The Impact of Background Complexity on Social Media Engagement and Purchase Intentions: The Role of Influencer Type and Sponsorship Disclosure

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Abstract

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Yichen Han

As social media continues to play an increasingly prominent role in people's daily lives, numerous brands leverage sponsored content on these platforms to garner attention and attract potential consumers. In this research, I focus on understanding how the background complexity of images used in social media posts can influence both social media engagement and purchase intentions. In a first study, I investigate the potential moderating role of influencer type on the impact of background complexity on social media engagement, as well as purchase intentions. In a second study, I analyze whether sponsorship disclosure plays a moderating role in this interaction. The findings revealed that background complexity did not significantly impact social media engagement or purchase intentions. Furthermore, influencer type and sponsorship disclosure did not have a significant influence on these outcomes. Despite this, my research still offers valuable insights and avenues for future research. Specifically, this research suggests various practical implications for brands and marketers when crafting sponsored content for social media platforms. It also sheds a light on the roles of background complexity, influencer type, and sponsorship disclosure in shaping individuals' social media engagement and purchase intentions.

Key words: image background complexity, social media engagement, purchase intentions, influencer, sponsorship, disclosure

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Introduction

Imagine that you are scrolling through your Instagram feed and stumble upon a post by an influencer named "foodhunter." In this post, foodhunter is endorsing a new restaurant. The image in the post features a salad placed on a table with a simple background. Based on the image alone, how likely are you to leave a like and comment on the post? How likely are you to consider dining at this restaurant? Now, suppose that instead of a simple background, the table is decorated with flowers and candles. Would this change your likelihood of liking and commenting, or even going to the restaurant? Would foodhunter's popularity affect your decision? Would your intentions change depending on whether the post was sponsored or not? These questions are important for brands, business owners, and marketers. Understanding consumers' thoughts and feelings allows them to design content posted on social media platforms more effectively, attracting more attention.

With the development of science and technology, traditional media such as newspapers, TV, radio, and magazines are no longer the mainstream channels for people to obtain information (Mangold & Faulds, 2009). The popularity of mobile phones and the Internet has promoted the popularity of social media (Kaplan, 2012). Nowadays, many people use social media to share their lives, such as scenery, pets, photos of themselves, and even food. According to Stacy Jo Dixon (2024), 3,049 million people are using Facebook, 2,491 million of people are using YouTube, and 2,000 million people are using Instagram. As a result, an increasing amount of research has been conducted on understanding the impact of social media on consumers.

Many previous studies have explored social media engagement in relation to various aspects of social media content, including visual elements such as color, layout, and design of social media posts, as well as the richness of social media (Cao et al., 2020; Bazi et al., 2023; Dolan et al., 2019). While image content in posts has also been discussed, researchers have mainly focused on image characteristics such as color, image quality, and image source (Li & Xie, 2019). Another important visual element, visual complexity, has been shown to influence people's emotions and feelings, although previous findings are inconsistent. Some studies have found that individuals are more drawn to complex images, while others have found a preference for simpler ones (Deng & Poole, 2010; Garner, 1974). Different from visual complexity, image background complexity refers to the complexity of the environmental factors surrounding the focal product. It is also a crucial factor influencing the perception of the focal product. Therefore, when the background complexity of an image is high, it can distract from the focal product (Wang et al., 2020). These earlier studies primarily focus on the overall complexity of the image. However, it just as important to consider how the complexity of the background of such images affects people's emotions and attitudes.

When discussing social media marketing, influencers also play a significant role. Today, influencers have cultivated large followings on social media platforms such as Instagram, YouTube, Twitter, and TikTok (Campbell & Grimm, 2018). Followers trust influencers' recommendations and often engage with or purchase the products they endorse (Djafarova & Rushworth, 2017). It is important to note that researchers categorize influencers into five types based on their follower count: nano-influencers, micro-influencers, macro-influencers, mega-influencers, and celebrity influencers (Campbell & Farrell, 2020). In this article, however, I will primarily focus on two types of influencers: micro-influencers and macro-influencers.

Finally, how sponsorship disclosure affects consumer behaviour on social media is also important to study. For example, as a popular platform for social media advertising, Instagram imposes strict restrictions and supervision on advertisements posted by brands, advertisers, and influencers. In 2017, Instagram introduced the "Paid partnership with" tag, placed below the influencer's name, to enhance transparency in advertising (Instagram, 2017). However, to comply with FTC policies, additional hashtags such as #ad, #sponsored, #sponsoredpost, and #workingwith are recommended (Martens & Wheat, 2017). Despite these efforts, some problems have emerged. According to previous literature, some researchers argue that such hashtags may cause influencers to lose credibility (De Veirman & Hudders, 2020). On the other hand, others believe that these hashtags demonstrate the honesty of the influencer, thereby enhancing consumers' favorable impressions of them (Dhanesh & Duthler, 2019; Lou et al., 2019).

Given the importance of background complexity, influencer type, and sponsorship disclosure in shaping consumer behaviours, I propose the following research questions: Does the image background complexity and influencer type affect social media engagement and purchase intentions? Does the effect of background complexity on social media engagement and purchase intentions depend on influencer type? And does sponsorship disclosure interact with image background complexity and influencer type to affect social media engagement and purchase intentions?

This thesis will begin with a review of prior literature on social media engagement and purchase intentions. Additionally, the study will explore literature on image background complexity, focusing on the distinction between high and low background complexity and their impact on consumer social media engagement and purchase intentions. Subsequently, the literature review will cover influencer marketing, influencer types, and influencer credibility, examining how influencer types may moderate the relationship between image background complexity and consumer social media engagement and purchase intentions. Furthermore, the review will address literature on disclosure and how it may moderate the interaction effect between image background complexity and influencer type. Drawing from these literature findings, this thesis proposes four hypotheses to be tested through two experiments. Lastly, the thesis will conclude with a discussion of the results and their implications for marketers and researchers, along with highlighting future research directions and limitations.

Theoretical Background

Social Media Engagement

With the advent and rise of social media platforms, the way consumers interact with each other and with brands is no longer passive (Dolan et al., 2019; Malthouse et al., 2013). Previous research defines engagement as a construct that varies according to topic (who: for example, customers and consumers), focal object (what: for example, brand, product, and advertising), and context (place: for example, retail, service, and online); Brodie et al., 2011; Brodie et al., 2013; Ferreira et al., 2020; Hollebeek, 2011a; Jaakkola & Alexander, 2014; Muntinga et al., 2011; Vivek et al., 2014. Some researchers also define engagement as a psychological process which promotes brand loyalty (Bowden, 2009). Its main characteristics include emotional, cognitive, and behavioural interaction with the brand (Brodie et al., 2011). As for social media engagement, according to Cao et al. (2020), it refers to consumers' active participation in marketing content on social media platforms such as Facebook and YouTube. Therefore, for social media engagement, measurement indicators include two categories: the first is a direct reply to the original post, including likes, comments, and favorites. The second type is sharing the original post (Li & Xie, 2019). These activities can promote participation and interaction with other members on the platform, as reported by Kumar et al. (2016). However, the driving factors of these two types of approaches are quite different (Buechel & Berger, 2017). Sharing is more public, and all followers of the sharer can see the shared content. Compared with sharing, likes are more private and directional because it directly affirms the posted content but does not spread the content (Li & Xie, 2019). The difference between the two results in different levels of participation. Obviously compared to sharing and commenting, likes are the most basic form of participation (Malthouse et al., 2013).

Extensive research on word-of-mouth (WOM) indicates that various factors influence user engagement online. Berger (2014) conducted a comprehensive review of behavioural drivers in online word-of-mouth, highlighting two prominent factors: the inclination toward self-enhancement and the motivation to provide valuable information. Individuals aim to shape others' perceptions of them through their online expressions (Chung & Darke 2006), and they are more likely to share useful information to project intelligence and helpfulness (Berger and Milkman 2012). The content and manner of expression also play a crucial role in influencing user engagement on social media.

Purchase Intentions

Recent research by Kang et al. (2020) found that visual complexity affects consumers' pleasure and excitement, thereby influencing their purchase intentions. Prior research suggests that higher visual complexity attracts people's attention more, increasing the likelihood that they will stop and watch the advertisement (Geissler et al., 2006; Lavie & Tractinsky, 2004; Nadkarni & Gupta, 2007). And more interesting, research has shown that information provided in the background can also help consumers understand and identify the focal product more easily, thereby increasing their purchase intentions (King et al., 2019; Orquin & Loose, 2013; Orquin et al., 2018). Wu et al. (2016) also found that complex designs can provide rich information, thereby improving consumers' evaluation of product quality. This type of information can induce pleasure in consumers, thereby increasing their purchase intentions (Ha & Lennon, 2010; Huang et al., 2017; Guido et al., 2017; Kusumasondjaja & Tjiptono, 2019; Wang et al., 2017). However, overly complex designs may impede consumers' ability to grasp the focus and distract them from the information and brand, reducing their purchase intentions (Pieters et al., 2010; Pracejus et al., 2013; Reber et al., 1998; Wong et al., 2015).

Visual Complexity

Attneave (1954) and Donderi (2006) proposed the visual complexity theory, asserting that images often contain redundant concepts. More specifically, they found that images are more complex when they exhibit lower levels of redundancy. Deng and Poole (2010) believe that visual complexity refers to the diversity of relationships between parts. Pieters et al. (2010) applied this to advertising and divided the visual complexity of advertising into feature complexity and design complexity. They argue that feature complexity utilizes unstructured variations in the visual characteristics of image pixels, whereas design complexity utilizes structured variations in specific shapes, objects, and their arrangement in an advertisement. Feature complexity looks at the details and basic visual features of the ad, color, brightness, and edge variations, as well as more detailed information (Adaval et al., 2018). Advertisements with such features are deemed more complex. In addition, Pieters et al. (2010) summarized the design complexity into six principles: number of objects, irregular objects, dissimilarity of objects, details of objects, asymmetry of object arrangement and irregularity of objects arrangement.

