The AI Penalty: Exploring User Perception and Engagement with AI-Generated Content on Instagram

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ABSTRACT
The rise of AI in social media has brought about various applications such as chatbots, filters, and virtual influencers. However, it remains unclear whether differences exist in the perception of AI-generated images and captions across different topics (*consumer and creator lifestyle*) and whether labeling such content as AI-generated impacts user responses. This study explores how AI-generated Instagram posts affect user engagement (liking, sharing, commenting) and perceptions of authenticity, credibility, creativity, and originality. We conducted an online questionnaire and analyzed the responses of 271 participants using multiple linear regressions and mediation analyses. The findings reveal expected results, such as AI-generated content, especially images, being perceived and interacted with more negatively than user-generated content. However, there were also unexpected outcomes, including the revelation that labeling AI-generated content does not significantly affect consumer responses. Surprisingly, in *consumer lifestyle content*, an AI-generated caption can lead to improved perceptions and greater engagement. We discuss these findings' practical implications and suggest future research directions.

KEYWORDS
influencer marketing, AI-generated content, user-generated content, social media engagement, labeling

TRACKS
Consumer Behavior, Digital Marketing

INTRODUCTION

AI-powered features such as chatbots, facial filters, and virtual influencers have become increasingly common on platforms like Instagram, Facebook, and TikTok, reshaping how content is produced, distributed, and consumed (Cao et al., 2023). As AI technology becomes more sophisticated, it not only augments human creativity but also generates new forms of content, from text-based captions to hyper-realistic images. Virtual influencers, such as human-like *@lilmiquela* (2.5 million followers on Instagram) and anime-like *@noonoouri* (485k followers on Instagram), are prime examples of AI-generated characters who have amassed millions of followers, challenging traditional perceptions of authenticity and engagement in social media marketing (Arsenyan & Mirowska, 2021).

Despite the widespread use of AI-generated content (AIGC), little is known about how users perceive these new forms of media compared to traditional user-generated content (UGC). Studies have begun to explore how AI influences user engagement, trust, and authenticity in online spaces (e.g., Brüns & Meißner, 2024; Kang & Lou, 2022), but the specific effects of AI-generated images and captions remain under-researched. For instance, while AIGC can enhance creativity and efficiency in marketing campaigns, there is an ongoing debate about whether such content diminishes the personal touch and authenticity consumers typically associate with human influencers (Li et al., 2023). Furthermore, the question of transparency has become critical: (mandatory) labels indicating AIGC can shape user perceptions, especially within the context of influencers. Influencers and their content on platforms like Instagram can broadly be categorized into two key themes: *consumer lifestyle* and *creator lifestyle*.

Consumer lifestyle influencers primarily focus on aspirational and hedonistic consumption (Hirschman & Holbrook, 1982). They showcase luxury or specialized products, services, and experiences, aiming to inspire followers to adopt similar lifestyles or purchase similar products. These influencers often act as intermediaries between brands and consumers, emphasizing the aspirational aspects of ownership and enjoyment. *Creator lifestyle influencers*, in contrast, use their platforms to exhibit expertise and creativity in fields like crafts, hobbies, or sports. They generate educational or skill-based content that resonates with followers seeking to learn, replicate, or engage in similar activities. This aligns with passionate authenticity (Audrezet et al., 2020), where influencers are intrinsically motivated to share their passions, emphasizing creativity over mere consumption.

Both types of influencers rely heavily on visual and textual content to engage audiences, and their use of AIGC in captions or images must align with their respective goals. For consumer lifestyle influencers, transparency in labeling AIGC helps maintain trust in promotional content, while for creator lifestyle influencers, labels emphasize the role of AI as a supportive, rather than substitutive, tool in the creative process. While some studies suggest that clear sponsorship labeling can positively influence perceptions of authenticity in influencer marketing (De Veirman & Hudders, 2020), this effect may vary for AIGC, depending on the influencer's category.

This study specifically aims to investigate this research gap in more detail by investigating the following research question: *What influence do combinations of AI (and/or user-) generated images and captions have on consumers' perception and engagement depending on the intention of the content (consumer vs. creator lifestyle influencers)?*

To answer the research question, we conducted an experiment using AI-generated mock-ups from existing content on Instagram. The experiment studies how labeling and context-specific use of AI affects consumer perception (authenticity, originality, creativity, and credibility) and engagement (like, comment, and share). Our results offer three contributions:

1. The study indicates that AI-generated images negatively impact perception and engagement, while AI-generated captions improve engagement, especially with likes. Strategic AI tools tailored to specific content categories can optimize results for companies and influencers.
2. The study emphasizes that context is decisive in how AIGC is perceived. For example, AI-generated images no longer negatively influence engagement in the *creator lifestyle category* (e.g., baking), while AI-generated captions have adverse effects. It suggests that the strategic use of AI must be tailored to the respective content category for desired results, offering valuable insights for influencers and brands.
3. Labeling AIGC does not significantly affect consumer perception or engagement. This finding may prompt companies to use AI tools more creatively without worrying about adverse reactions to labeling.

BACKGROUND and HYPOTHESES

AI-generated Content in Social Media

AI plays a significant role in various aspects of social media, including advertising (Du et al., 2023; Gupta et al., 2023), social bots (Ferrara et al., 2016; Liu, 2019), content creation (Chaisatitkul et al., 2024; Ho et al., 2022; Hua et al., 2024; Huang et al., 2018; Ramesh et al., 2022), and virtual influencer development (Thomas & Fowler, 2021). There are conflicting views on AIGC, with some suggesting it is often perceived as inauthentic and less likely to provoke interaction compared to UGC (Menczer et al., 2023; Mink et al., 2022), while others argue that human influencers may generate lower interaction rates and that AI influencers could build trust by portraying specific characteristics such as attractiveness, credibility, and congruences (Alboqami, 2023; Arsenyan & Mirowska, 2021). Virtual influencers are noted for their ability to evoke escapism through less emotionally demanding content, leading to increased audience interaction (Mirowska & Arsenyan, 2023). The uncanny valley concept is especially relevant to virtual influencers, describing the discomfort experienced when engaging with human-like technologies (Ciechanowski et al., 2019).

