Addictive Behaviors Reports 15 (2022) 100417

Contents lists available at ScienceDirect

Addictive Behaviors Reports

journal homepage: www.elsevier.com/locate/abrep

Predicting comments on Facebook photos: Who posts might matter more than what type of photo is posted

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A R T I C L E I N F O

Keywords:
Facebook
Photo
Objective data
Comment
Machine learning

A B S T R A C T

The number of likes and comments received to social media posts and images are influential for users' self-presentation and problematic Facebook use. The aim of this study was to highlight the most relevant factors predicting the popularity (i.e., the probability to receive at a least a comment) of Facebook photos based on: (i) Facebook user-related features; (ii) Facebook photo-related features; and (iii) and psychological variables. A mixed approach was used, including objective data extracted from Facebook (regarding users' characteristics and photo features) as well as answers to a questionnaire. Participants were 227 Facebook users (M = 25.01*(1.05)* years). They were asked to answer a questionnaire and provide a copy of their Facebook profile data. A total of 180,547 photos receiving a total of 122,689 comments were extracted. Results showed that user-related features (Facebook network and activities) were the most relevant in predicting image popularity accurately. It seems that who posts a Facebook photo matters more than the type of photo posted and the psychological profile of the user. Results are discussed within a psychological perspective.

Future research should look at the sentiment (positive vs. negative) of the comments received by different types of photos. This is the first study exploring what makes a Facebook photo popular using objective data rather than self-reported frequency of Facebook activity only. Results might advance current methods and knowledge about potential problematic behaviors on social media.

1. Introduction

In the last years, the volume of activities on social media has been continuously growing around the world with photo sharing, and especially selfie-sharing, representing one of the most frequent reasons to use social networking sites, like Facebook and Instagram (e.g. Boursier et al., 2020a; Chae, 2017). Research has been indicating that the number of likes and comments received to social media posts and images are influential for users' self-presentation and self-esteem (e.g., Chua & Chang, 2016; Mehdizadeh, 2010), and may lead to potentially problematic social media use (e.g., Boursier et al., 2020b). Facebook is currently the most widely used social network with about 2.9 billion monthly active users as of June 2021 and about 350 million photos uploaded daily (Omnicore Agency, 2021). However, despite the enormous number of photos uploaded daily on social media, only a small minority receives a reaction in terms of likes or comments (Khosla et al., 2014). The current study aims to understand what makes certain Facebook photos more popular than others in terms of estimated comments to be received. Specifically, we estimated the probability that a photo posted on Facebook would receive at least one comment based on: psychological variables (i.e., problematic Facebook use and individual differences), user-related features (i.e., individual characteristics of Facebook profiles), and photo-related features.

1.1. *Problematic Facebook use and psychological characteristics involved in photo-related activities on social media*

Problematic Facebook use (PFU) has been defined as the use of Facebook characterized by preference for online social interactions, mood regulation through Facebook use, cognitive and behavioral

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https://doi.org/10.1016/j.abrep.2022.100417
Received 23 November 2021; Received in revised form 18 February 2022; Accepted 23 February 2022
Available online 25 February 2022

deficient self-regulation (e.g., obsessive Facebook-related thoughts and compulsive Facebook use), and impairments in daily life, job/school problems and family/peer conflicts due to unregulated Facebook use (Marino et al., 2017a). In the context of rewarding activities like photo sharing for feedback seeking on social media, it could be the case that the problematic features of social media use might be involved in an addictive "behavior-reward feedback loop" (Hawk et al., 2019, p. 66). In that, PFU can be associated to reward and gratification mechanisms as well as personality traits (Guedes et al., 2016). From a psychological viewpoint, it has been pointed out that, among the many functions available on social media, users tend to manage photos and albums on their social media profile for identity establishment and self-presentation motivations (e.g., Boursier et al., 2020a; Eftekhar et al., 2014). Facebook has become the place for self-expression through sharing photos, interests, and contents able to give the desired impression to others (Błachnio et al., 2016). Facebook users may tend to carefully select the contents to be posted for presenting the side of their selves they want to share with Facebook friends (e.g., Haferkamp et al., 2012). In turn, with regards to selfies, concerns related to social appearance were found to be associated with higher levels of problematic social media use (Boursier et al., 2020b).

It is common to consider Facebook an easy means to interpret users' individual differences in managing their image and identity (e.g., Pempek et al., 2009; Saslow et al., 2013; Siibak, 2009; Tosun, 2012; Van Der Heide et al., 2012). From this viewpoint, Eftekhar and colleagues (2014) stated that "online behaviors tend to mimic what would be expected of an individual's offline personality characteristics" (p. 162). A number of studies have investigated the relationship between individual characteristics and preference for different Facebook activities (e.g., Marino et al., 2017a). As an example, Facebook and other social media users high in narcissism and emotional instability have been found to post photos as a preferred activity (Ksinan & Vazsonyi, 2016; Nadkarni & Hofmann, 2012). Similarly, those high on extraversion have tended to upload more photos (e.g., Eşkisu et al., 2017). Moreover, Rui and Stefanone (2013) have argued that users' self-esteem is staked in others' recognition, as giving a positive image of themselves is crucial in self-promoting in the public sphere. Furthermore, many studies have described that Facebook users are driven by certain motives to use the social network in order to satisfy both instrumental and psychological needs (Marino et al., 2018a). From this perspective, researchers have been attempting to understand Facebook users' profiles and online behaviors based on individual characteristics and vice versa (Gosling et al., 2011; Settanni & Marengo, 2015).

