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ARE IMAGES FOR IMAGINATION OR REAL IMAGE OF ONE'S?FILTERING TRUTH ON INSTAGRAM

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ABSTRACT

Popularity on Social Media relies on how many positive attention (i.e. likes/comments) one is getting from his/her online groups. In order to receive more positive attention people use filters when post their photographs on social media platform like Instagram. The present study applied a mixed methods approach to conduct a descriptive analysis of #nofilter use by Instagram users. Putting #nofilter on the photo users are trying to show that they did not edit/manipulate their images. Of particular interest were those who used #nofilter but did filter their images. A text analysis of 16,448 images was conducted using Netlytic, reveling the largest content category as 'appearance'. A content analysis was used to examine authors of #nofilter images whom did use a filter, and photo-coding scheme for this group of images was implemented. Of 16,448 images collected that used #nofilter, 12% did in fact use a filter. After deletions 1344 images remained. Results suggest the majority of accounts were personal, and belonged to females and of the images, majority had people in them. People using #nofilter do in fact filter their images and research into the reasons for sham on social media is needed.

Keywords: Instagram, Social Media, Photographs, Editing Filters

1.Introduction

Revelation of the prototypical body on media stimulates body discontent in males and females (Dakanalis et al., 2014; Harper & Tiggemann, 2007; Mask & Blanchard, 2011). Body dissatisfaction in males may be due to the societal pressure (driven home by the media) to be muscular, mesomorphic(inverted triangle), and have low amounts of body fat (Lorenzen, Grieve & Thomas, 2004; McCabe & Riccaiardelli, 2005; Tylka, 2011). Whereas societal pressure to be thin and more recently to also be fit and muscular (which contradicts being thin to some extent) drives body dissatisfaction in women (Harper & Tiggemann, 2007; Holland & Tiggemann, 2016; Lew, Mann, Myers, Taylor & Bower, 2007). Unfortunately, struggling for an impractical and, most often, unachievable body ideal has been shown to not only lead to body dissatisfaction but also reducedconfidence and disordered eating habits, regardless of gender (Dohnt & Tiggemann, 2006; Hatoum & Belle, 2004; Mayo & George, 2014; Slevec & Tiggemann, 2011).

Recent findings suggested that it is not only exposure to typical forms of media (i.e., television, magazines, etc.) but also social media that is creating these unachievable, media-strengthened, societal body ideals and, thus,potentially contributing to increased body dissatisfaction, decreased self-esteem, increased negative mood states, and increased disordered eating behaviours(Fardouly, Diedrichs, Vartanian & Halliwell, 2015; Lewallen &Behm-Morawitz, 2016; Kim & Chock, 2015; Sidani, Shensa, Hoffman, Hanmer & Primack, 2016). In addition, unlike television and magazine viewing, social media permits for dynamic engagement. For instance, social media users are able to create their own profiles and accounts, which allow them to post and/or share messages or images that represent themselves to the world as they see fit.

Although research into social media usage and its impact on users' psychological and emotional states is still in its infancy, many investigations have been focused around using the social comparison theory (Festinger, 1954) to provide a potential explanation (Chae, 2016; Tiggemann & Zaccardo, 2015). The social comparison theory suggests thathumans are constantly seeking ways to evaluate their own abilities, appearances, or opinions. In the absence of an objective way to do so, humans will subjectively compare their abilities and opinions to those of others who are similar to them (i.e., in age, gender, interests, etc.; Festinger, 1954). Unfortunately, this social comparison between ordinary people and the ideal body portrayed by the media creates an upward comparison that cannot be achieved, thus leading to negative psychosocial effects (Engeln-Maddox, 2005; Tiggemann & Polivy, 2010).

Similarly, with the rise in popularity of social media, users have a seemingly unlimited source of social comparisons.Interestingly, Chrisler, Fung, Lopez, and Gorman (2013) investigated Twitter user's reactions to the 2011 Victoria's Secret Fashion Show and found that there were many tweets that contained upward social comparisons to the fashion show models like "Victoria's Secret Fashion Show. Just there to remind you that yes, you are still fat" and "I dunno why I'm watching this Victoria's Secret fashion show. I can only fit the perfume". However, not only can people compare themselves to celebrities in the media but social networking sites are unique in that users now have the ability to compare themselves and their appearance to friends, family, and acquaintances (Chua & Chang, 2016; Santarossa, Coyne, Lisinski & Woodruff, 2016).