The advancing capabilities of Generative AI (Gen-AI) have made discerning between real and AI-generated photos increasingly difficult (Lu et al., 2023). The trustworthiness of AI-generated profiles and content is reduced compared to those created by humans (Mink et al., 2022). However, there are studies where AI-generated faces (GAN) are rated as more genuine than real ones (Tucciarelli et al., 2022). While Gen-AI facilitates content generation, it also has the potential to produce substandard or misleading content, potentially diminishing user engagement and undermining trust in the platform (Jakesch et al., 2019). Taken together, we hypothesize:

- ***Hypothesis 1a:*** *In contrast to user-generated images, AI-generated images reduce consumer content perception (authenticity, credibility, creativity, originality).*
- ***Hypothesis 1b:*** *In contrast to user-generated captions, AI-generated captions reduce consumer content perception.*
- ***Hypothesis 2:*** *The more positive the perception of the content, the higher the engagement.*
- ***Hypothesis 3a (mediation):*** *AI-generated images reduce perception and therefore the consumer's engagement.*
- ***Hypothesis 3b (mediation):*** *AI-generated captions reduce perception and therefore the consumer's engagement.*

Labeling of AI-generated Content

When followers are aware of the influencer's true nature—whether human or virtual—perceived differences can increase (Mirowska & Arsenyan, 2023); with virtual influencers clearly identified as AI, questions arise about whether other AIGC, like images or captions, must also be labeled. Research suggests that proper disclosure, especially for non-paid advertising partnerships, can positively impact perceptions of authenticity (De Veirman & Hudders, 2020). Numerous studies have examined the role of disclosure in influencer marketing, highlighting its effect on authenticity and engagement (Audrezet et al., 2020; Boerman et al., 2017; Evans et al., 2017; Kim & Kim, 2020). However, especially in connection with Gen-AI, Wittenberg et al. (2024) found that labeling AI-generated images can significantly reduce the likelihood of users engaging with misleading content. Furthermore, labeling AI-generated advertisements influences consumer behavior by enhancing psychological and behavioral engagement, with psychological engagement as a mediating factor (Du et al., 2023). However, labeling texts as AI-authored tends to reduce their perceived credibility—AI authorship lowers message and source credibility, anthropomorphism, and perceived intelligence (Lermann Henestrosa & Kimmerle, 2024). Hua et al. (2024) further explore the challenges of indexing AI-generated UGC, emphasizing concerns over authenticity and misinformation.

- ***Hypothesis 4:*** *Labeling AIGC (images and captions) increases consumer content perception and thus the engagement rate.*

Influence of Thematic Intentions

Most influencers group around two major themes: first, *consumer lifestyle*, i.e., consuming specialist or lavish products, services, or experiences, sharing these experiences with their followers; second, *creator lifestyle*, i.e., showing expertise for example, in crafts, hobbies, or sports, while educating their followers about it (Berger, 2024). The intention behind creating and sharing content differs (Berger, 2014), with practical utility significantly impacting online transmission (Berger & Iyengar, 2013). Prior studies emphasize the importance of online content's practical, interesting, and surprising value for encouraging engagement (Berger & Milkman, 2012; Rooderkerk & Pauwels, 2016). Surprising and interesting content spreads widely because people share it to entertain others. Similarly, useful and positive content is shared because it helps others, generates reciprocity, or boosts the sharer's reputation as knowledgeable or helpful (Berger & Milkman, 2012). For *consumer lifestyle influencers*, AIGC could be perceived as less genuine.

Conversely, AI-generated captions might enhance creativity and engagement in the creator lifestyle category, where educational value is critical, provided users know the content's AI origins. Social transmission goes beyond mere value exchange or self-presentation (Berger & Schwartz, 2011). Authenticity results from a perception that a person behaves according to his or her true self (Moulard et al., 2015). To spark perceptions of authenticity, influencers must demonstrate a genuine passion for a specific topic (Audrezet et al., 2020), such that their content and social media activities appear driven by their intrinsic motivations, not commercial goals (Leung et al., 2022). Here, we assume there is a link to consumer perceptions that *creator lifestyle content* (intrinsically motivated) leads to higher engagement than content that shows how the influencer consumes something (related to commercial purposes). Further, the informational value of *creator lifestyle content* is independent of its generation, whether AI-generated or human-generated. This information is mainly contained in the captions in generic posts with pictures and captions. As a result, we expect a detrimental AI effect to be category-specific and may not affect useful information by *creator lifestyle influencers* (e.g., workouts, recipes, how-to-dos). For this study, we expect:

- ***Hypothesis 5:*** *Category (consumer or creator lifestyle) moderates the effect of AIGC on perception (authenticity, originality, creativity, and credibility).*

The hypotheses developed are listed in the conceptual model including all variables (see *Figure 1*). To test these hypotheses, we conducted an experimental study in the context of social media content in *consumer lifestyle* and *creator lifestyle influencer* versions.