However, beyond active posting to fulfill psychological needs or to deal with PFU and despite Facebook users can "reasonably expect timely and frequent positive feedback" (Panek, Nardis, & Konrath, 2013, p. 2006), less is known about the feedback users actually receive from their Facebook friends. Indeed, given the relevance of reciprocity in social online context (Surma, 2016), it could be argued that, despite the efforts made by Facebook users to satisfy their needs, and despite such efforts could result in problematic use, their friends' attention might play a crucial role in the actual satisfaction of psychological needs. Therefore, it is crucial to understand which kind of images and which kind of users' characteristics are more likely to be "popular" in terms of receiving feedback (sharing, comments or likes).

1.2. *Popularity prediction of photo posted on social media*

In the context of images popularity prediction, Khosla and colleagues (2014) showed how to predict the views count of an image on Flickr. Specifically, they demonstrated that image content (such as, type of scene and color prevalence) and social cues (such as, number of users' contacts) are crucial in estimating the popularity of a photograph, with social cues having larger influence on popularity than image content. 'Social cues' include the number of images uploaded by each user and the number of groups the user belongs to: taken together, such cues have been found to increase the likelihood of image popularity. Conversely, with regards to the type of scene, images with open scenes (e.g., landscapes without people) tended to be viewed less frequently. Moreover, color prevalence played a role: images with red and yellow colors were more popular (Khosla et al., 2014).

Similarly, Totti and colleagues (2014) found that the popularity of a Pinterest image (measured using the number of shares) was better predicted by social cues rather than by visual attributes (i.e., brightness, contrast, sharpness, of images and concepts represented by the images). However, they also argued that visual features might be more accurate in the prediction of popularity and dissemination of a picture through the web.

McParlane and colleagues (2014) provided a useful classification of features involved in images popularity prediction in Flickr. They proposed that an image can be classified according to its context and content. With regards to context, they considered features like time (of photos taking/posting), day (weekdays vs. weekend), season, device, size of pixels, presence of flash, and orientation (landscape vs. portrait). With regards to image content, the authors recommended to consider the type of scene (outdoor vs. indoor), the main content of the scene (party, home, food, etc.), the number of present faces, and the dominant color of the photo. Results from their study showed, for example, that images containing people are viewed more frequently as compared to nature images, which received the highest number of comments. Moreover, it seemed that day type and orientation were the variables responsible for the highest number of comment prediction.

1.3. *Comments as proxy of photos popularity*

So what about users' characteristics? McParlane showed that the combination of these features and user variables (e.g., gender, number of contacts, etc.) may be more informative in predicting photos popularity.

Based on a small number of previous studies (e.g., McParlane et al., 2014), receiving at least a comment in a Facebook photo can be considered as a proxy of images popularity. Indeed, in line with McParlane and colleagues (2014), comments represent an explicit feedback for Facebook users and help in understanding online behavior. Moreover, recent research (e.g., Zell & Moeller, 2018) suggested that comments are more likely to be posted with greater effort-fullness than likes (which are often clicked more automatically). Thus, it could be the case that comments might represent a genuine sign of interest to posts and photos. Since the number of comments is the only objective indicator available in the downloaded Facebook profiles, for the purpose of the current study such an indicator has been used as a proxy of popularity.

As explained below (see Data collection section) the majority of the photos included in the current study did not receive any comment thus demonstrating that most of the photos usually do not get attention (see also Khosla et al., 2014). On the other hand, the remaining minority of Facebook photos do get attention but the reason for popularity is currently unclear. The existing literature on prediction of popularity has been mostly focusing on text contents gathered from social media like Twitter (e.g., Hong, Dan, & Davison, 2011; Quesenberry and Coolsen, 2019; Totti et al., 2014) and, more recently, on Flickr and Pinterest online images (McParlane et al., 2014). Much less is known about image popularity prediction on Facebook. Moreover, the attention of researchers so far has been focused on either "technical" and user features or psychological variables.

1.4. *Aim of the study*

The current study adopted a complementary approach as it is grounded on previous studies related to both: (i) psychological models (individual differences and PFU; e.g., Marino et al., 2018b), and (ii) images popularity prediction (McParlane et al., 2014; Khosla et al., 2014). With regards to psychological variables, along with PFU, self-esteem, personality traits, and mental health were specifically selected and included in the current study as a *meta*-analysis showed that they constitute the group of variables most commonly investigated in the field of Facebook use (Marengo et al., 2021) and are clearly associated with PFU (Marino et al., 2018b). Specifically, it is often argued that problematic social media users tend to manage their identity online and engage in compulsive online behaviors; similarly, people low in self-esteem and emotional stability are likely to seek reassurance from others on social media. Moreover people with low well-being are at major risk to engage in excessive and problematic online behaviors (Hawi & Samaha, 2017). For this reason, based on the literature reviewed above, it is plausible to assume that problematic users, and users with certain psychological profiles (personality traits and mental health) might be more likely to engage in a 'strategic' management of Facebook profiles in order to gain attention from others (such as, self-identity promotion via photo selection), which, in turn may be vulnerable to feedbacks received from others. However, the lack of studies in this field, indicating what really makes an image popular, hampers the possibility to provide specific a priori hypothesis. For this reason, the aim of this study was to explore and highlight the most relevant factors predicting the popularity of a Facebook picture, using three groups of variables: (i) Facebook user-related features; (ii) Facebook photo-related features; and (iii) and psychological variables (PFU, personality traits, self-esteem, and positive mental health; see Section 2.2).

2. Material and methods

2.1. Data collection

A convenience sample of Italian Facebook users was recruited at the University of [blinded for review]. During four different courses (of Statistics, Psychology, and Economics), a total of 356 university students were asked to take part to the study with 227 voluntarily choosing to participate. The final sample comprised of 180 females and 47 males, with a mean age of 25.01 years (*SD* = 1.05; range = 19–28 years). Participants were asked to: (i) answer an online questionnaire (see paragraph 2.2.1); and (ii) provide a copy of their Facebook profile data obtained through the function "download a copy of your Facebook data" available in the settings section of their profile (full instructions for downloading data from Facebook accounts are presented in the following official Facebook link: https://www.facebook.com/help/131112897028467/) (see paragraph 2.2.2).

