Seeing Light in the Dark: Investigating the Dark Side of Social Media and User Response Strategies

Article *in* European Management Journal · October 2019

DOI: 10.1016/j.emj.2019.10.001

4 authors:

Sean Sands
Swinburne University of Technology

Colin Campbell
University of San Diego

Carla Ferraro
Monash University (Australia)

Alexis Mavrommatis
ESADE Business School Barcelona

European Management Journal xxx (xxxx) xxx

Contents lists available at ScienceDirect

European Management Journal

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

Seeing light in the dark: Investigating the dark side of social media and user response strategies

Sean Sands [a], Colin Campbell [a, b, *], Carla Ferraro [a], Alexis Mavrommatis [a, c]

[a] Department of Management and Marketing, Swinburne University of Technology, Hawthorn, VIC, 3122, Australia
[b] Department of Marketing, University of San Diego School of Business, 5998 Alcala Park, San Diego, CA, 92101, USA
[c] Department of Marketing, ESADE Business School, Av. de Pedralbes, 60-62, 08034, Barcelona, Spain

ARTICLE INFO

Article history:
Received 10 January 2019
Received in revised form
22 August 2019
Accepted 3 October 2019
Available online xxx

Keywords:
Social media
Dark side
Addiction
Coping strategies
Negative consequences

ABSTRACT

Social media affords brands and users a variety of benefits. However, a recent stream of research identifies a multidimensional dark side to social media. We contribute to this growing body of research in four key ways. First, we empirically investigate user perceptions of the dark side of social media in terms of the risks proposed by Baccarella et al. (2018), confirming the existence of six of the seven risks. Second, we identify and empirically investigate the strategies with which users seek to reduce the social media risks. Third, we develop scales to assess both the social media risks and user reduction strategies. Finally, we conduct segmentation analysis to empirically investigate how users differ in terms of their perceived social media risks and risk reduction strategies. Taken together, our findings provide a validated framework of, and scales to measure, user perceptions of, and responses to, the dark side of social media.

1. Introduction

Social media is incredibly prevalent, with Pew Research (2018) reporting that over two-thirds (68 percent) of U.S. adults use Facebook, with three-quarters of users accessing the site daily. Usage of social media is even higher amongst younger users, with 88 percent of 18 to 29-year- olds using any form of social media. Despite the tremendous benefits that social media offers both users and brands (e.g., Ellison, Steinfield, & Lampe, 2007; Kumar, Bezawada, Rishika, Janakiraman, & Kannan, 2016; Sabate, Berbegal-Mirabent, Canabate, & Lebherz, 2014), knowledge of a "dark side" of social media is emerging. Indeed, social media sites such as Facebook are experiencing a surge in the occurrence of questionable activities, ramping up reporting and monitoring efforts in response (Swant, 2018; Tiku, 2018).

Social media's reported negative effects are diverse, having been broadly categorized in terms of a deterioration of civic engagement, a loss of privacy, decreased public safety, and an increase in cybercrime (Bolton et al., 2013). These effects vary in terms of being internally (self) or externally (others) imposed on users. Self-imposed negative effects can result from excessive usage, such as addiction (O'Keeffe & Clarke-Pearson, 2011; Andreassen, Pallesen, & Griffiths, 2017) or subsequent psychiatric disorders (Andreassen et al., 2016), depression (O'Keeffe & Clarke-Pearson, 2011; Lin et al., 2016), or self-esteem issues (Andreassen et al., 2017; Valkenburg, Peter, & Schouten, 2006). In contrast, known or unknown "others" (e.g., perpetrators) can also drive negative effects, such as bullying (O'Keeffe & Clarke-Pearson, 2011), the invasion of privacy (Pai & Arnott, 2013), the spread of fake news (Allcott & Gentzkow, 2017), trolling (Buckels, Trapnell, & Paulhus, 2014; Hardaker, 2010) and hate speech (Ben-David & Matamoros-Fernandez, 2016).

While further research on the dark side of social media is both necessary and important, understanding and categorizing such far-ranging negative effects has been challenging in the absence of a comprehensive frame. Baccarella et al. (2018) develop a framework to organize the varied negative effects of social media. Based on an established framework for understanding social media functionalities (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011), Baccarella et al. (2018) categorize and dimensionalize the "dark side" of social media across seven areas of concern, or risk: *Conversations, Sharing, Presence, Relationships, Reputation, Groups, and Identity*. By developing an organizing framework for social media

* Corresponding author. Department of Marketing, University of San Diego School of Business, 5998 Alcala Park, San Diego, CA, 92101, USA.
E-mail addresses: ssands@swin.edu.au (S. Sands), colincampbell@sandiego.edu (C. Campbell), cferraro@swin.edu.au (C. Ferraro), alexis.mavrommatis@esade.edu (A. Mavrommatis).

https://doi.org/10.1016/j.emj.2019.10.001
0263-2373/

risk, their contribution opens doors for new research and explicitly calls for empirical work on the topic. We adopt Baccarella et al.'s (2018, p. 433) definition of the "dark side" as the "negative consequences that consumers and communities face from social media."

