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Journal of Retailing and Consumer Services

Journal homepage: www.elsevier.com/locate/jretconser

‘What’s in a Like?’: Hiding Likes on Instagram and its Effect on Influencer Marketing

Matthias van der Waal

LIACS, Leiden University, Niels Bohrweg 1, 2333 CA Leiden, The Netherlands.

ARTICLE INFO

Article history:
Received 30 August 20

Keywords:
E-WOM; influencer marketing; Instagram; social influence; social media marketing

ABSTRACT

This study sheds light on a growing type of electronic word-of-mouth, influencer marketing, which has become increasingly important to marketeers. Their expertise in creating non-disruptive advertisements for their trusting audience have resulted in brands increasing their budgets for this effective marketing strategy. Instagram is one of the most used platforms by these opinion leaders, but the platform’s decision to hide the numerical like-counter on Instagram might affect influencer marketing. This study aims to identify what that effect is by exploring the like’s information value through its power to affect influencer and brand perceptions. Furthermore, the effect of hiding the like-counter on influencer and audience behavior is explored. Findings from this research suggest that Instagram influencers are not affected by the like-count no longer being publicly visible. Influencers were not perceived differently across different liking conditions (high, low or hidden likes), neither were brands. Additionally, no trends were observed in the audience’s liking behavior after the like-counter was hidden.

1. Introduction

With the massive growth of social media over the past decade, companies and scholars have realized the importance of influencer marketing (IM). As consumers increasingly turn to social media to inform their purchasing decisions, influencers have emerged to advise these information seekers (Arnold, 2018; Gashi, 2017). In their time on the platform, influencers have learned how to create strong content and to adapt to ever changing trends. Consequently, they are characterized by large followings and, since they often position themselves in a niche, are perceived to be experts in their fields (Lou & Yuan, 2018). Due to this combination of knowledge of social networking sites (SNS), their field of interest and having a dedicated audience, advertisers’ budgets for IM are growing rapidly (Influencer Marketing Hub, 2020; Schomer, 2019). This often results in highly convincing brand endorsements known as native advertising, “a term used to describe a spectrum of new online advertising forms that share a focus on minimizing disruption to a consumer's online experience by appearing in-stream” (Campbell & Marks, 2015, p. 12). Native advertising has been popularized because, unlike traditional advertising, it appears more authentic and credible as it is seamlessly integrated in the influencers content, lowering resistance to the advertisement (Taylor, 2017). This is strengthened by the relationships that the influencers strive to make with their audience which, besides their expertise, make them credible sources of information (Steffes & Burgee, 2009). As a result of the dissemination of such advertising amongst their disproportionately large audiences, influencer marketing has become a multi-billion dollar industry (Schomer, 2019; Statista, 2020).

The largest concern for marketeers is the selection of influencers that are appropriate for the brand and goal of a campaign (Influencer Marketing Hub, 2020). The criteria can be quite complex (e.g. brand fit, content quality etc.), but looking at reach and engagement often serves as the starting point in the selection process. While reach obviously allows wider diffusion of the message, it has also been investigated more in-depth. It was found that influencers with a large following (a large component of reach) are perceived more likeable, due to high popularity, and perceived to have higher opinion leadership in some cases (De Veirman, Cauberghe & Hudders 2017). High perceived likeability and opinion leadership are factors that might affect how the promoted brand may be perceived and affect the purchase intention of the audience (Casaló, Flavián & Ibáñez-Sánchez, 2018; Vien, Yun & Fai, 2017). This makes influencer reach an important criterion. A highly engaged audience is important if a relevant brand wants to sell a product, because engagement is often indicative of interest. To the best of our knowledge little-to-no research covers the effect of engagement metrics on influencer perception.

Instagram has made recent changes to one if its engagement metrics, the like, which provides a research opportunity on the effect of how engagement metrics affect influencer perceptions. Instagram started as Burbn, a location-based app to find the best bourbon in an area, created by Kevin Systrom and Mike Krieger in 2010. Realizing the app could not compete with others, Instagram was created, which allowed people to instantly upload a square-frame photo to their timeline and apply filters to them (Leaver, Highfield & Abidin, 2020). The immediacy was important, but it was ultimately the communication which photography allowed that made it so successful. Furthermore, it was the integration of the square frame, filters and sharing, which previously were found in separate apps, that made it popular (ibid). Ten years after its conception, the app is one of the largest social media platforms with over 1 billion users and favored by influencers. Instagram has become an influencer-rich platform over time and is deemed most effective by marketers (Feldman & Richter, 2019). It is also the SNS with one of the highest engagement rates, between 0.7-7.2% (Leone, 2019; Influencer Marketing Hub, 2020).

Instagram seems to lend itself well to influencer marketing, but this could potentially change with the announcement that Instagram made at the Facebook F8 conference in May 2019. The platform was to test and would later enforce hiding the like-counter in several countries (see image 1) for mental health reasons of its users (Abril, 2019).

Image 1. A screenshot from Instagram's interface. The bottom left showing that the option to like (heart) remains. Underneath, instead of showing an enumeration of the like count (e.g. 123 likes), a textual indication is given that people like the content.

