaded file.

Driving Engagement with Virtual Influencer Content – Integrating Computer Vision, Text Analysis and Manual Coding

Short Paper

Kevin Schwehm
University of Wuerzburg
Wuerzburg, Germany
kevin.schwehm@uni-wuerzburg.de

Steven Schwehm
University of Wuerzburg
Wuerzburg, Germany
steven.schwehm@uni-wuerzburg.de

Jana-Kristin Prigge
University of Wuerzburg
Wuerzburg, Germany
jana-kristin.prigge@uni-wuerzburg.de

Abstract

Virtual influencers have started to amass significant followings on online social networks and to collaborate with popular brands. However, the content characteristics driving the engagement with virtual influencer posts are still unexplored. This study addresses this knowledge gap by analyzing a unique dataset comprising over 25,000 posts from 171 influencers gathered using Google Cloud Vision and Instagram Graph API data. We conduct hierarchical negative binomial regression models for both likes and comments and find that posts displaying emotions such as anger and joy result in substantial increases in engagement metrics. Additionally, interactive posts using hashtags or tags also generate more engagement. Moreover, we present our remaining work which includes incorporating text characteristics (e.g., sentiment and emotional congruence) and manually coded content types (informative, entertaining, remunerative, and relational formats) into the model as well as post-hoc analyses and robustness checks to further disentangle the effects identified.

Keywords: virtual influencer, social media, content analysis

Introduction

A new type of social media influencers has appeared in online social networks, such as Instagram, TikTok or Twitter. So-called virtual influencers (VI) defined as "computer-generated personalities" (Miao et al. 2022, p. 86) have started to gain a large following online and appear able to achieve millions of followers. For example, the human-like VI "LilMiquela" is currently at 2.8 million followers on Instagram and the anime-like character "Noonoouri" already gained 403.000 followers. Besides these somewhat realistic virtual characters, also more "exotic" VI types can be successful as well, such as "Nobodysausage", a virtual sausage with 5.1 million followers or "Guggimon", a horror bunny, with 1.4 million followers.

However, VIs do not only gain large followings despite not being real, they also collaborate with brands such as Prada or Calvin Klein (Miao et al. 2022, p. 86) and thus directly compete with real influencers (i.e., truly existing, human influencers) such as Chiara Ferragni. Because VI are managed by real humans or

management teams, they bear much lower risk for undesirable posts and – owing to their more homogeneous and focused fan group, often exhibit much higher engagement rates (Baklanov 2020). As of April 2023, there were over 170 VIs listed on a popular blog called Virtual Humans (Virtual Humans 2023). Unsurprisingly, there is increasing academic interest on the topic (Miao et al. 2022) and in recent reviews on social media influencers (Hudders et al. 2021; Vrontis et al. 2021). Research on VIs, however, is still nascent and mostly limited to psychological factors influencing the relationship towards VIs or their endorser effectiveness (e.g., Deng and Jiang 2023; Franke et al. 2022; Sands et al. 2022). Besides these important topics, however, it is also crucial to understand which content characteristics drive engagement (e.g., likes and comments) with their content, particularly considering the rise of tools such as ChatGPT, Midjourney or Dall-E, that make it much easier to fill VI accounts with high quality text and images.

To the best of our knowledge, this study is the first to analyse the content characteristics driving engagement with VIs on social media, hereby helping to answer the following research question (RQ):

RQ: Which content factors drive the behavioral engagement (i.e., liking and commenting) with VI content on social media on a media, text and content type level?

The analysis and the remaining work presented in this short paper aim to provide initial insights on this topic with a special focus on the effect of emotions across several content layers used repeatedly within content analyses: the media level (emotions displayed by the virtual characters in the images), the text level (e.g., sentiment on the text level, and sentiment congruence between text and media objects) and the interaction of emotions with overall content types such as informative, entertaining, remunerative, relational content (e.g., Dolan et al. 2016) and more specific categories often used by VIs such as ethical or moral issues (e.g., VI Noonoouri often posts about sustainability issues). The latter two are subject to remaining work and will help zoom in on the effects of emotions within VI posts identified through the first analysis and potentially also point towards boundary conditions and interaction effects in this regard.