This paper builds on Baccarella et al. (2018) framework of the dark side of social media in several ways. First, we directly answer their call for research that operationalizes their proposed framework by qualitatively developing and empirically testing items to assess dimensions of social media risk. Such work not only helps to validate Baccarella et al. (2018) framework, but more importantly develops a common measurement scale for future research. Second, we qualitatively identify strategies employed by users to reduce social media risk. We also develop and test items to measure these strategies. Finally, we employ Latent Class Analysis (LCA) to model how users differ in terms of their perceived social media risks. Each user segment is then profiled in terms of the strategies employed to reduce social media risk, social media addiction, and demographic characteristics. Bringing these elements together, this paper develops a comprehensive understanding of how users perceive and respond to the dark side of social media. In concluding, we provide several opportunities for further empirical work to extend our knowledge on social media's dark side, in particular for younger and vulnerable consumers.

2. The dark side of social media

Social media can be a double-edged sword, both for users and brands (Baccarella et al., 2018; Turel, Soror, & Steelman, 2017). On the one hand, social media provides brands with the ability to connect with users and build brand engagement (Hollebeek, Glynn, & Brodie, 2014). It also gives users the ability to connect with friends and family and a means to seek and discover new brands, compare alternatives, and read comments and reviews from other users. However, social media also has dark sides. In a comprehensive review and conceptualization article, Baccarella et al. (2018) provide new insight into the dark side of social media, developing seven distinct social media building blocks in the form of risks. We briefly describe each of the social media risks below.

2.1. Conversations

By its very nature, social media enables users to communicate with fellow users via a range of functions, including "Like," "Reply," "Comment," and "Direct Message." While certainly beneficial, the open exchange of ideas and information on social media also presents risks. These include the ability to post false or incorrect information, to coerce or aggressively engage with others, or to engage in bullying behavior.

2.2. Sharing

As part of the process of communicating with others on social media, users post content and information for others to view, as well as receive content from others. Social media thus enables data to be easily transmitted between users, sometimes in a viral fashion. In most cases, this behavior is harmless, but it can also have damaging consequences. Such consequences include the sharing of private or sensitive photos or videos without consent, or even the amplification of content foolishly posted online. Sharing also includes damage caused by receiving or unknowingly being exposed to inappropriate or undesirable content.

2.3. Presence

A valuable function of social media is the ability to see when and where others are online, since this facilitates synchronous conversations. A risk to this functionality is that information about one's location and activities are unknowingly revealed or used in an undesirable manner. While this risk spans any information that a social media site can reveal (i.e., being online), data on a user's physical location is typically the most sensitive.

2.4. Relationships

The exchange of information and connectedness provided by social media can forge and deepen relationships. However, social media can also be used to stalk, harass, and bully users. While such issues certainly pose a safety risk, they also highlight the psychological harm that being exposed to too much curated information on others' lives can cause.

2.5. Reputation

Since social media enables content to be easily posted, shared, and traced back to an individual, it also presents reputation risk. Content can be shared that damages the reputation of a sharer or others. The fact that digital content is easily archived and copied can make the long-term reversal of such damage near to impossible.

2.6. Groups

Social media is an important platform for users to connect with individuals who share similar interests. This ultimately helps users make new connections and express identity through affiliation. Unfortunately, the ability to form groups can drive people apart by magnifying perceived differences and fostering exclusion. In the extreme, private or closed groups can also act as breeding grounds for hate and violence.

2.7. Identity

Finally, the use of social media typically entails the generation and sharing of personally revealing content and actions. This information can not only impact how others perceive (see *Reputation*) or are able to locate an individual (see *Presence*) but presents a risk for how much others – as well as social media entities themselves – know about users.

3. Reducing social media risks

The risks posed by social media are likely to prompt a variety of different strategies to counter, mitigate, or reduce them. Since research is only beginning to identify these different strategies, a comprehensive listing is yet to be developed. Below, we synthesize prior research exploring how users manage the possible risks of social media, identifying a variety of general strategies and tactics.

3.1. Balancing perspectives

Social media can create so-called 'echo chambers', whereby only a user's existing beliefs are reinforced and opposing ideas are shut out. This phenomenon is often deemed social 'contagion' because it mimics the spread of disease (Brady, Wills, Jost, Tucker, & Van Bavel, 2017). For many, ideas and perspectives are formed from 'others' that we are socially connected to and are frequently transmitted through social networks. This can intensify views, contributing to social extremism and political polarization (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). However, some research has found that social media can have a converse effect, exposing users to a greater diversity of ideas (Flaxman, Goel, & Rao, 2016). For instance, an analysis of 3.8 million Twitter users finds that many topics are initially discussed broadly on social media before shifting to more polarized conversations (Barberá et al., 2015). The study concludes that users may be open to a more diverse range of ideas than previously suggested. We believe that underpinning this finding is a polarization in innate human desire: on the one hand, a desire to be informed and, on the other, a desire to be insulated, i.e., in an "information bubble." For some users, this desire may drive intentional exposure to diverse views and perspectives. For these users, social media may assist in maintaining a balance of perspectives.