From a mental health standpoint, this makes sense as the like is sometimes used as a part of a reputation system. Reputation systems are a vital way of knowing who we can trust in our network. Gossip was one way to do this prior to online media, in which interlocutors share their thoughts about people, who they trust and so on (Dunbar, 1998; Rheingold, 2007). In the online space, rating systems for profiles are used to "police the quality of the content and transactions exchanged through sites" (Rheingold, 2007). While the like was probably not intentionally made for this purpose and it might not be as explicit as on for example eBay, where feedback about a buyer/seller are turned into a numeric rating (see Resnick & Zeckhauser, 2002), a like on Instagram can have the same effect. This means that the like has the possibility to reflect on the person and be interpreted as a notion of popularity. Consequently, it can negatively affect the mental health of a 'regular' user to focus on these metrics and comparing them to their peers (Leventhal, 2019). For influencers, however, this might be valuable information for their audiences when they look for opinion leaders. This is also the reason they voiced their concern when this change was announced (Paul, 2019; Constine, 2019).

This research explores the effects of removing the like-counter on Instagram on influencer marketing. More specifically, this research looks at how high, low and hidden likes effect the perception of the influencer and the endorsed brand through an experimental design. Furthermore, the effect of hiding the number of likes will be further researched by data analysis. Data from Instagram regarding the number of likes, comments and hashtags is used to see how the change has affected audience and influencer behavior. This study thus adds value to the field of electronic-word-of-mouth and influencer marketing by 1) understanding how an influencer's number of likes affects perceptions towards the influencer and the brand he/she promotes 2) by exploring how Instagram's managerial decision to hide the number of likes, affects consumer and influencer behavior. Lastly, this study contributes to literature regarding opinion leadership and identify it, the largest challenge in influencer marketing (Influencer Marketing Hub, 2020). This is done by getting a better understanding of the information value that the like has and how it might shape consumer's perception about the influencer and the promoted brand.

Since little prior research exists about the importance of metrics in influencer marketing, first an outline will be given of relevant concepts, most notably why the like might be important to IM on this platform. Next, the two studies are outlined. The results are then presented, after which they are discussed and pointers for future research are given.

2. Theoretical Background

2.1. Word-of-Mouth Marketing: Offline and Online

In order to understand what influencer marketing is and why it is as effective as it is, the underlying concept of electronic word-of-mouth (eWOM) must be explained. This is the online counterpart of traditional word-of-mouth (WOM), in which people exchange information with others in their network through face-to-face conversations. Such information exchange occurs between two types of interlocutors: the opinion leader and the opinion seeker (Gilly et al, 1998, as cited in Chu & Kim, 2011, p. 50). The subject matter need not be commercial, however, because people constantly seek information about products, WOM has become an effective tool for influencing consumers' attitudes and behavior. Its success is due to people perceiving personal connections in their network as more credible than when a message is directly communicated from a company through mass media (East, Hammond & Lomax, 2008). Most of this holds true for eWOM, except that communication now occurs on a much larger scale and online. This means that it is no longer on a strictly one-to-one basis ─ although it can be ─ instead it can also be on a one-to-many basis, as is the case with social media. Furthermore, because it is on a world-wide scale, the information exchange no longer has to be between people who have a personal connection. In fact, many online platforms keep user data relatively private meaning that the information exchange can also occur between anonymous consumers (Chu, 2009, p. 15).

A plethora of research on the effectiveness of eWOM exists. Several studies find that eWOM is one of the most effective ways to influence consumers purchasing intent and brand image (e.g. Jalilvand & Samiei, 2012; See-To & Ho, 2014; Fan & Miao, 2012). Research underlines the importance of trust and the formation of communities/relationships online for this strategy to work well. As previously mentioned, this in part because peers trust each other over what the company communicates (East, Hammond & Lomax, 2008). This is attributed to source credibility, i.e. the extent to which a source is found to be reliable, competent and consequently trustworthy, as well as their perceived motivation for sharing information (Petty and Cacioppo, 1986; Wu & Wang, 2011). Furthermore, relationship factors such as stronger tie strength between the opinion leader and opinion seeker is also important in effective eWOM (Stuart, Teng, Khong, Goh & Chong, 2014; De Bruyn & Lilien, 2008). Tie strength refers to "the level of intensity of the social relationship between consumers or degree of overlap of two individuals' friendship [which] varies greatly across a consumer's social network" (Steffes and Burgee, 2009, p. 45).

Most research on eWOM is often about platforms that allow people to review products, less about social media. This is problematic due to anonymous nature of these types of eWOM, in which the opinion leader is often unknown. This makes it harder to establish credibility or assess tie strength (Chatterjee, 2001; Schindler & Bickart, 2005, as cited in Lee & Youn, 2009). Furthermore, the research that does exist on social media in relation to eWOM is limited and often concerns interactions between friends and family who have connections to each other offline (e.g. Erkan & Evans, 2016; Daugherty & Hoffman, 2014; Stuart et al., 2014). Nonetheless, this disregards the other types of influence that happens on SNS.