We present the results of the first analysis regarding the effects of displaying emotions on likes and comments using data obtained via the Google Cloud Vision API (application programming interface) within this study. Emotions have been studied in numerous studies and were found to impact engagement with content in several contexts (e.g., Berger and Milkman 2012; Li and Xie 2020). We observed significant relationships in our analysis. Posts expressing anger and joy showed notable increases in engagement metrics. Additionally, posts incorporating tags and hashtags garnered higher levels of engagement. Our study leveraged a unique dataset derived from a web scraper, identifying over 170 VI and collecting metadata for their posts using the official Instagram Graph API. Furthermore, we obtained facial emotion data for approximately 25,000 images through the Google Cloud Vision API. Our ongoing work will also incorporate text characteristics related to the linguistic style used and manual coding data for more specific content types, with an anticipated completion date of October 2023. In the following sections, we will discuss the related literature on VIs and social media content analyses which we then use to derive our hypotheses. Subsequently, we explain our influencer selection process, the variables used, the data acquisition approach and present the results of the first of our three analysis layers for both likes and comments. We close with a section on the remaining work and the limitations of this study.

Related Literature

Social Media Influencers

Research on social media influencers has gained substantial academic attention, evident in recent literature reviews (e.g., Fowler and Thomas 2023; Hudders et al. 2021; Vrontis et al. 2021). These studies delve into various aspects of influencer marketing, ranging from parasocial relationships with followers to disclosure of commercial collaborations, and specific content traits in influencer posts. However, the majority of these studies predominantly analyses real, existing influencers (e.g., Hughes et al. 2019; Wies et al. 2023).

When analyzing the literature concerning VIs, we noted three key points. First, existing studies have limitations in their VI selection since they concentrate on a subset of very popular VI accounts, thus leaving many other VIs unexplored. Second, studies categorize VIs into distinct types, namely human-like, anime-like, and non-human VIs. Third, no study has systematically examined the content characteristics driving engagement with VI posts. A large part of these studies compare VIs and real influencers.

For example, by comparing real (human) influencers with human-like VI (i.e., VI that look like humans, such as LilMiquela) and anime-like VI (i.e., VI that look like anime characters, such as Noonoouri), Arsenyan and Mirowska (2021) report that VIs receive more engagement overall compared to human influencers and that the human-like VIs received the least positive engagement compared to the other influencer types. Additionally, Choudhry et al. (2022), who explored human-like, anime-like and non-human VI (i.e., VI that are apparently not human at all, such as Guggimon) report that user engagement is primarily driven by visual appeal, sense of mystery, and creative storytelling. The study by Sands et al. (2022) detects that VIs are perceived as less trustworthy and more social-psychologically distant than human influencers but also that they evoke greater word-of-mouth intentions. Similarly, Franke et al. (2022) report that it is difficult for consumers to recognize human-like VI as not being real and they tend to have more positive attitudes towards human endorsers.

Furthermore, we also identified ongoing work that was presented at recent conferences and focuses on trust perceptions (Hofeditz et al. 2022) and the advertising effectiveness (Dabiran et al. 2022) of VI. Besides these studies that primarily evaluate perception and engagement-related differences between VIs as well as between VIs and real influencers, there is also a first study examining potential ethical and ontological concerns regarding VI (Robinson 2020). Overall, we can conclude that the VI selection within these studies is still centered around a few very popular accounts and no study has so far analyzed the content characteristics that help build successful VI profiles despite the natural relevance of this topic.

Social Media Content Analyses

The second research stream deals with social media content analyses. Not only has engagement with social content been studied across various platforms, but also a variety of topics and different contexts have been considered. For example, researchers have studied engagement drivers on Facebook (Hughes et al. 2019; Villarroel Ordenes et al. 2019) and blogs (Hughes et al. 2019), YouTube (Tellis et al. 2019), Instagram and Twitter (Hartmann et al. 2021), TikTok (Wahid et al. 2019), and even within newspapers (Berger and Milkman 2012). Moreover, contexts in which content has been analysed range from elections (Mallipeddi et al. 2021), online social influencers (Hughes et al. 2019), online wildlife trade (Feddema et al. 2020), airlines (Li and Xie 2020), luxury brands (Liu et al. 2021), soccer teams (Meire et al. 2019), to creative strategies on online social networks (Ashley and Tuten 2015).