Of particular interest is the social networking site Instagram and the psychosocial outcomes it can have on its users. Instagram is a social media network where users can take a picture and then post it for others to see. Although, before posting their photo, users are able to make many changes such as adding or removing borders, cropping, rotating, or straightening the photo, as well as applying a filter to make their photo look even better (Instagram, 2016) After posting their photo, other users (known as followers) can 'like' or comment on the photo. This 'like' or comment can represent peer acceptance, being seen as cool and popular, andpotentially increase a user's self-esteem (Burrow & Rainone, 2016; Sheldon & Byrant, 2016). Unfortunately, due to emphasis and importance society puts on the ideal body, many users are now relying on photo editing techniques, like filtering, in order to receive more positive attention (i.e., likes, comments). For example, Chae (2016) found that females who spent more time on social media sites had increased behaviours of self-editing photos. In addition, two other studies found that those who did engage in photo editing behaviours were more likely to have greater body and eating concerns (McLean, Paxton, Wertheim & Masters, 2015; Santarossa, 2016). Although many photo-shopping apps like "Visage Lab" and "Facetune" exist, one of the easiest ways to edit a photo existswithin the Instagram app itself. As previously discussed, Instagram allows users to filter their pictures. These filterscan alterpictures by intensifying shadows, brightening highlights, making the photo lighter, giving it a vintage look, smoothing/washing out skin tones, and countless other effects (Messiah, 2016).

Although research into why people filter their pictures is limited, a few suggestions have been made. One qualitative study in which participants were specifically asked their reasons for filtering pictures revealed that "improving aesthetics" (i.e., enhancing the photo and correcting for things like brightness and contrasts) was a popular reason (Bakhshi, Shamma, Kennedy & gilbert, 2016). It was also found that adding a vintage effect, highlighting objects, manipulating colours, and making photos appear more fun and unique were other reasons (Bakshi et al., 2016). In addition, Staff Writers (2016) has suggested that certain filters will enable a user to get more likes, with finding that the most used filter globally is 'Clarendon' and that when applying a filter to selfies specifically, 'Slumber' and 'Skyline' are the most popular. As such, the use of the hashtag "#nofilter" is of particular interest to the authors of this paper. By using the hashtag "#nofilter"users are making a point of saying that they did not edit/manipulate their photos.Therefore, the purpose of this study was to use Instagram to discover popular/emerging themes/text around *#nofilter* images. Due to the importance of 'likes' and comments, we hypothesized that users posting images with the *#nofilter* hashtag would use a filter, and so a second objective was to investigate author characteristics and photo content of *#nofilter* photos when filters had been used.

2.Methods

A mixed methods approach was utilized for this study. A text analysis was conducted using the Netlytic program (Gruzd, 2016), a content analysis was used to further examine authors of *#nofilter* images whom did in fact use a filter on their image, finally a photo coding scheme for this group of images was implemented. Each method is further discussed below.

Data collection (image selection) and Netlytic analysis

Using the Netlytic program (Gruzd, 2016), an open sourced software, all tagged media with the *#nofilter* hashtag on Instagram were downloaded (i.e., when the post was tagged, not necessarily when it was posted). The download occurred on October 20th2016 (captures all posts every hour for a set period of 7 days). Netlytic(Gruzd, 2016) captured all public profiles but may have returned publically shared photos from users with otherwise private profiles (e.g., if they originally shared the photo/file from another social network via a direct link/URL).

The Netlytic program (Gruzd, 2016) finds and explores emerging themes of discussion on social media sites. Specifically for this study, Netlytic was used to identify popular topics in the *#nofilter* dataset, as measured by word frequency. Furthermore, Netlytic (Gruzd, 2016) creates categories of words and phrases to represent broader concepts (i.e., positive vs negative words), and then automatically identifies and counts what records in the dataset belong to what category. An output file (in excel) was created that reported the link to the image (which has been tagged with *#nofilter*), publication date, author of the comment (users who commented on the image), the record (the actual comment left by the author on the image), the geographical location, to whom the post was directed (if applicable), the number of likes the image received on Instagram, and the name of the Instagram filter used on the image. The records (*N* = 16,448) were downloaded from the Netlytic program (Gruzd, 2016), duplicates were removed and records were then sorted into one of two categories: (1) *#nofilter* images that did not have a filter (*N* = 13907; these images were only assessed for text analysis using the Netlytics), or (2) *#nofilter* images that did have a filter (*N* = 1630), of these 286 were images that were unavailable and, therefore, removed (*N* = 286 deleted), leaving a remaining 1344 images used in further analysis.