2.2. Influencer Marketing

As the name suggests, influencers are a type of opinion leader. In this type of marketing strategy, these influential individuals are targeted and the networks they have built, rather than targeting the market as a whole (Woods, 2016). Instead of companies forming the relationships with the customer, influencers often have a community at their disposal. This community tends to follow this influencer because they are interested in the content they create and their lives. What arises is a so-called parasocial relationship, in which individuals attach feelings of affection to a persona, often celebrities. Sociologists Richard Wohl and Donald Horton (1956) first proposed the concept of parasocial interactions to explain how audiences developed a connection to prominent figures in the media. According to them, it constitutes a one-sided love of an individual who spends emotional energy and attention in a media symbol. This induces a feeling of kinship and association that lets them feel like they know the celebrity, even though the celebrity has no idea of the individual's existence (Rihl and Wegener, 2019). At least, that is how it used to be prior to the parasocial interaction that social media allows. Formerly, media was much more one-way. Nowadays viewers can chime in on social media with queries, demands and feedback on what a creator makes or says (Farokhmanesh, 2018). While the celebrity often regards their fans as a collective only, sometimes they know of or engage with individual fans and see them as a recognized component of their parasocial network (Stever and Lawson, 2013, p. 349).

Research has indicated that, like traditional TV personalities, Youtube influencers have parasocial relationships with their audience, the strength of which is comparable to those in real-life (Chen, 2016). A reason that this effect is stronger online might be because these Youtubers, like Instagram influencers, often let audiences partake in their personal lives more so than on TV. Their livelihoods depend on the bond they create. Hence, they curate their online personalities to maintain and grow their audience. To do so, Youtubers frequently engage with them on various platforms to stay relevant and increase parasocial interaction (e.g. commenting on posts, shouting out individual fans etc.). The frequent repetition of those moments is what creates stronger parasocial relationships (Rihl and Wegener, 2019). The more often they share, the stronger the suggestion of friendship and the feeling of shared experiences (Horton and Wohl, 1956). In fact, Horton & Wohl state that the continuous observation of these influencers makes them feel like they are engaging in a face-to-face exchange, rather than passive observation (p. 216).

This parasocial relationship is comparable to WOM with face-to-face communication between a trusted opinion leader from one's social network and an information seeker. Although it could be argued that picking up on social cues is inherently a way we assess the credibility of our interlocutor (e.g. Bryan, Perona & Adolphs, 2012; Sheth et al., 2011), it has been found that having a parasocial relationship has an even larger impact on purchasing intent compared to credibility (Sokolova & Kefi, 2019). The research that suggest that there is only a 7 percent difference between how much a person relies on the recommendation made by a friend (56%) versus one made by an influencer (49%), might be attributed to the fact that these two factors are what characterize influencers (Swant, 2016). Influencer marketing thus combines the important relational and credibility aspects with the scalability of the internet, which makes it such an effective form of eWOM.

2.3. Engagement Metrics and IM

Engagement metrics on social media come in many forms and vary per platform. Hoffman and Fodor (2016) classified various types of social media platforms and their respective engagement metrics in their research, identifying four on Instagram. Apart from the like, Instagram has three other metrics of engagement by which they can be identified. Users can see another user's number of views (video), replies/comments and their follow count. The "like", however, is one of the earliest metrics of engagement that Instagram had and probably the most prolific on all platforms. The button can be found beneath the content, in the form of a heart, and can be double tapped by the audience to communicate positive feelings towards the post. In fact, engaging with content, by for example liking a post, has been shown to aid the formation of positive brand image and brand equity (Coursaris, Van Osch, Balogh & Quilliam, 2014).

Research into the relationship between engagement metrics and purchasing intent finds that out of the other metrics available, the like is the strongest predictor for offline behavior. Meaning that once a user likes content in which a certain product is promoted, they are more likely to then go out and buy or consume the product (Alhabash, McAlister, Lou & Hagerstrom, 2015). A second research further confirms this, concluding that small interactions can have a long-term effect on sales because they are more likely to attract audiences with similar interests (Stephen & Galak, 2012). This can be explained by how most social media platforms rely on algorithms to spread content. When a user engages with content the chance that someone in their network will also see it increases, i.e. increasing reach. Lastly, when content with high information quality is paired with many likes, a consumers' urge to buy impulsively increases (Chen, Su & Widjaja, 2016).

Nonetheless, social media have changed and grown massively which results in some research claiming that the "like" is no longer a sufficient metric. When social media started off there were few tools available to accurately measure risk of investments in SMM. However, as the importance has grown, platforms created functionalities with which users have access to more metrics than the publicly observable ones. Gil Eyal, founder of an influencer marketing platform called HYPR, claims that the "like" expresses very little due its binary nature. He also claims that likes are very easily manipulated, and that research done by his company showed that 64% of influencers buy likes (Paul, 2019). Other research corroborates this, finding that most of the public metrics can be bought (De Micheli & Stroppa, 2013; Calzolari, 2012, as cited in Baym, 2013). Adding to this is the mutual exchange of likes under the hashtag #Likeforlike, where people "like" each other's posts simply to seem more popular and/or increase reach. In this case, the like is purely a passive action in which users disregard the content and simply "like" it for personal gain.

While research is divided on the usefulness of likes as an accurate measure, it can be expected that likes do have importance to a certain extent. An analysis of the arguments provided against the "like" suggest an underlying importance of likes to gain credibility and exposure, especially the former being important to the functioning of an influencer. Not only does Instagram's algorithm favor engaging profiles, but people also value content that has been engaged with more, as the warranting principle suggests. This principle implies that people weigh information generated by other people highly, when making judgements about a certain person. Scissors, Burke, & Wengrovitz (2016) say that likes, despite containing less text-based information than comments, are still other-generated content. Likes thus have information value, particularly being indicative of popularity and personality characteristics (p. 1502).