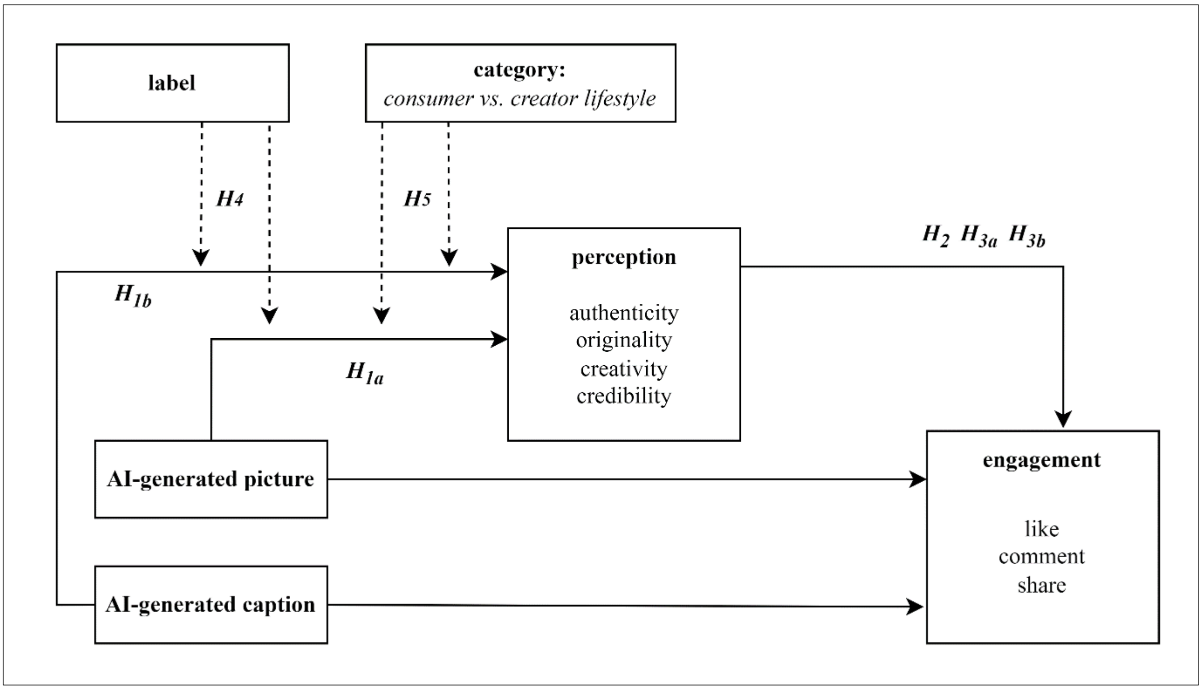

Figure 1: Conceptual Model

METHOD

Randomization of Stimuli

This study randomly assigned participants to one of seven groups for *consumer lifestyle influencer* and *creator lifestyle influencer*. They were randomized into both categories, one after the other. Each group viewed an AI-generated or user-generated picture paired with an AI-generated or user-generated caption. An additional label indicating that the content was AI-generated was applied (see *Table 1*).

Table 1: Randomized combination of AI and user-generated images and captions with and without labeling for the category's consumer vs. creator lifestyle (incl. dummy variables designation)

Group	Picture is …	Caption is …	Powered by …	*AI-generated picture*	*AI-generated caption*	*labeling AI*	*AI*
1	AI-generated	AI-generated		*1*	*1*	*0*	*1*
2	AI-generated	AI-generated	ChatGPT & getimg.ai	*1*	*1*	*1*	*1*
3	AI-generated	user-generated		*1*	*0*	*0*	*1*
4	AI-generated	user-generated	getimg.ai	*1*	*0*	*1*	*1*
5	user-generated	AI-generated		*0*	*1*	*0*	*1*
6	user-generated	AI-generated	ChatGPT	*0*	*1*	*1*	*1*
7	user-generated	user-generated		*0*	*0*	*0*	*0*

Characterization of the Stimuli

Influencers were chosen according to several criteria, including follower count, perceived accessibility, authenticity, expertise, and cultural contribution (Campbell & Farrell, 2020). As a result, macro-influencers (100k to 1 million followers) were selected. For the *consumer* *lifestyle category*, Justine Schluetter (*@justineschlue*), with 240k followers, was chosen, and for the *creator lifestyle category*, the account *@einfachbacken*, with 502k followers. Using the online tool Media Modifier (for carousel posts), two images of a post by the influencer were recreated with the help of AI for the *consumer lifestyle content* (see *Appendix A*), and three images of the second account for the *creator lifestyle content* (see *Appendix B*), with adjustments made to the like counts ("liked by others") and the comment section ("view all comments"). Efforts were made to closely match the color schemes, mood, tone, and length of the AI-generated posts with those of the UGC. Additionally, AI-generated profile names were created for both accounts using ChatGPT. The following *Figure 2* shows the AI-generated contributions of the two accounts, whereby a single-person image with a simple outfit and brief description (including hashtags) was selected and recreated for the *consumer lifestyle category* (account: *@juliemueller*) and a simple strawberry cake recipe (listing the ingredients, step-by-step instructions including hashtags and emojis) for the *creator lifestyle category* (account: *@leckerschlemmen*).

Figure 2: Example image (first image of the AI-generated carousel post) for both accounts

Variables

Table 2 lists all variables used for the analysis with corresponding items from the questionnaire or specific composition.

Table 2: Overview of variables and questions

<table>
<tr><th rowspan="2">Variables</th><th>Items</th><th>Scales</th><th>Factor Analysis (if necessary)</th></tr>
<tr><th colspan="3">alternatively: Creation of the Variables</th></tr>
<tr><td colspan="4"><u>Dependent Variables</u></td></tr>
<tr><td>like</td><td>How likely is it that you would like this post?</td><td rowspan="3">1: very unlikely to 5: very likely</td><td rowspan="3">new factor-variable: consumer engagement
factor loadings:
- share (0.753)
- comment (0.615)
- like (0.505)
Cronbach's α: 0.633</td></tr>
<tr><td>comment</td><td>How likely is it that you would comment on this post?</td></tr>
<tr><td>share</td><td>How likely is it that you would share this post?</td></tr>
<tr><td colspan="4"><u>Independent Variables</u></td></tr>
<tr><td>AI-generated picture</td><td colspan="3">dummy variable with 0 = user-generated picture and 1 = AI-generated picture</td></tr>
<tr><td>AI-generated caption</td><td colspan="3">dummy variable with 0 = user-generated caption and 1 = AI-generated caption</td></tr>
<tr><td>AI</td><td colspan="3">dummy variable with 0 = no AI-generated content at all and 1 = AI-generated content (picture or caption) → (n: 0 = 75 and 1 = 454)</td></tr>
<tr><td colspan="4"><u>Moderating Variables</u></td></tr>
<tr><td>category</td><td colspan="3">dummy variable with 0 = consumer lifestyle content and 1 = creator lifestyle content</td></tr>
</table>