Unsurprisingly, several content characteristics have been identified as engagement drivers. First, the huge potential of emotions to trigger engagement with social media content have been discussed in the literature (e.g., Berger and Milkman 2012; Dolan et al. 2019; Feddema et al. 2020; Tellis et al. 2019; Wahid et al. 2023). For example, Berger and Milkman (2012) found that both positive and negative activating emotions increase virality and Tellis et al. (2019) find that positive emotions increase sharing behavior. Additionally, social media text characteristics have also been linked to engagement, for example by analysing sentiment scores (Wahid et al. 2023; Li and Xie 2020; Berger and Milkman 2012; Stieglitz and Dang-Xuan 2013). Researchers have also began to investigate interactions between and congruence of media object and text design (e.g., Li and Xie 2020). Additionally, pertinent content categories that are manually coded (e.g., informative, relational, remunerative and entertaining content) are also frequently used to study engagement (Dolan et al. 2016; de Vries et al. 2012; Muntinga et al. 2011). These aspects are essential for our remaining work but not elaborated on further due to space restrictions. Lastly, despite the breadth and depth of user engagement research overall, the VI context remains unexplored.

To conduct content analyses, two primary approaches are used within these studies. The first comprises manual coding, which is often performed by multiple coders (e.g., Hughes et al. 2019) to reduce bias. This allows for precise coding of variables but the amount of posts that can be analyzed is limited due to the manual work. An alternative approach relies on automated coding, for example via the Google Cloud Vision API to detect facial emotions or objects (Li and Xie 2020; Philp et al. 2022). This allows for the analysis of a larger number of posts. Particularly the application of computer vision through this API has gained popularity (e.g., Li and Xie 2020; Philp et al. 2022; Nanne et al. 2020). For example, Philp et al. (2022) used computer vision to evaluate the typicality of food content and Li and Xie (2020) studied content of airlines and SUVs and found that the mere presence of images and happy faces enhances engagement.

Conceptual Framework and Hypotheses Development

Figure 1 summarizes the modeling framework for the analysis of this short paper and provides an outlook on the remaining work including interactions between the media object, content type, and text design.

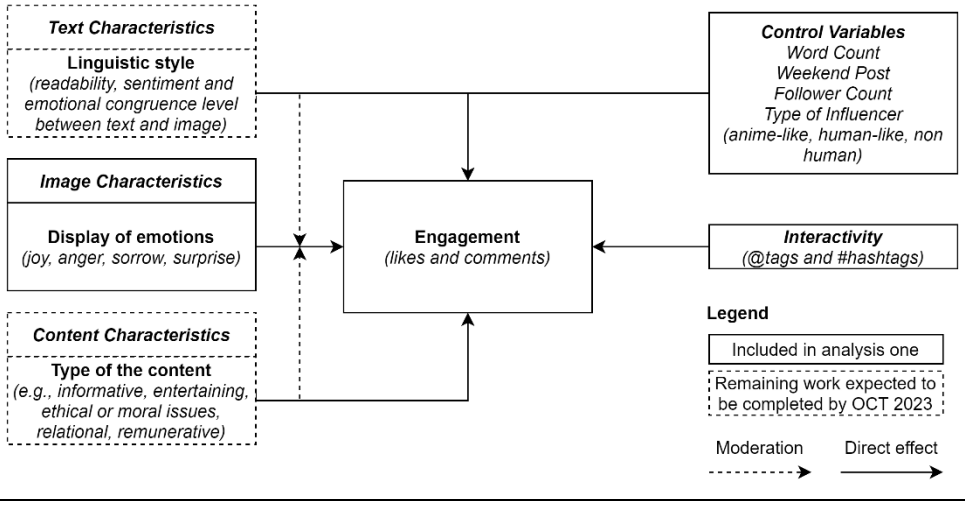


Figure 1. Modeling Framework

We argue that clearly displaying emotions is very promising in a VI context, too and they are thus the focus of analysis 1. Displaying emotions is likely to be related to interesting content through the means of storytelling since posts clearly highlighting emotions such as anger and joy let followers virtually take part in crucial moments of the VIs' lifes. For example, by sharing achievements or personal events like falling in love, talking about failures or health issues, the VIs might create stories that are more interesting and engaging compared to more neutral posts such as selfies or showing outfits, hereby activating users and provoking engagement. Hence, we propose the following hypotheses for analysis 1:

H1a-d *Posts displaying clear emotions of a) anger, b) joy, c) surprise, and d) sorrow generate higher levels of engagement (likes, comments) compared to neutral posts.*

Furthermore, Instagram offers features such as hashtags and tags to make posts more interactive which has been shown to impact engagement (de Vries et al. 2012; Liu et al. 2021). These features improve the visibility of the posts and make them more searchable, which is especially important for new or less known accounts, such as those of newly established VIs. Other studies using manual coding have even differentiated between the degree of interactivity (de Vries et al. 2012) which we will consider in analysis 2 and 3 and in our post-hoc analyses (remaining work). Thus, we further hypothesize:

H2: *Interactive posts (i.e., posts that use hashtags, tags, or both within their caption) generate higher engagement compared to non-interactive posts.*

In the following sections, we present analysis 1 including the data acquisition, modelling challenges and results. The remaining analyses 2 and 3 as well as robustness checks and post-hoc analyses are planned to be completed by October 2023 (see section on remaining work at the end of this short paper).

Model Development and Analysis

Data Acquisition and Variable Operationalization

Our study derives variables through both manual and automated approaches across several analyses. The results of the first analysis are reported in this short paper and comprise the effects of emotions displayed within VI posts. To do so, we first had to identify the VIs. Hereby, our approach was two-fold and included a screening phase of VIs mentioned in studies and the extraction of VI accounts found within in a popular blog on the topic (Virtual Human 2023) through a webscraper built with Selenium in Python. As mentioned

previously, the number of different VIs considered within studies is limited. Scraping the blog, however, helped identify a large number of accounts across multiple categories. This led to a list of more than 170 VI. For every VI, we then identified the Instagram username which we used to query the official Instagram Graph API in order to extract every post in their profile including metadata such as the amount of likes and comments for each VI account. We also doublechecked the VIs identified before performing the analysis and excluded accounts related to popular brands such as Barbie and Minniemouse.

This lead to 27,599 Instagram image posts by over 170 VI that generated 169,934,792 likes (mean = 6,742.37 , sd = 18,308.72 , max = 655,330) and 3,643,778 comments (mean = 142,34 , sd = 643.63, max = 37,694).

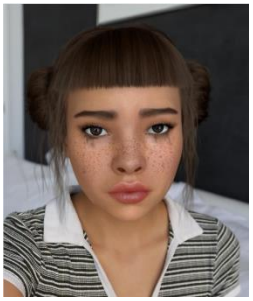
Anger	***Joy***	***Surprise***	***Sorrow***
			
Post (Base URL = https://instagram.com/p/)			
Image: CWrLHpQlL8b	Image: BbkvX3LF_DR	Image: CQMZXiAlVq2	Image: B2M-MxUl_05
Bvad_eHnyBl	Bv8T9v-Drrm	CQIiWQdjfy3	CHQnYh2BVTn
CREorKxM7ep	CWbS8QOJMbP	CCqehPbFAMe	Cc6j8A5PQXx

Table 1. Exemplary Posts And Their Classification By The Google Cloud Vision API

The image urls were provided by the Instagram Graph API and we used them to download every image for the posts for which we then obtained facial emotion data via the Google Cloud Vision API. This API is a deep learning-based tool from Google that can tag images with different features such as facial emotions or objects. The tool uses pre-trained models to recognize features present in images (Google Cloud 2023). For each image, the API provides confidence scores for all features. Research has shown that high confidence scores (>60) from the Cloud Vision API are very close to human classification (Klostermann et al. 2018; Li and Xie 2020; Nanne et al. 2020; Philp et al. 2022). We use the API to encode Instagram images using the 'faces and emotions' feature. Since it is not obvious that the Google Cloud Vision API will also work for virtual characters, we validated the classified emotions (anger, surprise, sorrow, and joy) and found no systematic issues with regard to their classification. However, we highlight potential limitations in this regard at the end of this study. Regarding interactivity, we test the impact of an overall interactive status (i.e., posts using either hashtags, tags, or both versus no interactivity). Within our future work, we aim to conduct post-hoc analyses, include text variables and manual coding to disentangle the effects in this regard. To make the topic more accessible, Table 1 highlights a series of posts including their classification.