Filter descriptive's and image poster's content analysis

Among the 1344 images that used a filter within the *#nofilter* dataset, supplemental data were collected by linking to the image to take note of the image posters' gender and if the account was personal or not personal (i.e., a promotional account). The author's total number of posts to date, number of followers, and number of people they were following was also recorded. A following to follower ratio (FFR) was calculated for each user (number of followers/number following). A multiple linear regression analysis was performed to examine gender and number of posts (as predictors) on FFR (dependent variable) among the *#nofilter* sample. Data were analyzed using SPSS version 22 for Windows (IMB Corp, 2012).

In order to determine the popularity of an image, a composite variable was created by dividing the total number of likes on the image by the number of followers the author had. For example, if an author has a lot of followers, the image has a higher likelihood of garnering more likes as compared to an author with fewer followers. Therefore, this was a way to equalize the likes (i.e., popularity) across images. A one-way ANOVA was conducted to compare the effect of account type (i.e., personal vs. not personal) and popularity of the image.

Coding of images

Images were coded in content categories (people, scenery, food, or other), however, images could be coded in multiple content categories. For example, if an image included a person walking through woods the image was coded in both 'people' and 'scenery' content categories. A chi-squareanalysis was used to examine the relationship between gender (of the poster of the *#nofilter* image) and content category.

3.Results

Text and network analysis

Among the 13,907 #nofilter images that did not use a filter, there were unique 253,460 words associated with the posts (in the description of the picture or in the comment section) as compared to the 1630 records downloaded of *#nofilter* images that did use a filter, which had 34052 unique words associated with the post.The top 30 most commonly used words, not including #nofilter which was the top word, are described in Table 1 for both datasets. Netlytic (Gruzd, 2016) manually generated 10 categories based on the commonly used words, and the distribution of these word/phrases can be seen in Figure 1.

Filter descriptives and image posters' content analysis

Table 2 displays specific filter names and the frequency of *#nofilter* images that used that filter. Furthermore, as displayed in Table 2, likes and popularity (like/followers) of specific filters used can be examined. Authors' content analysis was conducted on the 1344 images that remained after deletions. The majority of accounts were identified as personal accounts (90%) opposed to not personal (10%). Furthermore, the majority of personal accounts belonged to females (*n*= 743; 55%) compared to males (*n* = 460; 34%). Among the images (*N* = 1344), likes on their *#nofilter* image (*M* = 5.01, *SD* = 19.89), total number of posts (*M* = 642.41, *SD* = 1329.54), total number of followers (*M* = 1625.64, *SD* = 6339.11), and total number following (*M* = 649.92, *SD* = 1012.75), was also collected. A one-way ANOVA was conducted to compare the effect of account type (i.e., personal vs. not personal) and popularity of the image, however, findings were not significant (F (1, 1334) = .07, $p = .799$). A multiple linear regression was calculated to to examine gender and number of posts (as predictors) on FFR (dependent variable) among the *#nofilter* sample. A significant regression equation was found (F (2, 1330) = 9.21, $p < .001$), with an R^2 of .014. Specifically, number of posts was a statistically significant predictor for FFR,with FFR increasing by 0.002 for each post.

Coding of images

Of the 1344 images, 704 (52%) had people in them, 425 (32%) were of a scenery, 82 (6%) contained some sort of food, and 294 (22%) were categorized as other (i.e., animal, quote, art piece). A chi-square test of independence was performed to examine gender (of the poster of the *#nofilter* image) and content category, results can be found in Table 3.

4.Discussion

This study aimed to use Instagram to discover popular/emerging themes/text around *#nofilter* images, with greater analysis into instances when filters were used on these images. Furthermore, the current study sought to investigate author characteristics and photo content of *#nofilter* photos when filters had been used. Little research has been conducted with Instagram, with less done on filtering pictures, and to the authors' knowledge no other study has examined the concept of deceiving your social media audience by using the *#nofilter* but in turn using a filter on the image. The fact that 12% of the current sample consisted of images that had been tagged with *#nofilter* but were filtered may be alluding to the idea that societal pressures to achieve an ideal beauty are causing social media users to use photo editing techniques, like filtering, in order to receive more positive attention (i.e., likes, comments). However, what is more interesting, and although beyond the scope of the current study, is why users feel the need to be deceitful to their social media audience in such a way.Perhaps social media is creating an environment with in which the individual needs to create a social media persona, perhaps not based on individual expression, but on virtually constructed social norms (Jong & Drummond, 2013).