<table>
<tr><td>labeling AI</td><td colspan="4">dummy variable with 0=no labeling and 1=labeling
- for AI-generated picture: “powered by getimg.ai”
- for AI-generated caption: “powered by ChatGPT”</td></tr>
<tr><td colspan="5"><u>Mediating Variables</u></td></tr>
<tr><td>authenticity</td><td>authenticity (real, according to the facts)</td><td rowspan="4">1: not applicable to 5: applicable</td><td rowspan="4">consumer perception factor loadings:
- authenticity (0.844)
- originality (0.676)
- creativity (0.649)
- credibility (0.823)

Cronbach’s α: 0.836</td><td rowspan="4">limited perception factor loadings:
- authenticity (0.885)
- credibility (0.885)

Cronbach’s α: 0.879</td></tr>
<tr><td>originality</td><td>originality (original, unique in its kind)</td></tr>
<tr><td>creativity</td><td>creativity (creative, having ideas and realizing them creatively)</td></tr>
<tr><td>credibility</td><td>credibility (true, appearing reliable)</td></tr>
<tr><td colspan="5"><u>Control Variables</u></td></tr>
<tr><td>gender</td><td colspan="4">dummy variable with 0 = female and 1 = male</td></tr>
<tr><td>age</td><td>How old are you?</td><td colspan="3">with open input field</td></tr>
<tr><td>experience in content creation</td><td>How would you rate your experience in creating and publishing content on social media?</td><td colspan="3">1: not experienced to 4: very experienced</td></tr>
</table>

Structure of the Questionnaire

The questionnaire comprised 17 questions in total. The first five questions focused on participants' social media usage, including *experience in content creation*, frequently used platforms, daily usage time, and preferred content categories. These questions offered predefined response options, with some allowing open-ended inputs, and were used to describe the sample and generate initial interest. Questions 6 to 13 formed the survey's core, assessing the likelihood of interacting with the content (liking, commenting, sharing; *dependent engagement variables*) and participants' evaluation of common characteristics (authenticity, originality, creativity, credibility; *perception variables*). Definitions of these measured variables were provided to ensure participants' understanding. Finally, socio-demographic data, including gender, age, marital status, and educational background, were collected.

Description of the Sample and Data Correction

The survey was conducted in September 2023 by contacting German university students and their direct environment. After data correction, 271 data sets remained from the 300 completed questionnaires. Due to the separate consideration of the category’s *consumer and creator lifestyle influencer*, each of the 271 participants can provide two data points, which produces a final data set of n = 542. As expected from a sample consisting primarily of students, the mean age was 22.5 years (SD_{Age} = 4.58), with 94% identifying as female (additional analyses in *Appendix C*). All subsequent analyses were conducted using the JASP software.

FINDINGS

To test the hypotheses, we conducted several analyses. These show that AI-generated images negatively impact perception *(supporting H1a)* and engagement. In contrast, AI-generated captions positively influence engagement (especially likes) but have no significant influence on consumer perception *(rejecting H1b)*. The multiple regression also shows a positive influence for the general influence of higher perception on engagement *(supporting H2)* – but only for authenticity, creativity, and credibility (see *Table 3*).

Table 3: Multiple regression analyses

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent Variable	*like*	*like*	*consumer engagement*	*consumer engagement*	*consumer perception*	*credibility*
Independent Variables						
(intercept)	***3.049 **** (0.318)	***0.942 **** (0.155)	***0.354 *** (0.126)	***1.485 **** (0.127)	***3.212 **** (0.180)	***3.183 **** (0.223)
AI-generated picture	***-0.325 *** (0.159)			***-0.191 ** (0.102)	***-0.500 **** (0.102)	***-0.416 **** (0.127)
AI-generated caption	***0.368 *** (0.159)			0.114 (0.102)	0.111 (0.103)	0.192 (0.127)
labeling AI	0.163 (0.245)			0.033 (0.157)	-0.037 (0.158)	-0.040 (0.196)
category (creator = 1)	***0.901 **** (0.197)			***0.722 **** (0.126)	***1.120 **** (0.127)	***1.477 **** (0.157)
picture x label	-0.153 (0.218)			0.060 (0.140)	0.005 (0.141)	-0.055 (0.175)
caption x label	-0.191 (0.220)			-0.124 (0.141)	-0.096 (0.142)	-0.027 (0.176)
picture x category	0.308 (0.196)			0.058 (0.126)	***0.338 *** (0.126)	***0.454 *** (0.157)
caption x category	***-0.459 *** (0.197)			-0.068 (0.126)	-0.203 (0.127)	***-0.278 ** (0.158)
authenticity		***0.206 **** (0.062)	***0.131 *** (0.040)			
originality		0.063 (0.051)	0.025 (0.033)			
creativity		***0.206 **** (0.051)	***0.202 **** (0.033)			
credibility		***0.184 *** (0.061)	***0.105 *** (0.039)			
Controls						
Age	***-0.031 *** (0.011)				***-0.016 *** (0.007)	***-0.014 ** (0.008)
experience in content creation	***0.160 *** (0.066)		***0.125 *** (0.039)	***0.151 **** (0.042)		
Summary						
Adjusted R^2	0.145	0.276	0.321	0.211	0.428	0.445
F(df)	10.188(10)	52.445(4)	52.072(5)	17.072(9)	45.977(9)	49.266(9)
n	541	541	541	541	541	541

*Note: *p ≤ 0.1, **p ≤ 0.05, ***p < .001, standard errors in brackets, significant results (p ≤ 0.1) marked in bold.*

Mediation analyses were carried out for the other hypotheses (see *Table 4*), showing the interactions between the variables (mediations and moderations).