3.2. Minimizing usage

Research on internet addiction links technology use with the undermining of social interactions (Dwyer, Kushlev, & Dunn, 2018; Young, 1999). Drawing on this literature, one possible method users might employ to counter the risks posed by social media is simply minimizing their usage. Indeed, this is one tactic suggested to reduce the harmful effects of internet and social media addiction (Dwyer et al., 2018; Kushlev & Dunn, 2017; Young, 1999). Minimizing social media usage is also suggested for users facing cyberbullying, especially if use proves harmful (Carter, 2013), as well as for users concerned with the possible negative effects on their relationships (Turkle, 2016; 2017). For these reasons, users may react to the negative effects of social media by minimizing usage. Indeed, various social media applications and phone devices, such as iPhone, have started helping users keep track of the time they spent on social media, in efforts to help prevent excessive usage. For instance, Apple's Screen Time feature provides reports outlining user behavior and total time spent using different apps and features (Miles, 2019).

3.3. Masking identity

A wide body of research investigates how users respond to online privacy concerns, ranging from refusing to use a site or service, refusing to provide personal information, to the provision of misinformation (Dommeyer & Gross. 2003; Krasnova, Günther, Spiekermann, & Koroleva, 2009; Sheehan & Hoy, 1999; Son & Kim, 2008; Youn, 2009). In the context of social media, Krasnova et al. (2009) find that users tend to reduce the amount of information disclosed in response to their privacy concerns, as well as becoming more conscious about the information they reveal. Studies find these effects occur in both adults and young adults (Milne, Rohm, & Bahl, 2004; Sheehan & Hoy, 1999). As such, we expect users to exhibit similar behavior in response to privacy risk in the context of social media.

3.4. Self-regulating shared content

In the age of social media, it is not uncommon to hear of individuals "oversharing," which is described as posting trivial events, suggestive photos, or brag-worthy events (Radovic, Gmelin, Stein, & Miller, 2017). In other cases, users share events that self-incriminate, such as the instance of a Taco Bell employee who posted images of himself defiling food items and was fired as a result (Broderick & Grinberg, 2013). Most students are also aware that many universities and employers now screen social media as part of standard recruitment practices (Firozi, 2011). Many users are therefore cognizant – as well as advised – to clean up their social media timelines, as well as take care in what they share (Chen, 2018) for fear of personal or career-related repercussions. While the notion of restricting or self-censoring what is shared on social media is generally linked to career concerns, it is likely that self-regulating social media content is a strategy that addresses the dark side of social media more generally.

3.5. Reporting inappropriate posted content

We also expect that users may react to some social media risks in a more confrontational manner. One strategy that users use to reduce privacy risk is openly expressing their anger or anxieties (Sheehan & Hoy, 1999; Son & Kim, 2008). This can be either directed at a firm or to other users and can occur either in a private or public manner. Likewise, in the context of cyberbullying, external coping strategies are identified as an effective and recommended means of confronting perpetrators (Kristensen & Smith, 2003; Patchin & Hinduja, 2006). This can include alerting others of the behavior or confronting the cyberbully. By directly calling out offensive behavior, this strategy is meant to both rally support from others and frighten and shame the bully into retreat. We argue that similar behaviors are likely to occur if a user sees inappropriate content posted on social media. This behavior is also encouraged by social media platforms, such as Facebook, which recently increased its investment in user-reporting tools (Swant, 2018; Tiku, 2018).

4. Study

This research sets out to conceptualize, and quantify, the dark side of social media. Given the newness of the phenomena investigated, we approach our study in three stages. First, with the help of experts, we generate scale items to assess the dark side of social media in terms of risks and related strategies that users employ to reduce them. Second, using a large sample of users, we empirically test the scale items developed. This also provides insight into the conceptualizations underlying both constructs. Finally, we conduct segmentation analysis to understand the heterogeneity of user perceptions of, and responses to, the dark side of social media. Fig. 1 provides a visual overview of the key steps and a description of the methodological process.

Stage 1: Item generation and selection

Following a review of the literature, we developed 29 items measuring the seven risks and 25 items measuring the five risk reduction strategies. With construct conceptualization best practices in mind, and in consultation with a variety of sources (Churchill, 1979; MacKenzie, Podsakoff, & Podsakoff, 2011), the items were developed in two stages. Each of the four authors first separately developed items for the dimensions of both constructs. The authors then compared and discussed the items, refining and clarifying language and phrasing. To further assess the initial items, seven academics experienced in social media research and teaching were asked to review the items and their overarching conceptualization. The academics were provided with information on relevant literature, descriptions of the risks and risk reduction strategies, and lists of the initially developed items. Feedback from these experts led to a refinement of the items, as well as the identification of using multiple social media personas as an additional reduction strategy. This process culminated in the identification of 14 items to assess the social media risks and 14 items to assess strategies to reduce risk, displayed in Tables 1 and 2, respectively.