Visual complexity is a crucial aspect for examining images on social media and its impact on user experience, with differing perspectives in current research. Li and Xie (2019) introduced three effects of image content: the pure presence effect, image feature effect, and image-text fit effect. The image feature effect suggests that image content in social media posts can offer information independently of text content, enhancing the overall appeal of the post. However, images with dull or low-quality content may have counterproductive effects, resulting in decreased user engagement. Garner (1974) posited that less information in an image leads to a more positive evaluation. Wang et al. (2020) discovered that images with higher background complexity attract more attention, though viewers often focus on the background rather than the main product. Tang et al. (2013) emphasized the pleasing nature of photos with a clear subject compared to those with distracting backgrounds. In contrast, Deng and Poole (2010) suggested that increasing visual complexity on web pages could positively influence users' arousal perceptions. Berlyne (1971) found a preference for moderate complexity due to the interaction between reward and aversive brain systems. Therefore, by understanding how simple (vs. complex) image backgrounds appeal to users, we can further understand user engagement.

Although previous studies have produced conflicting findings regarding background image complexity, images with low background complexity may be more welcomed on social media than those with high background complexity. This could be attributed to their alignment with the human brain's rules for processing visual information, making them more effective at attracting users' attention and reducing cognitive load (Berlyne, 1971; Rosenholtz et al., 2007). In addition, considering the focus of this study on Instagram posts, users of the platform are typically exposed to a plethora of information. Consequently, they tend to swiftly browse through the content. Therefore, when encountering a post featuring a prominent focal product against a simple background, it might immediately capture their attention. In these conditions, it is plausible that low background complexity (compared to high background complexity) can increase social media engagement and purchase intentions. Formally, I hypothesize:

> ***H1**: Images on social media with low background complexity, compared to high background complexity, will a) increase social media engagement, and b) result in higher purchase intentions.*

Influencer Marketing and Social Media

Current research offers varying definitions of influencers. According to Campbell and Grimm (2018), influencers are individuals who post on social media in exchange for payment. Lou and Yuan (2019) suggest that social media influencers are ordinary people with expertise in a specific field, distinguishing them from celebrities. Jin and Phua (2014) define influencers as individuals deemed socially influential due to their substantial follower count. In contrast, Garcia (2017) views content from influencers as inherently viral.

According to 2023 statistics, the global influencer marketing market has surged to 21.1 billion USD, a more than threefold increase since 2019 (Statista, 2023). Campbell and Farrell (2020) attribute this growth to the convergence of five forces. Firstly, there has been a notable shift in consumer media consumption from print to online platforms. Secondly, consumers exhibit varied responses to online advertising. Additionally, the widespread use of social media platforms means that consumers now spend most of their time engaging with these channels. Furthermore, social media plays a pivotal role in expanding the consideration and evaluation stages of consumer decision-making processes. Lastly, the Internet facilitates the easy aggregation of consumers with common interests. Presently, Instagram boasts the highest number of users among social media platforms, approximately 1.35 billion (Statista, 2023). And there are currently 177, 000 influencers on Instagram in the United States (Jo Dixon, 2023). This shows that Instagram holds a leading position among all social media platforms and is considered the most influential platform (Vrontis et al., 2021). While TikTok and YouTube have substantial user bases, Instagram remains the most strategically significant channel for influencer marketing activities (Statista, 2023). Therefore, some marketers shifted their focus to influencers, capitalizing on their skills and strong connections with target audiences. This has given rise to a swiftly growing and increasingly influential group of influencers, marking a significant shift in online marketing (Campbell & Farrell, 2020).

Influencer Types

Campbell and Farrell (2020) categorize influencers into five groups: celebrity influencers, mega-influencers, macro-influencers, micro-influencers, and nano-influencers. Additionally, recent years have witnessed the emergence of virtual influencers—CGI entities that resemble humans but lack human existence—gaining substantial followings (Vrontis et al., 2021). In my studies, I mainly focused on micro-influencers and macro-influencers. Previous research indicates that micro-influencers usually have between 10,000 and 100,000 followers and are often perceived as more authentic and trustworthy compared to more prominent influencers. This authenticity enables them to better cater to the needs and interests of their followers. However, their reach is smaller than comparison to macro-influencers. Macro-influencers, on the other hand, typically have between 100,000 to 1,000,000 followers, making them more widely recognized than micro-influencers. However, their services also come at a higher cost. (Campbell & Farrell, 2020; Chen, 2023; De Vries, 2019; Janssen et al., 2022; Ozuem & Willis, 2022)

Using likes as an indication of influencer status is also supported by the literature (Hong & Cameron, 2018; Kim & Xu, 2019; Reich et al., 2012). Kim and Xu (2019) argue that consumers have positive evaluations of social media content based upon the number of likes. In addition, both scholars and practitioners point out that the number of likes is often indicative of the size of an influencer's following and labeled as the "Like Follower Ratio" (Kim & Xu, 2019). Studies also show consumers perceive more credibility in messages based upon the number of likes (Hong & Cameron, 2018). In further support, other studies suggest that likes related to a certain message are more influential as they indicate the peer groups' endorsement of that message (Reich et al., 2012); thus, suggesting likes are a key influential factor for influencer marketing.

Influencer Credibility

According to Janssen et al. (2022), influencers' persuasiveness originates from their unique role as "super peers," characterized by authenticity, relevance, and approachability. Tafesse and Wood (2021) further emphasize that social media influencers are perceived as real individuals with similarities to their followers. However, consumer perceptions vary across different influencer groups. In comparison to traditional celebrities, influencers are considered more trustworthy, relatable, and aspirational (Janssen et al., 2021).

In addition, micro-influencers exhibit higher authenticity and trust than macro-influencers (Campbell & Farrell, 2020). This is primarily because consumers perceive macro-influencers as attempting to outperform micro-influencers using their higher visibility. Influencers, being more persuasive, encounter resistance or indifference from consumers who reject content perceived as overly persuasive (Friestad & Wright, 1994; Kay et al., 2020). This implies that consumers prefer social media influencers who are approachable (with lower levels of followers and likes) and transparent (disclosing when a post is sponsored). As a social media influencer's follower count increases, consumers may adopt a more skeptical attitude (Kay et al., 2020). Consequently, when a product is endorsed by a small influencer compared to a large one, it conveys a greater sense of authenticity, resulting in more positive product reviews (Park et al., 2021). This highlights the greater effectiveness of micro-influencers over macro-influencers in improving consumer outcomes (Kay et al., 2020). Given this trend, it is crucial to study the differential impact of micro and macro influencers on consumer behavior. Furthermore, previous research has shown that the complexity of images posted on social media affects users' perceptions and behaviours (Lavie & Tractinsky, 2004). Images with lower background complexity are generally considered more visually appealing and easier to process, thereby increasing engagement rates (Kusumasondjaja & Tjiptono, 2019). However, the impact of image background complexity may vary depending on the type of influencer sharing the content. In this scenario, the authenticity of the micro-influencer instills viewers with confidence that the food and environment depicted in the image are genuine. This belief leads them to anticipate a similar dining experience at the restaurant, thereby enhancing their social media engagement and purchase intentions. Moreover, due to the lower authenticity associated with macro-influencers compared to micro-influencers, they are less likely to positively influence social media engagement and purchase intentions. However, given their higher visibility and influence, social media engagement and purchase intentions are unlikely to be negatively affected. Thus, I propose:

> ***H2:*** *Consumers who view a post by a micro-influencer, compared to macro-influencer, will be a) more likely to engage with the brand and b) show higher purchase intentions.*

> ***H3****: Images on social media with low background complexity (vs. high background complexity) will a) increase social media engagement, and b) result in higher purchase intentions when shared by a micro-influencer. However, when shared by a macro-influencer, image background complexity will not impact a) social media engagement, and b) purchase intentions.*

Disclosure

Influencer marketing is a form of hidden advertising, where paid content appears to be free (Brown & Hayes, 2008). While beneficial for merchants, consumers may struggle to distinguish between authentic posts and advertisements, making them susceptible to deception (Dhanesh & Duthler, 2019). Consequently, disclosure content in this type of advertising has become crucial in aiding consumers in making informed judgments. However, previous research has presented varying perspectives on the impact of disclosures on consumers. Boerman et al. (2017) discovered that such misinformation could negatively affect consumer responses to advertising. Such disclosures may also elicit critical consumer attitudes toward sponsored content, resulting in negative perceptions of the brand, influencer, and the content itself (Van Reijmersdal et al., 2020). The disclosure of information may result in consumer mistrust of influencers, consequently diminishing the efficacy of celebrity endorsements and reducing the likelihood of consumers sharing the information (Boerman et al., 2017). Highly commercialized posts could lead to a decline in credibility, potentially causing people to unfollow influencers who excessively promote advertisements (De Veirman & Hudders, 2020; Martínez-López et al., 2020; Djafarova & Trofimenko, 2019).