Table 4: Mediation analysis with consumer perception as mediator and consumer engagement as dependent variable

Effects	Estimate	Standard Errors	Lower 95% CI	Upper 95% CI
Model 1 – *mediator: consumer perception and dependent variable: consumer engagement*				
Indirect Effects				
AI-generated picture → perception → engagement	***-0.188 ****	***0.043***	***-0.273***	***-0.103***
AI-generated caption → perception → engagement	0.044	0.039	-0.033	0.120
labeling AI → perception → engagement	-0.021	0.060	-0.138	0.097
category (creator = 1) → perception → engagement	0.430	0.066	0.301	0.559
picture x label → perception → engagement	0.002	0.053	-0.103	0.106

caption x label → perception → engagement	-0.029	0.054	-0.135	0.077
picture x category → perception → engagement	***0.125 *****	***0.050***	***0.028***	***0.223***
caption x category → perception → engagement	-0.080	0.049	-0.176	0.016
Direct Effects				
AI-generated picture → engagement	0.002	0.096	-0.187	0.191
AI-generated caption → engagement	0.068	0.095	-0.118	0.254
labeling AI → engagement	0.052	0.145	-0.233	0.336
category (creator = 1) → engagement	***0.292 *****	***0.125***	***0.046***	***0.537***
picture x label → engagement	0.057	0.130	-0.197	0.311
caption x label → engagement	-0.106	0.131	-0.363	0.150
picture x category → engagement	-0.079	0.117	-0.309	0.151
caption x category → engagement	0.025	0.117	-0.206	0.255
Total Effects				
AI-generated picture → engagement	***-0.186 ****	***0.102***	***-0.386***	***0.014***
AI-generated caption → engagement	0.111	0.102	-0.089	0.312
labeling AI → engagement	0.031	0.157	-0.277	0.339
category (creator = 1) → engagement	***0.721 ******	***0.126***	***0.474***	***0.969***
picture x label → engagement	0.059	0.140	-0.216	0.333
caption x label → engagement	-0.136	0.141	-0.413	0.142
picture x category → engagement	0.046	0.126	-0.200	0.293
caption x category → engagement	-0.055	0.127	-0.303	-0.193

*Note: *p ≤ 0.1, **p ≤ 0.05, ***p <.001, significant results (p < 0.1) marked in bold.*

The mediation analysis of the influence of AI-generated images on perception and engagement shows a significant negative indirect and total effect *(supporting H3a)*. However, this mediation cannot be confirmed for the AI-generated captions *(rejecting H3b)*. Here, a significant positive direct and total effect can only be seen in the modified variables, such as authenticity and credibility as mediators and likes as dependent variables (see *Appendix D*). Surprisingly, labeling AI generation does not affect consumer perception or engagement *(rejecting H4)*, which could not confirm previous findings (Du et al., 2023; Lermann Henestrosa & Kimmerle, 2024). These results may be influenced by the young sample of university students accustomed to using AI tools and being surrounded by AIGC.

However, there is an exciting correlation for *Hypothesis 5*, which we also tested with the mediation analysis. This shows that AI-generated images in the context of *creator lifestyle* images (baking cakes) have a significantly positive indirect mediation effect on perception and engagement. This relationship becomes more apparent in the second mediation model (see *Appendix D*), which shows that AI-generated images in the *creator lifestyle content* have a positive indirect effect via perception (authenticity and credibility) on engagement (likes). However, in the context of *creator lifestyle,* AI-generated captions have a significantly negative (direct, indirect, and total) effect via the perception on likes *(supporting H5)*. In *Figure 3*, this moderating effect of the category (*consumer vs. creator lifestyle*) also becomes clear again: the AI-generated images reduce perception and engagement for both topics. The situation is different for the AI-generated captions, where the AI-generated variant leads to higher values in perception and engagement, particularly in the *consumer lifestyle content category*. This may suggest that followers in this context prioritize the visual appeal or functional aspects of the products over the personal connection typically associated with human influencers. This implies that leveraging AI to craft captions can enhance engagement and positive perceptions for influencers and brands in the *consumer lifestyle* (products, services). AI tools can optimize captions to resonate more effectively with target audiences, utilizing trends, sentiment analysis, and personalized language to increase relatability and emotional connection. Influencers, especially in the *creator lifestyle* category, could use AI-generated captions to enhance content while maintaining human involvement in image creation. This blend ensures the creative touch remains authentic, while AI optimizes the messaging for better engagement. This suggests that content focused on crafts, hobbies, or sports might depend more heavily on authenticity and personal engagement, which AI-generated captions might disrupt.