Stage 2: Assessing social media risks and strategies to reduce risk

We next turned to empirically assessing the performance and

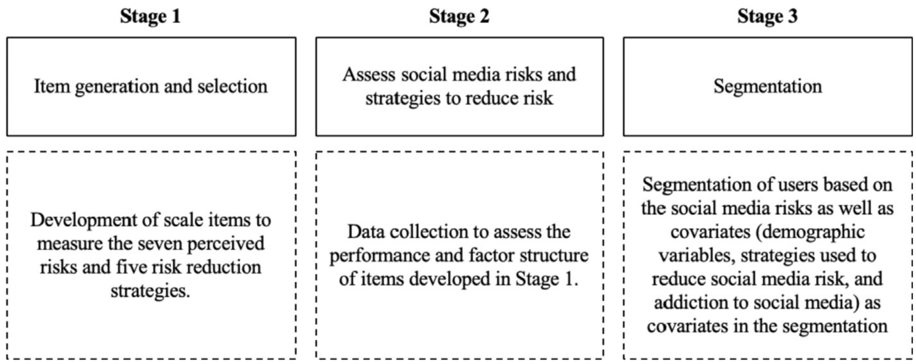

Fig. 1. Key steps and descriptions of the methodological process.

Table 1
EFA results for social media risks.

Item	Conversations	Sharing	Presence & Identity	Relationships	Reputation	Groups
I am concerned about threats and bullying on social media	0.745					
The potential for racist comments on social media makes me uneasy	0.667					
Social media makes it too easy for things to get leaked to others		0.647				
Social media makes it too easy to share inappropriate and undesirable content		0.574				
Sharing my location data on social media concerns me			0.798			
I am concerned about the privacy of my location data on social media			0.783			
I worry about others knowing too much about me from social media			0.507			
I am concerned about how much social media sites know about me			0.581			
Looking at social media makes me feel jealous of others				0.615		
I probably "creep on" or "stalk" people too often using social media				0.705		
Posting to social media makes me worried about my reputation					0.574	
I worry what my employer might think if they saw my social media					0.529	
Social media divides people into “camps”						0.719
Social media makes it easier to hate people different than you						0.700
Cronbach's Alpha	*0.74*	*0.78*	*0.82*	*0.66*	*0.65*	*0.74*

Note: Loadings less than 0.40 are not shown.

Table 2
EFA results for social media risk reduction strategies.

Item	Balancing perspectives	Minimizing usage	Masking identity	Self-regulating shared content	Reporting inappropriate posted content	Confronting inappropriate posted content	Multiple personas
I try to make sure my social media capture all perspectives on issues	0.807						
I like my social media to challenge my views	0.738						
I follow accounts to make sure my social media present me with both sides of arguments	0.793						
I have taken breaks from social media		0.651					
I have tried to post less often on social media		0.739					
I have tried to view social media less often		0.809					
I don't use my real name on social media			0.646				
I don't post my photo on social media			0.790				
I don't tag people in my social media posts			0.612				
I think twice before posting on social media				0.663			
I restrict what I post on social media				0.751			
I report inappropriate content I see on social media					0.604		
When others are aggressive on social media, I react						0.630	
I have both public (anyone can see) and private (restricted to friends) social media accounts							0.492
Cronbach's Alpha	*0.83*	*0.81*	*0.75*	*0.71*	-	-	-

Note: Loadings less than 0.40 are not shown.

factor structure of the items developed in Stage 1. Amazon Mechanical Turk (MTurk) was employed to collect data via an online questionnaire. Three-hundred and ninety-four adults (51.3 percent male, mean age = 36 years old, U.S. residents) participated in the study.

While the focus of Stage 2 was assessing the factor structure of items developed in Stage 1, we also included items for use in Stage 3 (segmentation). Respondents were first asked about their daily usage (minutes per day and platform) of the seven most popular social media platforms: Facebook, Twitter, Pinterest, Instagram, LinkedIn, Snapchat, and YouTube (Pew Research Center, 2018). Next, respondents were asked the 14 items (see Table 1) on the social media risks and then the 14 items (see Table 2) on user strategies to reduce risk. Both scales were measured using 7-point

Likert scales, ranging from 1 = *strongly disagree* to 7 = *strongly agree*. Social media addiction was also assessed using the Bergen Facebook Addiction Scale (Andreassen, Torsheim, Brunborg, & Pallesen, 2012) with phrasing adapted to reflect general social media addiction (Cronbach's Alpha = 0.96). The 18-item scale was assessed on a 5-point Likert scale, ranging from 1 = *very rarely* to 5 = *very often*. Demographic information was also collected. Presentation of items within each scale was randomized.