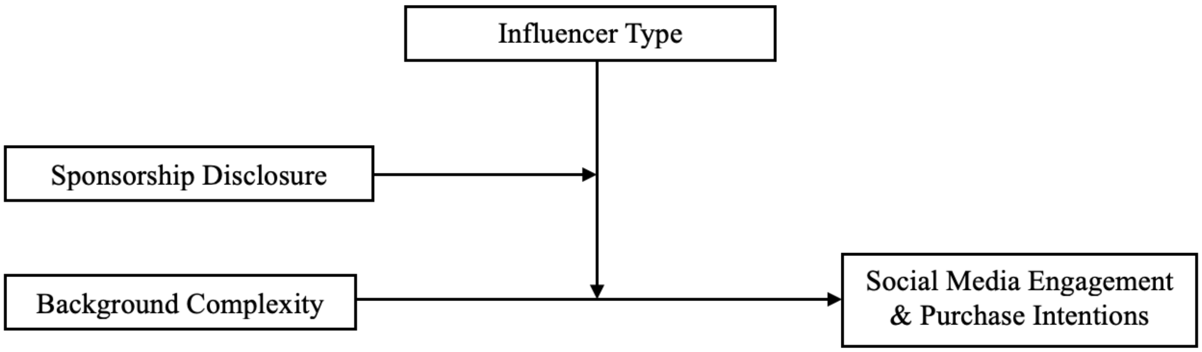
However, Evans et al. (2017) discovered that posts containing disclosures generated more endorsements than posts without them. This is primarily because, for followers, disclosure serves as a symbol of honesty and transparency on the part of the influencer (Dhanesh & Duthler, 2019). Consequently, such posts can achieve higher engagement, particularly active participation from the influencer's followers, such as likes and comments (Lou et al., 2019). Overall, this enhances their reliability and satisfaction with the influencers (Dhanesh & Duthler, 2019). Additionally, some studies have found that this type of disclosure content can increase brand recall, willingness to engage with posts, and higher brand liking (Boerman, 2020; De Jans et al., 2018). In addition to the two situations mentioned above, Lou et al. (2019) also found that consumers had slightly lower positive emotions toward influencer ads with unclear disclosures compared to undisclosed and fully disclosed ads. Previous research has yielded mixed findings regarding the impact of disclosures on consumer behavior. However, more recent studies have indicated that consumers generally trust and engage more with sponsored content when disclosures are included (Lou et al., 2019). Moreover, including disclosure content in the post can enhance the trustworthiness of the influencer and the authenticity of the post content, thereby attracting more engagement and stimulating interest in purchasing. Therefore, incorporating sponsorship disclosure is likely to have a positive effect on the interaction between background complexity and influencer type, Thus, regardless of whether the content is posted by a micro-influencer or macro-influencer, posts containing disclosures receive more social media engagement and purchase intentions. Based on this, I hypothesize that sponsorship will moderate the interaction between image background complexity and influencer type on behavioural outcomes. Specifically:

> ***H4****: When there is no disclosure, images with low background complexity (vs. high background complexity) will increase social media engagement, and result in higher purchase intentions when shared by a micro-influencer; when shared by a macro-influencer, however, image background complexity will not impact social media engagement nor purchase intentions. When sponsorship is disclosed, images on social media with low background complexity (vs. high background complexity) will increase social media engagement and result in higher purchase intentions, regardless of influencer type.*

Studies Overview

The four hypotheses proposed above will be tested across two studies. The first study focuses on testing hypotheses 1, 2 and 3 and investigates the impact of image background complexity and influencer type on social media engagement and purchase intentions. The second study aimed to build on the results of the first study by testing hypothesis 4 which explores the moderating role of sponsorship disclosure; please see figure 1 for the conceptual model. In my studies, I focused on food-related Instagram posts. In all posts, the influencers' name was the same, however, depending on the experimental condition, the image background complexity, number of likes, and the disclosure hashtag was manipulated. The studies were created using Qualtrics and all participants were recruited using Amazon's Mechanical Turk.

Figure 1. Conceptual Model



Pretest: Selecting Images with Differing Background Complexity

The primary goal of the pretest was to select the images with the highest and lowest background complexity to be used in the subsequent studies. To achieve this, and with permission from a restaurant owner, I visited a restaurant and used a salad to serve as the focal product of the image. I took four photos of the salad with the same angle and lighting, varying only the number of items on the table (that is, the image background). For instance, I varied the complexity of the background by removing vases, candlesticks, drinking glasses, and so on, from the table. These photos served as the stimuli used in this pretest. In addition to measuring the complexity of the background, I also measured participants overall attitudes towards each image. This was done to ensure that the images utilized in subsequent studies were aesthetically pleasing, and that participants held similar attitudes towards them.

Design and Participants

In the pretest, 113 participants were recruited using CloudResearch and were randomly assigned to view one of four images designed to vary in background complexity from least complex (image 1) to most complex (image 4). In exchange for their participation, the participants received monetary compensation. However, the incentive was only given if the individual answered the attention check question correctly.

Procedures

The experiment consisted of a single task, where participants were told to imagine that they were scrolling through their Instagram and saw a sponsored post for a new restaurant called The Salad Place. They were then shown a post from "foodhunter"; see appendix A for the experimental stimuli. Subsequently, participants were asked to what extent they perceived the image in the post as complex, simple, crowded, and overwhelming. All four questions were rated on a seven-point Likert scale (1 = "not at all," 7 = "very much"), and were borrowed from Guo and Hall (2009). To measure attitudes toward the post, participants were then asked to indicate their level of agreement with four items: likable, well-structured, interesting, and complete, using a seven-point Likert scale (1 = “not at all,” 7 = “very much”), borrowed from Geissler et al. (2006). After participants completed the questions above, they were asked to answer an attention check question and some demographic questions. To assess their attention, they were asked to answer the following question: “In this task, you were asked to imagine a sponsored ad for a new restaurant that offered what type of food?” There were three options: hamburgers, salads, and pizzas. To pass the attention check, and advance to the last section of the study, participants must select the correct option, which is salads. At the end of the survey, participants were asked to provide their age, gender, and to indicate which social media platforms they typically use from the following options: Facebook, Instagram, Snapchat, Twitter and “Other”.

Results

Data Exclusion

Prior to data analysis, participants were excluded based on one criterion: reporting technical issues. However, none of the participants reported any technical issues. As a result, the final sample consisted of n = 113 participants, with an average age of 26.61 (SD = 3.69). Additional demographic information is provided in table 1.

Table 1. Demographics (Pretest)

Age	**Percentage**
<=30	20.4%
31-40	44.2%
41-50	27.5%
51-60	5.4%
61-70	2.7%

Gender	**Percentage**
Male	42.5%
Female	55.8%
Prefer not to say	1.8%

Social media usage (five platforms are provided in the survey)	Percentage
One out of five	23.9%
Two out of five	18.6%
Three out of five	25.7%
Four out of five	31.0%
Five out of five	0.9%

Instagram usage	Percentage
Use Instagram	83.2%
Do not use Instagram	16.8%

Perceived Complexity

First, I conducted an ANOVA with background complexity as the independent variable and perceived complexity as the dependent variable (the Cronbach's alpha for perceived complexity was .832). The results revealed a statistically significant difference between the four images ($F(3, 109) = 7.22$, $p < .001$); refer to the third column in table 2 for the means and standard deviations for each image. To help determine which images were significantly different from each, post-hoc comparisons using Tukey HSD were conducted. The results indicated that the mean complexity for image 4 was significantly different than image 1 ($p < .001$), image 2 ($p = .001$), and image 3 ($p = .026$). However, there were no differences between images 1, 2 and 3 (all ps > .617).

Table 2. Complexity and Attitudes (Pretest)

	N	Complexity	Attitudes
Image 1 (35% female; M_{age} = 37.42, SD = 8.59)	26	Mean = 2.82** SD = 1.52	Mean = 4.93** SD = 0.90
Image 2 (39% female; M_{age} = 40.15, SD = 9.05)	26	Mean = 2.88** SD = 1.62	Mean = 5.51** SD = 1.21
Image 3 (48% female; M_{age} = 38.45, SD = 9.91)	29	Mean = 3.29** SD = 1.36	Mean = 5.10** SD = 1.27
Image 4 (47% female; M_{age} = 35.84, SD = 8.90)	32	Mean = 4.35* SD = 1.30	Mean = 5.06** SD = 1.46

*Notes: Means that that are marginally different from the scale midpoint (that is, 4) are indicated by * whereas those that are significantly different (p < .05) from the midpoint are indicated by ** .*

Ideally, the image selected to represent high complexity would be significantly higher than the midpoint (that is, 4 on the 7-point scale). Similarly, the image chosen to represent low complexity would be significantly lower than the midpoint. Thus, a series of one sample *t*-tests were performed to evaluate whether the mean complexity, for each image, was significantly different from the midpoint. The results showed that the mean complexity of images 1, 2 and 3 were all significantly lower than the midpoint ($t_{image\_1}(25) = -3.97$, p <.001; $t_{image\_2}(25) = -3.54$, p =.002; $t_{image\_3}(28) = -2.80$, p =.005). The mean complexity for image 4, however, was marginally higher than the midpoint ($t(31) = 1.53$, p =.068). Based only on this set of analyses, image 4 could be selected as the high complexity image. However, the decision to choose image 1, 2 or 3 for the least complex image is not as clear.

Attitude Score

I then conducted an ANOVA with background complexity as the independent variable and overall attitudes (Cronbach's alpha of .867) as the dependent variable. The results showed no significant effect ($F(3, 109) = 1.06$, p =.371), meaning that there were no significant differences in participants' attitudes towards the four images.

Next, one sample *t*-tests were performed to evaluate whether there were differences between the mean attitude scores and the mid-point. The results showed that all images were rated significantly higher than the midpoint ($t_{image\_1}(25) = 5.29$, p <.001; $t_{image\_2}(26) = 6.35$, p <.001; $t_{image\_3}(29) = 4.67$, p <.001; $t_{image\_4}(32) = 4.11$, p <.001). Thus, all four images were positively evaluated, and could be considered for use in subsequent studies. Please see the fourth column of table 2 for the mean attitude score and standard deviation for each image.

Additional Analyses

I noticed that the item "informative" had neutral responses across images in the pretest. Upon reflection, it seems that informativeness may not be a relevant measure. For instance, users engaging with social media posts about food may prioritize visual appeal over seeking informative content. Consequently, I decided to remove this item from the attitude measures in studies 1 and 2. Please see table 3 for the means and standard deviations for each of the items used to calculate overall attitudes.