In this research, the like is viewed as a form of endorsement. Firstly, this has been shown to affect liking behavior. More endorsement in the form of likes were shown to increase the likelihood of an individual liking a post (Sherman et al., 2016). This research expects that hiding the number of likes negatively affects liking behavior and will explore how number of hashtags and comments change because of that. It is expected that if liking behavior goes down, that influencers will use hashtags to increase reach and that users comment more instead of using the like button. Furthermore, Chaiken (1987) found large endorsements can sometimes positively affect skepticism that people might have about a message. This might be useful to brands. As discussed, native advertising already lowers the resistance to a message but large endorsement in terms of likes might lower this further. Research has indicated that lower ad skepticism has an effect on brand attitude (Chen & Leu, 2011). Hence, we expect high likes to result in lower ad skepticism and brand attitude.

H1: Hiding the like-counter on Instagram has a negative impact on how the promoted brand is perceived in terms of brand attitude, ad skepticism and ad recognition.

H2: Hiding the like-counter on Instagram has a negative effect on liking behavior.

H3: Hiding the like-counter on Instagram has a positive effect on number of comments and number of hashtags.

In regard to numerical metrics and influencer perception, De Veirman, Cauberghe & Hudders (2010) found that a large amount of followers is mostly linked to a higher perception of popularity which may lead to ascribing an influencer with more opinion leadership. These positive results are despite followers holding no text-based information. Potentially the like could be an indicator of popularity and opinion leadership. Moreover, it was found that an influencers' number of followers also positively affected consumers' perceptions about the brand the influencer promoted. Because both likes and followers are comparable, we expect that an influencer who is perceived as popular due to its number of likes might also be ascribed with more opinion leadership as compared to low likes. We also expect a higher number of likes to positively affect the likeability of the influencer.

H4: Hiding the like-counter on Instagram has a negative impact on influencers' perception in terms of ascribed opinion leadership, popularity, credibility and likeability.

In a similar vein to De Veirman, Cauberghe & Hudders (2017), the current research aims to explore how an influencer's number of likes affects both perceptions towards the influencers and the brand they promote. In addition to this, through scraping Instagram's available metrics this research explores if effects can be observed in audience liking behavior following the month in which the like-counter was hidden.

3. Method

To determine the effect that hiding the like-count has on influencer marketing, two studies have been devised. The first study investigates the effect of the like on influencer and brand perception by means of an experimental design. The second study is an analysis of liking behavior on Instagram, comparing trends before and after the like-counter was removed.

3.1. Study 1 – Influencer and Brand Perception

To investigate how hiding the like might affect influencer and brand perception, an online experiment was set up, similar to the study of de Veirman & Hudders (2017). Their survey about the effect of the number of followers on influencer and brand perception, was altered to fit the current research about likes. The main purpose of this experiment is to see if there is a difference between high and low likes and, consequently, how the condition of the hidden display of likes compares to this.

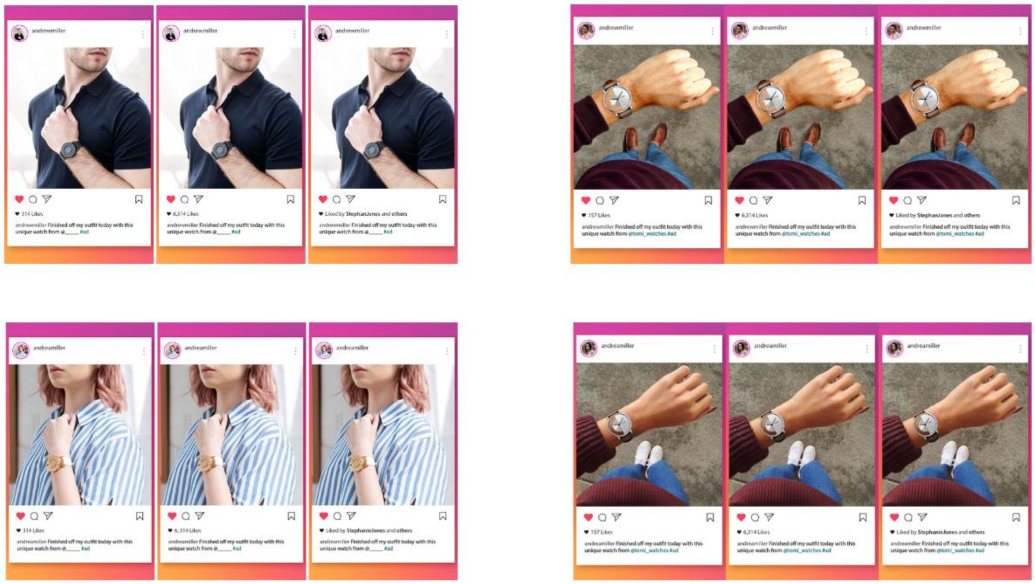

Image 2. On the left side, the visual stimuli for both genders used in the pilot version and on the right side the stimuli used in the final version.

Participants and design

The experiment consisted of a 3-condition (number of likes: low, high and hidden) between-subjects experimental design to explore the importance of the like in how users perceive influencers. A total of 101 Instagram users (46 females, MAge = 36.61 years, SDAge = 11.6) took part in the study on Amazon's mechanical Turk (Mturk), in return for a small payment. However, after filtering the data the final dataset contained 81 Instagram users (36 females, MAge = 36.26 years, SDAge = 11.24). Participants were excluded based on performance. In the case of failing attention checks, completing the survey under 60 seconds and outliers in the manipulation check (N = 3) answers were removed.