Exploratory factor analysis was employed to determine the structure of the scales assessing the social media risks and risk reduction strategies. Eigenvalues greater than 1 served as the construct structure selection criteria (Hair, Black, Babin, & Anderson, 2010). For the social media risks, results support a six-factor solution (accounting for 61 percent of the variance extracted), with five of the constructs reflecting the *a priori* dimensions proposed by Baccarella et al. (2018): *Conversations, Sharing, Relationships, Reputation, Groups*. Two of the constructs (*Presence* and *Identity*) proposed by Baccarella et al. (2018) load on a single construct and thus were combined. Table 1 shows the EFA factor loadings for the social media risks. For the strategies to reduce risk, results support a seven-factor solution (accounting for 64 percent of the variance extracted). Table 2 shows the EFA factor loadings for the strategies to reduce social media risk. While some factor loadings are medium (ranging from 0.5 up to 0.7) rather than high (greater than 0.7, as per Shevlin & Miles, 1998), we err on the side of including more information than less, given the exploratory nature of the study. As discussed more deeply in the future research section, we encourage further work on the construct dimensions and measurement scale items developed.

Stage 3: Understanding heterogeneity of user perceptions of, and responses to, social media concerns

We conducted a segmentation of users based on the social media risks (*Sharing*, *Presence* and *Identity*, *Groups*, *Conversations*, *Reputation*, and *Relationships*) identified in Stage 2. Additionally, we profiled each segment by adding demographic variables, the strategies used to reduce social media risk (*Balancing perspectives, Minimizing usage, Masking identity, Self-regulating shared content, Reporting inappropriate posted content,* and *Multiple Personas*) identified in Stage 2, and addiction to social media as covariates in the segmentation. Items for the social media risks and risk reduction strategies were averaged. Consistent with existing research (Andreassen et al., 2012, 2013; Wang, Ho, Chan, & Tse, 2015), items on the social media addiction scale were averaged to form a global measure.

LCA using Latent GOLD software (Vermunt & Magidson, 2002) was conducted to explore the extent to which the indicators and covariates differ between the resulting user segments. Segmentation analysis is commonly employed to understand heterogeneity in user populations (e.g., Konus, Verhoef, & Neslin, 2008). Fundamental to the approach is the assumption that the population consists of a finite and identifiable number of groups, each of which can be characterized by homogeneous preferences underlying their behavior, and that segment membership is probabilistic, based on the importance of different attributes. In conducting LCA, the latent variable (user segments) was considered categorical, taking on a range of possible values corresponding to segments and using a multinomial logit model to express the probabilities. For the segmentation analysis, the convergence criterion was set at 0.000001 (Collins & Lanza, 2010) and 50 random sets of starting parameters (Masyn, 2012) to reduce the likelihood of convergence to local maxima (McCutcheon, 2002). The local independence assumption was tested using Bivariate Residuals (BVRs) (Vermunt & Magidson, 2013). Model-fit statistics for solutions ranging from one to seven segments are displayed in Table 3.

Multiple criteria were used to select the preferred solution. First, the Bayesian Information Criterion (BIC) was used to compare relative model fit, and then segment profiles were considered in terms of over-extraction, class separation, and interpretability of results (Collins & Lanza, 2010; Masyn, 2012; Wedel & Kamakura, 2012). The preferred 5-segment solution was chosen based on having the lowest BIC value (Collins & Lanza, 2010) and displaying no evidence of over-extraction since the smallest segment was 9 percent of the sample. The solution also led to meaningful interpretation, as the clusters showed clear class separation. In contrast, solutions with additional segments resulted in smaller clusters with lower class separation. Based on the combination of these factors, the 5-segment model was deemed the final solution. Table 4 provides descriptive statistics for all segmentation variables (indicator and covariates). Indicator variables comprised average ratings for each of the six social media risks, as well as the average time spent using social media each day for each segment. All included variables were significant at $p < 0.001$. In addition, the overall social media risk (summated average of all risks) is calculated for each segment. For the covariates (age, gender, addiction, strategies used to reduce social media risk), a strong positive coefficient means that users who score high on the covariate are more likely to appear in that segment, whereas a large (magnitude) negative coefficient means users are less likely to be in the segment. Significant covariate coefficients were found for age (Wald = 15.29, $p < 0.05$), gender (Wald = 14.84, $p < 0.05$), and addiction (Wald = 40.47, $p < 0.001$), as well as for three of the seven strategies to reduce social media risk: reduction (Wald = 17.82, $p < 0.05$), privacy (Wald = 17.49, $p < 0.05$), and self-regulation (Wald = 25.76, $p < 0.001$).

4.1. Interpretation of segments

Findings suggest that users vary in terms of the social media risks they perceive and the range of strategies they employ to reduce these risks. In interpreting the heterogeneous nature of the dark side of social media, we draw on the results pertaining to segment profiles and their respective covariates (Table 4) to develop detailed descriptions of each user segment.

The first segment is the largest, representing one-third of users (33 percent). This segment has the second highest overall perception of social media risk (4.6), which is comprised of high levels of *Presence and Identity* (5.5), *Sharing* (5.3), and *Groups* (5.0). While still moderate, they are least concerned with *Relationships* (3.4). Members of this segment have one of the lowest average daily usages of social media at 1.8 h per day. However, despite this relatively low level of social media usage, members of the segment report a relatively high level of social media addiction (36.2), which is second highest among all groups. While the reported usage and level of addiction for those in this segment may seem contradictory, there are several possible explanations. For instance, much past research has found that self-reported usage statistics can be grossly under-reported by those with addiction, a group referred to as *deniers* (Rutherford, Cacciola, Alterman, McKay, & Cook, 2000).