Table 3. Items Used to Assess Attitude Scores (Pretest)

	N	Informative	Likable	Well-structured	Interesting
Image 1	26	Mean = 4.38 SD = 1.33	Mean = 5.31 SD = 0.84	Mean = 4.77 SD = 1.53	Mean = 5.27 SD = 1.25
Image 2	26	Mean = 4.62 SD = 1.80	Mean = 5.96 SD = 1.25	Mean = 5.77 SD = 1.21	Mean = 5.69 SD = 1.41
Image 3	29	Mean = 4.38 SD = 1.90	Mean = 5.38 SD = 1.27	Mean = 5.48 SD = 1.27	Mean = 5.17 SD = 1.51
Image 4	32	Mean = 4.59 SD = 1.66	Mean = 5.25 SD = 1.55	Mean = 5.16 SD = 1.57	Mean = 5.25 SD = 1.67

Discussion

Based on the complexity and attitude scores ratings, I selected image 4 to represent the high-complexity condition. However, determining which low-complexity image to use was more difficult based on similar ratings for background complexity and attitudes. Therefore, my decision relied on conceptual reasoning rather than solely on statistical differences. Upon reflection, all four images featured a colorful bowl of salad packed with ingredients. This suggests that even without altering the table setting, the focal product itself might present a high level of complexity for participants. Consequently, participants did not perceive significant differences when minor adjustments were made to the table setting. Therefore, I selected image 1 to represent the low-complexity condition and image 4 to represent the high-complexity condition. In addition, when examining the low-complexity image, apart from the focal product and some tableware, a significant area of blank space remains on the tabletop. This image could be perceived as incomplete, thus in subsequent studies, I replaced “informative” with “complete” as one of the items to measure attitudes.

Study 1: The Influence of Background Complexity and Number of Likes on Social Media Engagement and Purchase Intentions

The first objective of this study was to determine whether social media posts with low image background complexity, as opposed to high image background complexity, would result in higher social media engagement and purchase intentions (H1). A second goal was to examine whether a post by a micro-influencer, compared to macro-influencer, would make consumers more likely to engage with the brand and show higher purchase intentions (H2). Given that likes are indicative of the followership of social media influencers, and that likes are highly influential (persuasive) on consumer responses, we use likes as our basis to distinguish between different social media influencer types. And finally, this study aimed to assess whether influencer type moderates the effect of image background complexity on social media engagement and purchase intentions, specifically examining if posts with low image background complexity by micro-influencers can lead to higher social media engagement and purchase intentions, compared to macro-influencers (H3).

Design and Participants

In this study, 195 participants were recruited using CloudResearch and participated in a 2 (background complexity: low vs. high) × 2 (influencer type: micro-influencer vs. macro-influencer) between-subjects design. Participants were randomly assigned to one of four conditions. In exchange for their participation, the participants received monetary compensation. However, the incentive was only given if the individual answered the attention-check question correctly. Participants who did not correctly answer the attention-check question were removed from the following analyses.

Procedure

Participants were informed that they would be engaging in a task where they had to imagine scrolling through their Instagram feed and encountering a post from an influencer named "foodhunter". The post included an image featuring the food and ambiance of a fictional restaurant called "The Salad Place," and accompanying text containing the restaurant's fictitious name. To manipulate the complexity of the image background, participants were exposed to one of two different images. In the low background complexity condition, they observed a simple background in the post's image. In the high background complexity condition, the background of the image in the post was complex. These images were selected based on the pretest described earlier. For the manipulation of influencer type, the number of likes on the posts varied, and participants were exposed to one of them. In the micro-influencer condition, they saw 1,018 likes on the post, while in the macro-influencer condition, they saw 101,018 likes on the post. The images used in this study can be found in appendix B.

Participants were then asked to select whether the influencer who posted the content was either a micro-influencer or a macro-influencer based on the number of likes on the post they had just viewed. Next, image background complexity was measured using the same four questions in the pretest–that is, participants were asked to what extent they perceived the image in the post as complex, simple, crowded, and overwhelming (all on 7-point scales). To measure attitudes toward the post, participants were then asked to indicate how likable, well-structured, interesting, and complete the post was, using a seven-point Likert scale (1 = "not at all", 7 = "very much"), as adapted from Geissler et al. (2006).

To measure social media engagement, I measured their likelihood to like the post, to comment on the post and to share the post (publicly or privately), all on seven-point Likert scale (1 = "not at all", 7 = "very much"); Schivinski et al. (2016). I also measured their overall purchase intentions by asking participants to indicate how likely they are to check out the restaurant's website (1 = "not at all likely", 7 = "very likely"), how interested they are in eating at The Salad Place (1 = "not at all interested", 7 = "very interested"), how likely they are to eat at The Salad Place in the future (1 = "not at all likely", 7 = "very likely"), and finally, how likely they are to choose this restaurant the next time they want to eat a salad (1 = "not at all likely", 7 = "very likely"). These questions have been used in previous research (Smith et al., 2021) and were adapted to be consistent with the current study.

After participants completed all the questions above, they were asked to answer an attention check question and some demographic questions. To assess their attention, they were asked to answer the following question: “In this task, you were asked to imagine seeing a post on social media for a new restaurant. What type of food is offered at the new restaurant?” The choices provided were hamburgers, salads, and pizzas. To pass the attention check, and advance to the last section of the study, participants must select the correct option, which is “salads”. At the end of the survey, participants were asked to provide their age, gender, fluently spoken languages, technical issues, and the social media platforms they typically use. Additionally, two optional questions were included that measured what they believed the researcher wished to examine in this study, and whether they had any comments for the researcher. Please refer to appendix D for all the scales used in this study.

Results

Data Exclusion

Before data analysis, participants were excluded based on three criteria: 1) reporting technical issues, 2) failing to correctly identify influencer type, and 3) not paying attention to the task (for example, answering with repetitive responses such as 1, 1, 1, 1, 1 throughout the entire dataset). Technical issues were checked first, and none of the participants reported any technical issues. 51 participants, however, were removed for failing to identify influencer types. Specifically, 21 (10.77%) of participants in the micro-influencer condition, and 30 (15.38%) of participants in the macro-influencer condition, incorrectly identified the influencer type, and were removed. Three additional participants were removed because of repetitive responses. Thus, the final sample consisted of n = 141 participants with an average age of 41.77 (SD = 11.32); see table 4 for additional demographics. Excluding participants based on our three exclusion criteria ensured that the sample was composed of individuals who had not experienced any technical difficulties, had correctly identified influencer type, and had paid attention to the task, thus increasing the validity and reliability of the data.

Table 4. Demographics (Study 1)

Age	**Percentage**
≤30	12.6%
31-40	37.7%
41-50	31.1%
51-60	9.8%
61-70	6.3%
≥71	2.1%

Gender	Percentage
Male	63.8%
Female	35.5%
Non-binary/third gender	0%
Prefer not to say	0.7%

Social media usage (five platforms are provided in the survey)	Percentage
One out of five	27%
Two out of five	29.8%
Three out of five	29.1%
Four out of five	13.5%
Five out of five	0.7%

Instagram usage	Percentage
Use Instagram	69.5%
Do not use Instagram	30.5%

Manipulation Check for Perceived Complexity

As a manipulation check, I first calculated a measure of overall perceived complexity by averaging participants' responses to how complex, simple (reverse-coded), crowded and overwhelming they believed the image was. The Cronbach's alpha for perceived complexity was .894, indicating a high level of internal consistency among these items. An ANOVA was then conducted to analyse differences in perceived complexity as a function of condition, where 0 = low background complexity and 1 = high background complexity. The result showed a significant main effect of condition on perceived complexity ($F(1, 139) = 35.32$, $p <.001$). Specifically, the participants in the low background complexity condition perceived the image to be less complex ($M = 2.52$, SD = 1.24), compared to those in the high background complexity condition ($M = 3.92$, SD = 1.55). Hence, the manipulation check for the image background complexity was successful.

Testing for Potential Covariates

To begin with, the social media engagement measure was created by averaging participant' answers to three questions: how likely participants are willing to put a "like" on this post, how likely participants are willing to comment on this post, and how likely participants are willing to share this post (publicity or privately); the Cronbach alpha was .861. Similarly, a measure of purchase intention was created by averaging participants' answers to how likely they were to check out the restaurant's website, how interested they were in eating at The Salad Place, how likely participants were to eat at The Salad Place in the future, and how likely they were to choose this restaurant the next time they want to eat a salad; for this measure, the Cronbach alpha was .952.

To investigate potential covariates that may influence the relationship between background complexity and social media engagement and purchase intentions, five variables were considered: age, gender, social media usage, Instagram usage and attitudes. Firstly, the age of the participants ranged from 24 to 76, resulting in a 52-year age difference. This substantial age gap among the participants may have contributed to the differences in their responses. Secondly, given that women tend to be more involved in social media activities such as posting, liking, and commenting compared to men (Hampton et al., 2012), gender was also considered in this study. Thirdly, this research primarily centers on Instagram, thus, like previous experiments, use on this social media platform is relevant to consider (Dhanesh & Duthler, 2019; Evans et al., 2017). Fourthly, prior research suggests that attitudes may be influenced by background complexity. Stevenson et al. (2000) found that more complex backgrounds tended to result in less favorable attitudes. Therefore, I am considering participants' attitudes toward the images in the posts within this context. It was determined, prior to data analyses, that if any of the correlations between the potential covariate and either of the dependent variables had a p-value of less than .05, and a correlation of greater than .5 (indicating a moderate, or strong relationship), then these would be further investigated.

Age. The correlations between age and 1) social media engagement (r = -.12, p =.176), and 2) purchase intentions (r = -.03, p =.724) were not significant; thus, age was not included as a covariate in further analysis.

Gender. The correlation between gender and 1) social media engagement (r = .14, p =.107), was not significant. The correlation between gender and 2) purchase intentions (r = .21, p =.014) was significant, but weak. Thus, gender was not included as a covariate in further analysis.