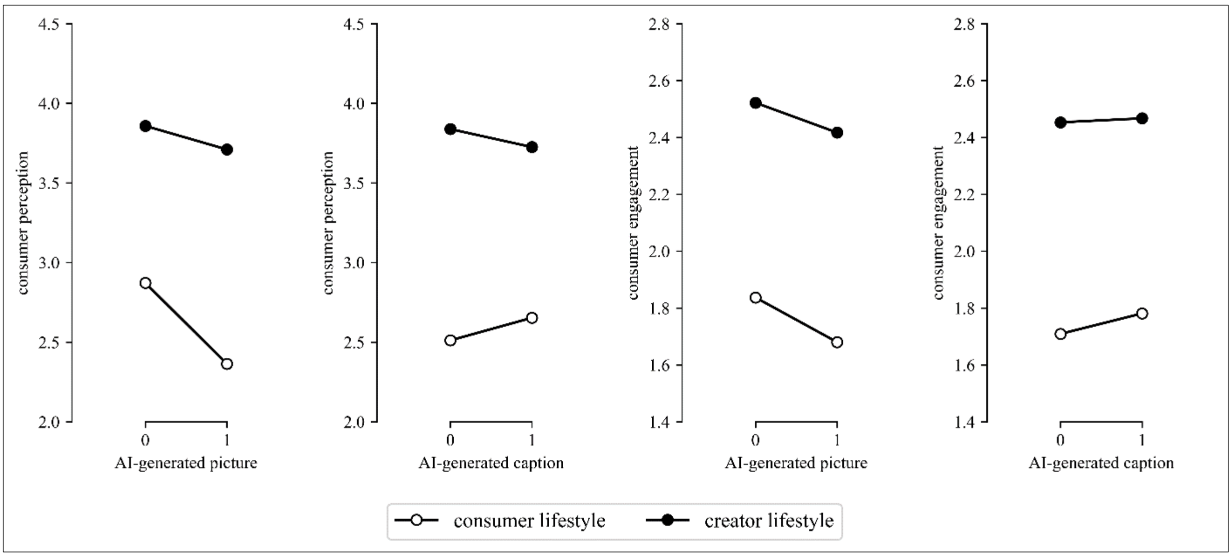

Figure 3: Correlation of AI-generated images and captions with the category's 'consumer lifestyle influencer and 'creator' on perception and engagement

DISCUSSION

This study can support previous findings (e.g., Menczer et al., 2023; Mink et al., 2022) on the negative perception of AIGC by focusing on images and captions. In addition, the findings of previous researchers on the importance of labeling in the advertising sector (e.g., De Veirman & Hudders, 2020) and AIGC (e.g., Wittenberg et al., 2024) were not confirmed. However, there is a correlation in the possible use of AI depending on the content of a social media post – it was shown that while AI-generated images have a negative effect for both categories analyzed here, this negative effect on the perception and engagement of followers is less pronounced in the *consumer lifestyle category.* Furthermore, text captions can be AI-generated and even positively affect select metrics (likes). However, what also emerges from this is the practical implication that content that relates to the creative process (*creator lifestyle influencers*) and, thus, the intrinsic motivation and creativity of the influencers may show a more negative impact on perception and engagement when using AI. Even if the use of AI, in principle, creates opportunities to generate cost-effectiveness and scalability from a brand perspective through virtual customer service, use as a brand ambassador in social media, or the utilization of higher interaction for the effective distribution of content (Sands et al., 2022), the content of the posts (*consumer vs. creator*) should be considered, particularly in UGC. There is a need for further research into the specifics of the topics analyzed, while our study is limited in the tested setup to only two categories (*consumer and creator lifestyle content*). The content and quality of postings have a significant influence on perception and engagement (Li & Xie, 2020), which could also be reflected in the categories. This also offers further opportunity to focus the caption on informational and emotional aspects (e.g., Berger, 2024; Berger & Schwartz, 2011). Further limitations exist in terms of age, gender, professional background, and our study design. This study relies on self-reported data, which may not accurately reflect real-world behavior due to the intention-behavior gap in survey research. Future research should use real-life engagement metrics to validate our findings. Collaborating with influencers or brands to analyze engagement data, like likes and comments, or conducting experiments with controlled Instagram accounts could provide deeper insights into user behavior. These methods would improve the study's external validity and offer actionable recommendations.