Table 3
Log-likelihood statistics for model selection.

Solution	LL	BIC (LL)	Npar	Class.Err.
1-Cluster	−6780.29	13644.24	14	0.00
2-Cluster	−6526.67	13286.42	39	0.07
3-Cluster	−6397.68	13177.68	64	0.09
4-Cluster	−6315.07	13162.03	89	0.11
5-Cluster	**−6235.15**	**13151.60**	**114**	**0.09**
6-Cluster	−6180.17	13191.07	139	0.10
7-Cluster	−6106.92	13193.97	164	0.08

Please cite this article as: Sands, S et al., Seeing light in the dark: Investigating the dark side of social media and user response strategies, European Management Journal, https://doi.org/10.1016/j.emj.2019.10.001

Table 4
Dark side of social media user segment profiles ($n = 394$).

	Cluster 1 (Concerned Enthusiasts)	Cluster 2 (Conscious Enthusiasts)	Cluster 3 (Unconcerned Casuals)	Cluster 4 (Private Elders)	Cluster 5 (Concerned Indulgers)	All Clusters
Segment size	33%	22%	21%	15%	9%	100%
Age - average in years*	36 years	32 years	38 years	42 years	32 years	36 years
Gender - Male*	63%	38%	56%	38%	49%	51%
Perceived social media risks						
Sharing*	5.3	4.4	3.9	5.9	6.7	5.0
Presence & Identity*	5.5	4.0	3.6	4.9	6.8	4.8
Groups*	5.0	4.0	3.5	4.7	5.6	4.5
Conversations*	4.5	4.3	2.2	4.4	5.9	4.1
Reputation*	4.0	3.6	1.9	1.9	4.6	3.2
Relationships*	3.4	4.3	2.2	1.7	3.7	3.1
Overall risk	4.6	4.1	2.9	3.9	5.6	4.1
Strategies used to reduce social media risk						
Balancing perspectives	3.9	4.1	3.3	3.8	3.4	3.8
Minimizing usage*	5.0	4.2	3.5	4.6	5.7	4.5
Masking identity*	4.1	3.1	3.3	4.3	5.1	3.8
Self-regulating shared content*	5.9	4.9	5.1	6.2	6.7	5.6
Reporting inappropriate posted content	4.0	4.2	3.4	4.4	4.9	4.1
Confronting inappropriate posting content	3.0	3.7	2.8	3.0	2.9	3.1
Multiple personas	4.0	4.0	3.0	2.9	4.1	3.6
Usage profile						
Average daily usage (hours)*	1.80	3.60	1.40	2.40	3.10	2.30
Addiction*	2.00	2.40	1.40	1.40	2.00	1.90

*Note: *Significant at 0.001*

Another plausible explanation could be that those in this segment are actively trying to manage their addiction by reducing their usage. Regardless of the explanation, the two most commonly employed risk reduction strategies for this segment are *Self-regulating shared content* (5.9) and *Minimizing usage* (5.0). Members of this segment are predominantly male (63 percent) and 36 years of age on average. Given that the segment has high levels of perceived social media risk relative to other segments and reports high levels of social media addiction, we label this segment *Concerned Enthusiasts*.

The second segment represents 22 percent of users. This segment has a reasonably high overall perception of social media risk (4.1), which is comprised of high levels of *Sharing* (4.4), *Relationships* (4.3), and *Conversations* (4.3). While their lowest concern is for *Reputation* (3.6), it is still relatively high compared to most other segments. Members of this segment have the highest average daily usage of social media at 3.6 h per day, as well as the highest level of social media addiction (44.0), suggesting this group are *admitters* in term of their addiction (Rutherford et al., 2000). The most commonly employed risk reduction strategy for this segment is *Self-regulating shared content* (4.9). Members of this segment are predominantly female (male = 38 percent) and among the youngest, being 32 years of age on average. Given the segment has both the highest level of addiction and the highest concern for what they (*Sharing*) and others (*Relationships*) post, we label this segment *Conscious Enthusiasts*.

The third segment represents 21 percent of users. This segment has the lowest overall perception of social media risk (2.9). While their highest concern is for *Sharing* (3.9), it is lowest compared to all segments. Their lowest perceived risk is *Reputation* (1.9). Members of this segment have the lowest average daily usage of social media at 1.4 h per day, as well as the lowest level of social media addiction (24.3). The most commonly employed risk reduction strategy for this segment is *Self-regulating shared content* (5.1), and members of this segment are the least likely of all to have actively tried to minimize their social media use (3.5). More members of this segment are male (56 percent) and they are the second oldest, at 38 years of age on average. Given that the segment has a low level of perceived social media risk and use social media much less than other segments, we label this segment *Unconcerned Casuals*.