Social Media Usage. The correlation between social media usage and 1) social media engagement (r = .31, p <.001), was significant, but weak. The correlation between social media usage and 2) purchase intentions (r = .10, p =.239) was not significant. Therefore, social media usage was not included as a covariate in the analyses.

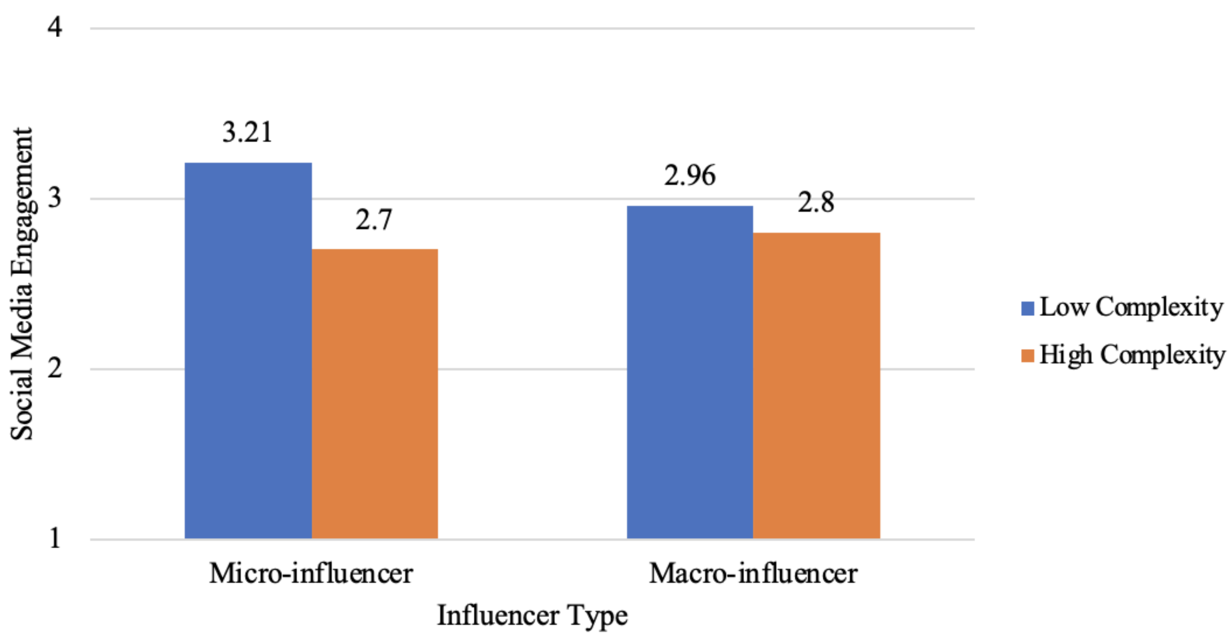
Instagram Usage. The correlation between Instagram usage and 1) social media engagement (r = .29, p <.001), was significant, but weak. The correlation between Instagram usage and 2) purchase intentions (r = .14, p =.107) was not significant. Therefore, Instagram usage was not included as a covariate in the analyses.

Attitudes. The correlation between attitudes (Cronbach's alpha = .884) and 1) social media engagement (r = .49, p <.001), and 2) purchase intentions (r = .65, p <.001) were both positively significant, and showed evidence of a strong relationship. However, additional analyses revealed a nonsignificant background complexity × influencer type interaction effect on attitudes (p =.424), thus this variable was not included as a covariate in further analyses.

Effects of Background Complexity and Influencer Type on Social Media Engagement

A 2-way ANOVA was conducted to analyze differences in participants' social media engagement as a function of background complexity and influencer type. The background complexity (0 = low complexity and 1 = high complexity) and the influencer type (0 = micro-influencer and 1 = macro-influencer) were entered as the independent variables, and social media engagement was entered as the dependent variable. The results revealed a non-significant main effect of background complexity ($F(1, 137) = 1.29$, $p = .259$) on consumer engagement, which does not support H1a, and a non-significant main effect influencer type ($F(1, 137) = .06$, $p = .803$), on consumer engagement, which does not support H2a. The results also revealed a non-significant background complexity × influencer type interaction ($F(1, 137) = .37$, $p = .543$). Specifically, in the micro-influencer condition, participants reported no differences in social media engagement between the low background complexity ($M = 3.21$, SD = 1.59) and the high background complexity ($M = 2.70$, SD = 1.59; $F(1, 137) = 1.48$, $p = .226$). Further, in the macro-influencer condition, participants reported no differences in social media engagement between the low background complexity ($M = 2.96$, SD = 1.91) and the high background complexity ($M = 2.80$, SD = 1.71; $F(1, 137) = .14$, $p = .707$). Although I did find the predicted non-significant effect in the macro-influencer condition, there was no significant effect of background complexity in the micro-influencer condition. Taken together, these results, unfortunately, do not support H3a. See figure 2 for a graphical depiction of the interaction.

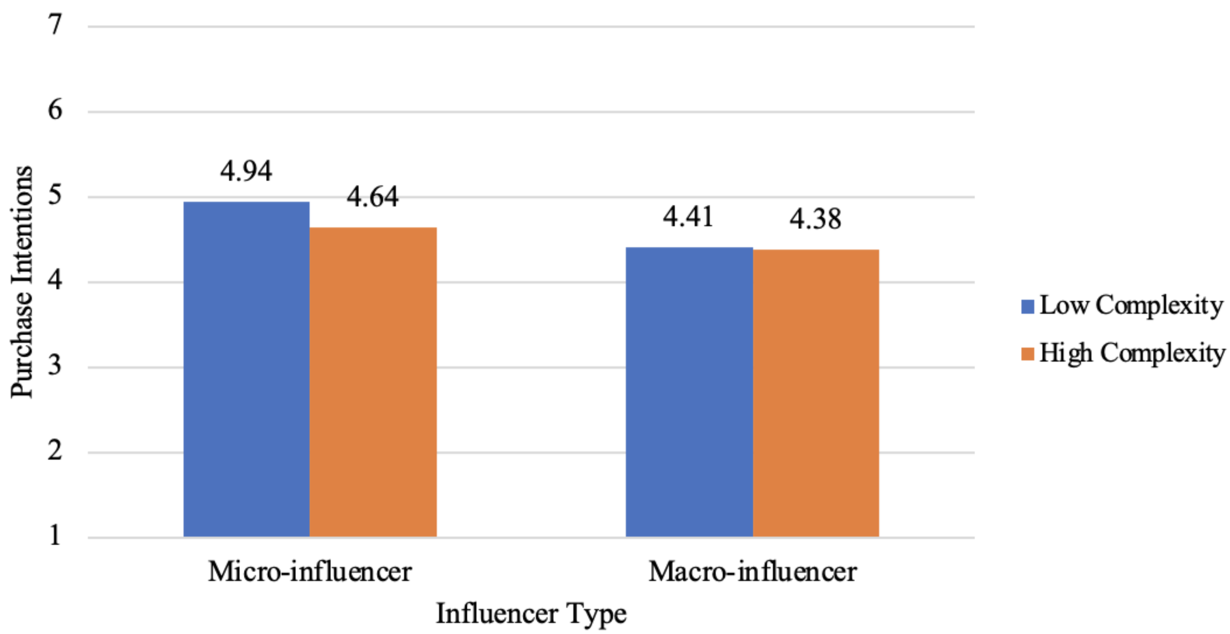
Figure 2. Background Complexity and Influencer Type on Social Media Engagement (Study 1)



Effects of Background Complexity and Influencer Type on Purchase Intentions

A 2-way ANOVA was conducted to analyze differences in participants' purchase intentions as a function of background complexity and influencer type. The background complexity (0 = low complexity and 1 = high complexity) and the influencer type (0 = micro-influencer and 1 = macro-influencer) were entered as the independent variable, and purchase intentions were entered as the dependent variable. The results revealed a non-significant main effect of background complexity ($F(1, 137) = .33$, $p = .566$) on overall purchase intentions, which does not support H1b, and a nonsignificant main effect influencer type ($F(1, 137) = 2.01$, $p = .158$), on overall purchase intentions, which does not support H2b . The results also revealed non-significant background complexity × influencer type interaction ($F(1, 137) = .23$, $p = .629$). Specifically, in the micro-influencer condition, participants reported no differences in purchase intentions between the low background complexity ($M = 4.94$, SD = 1.32) and the high background complexity ($M = 4.64$, SD = 1.45; $F(1, 137) = .55$, $p = .461$). Further, in the macro-influencer condition, participants reported no differences in purchase intentions between the low background complexity ($M = 4.41$, SD = 1.95) and the high background complexity ($M = 4.38$, SD = 1.74; $F(1, 137) = .004$, $p = .947$). Similar to the social media engagement measure, I did find the predicted non-significant effect of complexity on purchase intentions in the macro-influencer condition, but there was no significant effect of background complexity on this measure in the micro-influencer condition. Thus, the set of results, unfortunately, do not support H3b. See figure 3 for a graphical depiction of the interaction.

Figure 3. Background Complexity and Influencer Type on Purchase Intentions (Study 1)



Discussion

Overall, the results of study 1 did not support H1, which posited that images on social media with low background complexity, compared to high background complexity, would increase both social media engagement and purchase intentions. It also did not support H2, which hypothesized that social media posts created by micro-influencer, compared to macro-influencer, would increase both social media engagement and purchase intentions. Similarly, H3, proposing that images on social media with low background complexity (vs. high background complexity) would increase social media engagement and purchase intentions when posted by a micro-influencer, was not supported. In summary, no significant effects on social media engagement and purchase intentions were found based on image background complexity and influencer type, and influencer type did not play a moderating role in this process.