On average, profiles had 662.36 friends (SD = 371.92; range = 41–2349 friends) and 795.36 photos (SD = 968.73; range = 1–4967 photos). A total of 180,547 photos receiving a total of 122,689 comments were extracted from the 227 Facebook profiles and analyzed. Thirty four percent of the photos were classified as "indoor" (that is, they have an indoor setting) whereas the 24% were identified as "outdoor" (that is, a landscape of the photo), and the remaining were not classified by the algorithm because landmarks were missing. Each photo received, on average, less than one comment (M = 0.68; SD = 2.24; range = 0–50 comments).

All participants were assured of the confidentiality of both their responses to the questionnaire and "objective data" provided. All participants agreed to give their written informed consent. The Ethics Committee of Psychological Research at the University of [blinded for review] gave formal approval for this research.

2.2. Measures

2.2.1. Psychological variables

Participants were asked to complete a self-report questionnaire including four different scales.

Problematic Facebook Use. The Italian version of the Problematic Facebook Use Scale (Marino et al., 2017b) was used to assess problematic Facebook use (PFU). Participants were asked to rate their agreement with each item on an 8-point Likert type scale (from (1) "definitely disagree" to (8) "definitely agree"). Items were averaged to form a PFU score. Higher scores indicated higher levels of PFU (M = 1.94, SD = 0.90). The Cronbach's alpha for the scale in the current sample was α = 0.89 (95% CI: 0.88–0.91).

Personality Traits. The short form of the Italian version of the Big Five Questionnaire was used to assess personality traits (Caprara et al., 1993). It covers the Big Five personality traits: Agreeableness (M = 1.92, SD = 0.57; α = 0.75 [95% CI: 0.72–0.79]), Conscientiousness (M = 2.59, SD = 0.85; α = 0.80 [95% CI: 0.77–0.83]), Emotional Stability (M = 3.05, SD = 0.83; α = 0.78 [95% CI: 0.75–0.81]), Extraversion (2.21, SD = 0.71; α = 0.71 [95% CI: 0.66–0.75]), and Openness (M = 2.19, SD = 0.67; α = 0.65 [95% CI: 0.60–0.70]). The scale contains 20 items rated on a 5-point Likert type scale (from (1) "absolutely false for me" to (5) "absolutely true for me"). Items were averaged so that higher scores indicated higher levels on each trait.

Self-esteem. The Italian version of the Rosenberg Self-esteem Scale was used to assess self-esteem (Prezza, Trombaccia, & Armento, 1997). The scale contains 10 items rated on a 4–point Likert type scale (from (1) "strongly disagree" to (5) "strongly agree"). Items were averaged so that higher scores indicated higher levels of self-esteem (M = 3.00, SD = 0.57). The Cronbach's alpha for the scale in the current sample was α = 0.89 (95% CI: 0.88–0.90).

Positive Mental Health. Positive Mental Health (PMH) was assessed using the Social and Emotional Health Survey (SEHS-HE; Furlong et al., 2014; Marino et al., 2018c). The SEHS comprises four positive mental health domains: belief-in-self, belief-in-others, emotional competence, and engaged living. Taken together, these factors give an overall index score for positive mental health. The questionnaire contains 36 items rated on a 4-point or 5-point Likert type scale (from (1) "not at all true" to (4) "very much true" for belief-in-self and belief-in-others; from (1) "not at all like me" to (4) "very much like me" for emotional competence; from (1) "not at all" to (5) "extremely" for engaged living). Higher scores indicated higher levels of PMH (M = 2.93, SD = 0.35). The Cronbach's alpha for the scale in the current sample was α = 0.89 (95% CI: 0.88–0.91).

2.2.2. Facebook user-related features

A specific R package (library MyFbr available at https://github.com/livioivil/myFBr) was developed to extract information from the html pages downloaded by each participant. This package contains codes able to read information from the html pages, to transform such information into quantitative data, and to save data in a dataset. A specific time interval (12 months) was selected in order to create a dataset comprising data extracted from the same period of time for all participants' profiles. Specifically, we considered 12 months of Facebook behavior, from the date of the beginning of the research to the day the "youngest" account was created in our sample. Objective Facebook variables were matched with the answers to questionnaires in order to create a single dataset. User-related features are described in Table 1.

2.2.3. Facebook photo-related features

Photo-related features were extracted keeping into account both image context (size, orientation, time) and image content. Thus, Facebook photo-related features were classified in two sub-domains: (i) aesthetic features: including all those features that summarize main properties of an image, such as color dominance, Hue Saturation Brightness (HSV; Totti et al., 2014), blurriness; and (ii) object based features: including location, number of people count, and more generally object detection. In particular, Convolutional Neural Networks (CNN; Karn, 2016) pre-trained models were used because of their capability to deep dive into the pictures and exploit useful information automatically. Specifically, different neural network outputs (i.e., Vgg16, Place365 and Yolo) were considered (e.g., Rosebrock, 2017; Zhou et al., 2017).

Table 1
Description of (i) Facebook user-related features; (ii) Facebook photo-related features; (iii) and psychological variables.