When comparing top 30 words for *#nofilter* images that have and have not been filtered, only 4 out of the 30 words differed between the two groups. Interestingly, *#nocrop*, a hashtag used to describe an image that has not be cropped, was a top word used for *#nofilter* images that had been filtered, and not a top word for *#nofilter* images that had not been filtered. With cropping being another way to edit or enhance a photo, this finding may further suggest that users who post *#nofilter* images that have been filtered are trying to further emphasis the fact that they have not altered their photo, when in reality they have. Of the top words that were unique to *#nofilter* images that had not been filtered, three were hashtags about nature but the fourth was *#selfie*. Past research has also found the most popular filter used on a selfie (average number of likes per Instagram #selfie post) to be 'Normal' or no filter. Interestingly, this may suggest a sense of body positivity in that users believe their *#selfie* images (i.e., pictures of themselves) do not need to be filtered. Furthermore, the largest content category of word/phrases for the*#nofilter* images was associated with appearance, which has been associated with body dissatisfaction (McLean et al., 2015) and eating concerns (Santarossa, 2016). Results suggest that future research is needed to continue to explore the potential influence of on body image and other negative heath behaviours.

Similar to previous findings 'Clarendon' was found to be the most popular Instagram filter used on *#nofilter* images that did use a filter. Staff Writers (2016) suggested that the popularity of 'Clarendon' may be attributed to it not only being an "all-purpose filter" but also due to the fact that it is the most convenient to choose, as it is usually the default filter after the 'Normal' option when editing. The next most used filters in the current study were 'Juno', 'Lark', and 'Gingham', respectively, which have also been documented as highly used Instagram filters (Staff Writers, 2016). 'Juno' and 'Lark' add warmth and vibrancy to colour making it applicable for many types of photos and 'Gingham' "adds a vintage look" which appears to be highly sought after by Instagram users (Bakhshi et al., 2016; Staff Writers, 2016). Further research is needed to explore the ideas of why and how Instagram users may be selecting particular filters.

Past research (Santarossa et al., 2016), as supported by the social comparison theory (Festinger, 1954), reported peer influence to be associated with higher popularity of images (i.e., number of likes/followers). However, similar results were not seen in the current study, as personal accounts were not significantly associated popularity of images (i.e., number of likes/followers). However, the current study examined another measure of popularity, the FFR ratio. Previous literature has stated your FFR determines how "cool" you are online(Business Insider, 2014) and/or is a good indicator of popularity (Alshawaf & Wen, 2015). A multiple linear regression analysis revealed that a relationship existed between number of posts and FFR, suggesting that posting more will increase your FFR ratio and, in essence, social media popularity. Lastly, as the majority of images were of people (52%) and posted by females, future research should focus on peer relationships and popularity among female users and social comparison may be cultivated in images being displayed.

This study is not without limitations. First, the study's sample (N = 1334) of *#nofilter* images that used a filter is small, relative to the vast online world. Furthermore, sampling bias (day of week, seasonality) may exist, however, we assumed the data were collected on a random day and would be similar with multiple data collections. It may be more appropriate in the future to sample images over a longer time frame and/or at different time points within the year. Second, the Netlytic (Gruzd, 2016) program is unable to separate text or analysis by gender, making it difficult to make more specific associations within the dataset. It would be worthwhile to investigate gender differences among the types of posts/comments associated with *#nofilter* images in future research. Third, Netlytic (Gruzd, 2016) only documents Instagram filters, additional filtering and editing applications could have been used and would not have been accounted for in the current study. Lastly, analysis of the *#nofilter* images was limited to the attributes and dimensions coded.

Overall, the present study highlights that many people using *#nofilter* do in fact filter their images, with filters that have seen to be popular in other literature (Staff Writers, 2016). The present study suggested that *#nofilter* images that have a filter have generated a similar online conversation as *#nofilter* images that do not have a filter. Furthermore, the *#nofilter* images are associated with appearance which may suggest future research is needed into this hashtag and body satisfaction. As majority of the *#nofilter* images that have a filter are of people and have been poster by female users, specific focus should be placed on exploring the influence of self-presentation on body satisfaction. Further research into the reasons why people are being deceptive on social media is needed.