Modelling Challenges

Because the dependent variables in our study are count variables (likes and comments represented as integers) and because we detected overdispersion for the dependent variables (i.e., the variance is greater than the mean), we applied a negative binomial regression model, thereby following previous studies (Hughes et al. 2019, Li and Xie 2020; Stieglitz and Dang-Xuan 2013). Moreover, the collected data are hierarchical (i.e., posts are nested within the accounts), so that differences may exist between groups. Therefore, we calculated a hierarchical model using the accounts as group variables. In addition, selection issues may occur when not every VI is included (e.g., see analysis 2 which must be limited to posts in English and analysis 3 which can only be done for a small subset of posts due to manual coding). We account for this by using Heckman selection models (Heckman, 1979; Hughes et al. 2019) which allow to control for differences in account characteristics (e.g., gender, post frequency and age) within the main models.

Results of the Hierarchical Negative Binomial Model

Table 2 presents the results of the hierarchical negative binomial models for likes and comments. We transformed the coefficients (IRR = Incidence Rate Ratios) by applying the exponential function to convert them to changes in percentages. The number of posts differs between the like model (model with number of likes per post as dependent variable) and the comment model (model with number of comments per post as dependent variable) as the number of likes was not available for some posts during the data acquisition.

	Like model			**Comment model**		
Predictors	***% change***	***CI***	***p***	***% change***	***CI***	***p***
(Intercept)	-61.95	-81.42 – -22.09	**0.008**	-95.73	-97.95 – -91.12	**<0.001**
log(followers)	111.92	97.07 – 127.88	**<0.001**	82.88	69.79 – 96.97	**<0.001**
Human-like	*Reference*					
Anime-like	11.77	-23.93 – 64.21	0.571	-14.46	-41.70 – 25.50	0.424
Non human	9.23	-26.01 – 61.24	0.657	7.44	-27.05 – 58.24	0.716
Anger	97.43	53.57 – 153.81	**<0.001**	108.51	50.88 – 188.15	**<0.001**
Joy	34.88	30.62 – 39.28	**<0.001**	21.61	16.65 – 26.79	**<0.001**
Sorrow	6.56	-15.41 – 34.23	0.590	2.56	-23.93 – 38.26	0.868
Surprise	-17.96	-27.00 – -7.80	**0.001**	-19.66	-31.02 – -6.43	**0.005**
Interactive	17.77	14.24 – 21.42	**<0.001**	10.68	6.41 – 15.11	**<0.001**
Word count	0.01	-0.00 – 0.03	0.087	0.07	0.05 – 0.10	**<0.001**
Weekend	2.33	0.03 – 4.69	**0.047**	-9.17	-11.86 – -6.40	**<0.001**
Model metrics (AIC = Akaike information criterion, BIC = Bayesian information criterion)						
N_groups	168 username (groups in the hierarchical model)			171 username (groups in the hierarchical model)		
Observations	25,204			25,599		
AIC	422,629.7			238,844.1		
BIC	422,735.4			238,950.3		
Log-Likelihood	-211,301.8 (df=13)			-119,409 (df=13)		

Table 2. Results For The Likes And Comments Model

Discussion

Both hierarchical negative binomial models converged with 25,204 observations, revealing an AIC of 422,629.7 and a BIC of 422,735.4 for the like model and 25,599 observations, AIC of 238,844.1 and BIC of 238,950.3 for the comment model. As hypothesized, the amount of followers is significantly associated with the number of likes and comments a post receives in both models. With regard to the emotions displayed in the posts, the data reveal several interesting results. First, posts displaying anger generate more likes (97.43 %, $p < 0.001$) and comments (108,51 %, $p < 0.001$) compared to more neutral posts, hereby confirming ***H1a***. Moreover, displaying joy increases likes by 34.88 % ($p < 0.001$) and comments by 21.61% ($p < 0.001$), confirming ***H1b***. Interestingly, posts classified as surprise showed a negative association with both likes (-17.96 %, $p < 0.05$) and comments (-19.66 %, $p < 0.05$), contrary to ***H1c,*** while no effect was found for sorrow, leaving ***H1d*** unconfirmed ($p > 0.05$).