The fourth segment represents 15 percent of users. This segment has a moderate overall perception of social media risk (3.9), with their highest concerns for *Sharing* (5.9), *Presence and Identity* (4.9), and *Groups* (4.7). Their lowest concern is *Relationships* (1.7), which is the lowest among all segments. Members of this segment have a moderate average daily usage of social media at 2.4 h per day, as well as the second lowest level of social media addiction (25.3). The most commonly employed risk reduction strategy for this segment is *Self-regulating shared content* (6.2). Members of this segment are predominantly female (male = 38 percent) and are the oldest of any segment, at an average of 42 years of age. Given the high average age of users in this segment, and their greatest perceived risk being related to information leakages and privacy, we label this segment *Private Elders*.

The fifth, and smallest, segment represents 9 percent of users. This segment has the highest overall perception of social media risk (5.6), with high concern for all risks relative to other segments. Within this segment, their highest concerns are *Presence and Identity* (6.8) and *Sharing* (6.7). As with most other segments, their lowest concern is *Relationships* (3.7), although concern for relationships remains relatively high compared to all other segments. Members of this segment have the second highest average daily usage of social media at 3.1 h per day, as well as the second lowest level of social media addiction (25.3). The most commonly employed strategy for reducing social media risk is *Self-regulating shared content* (6.7), *Minimizing usage* (5.7), and *Masking identity* (5.1), reflecting an overall focus on privacy relative to all other segments. Members of this segment are relatively even in terms of gender (male = 49 percent) and are among the youngest at 32 years of age on average. Given that this segment has the highest level of perceived social media risk and is different from other groups in their use of Masking identity as a strategy to reduce risk, we label this segment *Concerned Indulgers*.

5. Discussion

Academic research continues to devote considerable attention to the evolution of social media. However, an important but largely overlooked research area is the negative consequences of social media. This paper expands the current understanding of how users perceive and respond to the dark side of social media. It does so by: (1) empirically investigating user perceptions of the social media risks identified by Baccarella et al. (2018), (2) identifying and empirically investigating how users respond in terms of seeking to reduce these risks, (3) developing associated scales to then map social media risk to user risk reduction strategies, and (4) empirically investigating user heterogeneity in perceptions of, and responses to, the dark side of social media. Taken together, our findings contribute to the current understanding of social media in several ways.

Beyond validating the dark side of social media in terms of perceived risks, we also synthesize and further develop an understanding of how users seek to reduce risk. This is important, as researchers have yet to develop a comprehensive framework of user response strategies to dark-side social media. We expect that as user concern for the negative effects of social media continues to grow, such understanding will be valuable to help organize future research on this topic. Likewise, the initial steps this paper takes toward developing scales for measuring social media risk and associated user response strategies pave the way for future empirical research on these topics.

Our segmentation findings further demonstrate that users differ in their perceptions of social media risk. Users can be classified in terms of five distinct segments, ranging from *Concerned Indulgers* (9 percent) to *Unconcerned Casuals* (21 percent). It is important to note that in addition to social media usage, all six distinct social media risks are significant drivers of segment membership. This finding further reinforces the value of Baccarella et al. (2018) framework.

Results of profiling each of the five segments provide further insights into users' social media risk reduction strategies. Our findings show that differences in perceptions of social media risk carry over to user response strategies. Segments are significantly different in terms of three risk reduction strategies: *Minimizing usage*, *Masking identity*, and *Self-regulating shared content*. Segments did not differ in terms of the other response strategies. At a broad level, these differences suggest that segments differ in terms of their use of more passive risk reduction strategies but are similar in terms of more active strategies, such as reporting or confronting unseemly content.

For firms, our paper provides several sources of value. First, we demonstrate that users are concerned about all social media risks. *Sharing*, *Presence and Identity*, and *Groups* are the most important concerns, while *Relationships* and *Reputation* are the least important. This information is valuable for advertisers and policy makers, as well as being particularly useful for social media organizations. Social media sites can be redesigned or tailored through privacy settings to help address these perceived risks. Second, our findings also provide insight into the most popular social media risk reduction strategies. *Self-regulating shared content* and *Minimizing usage* are the top two strategies, while *Reporting inappropriate posted content* and *Multiple personas* are the two least employed strategies. It is interesting to note that in practice social media platforms (e.g., Facebook and Twitter) use and encourage users to report inappropriate content. However, these findings suggest that these companies should reconsider the processes in place or come up with more effective techniques to enhance the users' willingness to share inappropriate content. It may be necessary for social media platforms to convey the efficacy of reporting as a trustworthy strategy that would help users when needed. Third, we suggest it is important for firms to consider their consumer base; and for those that find heightened concerns among their consumer base, increased effort could be spent in trying to mitigate these concerns. One way may be signaling the implementation of the specific risk-reducing strategies presented in this paper.

Given the popularity of *Minimizing usage* as a response strategy, brands should consider better understanding users in terms of their minimized behavior. Specifically, the developed scales can be employed to understand which risks and associated reduction strategies are predominant among a brand's users. If, as is likely, based on our data, a brand's consumers are striving to minimize their social media use, brands might consider the efficacy of their social media advertising expenditure and strategy. At a minimum, brands with consumers who are actively minimizing their social media use might consider advertising in a wider range of channels, outside of social networks. At a more nuanced level, our segmentation analysis reveals insight into the considerable heterogeneity that exists among social media users. Firms might use our scales, as well as their own data on variables such as age, to estimate the prevalence of different segment types among their consumer base.