Type	Name	Brief Description
Facebook user-related features	#gender	Male or Female
	#Friends	Number of Facebook friends
	%FriendsFemale	Proportion of female Facebook friends in user's network
	#Friendshiprequest	Number of friendship request by user
	#comments	Total number of comments (number of comments by user and friends)
	#Photos	Total number of photos uploaded
	#comm/ Photos_3months	Ratio between number of comments received and number of photos posted in the last 3 months
	#UpdatesUserImage	Number of profile photos
	#Post	Number of post by user
	#age	Date of birth
	#RelationshipsStatus	Single/ Engaged / No Info
	#WallActivities	status update, likes to other friends' post, shared contents, links, posts, new photos, total posts, participating to events
Facebook photo-related features	Image context (aesthetic features) Image content (object features)	- global image size index (width × height); - background: square; portrait, landscape, indoor, outdoor, season (image posted during spring, summer, autumn, winter); - channel indices: blurriness, lightness, saturation, intensity; - *569 content/objects extracted via vgg neural network estimated class probability* (e.g., dome, chocolate sauce, dough, pizza, cliff, geyser, lakeside, valley, violin, volleyball, television, scale, radio, pajama, necklace, website etc.; - *18 objects (yolo neural network outputs, # of elements identified)*: i. e., train, sheep, bicycle, motorbike, horse, sofa, cat, tvmonitor, bird, pottedplant, boat, dog, bottle, chair, car, person, people n. 1, people n. 3, group of people; - *185 scenes* (from Place165 neural network): e.g., nursing, swimming, home, church, ice, beach, stage, door, art, museum, shop, hospital, elevator, park, office, dressing, veterinarians, beer. [the complete list of objects is available upon request])
Psychological variables	*Problematic Facebook Use*	Total score of problematic Facebook use
	Personality traits	Big 5: agreeableness, conscientiousness, emotional stability, extraversion, and openness
	Self-esteem	Total score of self-esteem
	Positive Mental Health	An overall score of perceived subjective well-being

A comprehensive description of the variables extracted from the profiles and from each photo is provided in Table 1. Customized R and Python tools were developed for the data preprocessing (available at https://github.com/xlxlcyRuSReXxlxl/FacebookAnalysis).

2.3. Analysis

Our aim was to train a model that linked the presence of (at least) a comment in a post making use of all the measures described in paragraph 2.2. These would be the features used in the machine learning model. Feature engineering and data enrichment provided a very large number of features used to predict images popularity. Then, model selection was performed by training different models representing state of the art in Machine Learning field, such as ensembles (Xgboost, LGBoost), Multilayer Neural Networks and Support Vector Machine (e.g., Chen & Guestrin, 2016). For each model, grid search was applied on training data (75 % of the sample) in order to determine the optimal values of the parameters. When a target variable is unbalanced (that is, most of the pictures had no comments), F1 score is widely used as evaluation metric and it is preferred over other metrics such as accuracy. It represents the harmonic mean between precision and recall (also called sensitivity) and aims to minimize both false negatives and false positives. Because of the huge feature size, a preliminary selection phase was conducted, with the aim of reducing the noise in the data. In particular, inferential statistics and Machine Learning have been used as follows:

- performing univariate t-tests and retaining only features with significant p-value (alpha < 0.05);
- fitting XGBoost on training data and dropping out features having very low relative importance ($<$0.001).

The features come from three domains, namely: psychological variables (section 2.2.1), user-related features (section 2.2.2) and photo-related features (section 2.2.3). We exploited this structure and considered the model containing all or none of the features of a given domain (i.e. a total of 7 possible combinations: 1) only psychological variables– named as Psy; 2) only user-related – named as User; 3) only photo-related – named as Photo; 4) User-related and Psychological variables – named as User + Psy; 5) psychological and photo-related variables – named as Psy + Photo; 6) user-related and photo-related variables – named as User + Photo; and 7) all the three domains – named as User + Psy + Photo). For sake of simplicity, the best two models are reported below and discussed. The use of Machine Learning method, such as XGBoost, implicitly explores interactions among features. This advantage becomes a downside when the user wants to interpret these interactions. Therefore, in order to provide an in-depth exploration of the interaction between PFU and other psychological variables, we explored the interactions and we defined interaction plots as follow: we set first target feature and for each observation we drew a line of predicted outcome (i.e., the probability to get a comment in our case) ranging the values of the first target feature, while keeping fix the values of all other features. The lines are centered on the overall mean of predicted values and the color of the line is given by the value of the second target feature. This informal method allows to evaluate how the effect of the first target feature varies as a function of the second target feature. Remarkably, this plot results to be a standard interaction plot in the linear model. By using this tool, we explored the interactions between PFU and other psychological variables estimated by the model.

3. Results

As shown in Table 2, the two models with the highest F1 (i.e. User + Psy and User + Photo; both XGBoost) included user-related features, thus suggesting that user-related features are the most relevant in predicting image popularity accurately. Among the top 10 important features in each model (shown in Table 2 and Figs. 1 and 2), several user-related features emerged as important, such as number of friends, friends' requests, and wall activities. Conversely, the negative sing of *rho* (see Table 2) indicated that uploading new photos decreased the probability to be popular (i.e., probability to receive at least one comment); as well as the percentage of female Facebook friends appeared to be negatively associated with the likelihood of receiving comments.

With regards to photo-related variables, the "User + Photo" model (Fig. 2) showed the importance of both aesthetic features and object-

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Table 2
Results of the best two models predicting comments on Facebook photos.