One potential explanation for the absence of support for H1c is that the posts displaying surprise often show the VI while eating something or basic selfies and such posts might provide little entertaining or informational value, do not provoke engagement and are basically buffer posts. They also might not trigger discussions within the comments (compared to joyful posts about milestone achievements, or posts displaying anger). A possible explanation for the missing effect regarding sorrow might be that it is a rather deactivating emotion compared to more activating emotions like anger or joy (Berger and Milkman 2012) so that people might be more hesitant to engage with posts showing sorrow.

Regarding interactivity of posts, we support H2 by observing that posts using interactive elements (i.e., tags and hashtags) generate more likes (17.77 %, $p < 0.001$) and comments (10.68 %, $p < 0.001$). This seems reasonable considering that VIs represent a new topic and hashtags and tags (i.e., linking to other accounts) are valuable tools to reach new audiences who otherwise would not encounter such posts. Additionally,

posts published during the weekend generate more likes (2.83 %, $p < 0.05$) but fewer comments (- 9.17 % , $p < 0.001$). We obtained very similar results when calculating ordinary least squares models using log-transformed dependent variables and including the usernames as dummy variables. In the next section, we explain the remaining work of this study including post-hoc analyses and robustness checks.

Conclusion and Outlook on Remaining Work

This study offers initial insights into factors associated with engagement drivers of VI content with a particular focus on emotions displayed within the social media posts. Our findings indicate that posts displaying anger and joy are associated with higher levels of engagement in terms of the number of likes and comments they receive. We reveal similar results for interactive posts using hashtags and tags. In a second analysis, we aim to add text characteristics to the model (e.g., sentiment and emotional congruence between the media object and the textual elements of the post) for posts published in English. Lastly, we plan to add manually coded variables for content types (i.e., informative, entertaining, remunerative, relational) to our model to study potential interaction effects with the emotional setup of the posts. Our next steps in this regard are to code the posts with 3 coders each, thereby using interrater reliability metrics (e.g., as proposed by Shrout and Fleiss, 1979) to monitor coding conflicts.

We also plan to conduct post-hoc analyses to compare VI types (e.g. anime vs. human-like vs. non-human) and media types since the analysis of this short paper had to be limited to images. Finally, we plan to test the robustness of the results by using alternative engagement metrics and text characteristics (e.g., multiple libraries to deal with the emote usage on Instagram). We expect the remaining work to be completed by October 2023.

Limitations

The presented work is not without limitations. First, the results are likely to depend on the platform investigated and future studies should aim to validate the results in different contexts such as TikTok, Twitch, YouTube or Twitter. Second, the topic of VIs is still nascent. Some of the engagement success might simply be related to the exciting nature of this new phenomenon. Third, the results might not apply to all types of VI and the post-hoc analyses in this regard might disentangle the effects identified in the analysis. Moreover, although we did not identify classification issues, they may occur in the future due to new types of VIs or image generation approaches driven by tools such as Midjourney or Dall-E as well as more posts by the different VI subgroups (i.e., VIs resembling food). Lastly, while the results reported show significant effects for many of the predictors, they do not confirm causal relationships. Future studies and our remaining work should thus consider experimental setups, the addition of instrumental variables and alleviate potential endogeneity concerns (e.g., through propensity score matching as applied by Li and Xie 2020) to further disentangle the causes of the effects identified within this study.

References

Arsenyan, J., and Mirowska, A. 2021. “Almost human? A comparative case study on the social media presence of virtual influencers,” *International Journal of Human-Computer Studies* (155), 102694. **https://doi.org/10.1016/j.ijhcs.2021.102694**

Ashley, C., and Tuten, T. 2015. “Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement,” *Psychology & Marketing* (32:1), pp. 15-27. **https://doi.org/10.1002/mar.20761**

Baklanov, N. “The Top Instagram Virtual Influencers in 2020”, Hypeauditor, November 2020, (https://hypeauditor.com/blog/the-top-instagram-virtual-influencers-in-2020/, accessed April 17 2023).