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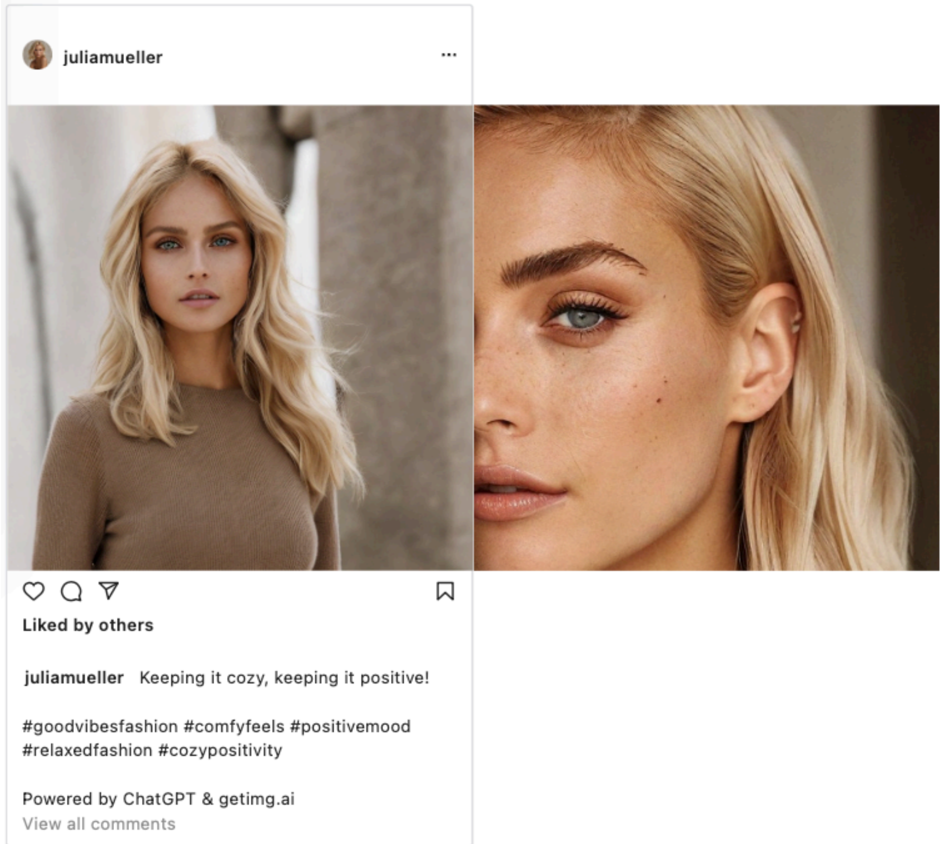
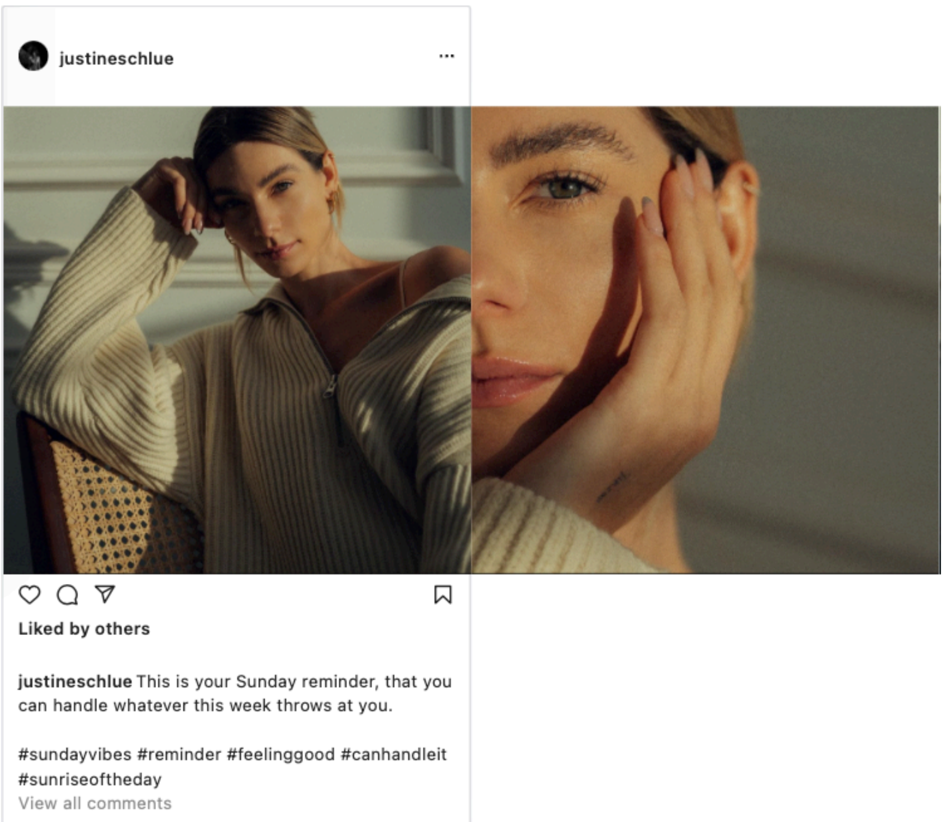
APPENDIX

Appendix A – Stimuli Consumer Lifestyle Influencer (the former AIGC and the latter UGC)





Appendix B – Stimuli Creator Lifestyle Influencer (the former AIGC and the latter UGC)

leckerschlemmen

Liked by others

leckerschlemmen 🍓🍰 Erdbeer Blechkuchen mit Sahne 🥛🍓

Zutaten:
300 g Mehl
200 g Zucker
200 g Butter
4 Eier
1 Päckchen Vanillezucker
1 Päckchen Backpulver
Frische Erdbeeren (zum Garnieren)
Frische Sahne (zum Garnieren)
Puderzucker (zum Bestäuben)

Schritt-für-Schritt-Anleitung:
1️⃣ Ofen auf 180°C vorheizen.
2️⃣ In einer Schüssel Mehl, Zucker, Butter, Eier, Vanillezucker und Backpulver zu einem Teig verkneten.
3️⃣ Den Teig auf einem Backblech ausrollen und glatt streichen.
4️⃣ Den Kuchen für ca. 30 Minuten im vorgeheizten Ofen backen, bis er goldbraun ist.
5️⃣ Nach dem Abkühlen den Kuchen großzügig mit frischer Sahne und frischen Erdbeeren toppen.
6️⃣ Zum Schluss mit Puderzucker bestäuben und servieren.
Jetzt wird es lecker und fruchtig! 😋🍓🍰

#ErdbeerBlechkuchen #SahneTopping #FruchtigerGenuss #Sommerkuchen #Kuchenträume #BackenMitLiebe #Kaffeeklatsch

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einfachbacken ···

Liked by others

einfachbacken Erdbeerkuchen vom Blech mit Schmand! 🍓
Mit Rezept 📌
Erdbeerkuchen vom Blech mit Schmand lieben wir schon seit unserer Kindheit. 😍 Der Boden wird mit Schmandcreme bestrichen und mit süßen Erdbeeren belegt. 😋 So schön saftig! ❤️

ZUTATEN FÜR DEN BELAG
1 Pck. Vanillepuddingpulver
60 g Zucker
450 ml Milch
600 g Schmand
2 Pck. Sahnesteif
1.500 g Erdbeeren
2 Pck. Tortenguss
50 g Zucker
450 ml Wasser

FÜR DEN TEIG
250 g weiche Butter
220 g Zucker
2 Prisen Salz
4 Eier (Gr. M)
300 g Weizenmehl (Type 405)
3 TL Backpulver
50 ml Milch
Etwas Fett für das Blech

ZUBEREITUNG
1. Schritt
Den Ofen auf 180 Grad Ober-/Unterhitze (Umluft: 160 Grad) vorheizen. Ein Backblech (ca. 38 x 45 cm) fetten. Für den Belag Puddingpulver mit Zucker und 4–5 EL der Milch glattrühren. Restliche Milch aufkochen, Puddingmischung zugeben und unter Rühren ca. 1 Minute köcheln lassen. In eine Rührschüssel umfüllen, mit Frischhaltefolie abdecken und etwas abkühlen lassen.