Model	F1	Specificity	Sensitivity	Accuracy	Top 10 Features	Gain	Cover	Frequency	*rho*
User + Photo	0.33	0.27	0.92	0.81	is_a_dome	0.167	0.081	0.055	-0.131
					Friends	0.079	0.085	0.075	0.018
					is_Square_Image	0.068	0.024	0.009	0.144
					Comm/Photos_3Months	0.068	0.046	0.055	0.036
					Image size	0.062	0.056	0.049	-0.0854
					FriendshipRequests	0.061	0.052	0.052	0.054
					is_a_website	0.054	0.046	0.040	0.083
					%FriendsFemale	0.039	0.064	0.058	-0.007
					Photos	0.037	0.057	0.043	-0.056
					People_in_photo	0.030	0.033	0.023	0.051
User + Psy	0.33	0.25	0.93	0.82	Photos	0.090	0.073	0.082	-0.067
					Comm/Photos_3Months	0.081	0.070	0.067	0.015
					FriendshipRequests	0.067	0.045	0.064	0.068
					WallActivities	0.063	0.034	0.050	0.012
					UpdatesUserImage	0.059	0.053	0.061	-0.015
					Posts	0.053	0.072	0.064	0.025
					Friends	0.049	0.056	0.038	0.035
					%FriendsFemale	0.040	0.035	0.038	-0.023
					Big5-Conscientiousness	0.037	0.029	0.020	0.009
					Problematic_FB_use	0.035	0.033	0.032	0.022

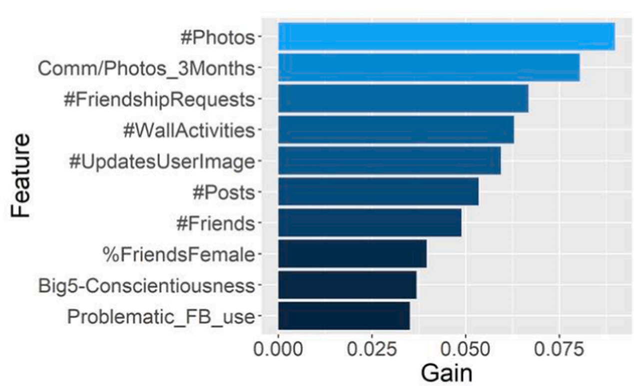

Fig. 1. Top 10 feature importance for the User + Psy model.

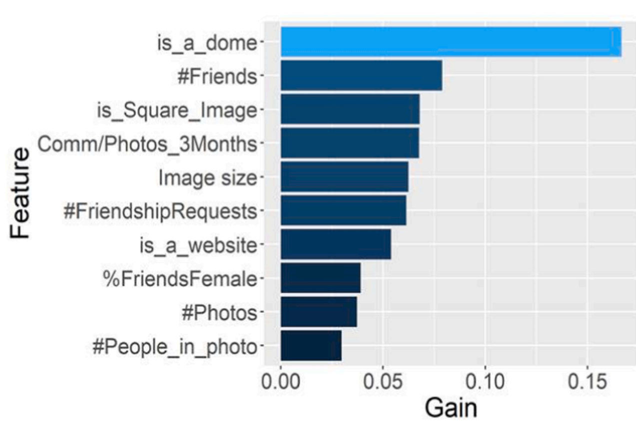

Fig. 2. Top 10 feature importance for the User + Photo model.

based features in predicting the popularity of a photo. Specifically, dome and image size were negatively associated with popularity, whereas people in photo, square in the background, and presence of websites increased the probability for a photo to receive at least one comment. With regards to the psychological variables, "User + Psy" model (Fig. 1) showed the positive importance of one personality trait (i.e., conscientiousness) and PFU in predicting popularity. To help the interpretability of these findings, we plotted the bivariate associations of popularity (i.e., probability to receive at least one comment) with conscientiousness and PFU, respectively (Fig. 3). Fig. 4 shows that popularity increases with the increase of conscientiousness. A similar pattern is observed for low-to-medium levels of PFU only.

With regards to interactions between PFU and other psychological variables, only two were suggestive and meaningful. Results suggested that users high in PFU are more likely to receive at least a comment to their photos when they are high in conscientiousness and low in agreeableness. Specifically, Fig. 5 explores the effect of conscientiousness in interaction with PFU (median split). A positive association between conscientiousness and the probability to receive a comment is strong for problematic Facebook users (i.e., higher than the median), while this association looks null for non-problematic users. Fig. 6 shows the effect of agreeableness in interaction with PFU (median split). A negative trend between agreeableness and the probability to receive a comment is markedly evident for problematic Facebook users (i.e., higher that the median), whereas this is not true for non-problematic users (i.e., lower than the median). Unfortunately, this study used sensitive data (i.e., Facebook data, private photos) and authors were not allowed to share data and materials.

4. Discussion

The main aim of the current study was to highlight what makes a Facebook photo popular in terms of probability to receive at least a comment, using a mixed technical-psychological approach. Results showed that Facebook user-related features constituted the best group of variables in predicting the popularity of Facebook photos. In other words, it seems that who post a Facebook photo matter more than the type of photo posted and the psychological profile of the user. More specifically, model comparison highlighted that the model including user-related features and psychological variables is roughly equivalent to the model including user-related features and photo-related features. Thus, user-related features emerged as best predictor of Facebook photo popularity. Indeed, results suggest that user's Facebook network and activities play an important role and objectively clarify which type of effort made by the user helps in gaining attention from others. As an example, along with the overall number of wall activities (e.g., friend requests; number of comments already received to photos posted in the last three months), specific activities, such as sending new friendship requests, appeared to increase the likelihood for the user's photo to gain attention from friends in terms of comments. This result appears in line with the self-promotion strategies chosen by users who tend to frequently update their status (e.g., Marshall et al., 2015). For example, previous studies (Carpenter, 2012) found that people high in narcissism