Manipulation stimuli

Instagram posts for two fictious influencers, a male (Andrew Miller) and a female (Andrea Miller), were created using commercial images from a watch brand (see Image 2). The gender of the respondent was matched to the gender of the Instagram influencers to avoid any effects related to gender identification. Both influencers had a similar age, style and watch model in the selected image. They were given identical captions: "Finished off my outfit today with this unique watch from @zigewatches #ad". Since the images depict influencers, the number of likes displayed underneath the image would have to be of a moderate size. However, since engagement is often only a small percentage of the following, the number for low likes was set at 314, based on small influencers with roughly 2-4k followers. For the high like condition, this was set to 6,314 and hidden likes followed the format used on Instagram ("Stephan(ie) Jones and other like this"). Each participant was randomly assigned to one of the 3 conditions and asked to carefully view the influencer's Instagram post and then fill out a questionnaire. These conditions were piloted on Mturk respondents (N=123). The pilot revealed that respondents failed both manipulation checks, people's distinction between high (M= 4.73, SD = 1.20) and low likes (M = 5.02, SD = 1.50) was statistically insignificant (t(80) = -.81, p = .071). Similarly, distinction in popularity between high (M=3,68, SD=.89) and low (M = 3.58 , SD = .85) likes was statistically insignificant (t(80) = .46, p = .895). This resulted in high anova significance scores, apart from product involvement which was almost statistically significant (F(2,120) = 3.22, p = .044).

In the revised version of the questionnaire changes were made to the stimuli and survey. The original images (both profile pictures and the posts) were changed to be near-identical, with the exact same watch on either influencer (see image 2). This was done to avoid interferences of how the variation in watch color and influencer appearance might have been perceived differently in the original images. Furthermore, a benchmark was added explaining what an influencer is and what a typical number of likes is for them, the latter simply being an average between the high and low likes condition. The low like condition was halved, to 157 likes, as to further ensure that low likes were perceived as such.

Measures

The items for the manipulation check measured participants' perceptions of the number of likes. Participants were asked if they found the influencer had a very small (= 1) versus very large (= 7) number of likes. Testing the effect on influencer perception and thus to test the fourth hypothesis, four measures were used. Perceived popularity was measured by a five-point semantic differential, asking participants if they found the influencer 'unpopular versus popular' (1 item). Ascribed opinion leadership was measured by Flynn, Goldsmith, and Eastmans' (1996) 5-point Likert-scale (4 items; 1 = strongly disagree, 5 = strongly agree; a = .796), adjusted to review others' opinion leadership. The influencer's overall likeability was measured using three items of Dimofte, Forehand, and Deshpande's (2003) scale for attitude toward the influencer (5-point semantic differential, a = .540). Source credibility was measured using Ohanian's (1990) 14-item scale (5-point semantic differential, a = .883).

In order to test the first hypothesis regarding brand perception, respondents were presented with an additional three measures. Brand attitude was measured by Spears & Singh (2004) 5-item semantic differential scale (a = .801). The extent to which the ad in the post was recognized was measured by using Van Reijmersdal et al.'s (2016) 5-point Likert-scale (3 items; 1 = strongly disagree, 5 = strongly agree, a = .705). Ad skepticism was measured by Lu, Chang & Chang's (2014) 4 item, 5-point Likert-scale (1 = strongly disagree, 5 = strongly agree, a = .744). An attention check was integrated in this category to filter out people who were

Table. 2 ANOVA scores

Measures		*Sum of Squares*	*df*	*Mean Square*	*F*	*Sig.*
Ascribed Opinion Leadership	Between Groups	3,172	2	1,586	2,045	.136
	Within Groups	60,487	78	,775		
Source Credibility	Between Groups	,983	2	,491	1,279	.284
	Within Groups	29,974	78	,384		
Popularity	Between Groups	4,381	2	2,191	1,655	.198
	Within Groups	103,273	78	1,324		
Ad Recognition	Between Groups	,389	2	,195	,359	.700
	Within Groups	42,278	78	,542		
Brand Attitude	Between Groups	,195	2	,097	,215	.807
	Within Groups	35,403	78	,454		
Ad Skepticism	Between Groups	,385	2	,193	,311	.734
	Within Groups	48,295	78	,619		

not reading the survey carefully enough. Lastly, a control variable was added to gauge respondent's interest in watches (Mittal, 1995; 3 items; 1 = strongly disagree, 5 = strongly agree, a = .233). For an overview of the used measures, refer to appendix A.

3.2. Study 2 – Liking Behavior

To see what the effect of removing the like has been on audience's liking behavior, Instagram data was analyzed based on the lists of influencers provided by (de Oliveira & Goussevskaia, 2020). Instagram's API has certain limitations to protect the privacy of its users and prevent unwanted behavior (e.g. bots). Consequently, a web crawler was used to collect the dataset of influencers through the webpage of Instagram (Ferguras, 2020).

Data Collection and Overview

Data collection was comprised of several phases. First, the provided list of influencers, which was originally collected in 2018, was pre-processed to filter out any usernames which were no longer accessible. Then following counts were checked and those with less than 1,000 followers were filtered out. This resulted in a total list of 2967 influencers. To investigate what trends might be observable before, after and while the like was removed, for each influencer all posts between January 2019 and March 2020 were collected resulting in a total of 759,611 posts. Per post the number of hashtags, likes and comments were collected, as well as the timestamp of when the content was posted. Not only will this dataset give insight into liking behavior, if a negative trend is observed the other metrics might reveal if influencers increase their hashtags, a common method employed to increase reach (Carter, 2016). The number of comments might indicate if users attempt to find other means to communicate to their influencer what they think about the post. The data was collected in June 2020.