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Table 1

Most commonly used words associated with #nofilter when a filter was used compared to when a filter was not used					
#nofilter when a filter was used			#nofilter when a filter was not used		
Term	Number of Messages	Number of Instances	Term	Number of Messages	Number of Instances
#love	491	498	#love	1956	2002
#photooftheday	476	478	#photooftheday	1921	1943
#amazing	413	417	#sun	1542	1556
#sun	411	412	#nature	1462	1470
#instamood	402	403	#instagood	1439	1467
#style	396	398	#amazing	1413	1433
#like4like	392	397	#like4like	1367	1384
#happy	390	395	#happy	1331	1349
#fashion	378	381	#instamood	1328	1343
#cute	366	366	#style	1287	1307
#family	348	350	#fashion	1265	1285
#cool	341	341	#cute	1246	1255
#lol	326	326	#beautiful	1184	1199
#hair	324	324	#picoftheday	1178	1188
#smile	324	326	#beach	1127	1152
#summer	323	323	#sky	1100	1101
#follow4follow	318	320	#summer	1099	1103
#beach	311	311	#follow4follow	1087	1093
#girls	294	294	#family	1081	1098
#fun	294	296	#hair	1078	1093
#friends	274	275	#cool	1051	1066
#instagood	259	263	#lol	1011	1023
#dog	257	257	#smile	999	1018
#hot	227	228	#sunset	991	994
#blur	224	224	#fun	957	978
#beautiful	215	217	#friends	885	889
#picoftheday	214	224	#instadaily	862	880
#nocrop	209	209	#girls	858	870
#instadaily	185	186	#dog	835	849
#bestoftheday	180	180	#selfie	766	775

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Table 2

Top 10 most frequently used filters on #nofilter images that used a filter

Filter Name	Frequency	Likes (*M*, *SD*)	Popularity (*M*, *SD*)
Clarendon	338	4.25, 10.70	0.018, 0.073
Juno	138	3.89, 7.00	0.014, 0.044
Lark	100	3.96, 8.23	0.018, 0.059
Gingham	79	3.51, 5.60	0.014, 0.043
Ludwig	76	3.24, 5.20	0.007, 0.015
Lo-fi	65	9.09, 41.13	0.024, 0.064
Mayfair	44	3.91, 8.94	0.014, 0.035
Aden	42	5.48, 15.02	0.012, 0.033
Valencia	41	5.46, 10.75	0.012, 0.039
Inkwell	36	3.24, 4.47	0.006, 0.010

Table 3

Results of Chi-square Test and Descriptive Statistics for Photo Type by Gender

	People[a]		Scenery[b]		Food[c]		Other[d]	
Gender	No	Yes	No	Yes	No	Yes	No	Yes
Unknown	100 (16%)	34 (5%)	108 (12%)	26 (6%)	117 (9%)	17 (21%)	70 (7%)	64 (22%)
Males	207 (33%)	253 (36%)	318 (35%)	142 (33%)	432 (34%)	28 (34%)	370 (35%)	90 (31%)
Females	329 (51%)	414 (59%)	487 (53%)	256 (60%)	706 (56%)	37 (45%)	606 (58%)	137 (47%)

Note.[a] $\chi 2$ = 14.14, df = 3. Numbers in parentheses indicate column percentages. $^*p < .01$

Note.[b] $\chi 2$ = 13.10, df = 3. Numbers in parentheses indicate column percentages. $^*p < .05$

Note.[c] $\chi 2$ = 12.23, df = 3. Numbers in parentheses indicate column percentages. $^*p < .05$

Note.[d] $\chi 2$ = 60.91, df = 3. Numbers in parentheses indicate column percentages. $^*p < .01$

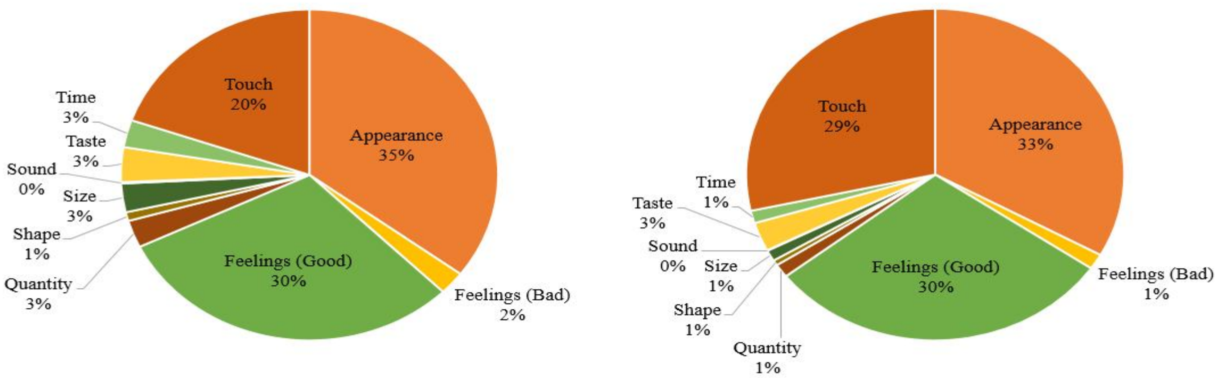

Figure 1. A comparison of categories of popular words/phrases associated with #nofilter images that did not use a filter (N = 13, 907 posts) and #nofilter images that did use a filter (N = 1630, 907 posts).