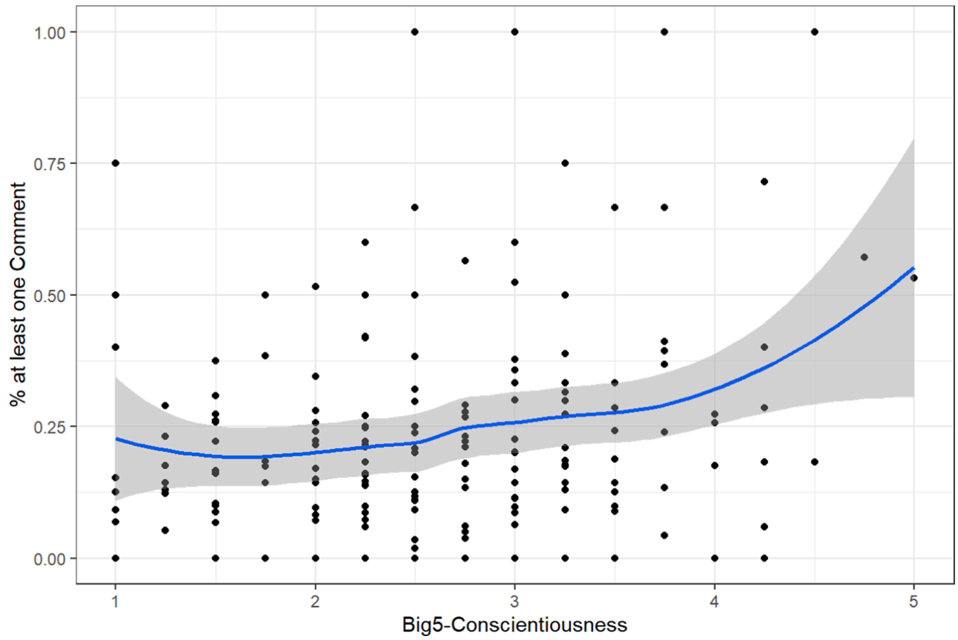

Fig. 3. Scatter plot individual Big5-Conscientiousness vs Probability of at least a comment (subject's average).

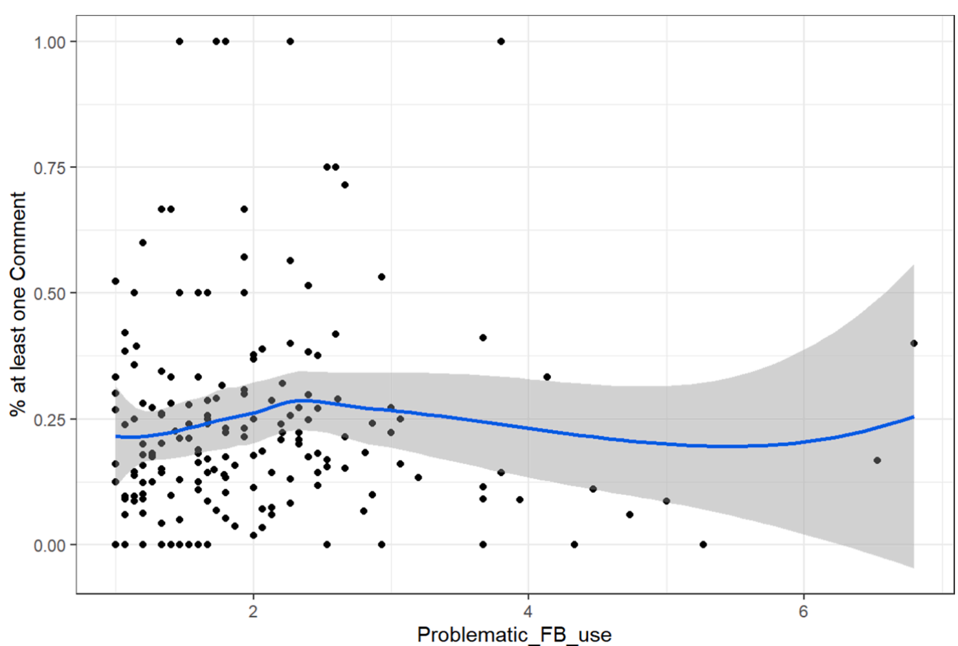

Fig. 4. Scatter plot individual Problematic Facebook Use vs Probability of at least a comment (subject's average).

frequently update their status, post more self-promoting content (Mehdizadeh, 2010), and seek to attract admiring friends to one's Facebook profile (Davenport et al., 2014). This suggests that their status updates will more frequently appear in their friends' home increasing the probability of their content and photos to be viewed and, maybe, commented. However, it should be noted that the association between the number of posted photos and the probability to gain a comment is negative (see Table 2). This means that the more a user posts an increasing number of photos, the less they are likely to receive comments. That is, posting less photos might increase the likelihood to gain attention.

With regards to psychological variables, conscientiousness and PFU emerged as important when taken together with user-related features (Fig. 1). It could be argued that more conscientious people may tend to behave in a systematic manner on Facebook, so that they may select the photo to be posted very accurately thus making it very likely to receive comments (see also Fig. 3). Similarly, some specific aspects of PFU may play a role in this context: for example, the preference for online social interactions lead users to engage in Facebook use in order to let others know about their worries and feelings. A study using objective Facebook data highlighted that users showing high levels of PFU tend to post more photos as compared with non-problematic users (Marino et al., 2017a), and, in turn, problematic users also tend to show lower level of subjective well-being (e.g., Marino, et al., 2018b; Marino et al., 2018c). This pattern of behaviors might possibly constitute a stimulus for friends to comment on problematic users' photos. Indeed, the cognitive preoccupation and the tendency to compulsive online behavior may be responsible for the increasing seek of attention from others (e.g., Marino