Berger, Jonah, and Katherine L. Milkman 2012. "What makes online content viral?," *Journal of Marketing research* (49:.2), pp. 192-205. **https://doi.org/10.1509/jmr.10.0353**

Dabiran, E., Wang, F., and Farivar, S. 2022. “Virtual influencer marketing: anthropomorphism and its effect,” in *Proceedings of Thirtieth European Conference on Information Systems*. **https://aisel.aisnet.org/ecis2022_rip/32/**

De Vries, L., Gensler, S., and Leeflang, P. S. 2012. „Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing," *Journal of Interactive Marketing* (26:2), pp. 83-91. **https://doi.org/10.1016/j.intmar.2012.01.003**

Deng, F., and Jiang, X. 2023. "Effects of human versus virtual human influencers on the appearance anxiety of social media users," *Journal of Retailing and Consumer Services* (71), 103233. **https://doi.org/10.1016/j.jretconser.2022.103233**

Dolan, R., Conduit, J., Fahy, J., and Goodman, S. 2016. "Social media engagement behaviour: A uses and gratifications perspective," *Journal of Strategic Marketing* (24:3-4), pp. 261-277. **https://doi.org/10.1080/0965254X.2015.1095222**

Dolan, R., Conduit, J., Frethey-Bentham, C., Fahy, J., & Goodman, S. 2019. "Social media engagement behavior: A framework for engaging customers through social media content," *European Journal of Marketing* (53:10), pp.2213-2243. **https://doi.org/10.1108/EJM-03-2017-0182**

Feddema, K., Harrigan, P., Nekaris, K. A. I., and Maghrifani, D. 2020. "Consumer engagement behaviors in the online wildlife trade: Implications for conservationists," *Psychology & Marketing* (37:12), pp. 1755-1770. **https://doi.org/10.1002/mar.21423**

Franke, C., Groeppel-Klein, A., and Müller, K. 2022. „Consumers' Responses to Virtual Influencers as Advertising Endorsers: Novel and Effective or Uncanny and Deceiving?," *Journal of Advertising*, pp. 1-17. **https://doi.org/10.1080/00913367.2022.2154721**

Fowler, K., & Thomas, V. L. (2023). Influencer marketing: a scoping review and a look ahead. Journal of Marketing Management, 1-32. **https://doi.org/10.1080/0267257X.2022.2157038**

Google Cloud. 2023: https://cloud.google.com/vision?hl=de, Last Accessed May 2nd 2023

Hartmann, J., Heitmann, M., Schamp, C., and Netzer, O. 2021. „The power of brand selfies," *Journal of Marketing Research* (58:6), pp. 1159-1177. **https://doi.org/10.1177/00222437211037258**

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error," *Econometrica*, (47:1), pp. 153–161. **https://doi.org/10.2307/1912352**

Hofeditz, L., Nissen, A., Schütte, R., and Mirbabaie, M. 2022. „Trust Me, I'm an Influencer!-A Comparison of Perceived Trust in Human and Virtual Influencers," in *Proceedings of Thirtieth European Conference on Information Systems*. **https://aisel.aisnet.org/ecis2022_rip/27/**

Hudders, L., De Jans, S., & De Veirman, M. 2021. "The commercialization of social media stars: a literature review and conceptual framework on the strategic use of social media influencers," *International Journal of Advertising* (40:3), pp. 327-375. **https://doi.org/10.1080/02650487.2020.1836925**

Hughes, C., Swaminathan, V., and Brooks, G. 2019. "Driving brand engagement through online social influencers: An empirical investigation of sponsored blogging campaigns," *Journal of Marketing* (83:5), pp. 78-96. **https://doi.org/10.1177/0022242919854374**

Klostermann, J., Plumeyer, A., Böger, D., and Decker, R. 2018. "Extracting brand information from social networks: Integrating image, text, and social tagging data," *International Journal of Research in Marketing* (35:4), pp. 538-556. **https://doi.org/10.1016/j.ijresmar.2018.08.002**

Li, Y., and Xie, Y. 2020. "Is a picture worth a thousand words? An empirical study of image content and social media engagement," *Journal of Marketing Research* (57:1), pp. 1-19. **https://doi.org/10.1177/0022243719881113**