2. Schritt
Für den Teig die Butter mit Zucker und Salz mit den Schneebesen eines Handrührgerätes auf höchster Stufe schaumig schlagen. Eier nach und nach zugeben und auf höchster Stufe weiterrühren. Das Mehl mit dem Backpulver mischen und abwechselnd mit der Milch unter den Teig rühren. Teig auf das vorbereitete Blech geben und glattstreichen. Im vorgeheizten Backofen ca. 20 Minuten backen.Komplett erkalten lassen.

3. Schritt
Den noch lauwarmen Pudding kurz glattrühren, dann Schmand und Sahnesteif unterrühren. Die Pudding-Schmand-Creme gleichmäßig auf dem erkalteten Boden verstreichen. Kuchen mindestens 1 Stunde im Kühlschrank kühlen.

#einfachbacken #erdbeerkuchen #erdbeeren #blechkuchen#schmand #creme #klassiker
View all comments

Appendix C – Additional data overview

	like	**comment**	**share**	**consumer engagement** like, comment, share	**authenticity**	**originality**	**creativity**	**credibility**	**consumer perception** authenticity, originality, creativity, credibility
AI-generated picture									
mean (0)	***3.197***	1.437	1.874	2.168	***3.563***	***2.887***	***3.261***	***3.592***	***3.349***
mean (1)	***2.990***	1.382	1.809	2.058	***3.184***	***2.602***	***2.921***	***3.408***	***3.054***
p	***0.047 *****	0.411	0.510	0.116	***<.001 ******	***0.004 *****	***<.001 ******	***0.075 ****	***<.001 ******
AI-generated caption									
mean (0)	3.018	1.379	1.868	2.086	3.352	2.758	3.070	3.458	3.183
mean (1)	3.127	1.425	1.816	2.121	3.349	2.705	3.070	3.511	3.184
p	0.297	0.492	0.599	0.617	0.975	0.593	0.995	0.611	0.995
labeling AI									
mean (0)	3.114	1.399	1.834	2.115	3.416	***2.802***	3.117	3.526	3.240
mean (1)	3.038	1.415	1.842	2.095	3.265	***2.628***	3.009	3.440	3.109
p	0.472	0.822	0.940	0.774	0.144	***0.078 ****	0.261	0.408	0.113
AI									
mean (0)	3.013	1.338	1.922	2.087	3.545	2.870	3.234	3.519	3.316
mean (1)	3.092	1.417	1.824	2.109	3.318	2.703	3.043	3.484	3.162
p	0.592	0.406	0.481	0.821	0.121	0.233	0.163	0.809	0.188
category (creator = 1)									
mean (0)	***2.683***	***1.299***	***1.280***	***1.751***	***2.613***	***2.303***	***2.661***	***2.708***	***2.594***
mean (1)	***3.480***	***1.513***	***2.395***	***2.461***	***4.089***	***3.151***	***3.480***	***4.269***	***3.773***
p	***<.001 ******	***0.001 *****	***<.001 ******	***<.001 ******	***<.001 ******	***<.001 ******	***<.001 ******	***<.001 ******	***<.001 ******
Gender									
mean (0)	3.092	***1.382***	1.829	2.100	3.335	2.739	3.084	3.478	3.184
mean (1)	2.906	***1.781***	1.969	2.212	3.594	2.531	2.844	3.656	3.175
p	0.397	***0.005 *****	0.501	0.441	0.233	0.316	0.235	0.415	0.958
general									
	3.081	1.406	1.838	2.106	3.351	2.727	3.070	3.489	3.184

*Note: *p≤0.1, **p≤0.05, ***p<.001, significant t-test results marked in bold (p≤0.1)*

Appendix D

Effects	Estimate	Standard Errors	Lower 95% CI	Upper 95% CI
Model 2 – *mediator: limited perception and dependent variable: like*				
Indirect Effects				
AI-generated picture → limited perception → like	***-0.285 ******	***0.066***	***-0.415***	***-0.155***
AI-generated caption → limited perception → like	0.088	0.059	-0.029	0.204
labeling AI → limited perception → like	-0.043	0.090	-0.220	0.134
category (creator = 1) → limited perception → like	***0.734 ******	***0.108***	***0.522***	***0.945***
picture x label → limited perception → like	0.006	0.080	-0.151	0.164
caption x label → limited perception → like	-0.021	0.081	-0.180	0.138
picture x category → limited perception → like	***0.242 *****	***0.077***	***0.092***	***0.393***
caption x category → limited perception → like	***-0.146 *****	***0.074***	***-0.292***	***$-3.347x10^{-4}$***
Direct Effects				
AI-generated picture → like	-0.022	0.151	-0.319	0.275
AI-generated caption → like	***0.283 ****	***0.149***	***-0.009***	***0.576***
labeling AI → like	0.171	0.229	-0.277	0.619
category (creator = 1) → like	0.184	0.200	-0.209	0.577
picture x label → like	-0.162	0.204	-0.561	0.238
caption x label → like	-0.146	0.206	-0.549	0.257
picture x category → like	0.036	0.185	-0.327	0.398
caption x category → like	***-0.311 ****	***0.185***	***-0.674***	***0.051***
Total Effects				
AI-generated picture → like	***-0.307 ****	***0.159***	***-0.619***	***0.005***
AI-generated caption → like	***0.371 *****	***0.160***	***0.057***	***0.685***
labeling AI → like	0.128	0.246	-0.353	0.610
category (creator = 1) → like	***0.918 ******	***0.198***	***0.530***	***1.305***
picture x label → like	-0.155	0.219	-0.585	0.274
caption x label → like	-0.166	0.221	-0.599	0.267
picture x category → like	0.278	0.197	-0.107	0.664
caption x category → like	***-0.457 *****	***0.198***	***-0.846***	***-0.069***

*Note: *p≤0.1, **p≤0.05, ***p<.001, significant t-test results marked in bold (p≤0.1)*