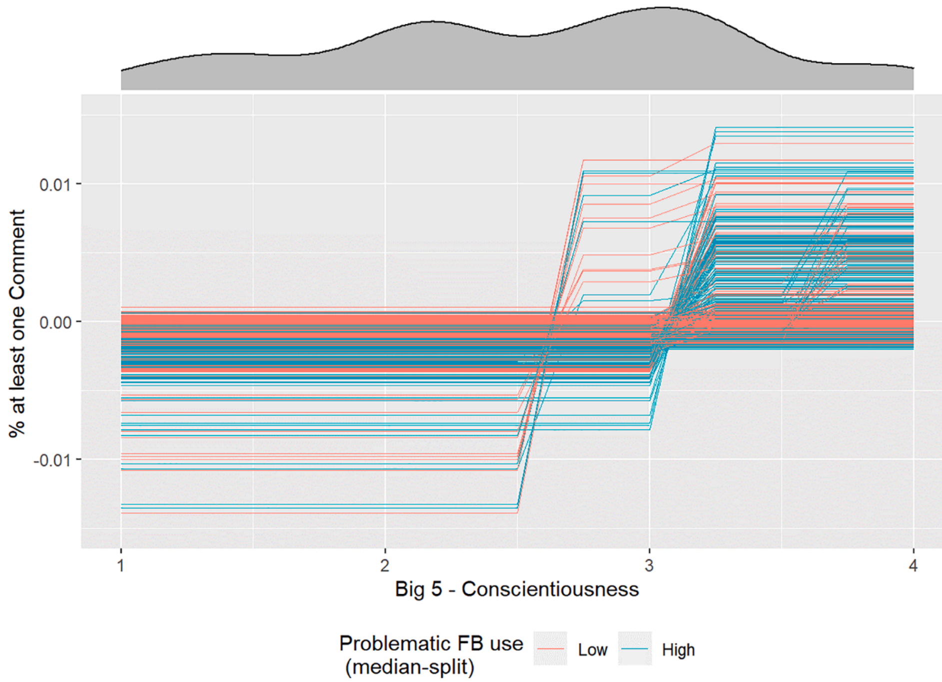

Fig. 5. Effect's plot of Conscientiousness in interaction with Problematic Facebook Use (median split). A positive association between Conscientiousness and the probability to receive a comment is strong for problematic Facebook users (i.e. higher that the median), while this association looks null for non-problematic users. See the main text for a description of how the plot is drawn.

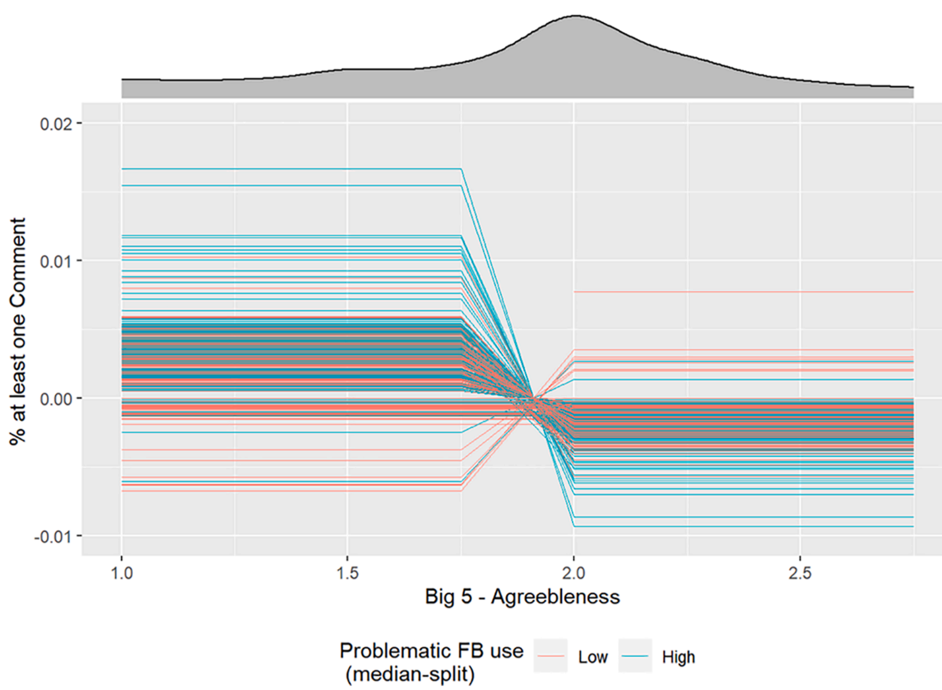

Fig. 6. Effect's plot of Agreebleness in interaction with Problematic Facebook Use (median split). A negative trend between Agreebleness and the probability to receive a comment is markedly evident for problematic Facebook users (i.e., higher that the median), whereas this is not true for non-problematic users (i.e. lower than the median). See the main text for a description of how the plot is drawn.

et al., 2017b). As a further explanation, young people usually have a network of Facebook friends characterized by similar characteristics and online attitudes (e.g., Marino et al., 2020). From this perspective, the homophily among young adults participating in this study and their friends might suggest that conscious and problematic users may have conscious and problematic friends, who, in turn are more likely to comment on participants' photos. Interestingly, Fig. 4 showed that PFU is likely to be positively associated with the probability to receive at least a comment when the levels of problematic use vary from low to medium, whereas for higher levels of PFU the association might follow a different pattern. This might be due to the extreme levels of PFU reported by a relatively low number of participants who are likely to post photos compulsively, probably decreasing the probability that all their photos would be noted and commented (e.g., Marino et al., 2017a).

However, it should be noted that Figs. 3 and 4 captured the bivariate association among variables of interest in contrast with the multivariate nature of the previous models showed in Figs. 1 and 2. Thus, these results should be considered with caution. Moreover, in order to provide an in-depth analysis of the psychological variables involved in this context and to partially overcome the issue of the complexity of the method used in the current study, explorative analyses including the interaction between PFU and personality traits revealed that users with high levels of PFU are more likely to receive comments if they are high in consciousness and low in agreeableness. Specifically, the effect of consciousness on increasing the likelihood to receive at least a comment is stronger in participants with high levels of problematic use, thus suggesting that the tendency to accurately select Facebook photos is likely to be related to excessive preoccupation about what happens on Facebook and negative social consequences due to Facebook, which are typical of problematic users. Opposite to what observed for conscientiousness, agreeableness seems not to be involved in comment prediction for users high in PFU. Previous studies indicated mixed results in the association between agreeableness and problematic social media use (Kircaburun et al., 2020; Marino et al., 2018). Choi et al. (2017) showed that friendly, generous users tend to like and comment contents shared by others. It could be the case that problematic users low in agreeableness are less likely to engage in Facebook for social maintenance purposes and for sharing interesting/cultural contents, in that agreeable users are likely to politely reply to comments received from others or to comment others' contents and might be less involved in self-promoting strategies.