Liu, X., Shin, H., and Burns, A. C. 2021. "Examining the impact of luxury brand's social media marketing on customer engagement: Using big data analytics and natural language processing," *Journal of Business research* (125), pp. 815-826. **https://doi.org/10.1016/j.jbusres.2019.04.042**

Mallipeddi, R. R., Janakiraman, R., Kumar, S., and Gupta, S. 2021. "The effects of social media content created by human brands on engagement: Evidence from Indian general election 2014," *Information Systems Research* (32:1), pp. 212-237. **https://doi.org/10.1287/isre.2020.0961**

Meire, M., Hewett, K., Ballings, M., Kumar, V., amd Van den Poel, D. 2019. „The role of marketer-generated content in customer engagement marketing," *Journal of Marketing* (83:6), pp. 21-42. **https://doi.org/10.1177/0022242919873903**

Miao, F., Kozlenkova, I. V., Wang, H., Xie, T., and Palmatier, R. W. 2022. „An emerging theory of avatar marketing," *Journal of Marketing* (86:1), pp. 67-90. **https://doi.org/10.1177/0022242921996646**

Muntinga, D. G., Moorman, M., and Smit, E. G. 2011. "Introducing COBRAs: Exploring motivations for brand-related social media use," *International Journal of Advertising* (30:1), pp. 13-46. **https://doi.org/10.2501/IJA-30-1-013-046**

Nanne, A. J., Antheunis, M. L., Van Der Lee, C. G., Postma, E. O., Wubben, S., and Van Noort, G. 2020. „The use of computer vision to analyze brand-related user generated image content," *Journal of Interactive Marketing* (50:1), pp. 156-167. **https://doi.org/10.1016/j.intmar.2019.09.003**

Philp, M., Jacobson, J., and Pancer, E. 2022. "Predicting social media engagement with computer vision: An examination of food marketing on Instagram," *Journal of Business Research* (149), pp. 736-747. **https://doi.org/10.1016/j.jbusres.2022.05.078**

Sands, S., Ferraro, C., Demsar, V., and Chandler, G. 2022. "False idols: Unpacking the opportunities and challenges of falsity in the context of virtual influencers," *Business Horizons* (65:2), pp. 777-788. **https://doi.org/10.1016/j.bushor.2022.08.002**

Shrout, P. E., and Fleiss, J. L. 1979. "Intraclass correlations: uses in assessing rater reliability," *Psychological Bulletin*, (86:2), pp. 420. **https://doi.org/10.1037/0033-2909.86.2.420**

Stieglitz, S., and Dang-Xuan, L. 2013. „Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior," *Journal of Management Information Systems* (29:4), pp. 217-248. **https://doi.org/10.2753/MIS0742-1222290408**

Tellis, G. J., MacInnis, D. J., Tirunillai, S., and Zhang, Y. 2019. "What drives virality (sharing) of online digital content? The critical role of information, emotion, and brand prominence," *Journal of Marketing* (83:4), pp. 1-20. **https://doi.org/10.1177/0022242919841034**

Villarroel Ordenes, F., Grewal, D., Ludwig, S., Ruyter, K. D., Mahr, D., and Wetzels, M. 2019. "Cutting through content clutter: How speech and image acts drive consumer sharing of social media brand messages," *Journal of Consumer Research* (45:5), pp. 988-1012. **https://doi.org/10.1093/jcr/ucy032**

Virtual Human 2023, https://www.virtualhumans.org/, Last Accessed May 2nd 2023

Vrontis, D., Makrides, A., Christofi, M., and Thrassou, A. 2021. "Social media influencer marketing: A systematic review, integrative framework and future research agenda," *International Journal of Consumer Studies* (45:4), pp. 617-644. **https://doi.org/10.1111/ijcs.12647**

Wahid, R., Karjaluoto, H., Taiminen, K., and Asiati, D. I. 2023. "Becoming TikTok Famous: Strategies for Global Brands to Engage Consumers in an Emerging Market," *Journal of International Marketing*, (31:1), pp. 106-123. **https://doi.org/10.1177/1069031X221129554**

Wies, S., Bleier, A., & Edeling, A. (2023). Finding goldilocks influencers: How follower count drives social media engagement. Journal of Marketing, 87(3), 383-405. **https://doi.org/10.1177/00222429221125131**

View publication stats