Study 2: The Moderating Role of Sponsorship Disclosure

In this study, I re-investigate the influence of image background complexity on social media engagement and purchase intentions (H1), the impact of influencer type on social media engagement and purchase intentions (H2), and their interaction (H3). The primary goal of this study, however, is to explore the moderating impact of sponsorship disclosure in the relationship between image background complexity and influencer type (H4). Specifically, in the absence of disclosure, images with lower background complexity (vs. higher background complexity) increase social media engagement and generate higher purchase intentions when shared by micro-influencers. However, when shared by macro-influencers, the image background complexity does not impact social media engagement and purchase intentions. In the presence of disclosures, images on social media with lower background complexity (vs. higher background complexity) increase social media engagement and lead to higher purchase intentions, regardless of influencer type.

Like study 1, I used the same Instagram post, except that to help participants more accurately determine whether the source of the post was a micro-influencer or a macro-influencer, I provided participants with information about the influencer's number of followers (to manipulate influencer type). Unlike study 1, however, I did not measure whether the participants correctly identified whether the influencer was a micro, or macro-influencer. Instead, I measured how popular the participants perceived foodhunter to be, based on the number of followers; this measure of perceived popularity was then used this as a manipulation check for follower count. Despite this change, the measurement of social media engagement, and purchase intentions, remained the same way.

Design and Participants

Like the first study, participants were recruited through CloudResearch. This time, 407 participants were randomly assigned to one of eight conditions in a between-subjects design: 2 (background complexity: high complexity vs. low complexity) × 2 (follower count: high follower count vs. low follower count) × 2 (sponsorship disclosure: with a disclosure vs. without a disclosure). As in the first study, participants received monetary compensation for participating, but rewards were only given if individuals correctly answered one attention check question. And those who did not pass the attention check question were removed from the following analyses.

Procedure

Similar to the first study, participants were instructed to imagine scrolling through their Instagram feed and encountering a social media post (see Appendix C). The post featured the influencer's name, "foodhunter," an image, the like count, and the restaurant's name, "The Salad Place." To manipulate image background complexity, participants viewed an Instagram post with either high or low background complexity. In this study, the manipulation method for influencer type was refined to eliminate previous confusion. In addition to using the same number of likes from the first study, participants were also informed about the influencer's number of followers. Participants in the micro-influencer condition were informed that "foodhunter" had 15,100 followers, while those in the macro-influencer condition were told that "foodhunter" had 515,000 followers. Finally, to manipulate sponsorship disclosure, participants in the disclosure condition saw Instagram posts with a "#Sponsored" hashtag, while those in the non-disclosure condition viewed posts without the hashtag. Other than these adjustments, the content of the post remains unchanged from study 1.

Following that, participants responded to two questions that measured how popular they believe "foodhunter" was based on the number of followers. Specifically, adapted from past research (Janssen et al., 2022), participants were asked to express their agreement or disagreement with two statements: "I think this influencer is popular" and "I think this influencer has many followers." Responses were recorded on a seven-point Likert scale (1 = "totally disagree", 7 = "totally agree"). The same set of questions related to image background complexity and attitudes employed in the first study were then utilized to gauge participants' perceptions of image complexity and attitudes toward the post. I also used the same items from study 1 to next measure participants' level of engagement and purchase intentions. Participants were then required to answer the same attention check question used in study 1. Correctly answered questions led participants to demographic questions and compensation, while incorrect answers resulted in an explanation for not receiving the promised payment. Please refer to appendix D for a comprehensive list of all scales used in this study.

Results

Data Exclusion

Before data analysis, participants were excluded based on two criteria: 1) reporting technical issues, and 2) not paying attention to the task (for example, answering with repetitive responses such as 1,1,1,1,1 throughout the entire dataset). Technical issues were checked, resulting in removal of three individuals. 12 participants were removed because of repetitive responses. Thus, the final sample consisted of n = 384 participants with an average age of 43.93 (SD = 12.71); see table 5 for additional demographics. By excluding participants based on the two exclusion criteria, I ensured that the sample comprised individuals who had not experienced any technical difficulties and had paid attention to the task and completed the survey. This approach enhances the validity and reliability of the data.

Table 5. Demographics (Study 2)

Age	**Percentage**
≤30	11.8%
31-40	35.6%
41-50	23.4%
51-60	17.3%

Age	**Percentage**
61-70	8.9%
≥71	3.2%

Gender	**Percentage**
Male	53.4%
Female	44.5%
Non-binary/third gender	0.3%
Prefer not to say	1.8%

Social media usage (five platforms are provided in the survey)	**Percentage**
One out of five	22.9%
Two out of five	33.1%
Three out of five	33.1%
Four out of five	10.7%
Five out of five	0.3%

Instagram usage	**Percentage**
Use Instagram	69.5%
Do not use Instagram	30.5%

Manipulation Check for Perceived Complexity

Similar to study 1, I first calculated perceived complexity (Cronbach's Alpha = .861, which indicates a high level of internal consistency for this scale). An ANOVA was then conducted to analyse differences in background complexity as a function of condition, where 0 = low background complexity and 1 = high background complexity. The results showed a significant main effect of condition on perceived complexity ($F(1, 382) = 96.10$, $p <.001$). Specifically, the participants in the low complexity condition perceived the image to be less complex ($M = 2.32$, SD = 1.18), compared to those in the high complexity condition ($M = 3.64$, SD = 1.43). Hence, the manipulation check for the image background complexity was successful.

Manipulation Check for Perceived Popularity

I first calculated a measure of perceived popularity by averaging participants' responses to how popular they believe the influencer is and whether they believe the influencer has many followers (r = .93, p <.001). An ANOVA was then conducted to analyze differences in perceived popularity as a function of follower count. Participants in the high follower count condition perceived the influencer as less popular (M = 5.88, SD = 1.04) than those in the low follower count condition (M = 4.16, SD = 1.44; F(1, 382) = 183.40, p <.001), thus our manipulation was successful.

Testing for Potential Covariates

Before testing potential covariates, same as study 1, measures of social media engagement (Cronbach's alpha = .857) and overall purchase intentions (Cronbach's alpha =.957) were created. Also like study 1, to investigate potential covariates that may influence the relationship between image background complexity and social media engagement and purchase intentions, five variables were considered: age, gender, social media usage Instagram usage and attitudes. The attitudes score in this study was created by averaging participant answers to four items: likable, well-structured, interesting, and complete (Cronbach's alpha = .865). It was determined, prior to data analyses, that if any of the correlations between the potential covariate and any of the dependent variables had a p-value of less than .05 and a correlation of greater than .5 (indicating a moderate, or strong relationship), then these would be further investigated.

Age. The correlation between age and 1) social media engagement (r = .05, p =.167) was not significant, but the correlation between age and 2) purchase intentions (r = .12, p =.012) was significant, but weak; thus, age was not included as a covariate in further analysis.

Gender. The correlation between gender and 1) social media engagement (r = .04, p =.418) was not significant, but the correlation between gender 2) purchase intentions (r = .11, p =.033) was significant, but weak; thus, gender was not included as a covariate in further analysis.

Social Media Usage. The correlation between social media usage and 1) social media engagement (r = .12, p =.015) was significant, but weak. The correlation between social media usage and 2) purchase intentions (r = .08, p =.137) was not significant; thus, social media usage was not included as a covariate in further analysis.

Instagram Usage. The correlation between Instagram usage and 1) social media engagement (r = .15, p =.003) was significant, but weak. The correlation between Instagram usage and 2) purchase intentions (r = .08, p =.102) was not significant; thus, Instagram usage was not included as a covariate in further analysis.

Attitudes. The correlation between attitudes and 1) social media engagement (r = .55, p <.001), and 2) purchase intentions (r = .64, p <.001) were both positively significant. Additional analyses revealed a non-significant complexity × influencer type × sponsorship interaction effect on attitudes (p =.907), thus this variable is not included as a covariate in further analyses.

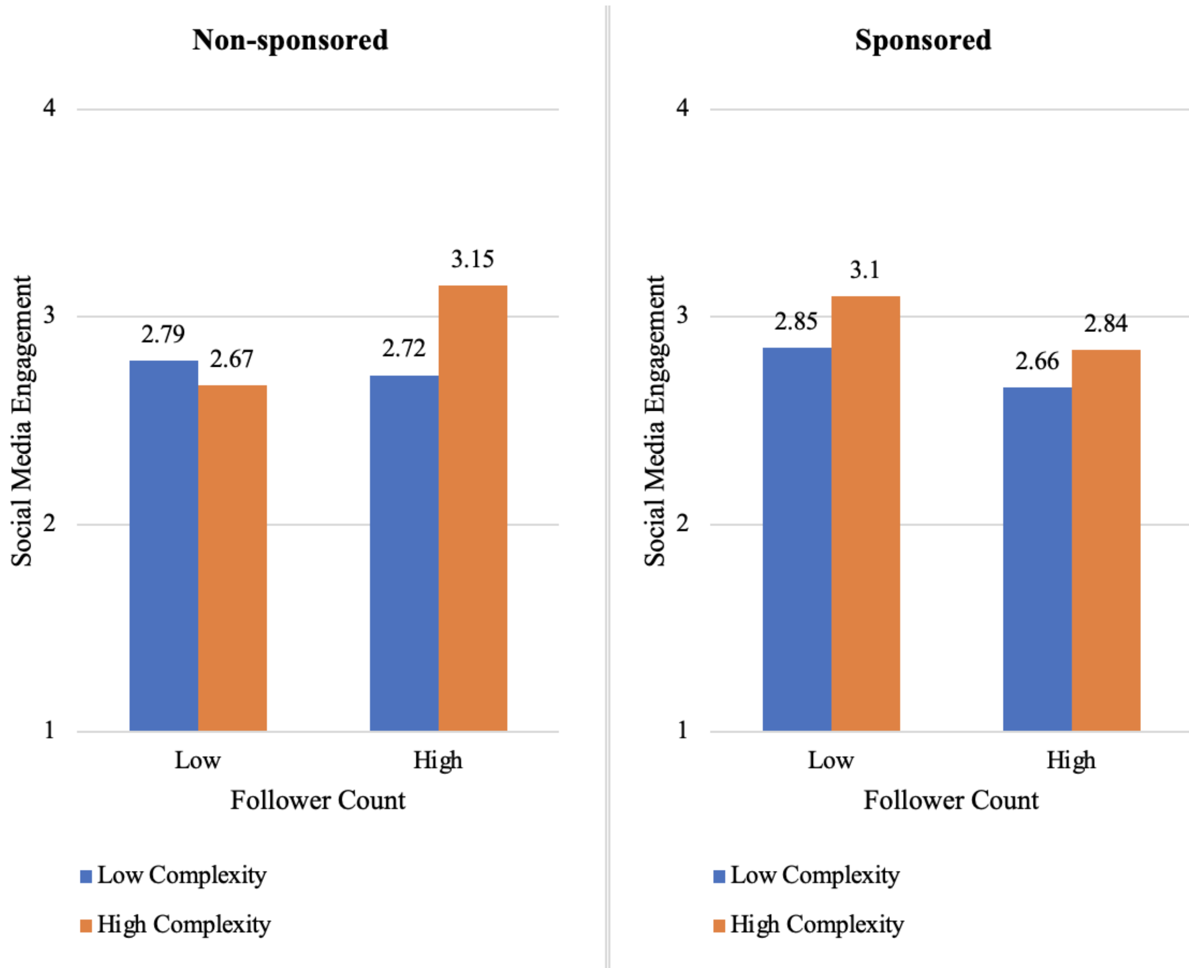
Effects of Background Complexity, Follower Count, and Sponsorship Disclosure on Social Media Engagement