Since influencer marketing is gaining popularity and new influencers are continually entering the field, there is little agreement about the categorization of influencers. This research follows the categorization of the research by de Oliveira & Goussevskaia (2019), who categorized influencers as followed:

- **Beginners**: 1,000 ≤ number of followers ≤ 10,000;
- **Micro-influencers**: 10,000 < number of followers ≤ 100,000;
- **Celebrities**: number of followers > 100,000.

Out of the collected dataset, 1213 were classified as beginners (N_{posts} = 233,341), 1493 as micro-influencers (N_{posts} = 415,425) and 261 as celebrities (N_{posts} = 110,944). In this way, it can be investigated if and how influencers of different sizes were affected differently.

4. Results

4.1. Study 1

Manipulation Check

Participants perceived the influencer's number of likes to be higher in the high (M = 5.71, SD = .86) than in the low number of likes condition (M = 4.28, SD = 2. 03, t(51) = -3.22, p < .001). The difference in mean between low and hidden (M = 4.61, SD = 1,64) indicate that the hidden is perceived higher than low likes. Regarding the difference in perceived popularity, a low number of likes was perceived to be a less popular post (M = 3.10, SD = 1,37) while a high number of likes was perceived more popular (M = 3.67 , SD = .70 , t(51) = -1.82, p < 0.001). Looking at the mean of hidden likes, show that it is perceived slightly higher than low likes (M = 3.25, SD = 1.21). The results indicate that the manipulations are satisfactory.

ANOVA Analysis

Due to low internal consistency likeability and the control variable were excluded as measures from the ANOVA. Looking at the means of the remaining variables, they are relatively close together, between 3,2672 and 4,0417 (see Appendix B, table 1). Furthermore, within each measure there is little difference between the means of each condition. The measures that differ the most in means are those of high (M = 3.74, SD = 1.04) and low likes (M = 3.26, SD = .877) in ascribed opinion leadership, as well as high (M = 3.95, SD = .649) and low (M = 3.26, STD = .877) likes in source credibility. Nonetheless, for ascribed opinion leadership no statistically significant difference between the groups was found ($F(2,78) = 2.05$, $p = .136$). Source credibility does not show a statistical significant difference between the high, low and hidden likes either ($F(2,78) = 1.28$, $p = .284$). Consequently, a Tukey multiple comparison shows no significant difference between the high and low conditions of opinion leadership ($p = .133$) and credibility ($p = .382$). Popularity was also not

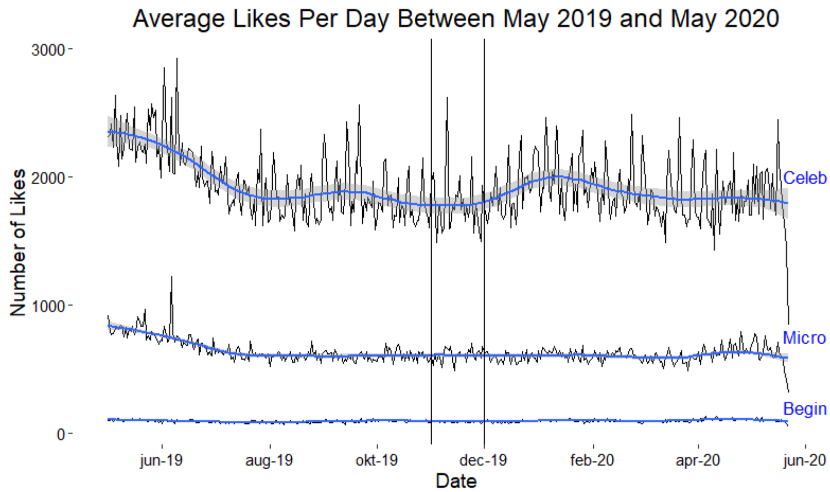

Image 3. Average number of likes plotted over time across the three categories of influencers. Two vertical lines indicate the beginning and end of November, when the change was made to the like-counter.

statistically significant (F(2,78) = 1.66, p = .198). Furthermore, there was no significant effect of likes on the advertisement related measures ad recognition($F(2,78) = .36$, $p = .700$), brand attitude($F(2,78) = .22$, $p = .807$) and ad skepticism($F(2,78) = .31$, $p = .734$) for the three conditions (see table 2). Due to lack of statistically significant scores, H1 and H3 are rejected.

4.2. Study 2

Results from scraping Instagram user data show that hiding the like on Instagram has had no negative impact on liking behavior. The loess regression shows no negative trend across the influencer categories after it has been removed, allowing this research to reject H2. Beginning and micro-influencers have quite a flat trend with little variability. Celebrities show both more variability and fluctuations in terms of trend, but nothing indicates they were impacted by the change (see image 3). On the contrary, in December and January there is a rise in number of likes. A similar occurrence is seen for number of comments for celebrity and micro-influencers, with a peak in comments in December (see Appendix C). Nonetheless, there is little indication that hiding the like-counter has resulted in more engagement in form of comments.