Overall, other psychological variables did not emerge among the most important ten factors. It should be noted that the machine learning method used in this study processed a number of variables, highlighting the top ten most influent features and suggesting that other variables are just less important in comment prediction. Indeed, results do not exclude that self-esteem, positive mental health and other personality traits might play a role but indicate that they are less influent in predicting the probability to receive at least one comment, as compared to the most important features. Indeed, despite the positive association between low self-esteem and social media use (e.g., Hawi & Samaha, 2017), the frequent tendency of users low in self-esteem to use social media to enhance their self-image might not be sufficient to explain photo popularity. It could be argued that, when the outcome pertains feedback received by others, the (problematic) quality of engagement in Facebook profile management may matter more than the sole intrinsic motive to use Facebook.

With regards to photo-related features, some features increased, and some others decreased, the likelihood to receive a comment. Interestingly, "is_a_dome" (that is, the probability for the photo to contain a church or a temple) appeared as the most important photo-related feature and decreased the probability to gain attention. A possible speculative explanation for this result may lie in the decline of interest in religion among young adults (e.g., Uecker et al., 2007). Contrary to common expectations, the image size was negatively associated with the probability to receive comments; that is, a photo with high resolution is not likely to be commented. It could be that professional photos are more likely to gain a huge number of "automatic" likes instead of time-consuming comments. In contrast, other photo contents increased the probability to receive comments, such as a city square in the background, the presence of people in the photo or containing the link to another website. It could be argued that users might be more interested in places visited by their Facebook friends and by social activities showed in photos. This might be due, among other reasons, to the emerging phenomenon of FOMO (Fear Of Missing Out; Alt, 2018), which drives people to constantly check and possibly comment others' photos. Indeed, people high in FOMO are characterized by a strong willingness not to miss what others are doing and social events posted on social media and tend to be curious about others' activities (Przybylski et al., 2013). As such, it could be that individuals high in FOMO have the tendency to comment on photos containing people and places because there are concerned about social exclusion and fear that friends are having fun without them (Sun, 2022). Future research investigating users' popularity and visibility should further explore the potential role of friends' levels of FOMO.

Finally, with regards to "is a website", it could be that the increasing likelihood of comments is due to the presence of links to other website (such as links to online newspaper, events or tutorials). The content of the news is more likely to be commented (politics, gossip, etc.) as users of social networking sites usually express and share their (dis)agreement about news (e.g., Pentina & Tarafdar, 2014).

4.1. Limitations

Several limitations of this study should be acknowledged. First, in current study the number of comments only was considered as an indicator of "popularity" and subsequent predictions have been made based on comments. In the context of Facebook, relying on the number of both likes and comments received by a photo could had been a preferable choice (e.g., Zell & Moeller, 2018). Or, as McParlane and colleagues (2014) considered the number of views received by pictures on Flickr, number of views might also be an indicator of popularity. However, information about likes and views were not available in the downloaded Facebook profiles used to gather objective data whereas number of comments are generally considered a plausible indicator of actual interest.

Secondly, the distribution of the number of comments is very skewed, thus generating technical problems in the modeling. We decided to slightly simplify the problem modeling only the probability for a posted photo to receive a comment. The response variable remains hard to deal due to the unbalancing of the sample 82% of photos without any comment and 18% with at least one comment. Future research – perhaps with larger datasets – may approach the problems with a more precise output (i.e. predicting the number of comments instead of the presence of at least one comment). Moreover, the sentiment of the comments was not investigated because it was beyond the scope of the study. Future research should also look at the type (positive vs. negative) comments received by different types of photo as it might, in turn, influence users' self-esteem and well-being (e.g., Marengo et al., 2021). Finally, this study did not include any assessment of specific photo-related behaviors (e.g., photo-manipulation) and motives to share photos on different types of social media. Future studies should include these aspects when investigating the psychological profiles of social media users.

4.2. Conclusions

The present study adds to previous ones in that the mixed technical-psychological approach allowed to highlight the most important features involved in the prediction of popular contents posted on social media. To the best of our knowledge, this is the first study exploring what makes a Facebook photo popular using objective data rather than self-reported frequency of Facebook activity only. Results might be useful in order to advance current methods in this field and in increasing the extant knowledge about potential problematic behaviors on social media beyond common sense. Moreover, results might be of value for practitioners tackling clients' worries due to expectation of online feedback from Facebook friends. Understanding (and predicting) how rare the reactions of Facebook friends are might, indeed, decrease the levels of anxiety, perceived isolation and problematic social media use. Indeed, problematic users are often involved in recurrent preoccupation about others' evaluations and tend to evaluate themselves based on number of followers and reactions received. Results of the present study suggest that despite the time-consuming efforts made by users, the attention gained is limited. Clinicians could share with clients the risk to engage in PFU by showing that popularity on social media might be due to a number of different factors and that the vicious cycle of posting, expecting feedbacks and judge themselves can be interrupted.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CRediT authorship contribution statement

Claudia Marino: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Ciro Lista:** Formal analysis, Writing – review & editing. **Dario Solari:** Methodology, Formal analysis. **Marcantonio M. Spada:** Supervision, Writing – review & editing. **Alessio Vieno:** Project administration, Supervision, Writing – review & editing. **Livio Finos:** Conceptualization, Methodology, Formal analysis, Writing – review & editing.

Declaration of Competing Interest

Given their role as an Editor, Spada M. had no involvement in the peer-review of this article and had no access to information regarding its peer-review. All other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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