To test for differences in participants' social media engagement based on background complexity, follower count, and sponsorship disclosure, a 3-way ANOVA was conducted. The background complexity (0 = low complexity and 1 = high complexity), the follower count (0 = low follower count and 1 = high follower count), and sponsorship disclosure (0 = non-sponsored and 1 = sponsored) were entered as the independent variables, and social media engagement was entered as the dependent variable. The results revealed a non-significant main effect of background complexity ($F(1, 376) = 1.23$, $p = .267$) on overall consumer engagement actions, and a non-significant main effect influencer type ($F(1, 376) = .003$, $p = .954$), on overall consumer engagement actions. The results also revealed a non-significant background complexity × follower count × sponsorship disclosure interaction ($F(1, 376) = .86$, $p = .353$).

To interpret the three-way interaction, I first considered the interaction between complexity and follower count in the non-sponsored condition. In this case, there was no main effect of background complexity ($F(1, 186) = .43$, $p = .515$), nor a main effect follower count ($F(1, 186) = .74$, $p = .390$), on overall consumer engagement actions. Further, the complexity × follower count interaction was not significant ($F(1, 186) = 1.35$, $p = .248$). Specifically, in the low follower count conditions, participants reported no differences in social media engagement between the low background complexity ($M = 2.79$, SD = 1.65) and the high background complexity ($M = 2.67$, SD = 1.60; $F(1, 186) = .13$, $p = .723$). Participants in the high follower count condition reported no differences in social media engagement between the low background complexity ($M = 2.72$, SD = 1.48) and the high background complexity ($M = 3.15$, SD = 1.78; $F(1, 186) = 1.67$, $p = .197$). This once again confirmed the finding from study 1 that image background complexity does not significantly affect social media engagement in macro-influencer condition.

For those in the sponsored conditions, the results showed no effect of background complexity ($F(1, 190) = .85$, $p = .357$), nor follower count ($F(1, 190) = .94$, $p = .332$), on consumer engagement. The results also revealed no significant complexity × follower count interaction ($F(1, 190) = .02$, $p = .890$). Specifically, in the low follower count conditions, participants reported no differences in social media engagement between the low background complexity ($M = 2.85$, SD = 1.68) and the high background complexity ($M = 3.10$, SD = 1.59; $F(1, 190) = .56$, $p = .456$). Participants in the high follower count condition reported no differences in social media engagement between the low background complexity ($M = 2.66$, SD = 1.51) relative to the high background complexity ($M = 2.84$, SD = 1.61; $F(1, 190) = .31$, $p = .578$). These results do not support H4. See figure 4 for a graphical depiction of the interaction.

Figure 4. Background Complexity, Follower Count, and Sponsorship Disclosure on Social Media Engagement (Study 2)



Effects of Background Complexity, Follower Count, and Sponsorship Disclosure on Purchase Intentions

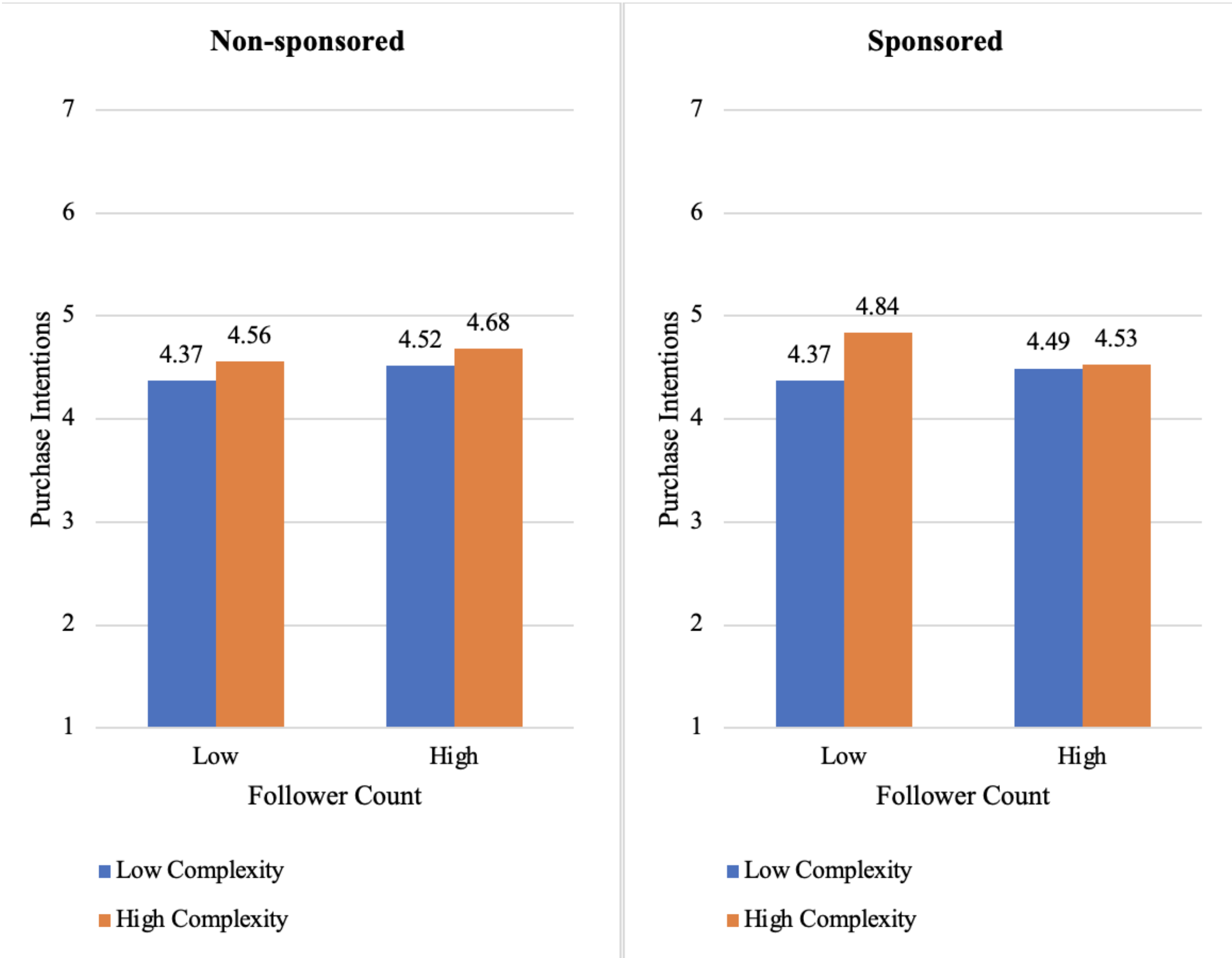
To test for differences in participants' purchase intentions based on background complexity, follower count, and sponsorship disclosure, a second three-way ANOVA was conducted. The background complexity (0 = low complexity and 1= high complexity), the follower count (0 = low follower count and 1 = high follower count), and sponsorship disclosure (0 = without a disclosure and 1 = with a disclosure) were entered as the independent variables, and purchase intentions was entered as the dependent variable. The results revealed a non-significant main effect of background complexity ($F(1, 376) = 1.75$, $p = .186$), and a non-significant main effect influencer type ($F(1, 376) = .01$, $p = .905$), on purchase intentions. The results also revealed a non-significant background complexity × follower count × sponsorship disclosure interaction ($F(1, 376) = .38$, $p = .537$) on purchase intentions.

To interpret the three-way interaction, I then considered the interaction between complexity and follower count in the non-sponsored condition. In this case, there was no main effect of background complexity ($F(1, 186) = .53$, $p = .466$), no main effect of follower count

($F(1, 186) = .30$, p =.583), and no complexity × follower count interaction ($F(1, 186) = .003$, p =.953) on purchase intentions. Specifically, in the low follower count conditions, participants reported no differences in purchase intentions in the low background complexity (M = 4.37, SD = 1.45) and the high background complexity (M = 4.56, SD = 1.90; $F(1, 186) = .31$, p =.582). Participants in the high follower count condition reported no differences in purchase intentions in the low background complexity (M = 4.52, SD = 1.61) relative to the high background complexity (M = 4.68, SD = 1.74; $F(1, 186) = .23$, p =.632). Just as with the social media engagement measure, I discovered the expected non-significant impact of complexity on purchase intentions in the macro-influencer condition.