Neither can a trend be observed regarding the use of hashtags around the time that the like-counter was hidden. The use of hashtags seems rather arbitrary and provides the most variable data but with slightly clearer trends. For beginner and macro influencers the use of hashtags seems to be going down over time. The loess of the celebrity data shows no such trend. Furthermore, there seems to be little relation between the use of hashtags and engagement in the form of comments or likes. There is no downward trend in engagement due to fewer hashtags for beginner and micro-influencers. Neither can a flat trend be observed in either engagement metric between October 2019 and February 2020, when the trend line stays relatively flat. Because no relationship can be seen between when the like-counter was hidden and number of hashtags/comments, H3 is rejected.

5. Discussion

This study has shed more light on a growing type of eWOM, influencer marketing, which has become increasingly important to marketeers. Their expertise in creating non-disruptive advertisements for their trusting audience have resulted in growing budgets for this highly effective marketing strategy. Despite its growth in use and success, little research has been done on influencer marketing. One area that requires research is methods for identifying influencers, as it is cited as the largest problem in the field. This study investigated if the like on Instagram, a popular but now-removed engagement metric, was used as a visual cue by audiences to form consumers' attitudes towards influencers and brands. No relation was found to indicate that this was the case and consequently suggests that the like is not a useful metric to identify influencers. Furthermore, this study explored how hiding the like might affect users' liking behavior. After hiding this metric, no change was observed in liking behavior. Since both studies corroborate each other, it can be concluded that hiding the number of likes on Instagram has had little impact on influencer marketing in terms of influencer/brand perception and liking behavior.

The present study was the first to investigate the relation between number of likes, a ubiquitous engagement metric, and influencer perception. The results from the online experiment show that users perceive influencers to be more popular with a higher number of likes. Hiding likes is perceived similar to low likes, which means that in line with the fourth hypothesis hiding likes on Instagram has a negative effect on popularity, in particular for influencers with larger followings. This corroborates the statement made by Scissors, Burke, & Wengrovitz (2016) claiming that likes are indicative of popularity. Nonetheless, no indication was found that an influencer is perceived more credible or likeable because of their number of likes. Neither is a significantly higher opinion leadership ascribed to those with more likes. Furthermore, the results indicate that likes have no significant effect on brand perception. None of the dependent variables mentioned in the first hypothesis show a significant affect in any of the conditions. Hence, this study shows that the like is not an effective social endorsement that could change perceptions about the influencer or brand. This is interesting when compared to research by De Veirman, Cauberghe & Hudders (2017), as one could argue the metrics are quite similar. Both follower count and like count are quantitative and indicate a form of endorsement by others. In this research the like does seem to create a strong enough 'bandwagon effect', in which the audience becomes susceptible for large endorsements and, as an effect, trust the information. Because no statistically significant differences were found, it can be concluded that likes hold too little information or persuasive value to affect how an influencer or promoted brand is perceived.

Lastly, in exploring the effect of removing the like-counter on Instagram on liking behavior no change in trends were observed after the change. No downward trends were observed after the hiding of the like in November 2019, despite influencers' worries that this would happen. This goes against the second hypothesis, which was based on prior research that more likes are more likely to garner more likes (Sherman et al, 2016). Lack of change in liking behavior, might explain a similar lack of change for the number of hashtags used, as influencers did not need to extend their reach to keep engagement up. Furthermore, the lack of a downward trend might indicate that people do might not like an image purely for popularity reasons, but for possible other factors involved. Since it is a visual-content based platform, the visual cues from the image itself might be more important than those surrounding it, such as the like. This might also explain a lack of trends in comments, in that the audience did not think they would need another way to show appreciation to their influencer, through for example comments.

6. Research Limitations and Future Research

During the process of this research, some limitations have been observed. One of the main limitations is the data availability on Instagram's API. There is no option to scrape the number of followers over time, only that at the current time of scraping. Instagram has the option for a user to instantaneously follow a user when they look at one of their images, placed next to the username. While the research does not indicate that the like is being used information of attitudes toward influencers, it would be interesting to see how influencer growth rate has been affected by the hiding of likes. Secondly, the use of MTurk could be a possible explanation for the results. While one can quickly get many results on this platform, it is hard to fully control the situation. Some might use MTurk as an easy means to make money without providing quality answers. While attempts were made to alleviate this, in data cleaning many users had to be removed from the dataset. Furthermore, it could be that respondents were a homogenous population in opaque ways. Hence, it might be worthwhile to see if a more controlled setting yields different results.

Due to the novelty of the research, there are primarily pointers for future research regarding what value the like has and how hiding it might affect influencer marketing. Firstly, the results could have been due to the large jump made between lack of prior research to the current research. It might be worth to deploy eye-tracking research with heatmapping as a first step. This type of research could reveal if audiences even use the like as a peripheral cue. Consequently, conclusions could be made about what users look at when they scroll through their feed, as well as how this behavior differs when encountering content from unknown influencers. Those results might better indicate whether pursuing this avenue of research is meaningful. Secondly, the theoretical background has indicated that tie-strength through parasocial interaction plays a large role in the effectiveness of influencer marketing. However, due to complexity reasons this research opted for an unknown influencer. Different results might be found when respondents are presented with an influencer with which they have had parasocial interactions. Tie-strength might also be further explored by the use of names in the different displays of likes (e.g. Liked by Stephanie Jones and others), to explore if having this names matters and if stronger tie strength to that named person has a stronger effect. Thirdly, due to the use of a list which included a list of influencers from all over the world the choice was made not to do a natural language processing analysis of the captions in the post (these were not scraped in the current study to speed up the scraping process). Such an analysis might reveal if, instead of using hashtags to potentially counteract any possible effect, followers were encouraged by the influencer to like the post. Furthermore, their list of names was gathered at the end of 2018 which could mean that these users already had established a strategy and routine on the platform. This could explain the lack of change in behavior, it might be interesting to explore how newer influencers handled the change differently. Lastly, to corroborate the results of this study it could be interesting to see if influencer agencies see similar trends for the influencers that they represent or if the same online experiment garners similar results on other SNS.