For those in the sponsored conditions, the results revealed a similar pattern. That is, there was no main effect of background complexity ($F(1, 190) = 1.36$, p =.246), no main effect of follower count ($F(1, 190) = .19$, p =.666, and no interaction effect ($F(1, 190) = .97$, p =.326), on purchase intentions. Specifically, in the low follower count conditions, participants reported no differences in purchase intentions between the low background complexity (M = 4.37, SD = 1.60) and the high background complexity (M = 4.84, SD = 1.38; $F(1, 190) = 2.29$, p =.132). Participants in the high follower count condition reported no differences in purchase intentions between the low background complexity (M = 4.49, SD = 1.38) relative to the high background complexity (M = 4.53, SD = 1.73; $F(1, 190) = .02$, p =.899). These results do not support H4. See figure 5 for a graphical depiction of the interaction.

Figure 5. Background Complexity, Follower Count and Sponsorship Disclosure on Purchase Intentions (Study 2)



Discussion

The results of study 2 did not find support for H1, which hypothesized that images with low background complexity on social media would increase social media engagement and purchase intention compared to images with higher background complexity. H2, which posits that social media posts created by micro-influencers would increase social media engagement and purchase intentions compared to macro-influencers, was also not supported. Likewise, H3 was not supported; that is, social media engagement and purchase intentions would increase when micro-influencers posted food images on social media with lower background complexity (vs. higher background complexity); when images were posted on social media by macro-influencers, background complexity would not impact social media engagement and purchase intentions. The results of this study found no evidence that sponsorship disclosure moderated the interaction effect between background complexity and influencer type, as proposed in H4.

General Discussion

Summary of Results

This study primarily explored the impact of background complexity on social media engagement and purchase intentions. Additionally, it examined the moderating role of influencer type and the impact of sponsorship disclosure on the effect of image background complexity on consumer behaviour. The findings revealed that H1 and H2 were not supported, indicating that background complexity and influencer type did not significantly affect social media engagement and purchase intentions. Furthermore, influencer type was not observed to moderate the interaction of background complexity on social media engagement and purchase intentions, thus H3 was not supported. Lastly, the research outcomes indicated that sponsorship disclosure had no significant impact on the interaction effect between image background complexity and influencer type, leading to the rejection of H4. However, the above results may be attributed to design flaws in the experiment and other influencing factors that were not considered.

Theoretical Contributions

This study contributes to the literature in several ways. For the first time, it integrates the five topics of image background complexity, influencer type, sponsorship disclosure, social media engagement, and purchase intentions into the discussion. Although the research results do not support any hypothesis, they can offer new directions and insights for future research. Additionally, this study identified some potential influencing factors. Social media usage and Instagram usage were found to have a weak correlation with social media engagement, while attitudes were strongly correlated with both social media engagement and purchase intentions. These findings could support future discussions on related topics in various contexts.

Managerial Implications

This study found that people's attitudes toward images are related to social media engagement and purchase intentions. Therefore, brands and influencers need to consider the aesthetics of their images when creating them to elicit a more positive attitude from viewers towards their posts. Additionally, although the research results did not find a significant impact of image background complexity on social media engagement and purchase intentions, in practice, attention can be paid to avoiding overly simplistic designs to ensure that viewers receive sufficient information. Similarly, overly complex designs should be avoided to prevent viewers from feeling overwhelmed and unable to locate promoted products. Furthermore, while this study did not find a significant impact of sponsorship disclosure on other variables, previous research suggests that brands and influencers clearly including disclosures when publishing sponsored content can increase the transparency of the content. Therefore, clearly stated disclosures in sponsored content can help viewers identify the type of post, recognize the authenticity of the brand and influencer, and ultimately, potentially increase their engagement and purchase intentions. Finally, based on previous research, brands with limited funds can opt for micro-influencers. Despite their smaller follower groups, the content they post is often considered more trustworthy, thus achieving effective promotion. If the brand has sufficient funds, they can also consider macro-influencers, who are more widely recognized.

Limitations and Future Research

This study, however, has some limitations which offer potential paths for future research. Firstly, the stimulus used in the study may have design flaws. The focal product (that is, the salad) may contribute to its complexity due to its rich color and variety of ingredients. Additionally, the restaurant environment depicted in the images is also visually rich, with greenery in the background, shadows, and three types of walls, potentially minimizing the perceived complexity differences between the images. Therefore, future studies could consider using simpler backgrounds (for example, white walls) and focal products to obtain more significant findings.

Secondly, the scenario of the paper was set in a restaurant, with the focal product being food. People's responses may vary based on their preferences for different types of food (for example, healthy foods or unhealthy foods) and types of restaurants (for example, fast food restaurants vs. upscale restaurants). Additionally, posts with different content may also yield different results, such as cosmetics products, technology products, and daily necessities. Therefore, in future research, attempts could be made to apply the topic of this article to different contexts.

Thirdly, this article employed a questionnaire to measure participants' social media engagement and purchase intentions. In future research, alternative methods and angles for measuring social media engagement and/or purchase intentions could be explored. For example, discuss the sub-dimensions of consumer engagement: enthusiasm, enjoyment, attention, absorption, sharing, learning, and endorsing (Dessart et al. 2015). Additionally, other marketing outcomes, such as brand awareness, customer loyalty, and actual consumer behavior, could be considered for investigation in future studies.

Lastly, since this study focused on Instagram, the results may not be applicable to other social media platforms. Each platform attracts distinct user demographics and features varied content types. For example, TikTok and YouTube mainly focus on video, while Instagram combines short videos and images, and X mainly focuses on images and text. So perhaps the impact of image background complexity on social media engagement and purchase intentions will be more significant on X. Hence, future research could explore similar topics on platforms like TikTok, YouTube, and X to broaden the scope of findings beyond Instagram.

Conclusion

Overall, this study did not find any significant impact of image background complexity and influencer type on social media engagement and purchase intentions. Additionally, whether a post is posted by a micro-influencer, or a macro-influencer was found to have no effect on the effect of image background complexity on social media engagement or purchase intentions. Similarly, sponsorship disclosure was not found to play a moderating role in these relationships. Thus, when scrolling through one's Instagram feeds, similar to the example provided in the introduction to my thesis, consumer behaviours may not be influenced by differences in image background complexity. Similarly, the popularity of the influencer associated with the post may not affect engagement behaviour. Moreover, regardless of whether a post is marked as sponsored content, our engagement and likelihood of purchase may remain unaffected. However, more research is needed to confirm whether the effects on engagement and purchase likelihood persist across different contexts and demographics.

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Appendix A

Pretest Stimuli

Image 1

Image 2

Image 3

Image 4

Appendix B

Study 1 Stimuli

Micro-influencer × Low Background Complexity

Macro-influencer × Low Background Complexity

Micro-influencer × High Background Complexity

Macro-influencer × High Background Complexity

Appendix C

Study 2 Stimuli

Micro-influencer × Low Background Complexity × Without Disclosure	**Micro-influencer × Low Background Complexity × With Disclosure**
	
Macro-influencer × Low Background Complexity × Without Disclosure	**Macro-influencer × Low Background Complexity × With Disclosure**
	

Micro-influencer × High Background Complexity × Without Disclosure

Micro-influencer × High Background Complexity × With Disclosure

Macro-influencer × High Background Complexity × Without Disclosure

Macro-influencer × High Background Complexity × With Disclosure

Appendix D

Survey Adapted Scale

Measure	**Study 1**	**Study 2**
Image Background Complexity (based on Guo & Hall, 2009)	Please rate the extent to which you perceive the image in the post above is complex. (1=not at all, 7=very much) Please rate the extent to which you perceive the image in the post above is simple. (1=not at all, 7=very much) Please rate the extent to which you perceive the image in the post above is crowded. (1=not at all, 7=very much) Please rate the extent to which you perceive the image in the post above is overwhelming. (1=not at all, 7=very much)	Same as those used in study 1.
Attitudes (based on Geissler et al., 2006)	Now rate the extent to which you perceive the image in the post above is likable. (1=not at all, 7=very much) Now rate the extent to which you perceive the image in the post above is well structured. (1=not at all, 7=very much) Now rate the extent to which you perceive the image in the post above is interesting. (1=not at all, 7=very much) Now rate the extent to which you perceive the image in the post above is complete. (1=not at all, 7=very much)	Same as those used in study 1.
Influencer Types (Kay et al., 2020; Janssen et al., 2022)	Based on the number of likes that this post received (that is, # likes), would you categorize "foodhunter" as a micro influencer or a macro influencer? (micro influencer or macro influencer)	Considering the number of followers this influencer has (that is, # followers), please indicate how much you agree or disagree with each of the statements below: I think that this influencer is popular. (1=totally disagree, 7=totally agree)

Measure	Study 1	Study 2
		I think this influencer has many followers. (1=totally disagree, 7=totally agree)
Social Media Engagement (based on Schivinski et al., 2016)	Based on this post, please indicate how likely you are to put a “like” on this post. (1=not at all, 7=very much) Based on this post, please indicate how likely you are to comment on this post. (1=not at all, 7=very much) Based on this post, please indicate how likely you are to share this post (publicly or privately). (1=not at all, 7=very much)	Same as those used in study 1.
Purchase Intentions (based on Smith et al., 2021)	Based on this post, how likely are you to check out the restaurant’s website? (1=not at all, 7=very much) Based on this post, how interested are you in eating at The Salad Place? (1=not at all, 7=very much) Based on this post, how likely are you to eat at The Salad Place in the future? (1=not at all, 7=very much) And finally, based on this post, how likely are you to choose this restaurant the next time you want to eat a salad? (1=not at all, 7=very much)	Same as those used in study 1.