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Appendix A
Overview of used measurements in study 1.

Manipulation Check

Andrew/Andrea Miller's Instagram post has a … amount of likes (1 = very small; 7 = very large).

Perceived Popularity

Do you find Andrew/Andrea Miller...

unpopular	0 0 0 0 0	Popular

Ascribed Opinion Leadership (Flynn et al., 1996)

- If I'd wanted lifestyle advice, I would turn to Andrew/Andrea Miller for advice.
- If I would follow Andrew/Andrea Miller on Instagram, I would pick products based on what she posts.
- Andrew/Andrea Miller's opinion on lifestyle could have an impact on me.
- Andrew/Andrea Miller could influence my opinions about lifestyle.

(1 = strongly disagree; 5 = strongly agree)

Likeability of the Influencer (Dimofte, Forehand, and Desphandé, 2004)

Do you find Andrew/Andrea Miller…

cold	0 0 0 0 0	warm
unlikeable	0 0 0 0 0	likeable
unfriendly	0 0 0 0 0	friendly

Source Credibility (Ohanian 1990)

Do you find Andrew/Andrea Miller…

unattractive	0 0 0 0 0	attractive
not classy	0 0 0 0 0	classy
ugly	0 0 0 0 0	beautiful
plain	0 0 0 0 0	elegant
insincere	0 0 0 0 0	sincere
undependable	0 0 0 0 0	dependable
dishonest	0 0 0 0 0	honest
unreliable	0 0 0 0 0	reliable
untrustworthy	0 0 0 0 0	trustworthy
not an expert	0 0 0 0 0	expert
inexperienced	0 0 0 0 0	experienced
unknowledgeable	0 0 0 0 0	knowledgeable
unqualified	0 0 0 0 0	qualified
unskilled	0 0 0 0 0	skilled

Brand Attitude (Spears & Singh 2004)

Do you find Tommi Watches…

bad	0 0 0 0 0	good
unfavorable	0 0 0 0 0	favorable
dislikeable	0 0 0 0 0	likeable
unappealing	0 0 0 0 0	appealing
unpleasant	0 0 0 0 0	pleasant

Ad Recognition (Van Reijmersdal et al. 2016)

Read the statements below carefully and indicate to what extent you agree (1 = strongly disagree, 5 = strongly agree).
The Instagram post…

- … is advertising.
- … is commercial.
- … contains advertising.

Ad Skepticism (Lu, Chang & Chang 2014)

Read the statements below carefully and indicate to what extent you agree (1 = strongly disagree, 5 = strongly agree).

- I think Andrew/Andrea Miller's Instagram post tells the truth.
- I don't believe what Andrew/Andrea Miller wrote in his / her Instagram post.
- I can learn real product information from Andrew/Andrea Miller's Instagram post.
- Please select 'Strongly disagree'.*

- After viewing Andrew/Andrea Miller's Instagram post, I have been correctly informed about the product information.

* Control question

Product Class Involvement (Mittal, 1995)

Read the statements below carefully and indicate to what extent you agree (1 = strongly disagree, 5 = strongly agree).

- … to me is very important.
- For me … do/does not matter
- … are an important part of my life.

Appendix B

Table 1. Descriptives of ANOVA

Measures		*N*	*Mean*	*Std. Deviation*	*Std. Error*	*95% Confidence Interval for Mean*
Ascribed Opinion Leadership	Low	29	3,2672	1,03925	,19298	[2,8719; 3,6626]
	High	24	3,7396	,87687	,17899	[3,3693; 4,1099]
	Hidden	28	3,3661	,68205	,12890	[3,1016; 3,6305]
Source Credibility	Low	29	3,7217	,62572	,11619	[3,4837; 3,9597]
	High	24	3,9494	,64937	,13255	[3,6752; 4,2236]
	Hidden	28	3,6964	,58729	,11099	[3,4687; 3,9242]
Ad Recognition	Low	29	3,9770	,79148	,14697	[3,6759; 4,2781]
	High	24	3,8194	,81043	,16543	[3,4772; 4,1617]
	Hidden	28	3,9643	,59725	,11287	[3,7327; 4,1959]
Brand Attitude	Low	29	4,0207	,72771	,13513	[3,7439; 4,2975]
	High	24	4,0417	,62130	,12682	[3,7793; 4,3040]
	Hidden	28	3,9286	,65820	,12439	[3,6733; 4,1838]
Ad Skepticism	Low	29	3,6034	,76624	,14229	[3,3120;]3,8949
	High	24	3,6458	,74058	,15117	[3,3331; 3,9586]
	Hidden	28	3,4821	,84418	,15953	[3,1548; 3,8095]

Appendix C
Study 2 results on Hashtags and Comments