6. Limitations and future research

As with any research, this study has certain limitations. First, our results are based on a cross-sectional study of social media users living in the United States. We encourage work to extend our findings to other countries, and in particular different cultures. Also, while we do not believe our findings will vary significantly over shorter periods of time, research exploring users' perceived social media risk and risk reduction strategies over longer periods may be fruitful. Social media continues to evolve, with new platforms developing and existing ones regularly evolving. To this end, our analysis provides a snapshot in time, given currently available social media platforms and associated concerns among users. It is likely that as social media evolves and new platforms become popular, the existence of new risks and subsequent strategies to reduce them will arise.

While we assess user strategies to reduce social media risk, we do not assess the perceived efficacy of these strategies. This focus is outside the scope of this research; however, we encourage research into user perceptions of how well each of the strategies works to reduce risks associated with social media usage. This direction also includes identifying moderators that affect the efficacy of each strategy. We also encourage research looking at the effect of risk reduction strategies, aside from the strategy of *Minimizing usage*, on users' social media behavior. It might be interesting to examine the extent to which reducing users' social media concerns is able to draw them back to social media.

With this research, we show that heterogeneity exists among consumers in terms of their perception of social media's dark side and that some consumers pro-actively managing or mitigating dark sides effects. However, opportunities remain for further empirical work on social media's dark side. One avenue for further research might be to consider relating social media risk with variables aside from social media usage. Social media risk might be correlated with reduced online purchasing, fear of data breaches, or even distrust of technology. Second, with this research we look at individual's actions, however research into group level responses might also uncover insight to how the dark side of social media is managed (i.e., via peer pressure). Third, our study focuses on consumers over the age of 18, however there are likely significant, and possibly different, dark side effects and response strategies for teens, preteens, or other vulnerable consumer groups. Research should also be encouraged to go one step beyond our study to investigate the actual efficacy of response strategies; in terms of how these strategies can positively impact consumers. Finally, an emerging behavior worthy of consideration is that of 'dark social', or the strategic behavior of not posting publicly, specifically posting to closed groups, or specifically using ephemeral media. This likely presents new challenges for detection and management.

The results presented here describe heterogeneous segments in terms of being stable states. However, it is likely that users may transition between segments over time. For instance, an individual user may transition from one segment to another or shift their behavior relative to additional factors. Such factors might include the individual's level of knowledge, expertise, or even changes in their usage (up or down). Future research might consider latent transition models that can estimate transition probabilities across time points, which are assumed to not be equal. In addition, both first order only transition models (i.e., only effect from t1 to t2, and from t2 to t3) and second-order transition models (including a direct effect from t1 to t3) could be considered.

Finally, our study is limited in that it is initial in nature. First, we note that some of the dimensions, such as *Reputation*, have relatively low factor loadings. This could be due to our data or to chance. It could also suggest that the dark side construct may benefit from further parsimony, similar to the case we observed with *Presence* and *Identity*. We encourage future research to validate and, if appropriate, potentially further reduce the dimensions of the construct. Second, while we conduct exploratory factor analysis as part of Stage 2 of data analysis, an important next step is to conduct confirmatory factor analysis. While this is a limitation in our study, we encourage further research to test our scale further, in particular with a wider variety of participants.

7. Conclusion

At a broad level, our findings contribute to social media knowledge by empirically validating the honeycomb framework developed by Baccarella et al. (2018). Our results confirm that all the social media risks identified are valid and significant. We further develop the work of Baccarella et al. (2018) by developing a scale to assess the dimensions of the dark side of the seven building blocks of social media. Such a scale provides a foundation to assess the risks of social media to individuals, communities, and organizations. It is important to note that our results indicate that the two original dimensions of *Presence* and *Identity* load on the same factor. *Presence* represents concerns about the privacy of a user's whereabouts and activities, while *Identity* reflects concerns about others or social media entities knowing too much about a user. Arguably, both the *Privacy* and *Identity* dimensions reflect a shared focus on privacy. Hence, it might be prudent to reconsider Baccarella et al. (2018) framework as comprising six, rather than seven, dimensions of social media risk. The implication of this might be a more precise, and concise, representation of social media risks, being: *Sharing*, *Conversations*, *Relationships*, *Groups*, *Reputation*, and *Privacy*.

Acknowledgments

We gratefully acknowledge the research assistants and academic experts who assisted in various stages throughout the study.

References

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *The Journal of Economic Perspectives, 31*(2), 211–236. https://doi.org/10.1257/jep.31.2.211.

Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., et al. (2016). The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychology of Addictive Behaviors, 30*(2), 252. https://doi.org/10.1037/adb0000160.

Andreassen, C. S., Griffiths, M. D., Gjertsen, S. R., Krossbakken, E., Kvam, S., & Pallesen, S. (2013). The relationships between behavioral addictions and the five-factor model of personality. *Journal of Behavioral Addictions, 2*(2), 90–99. https://doi.org/10.1556/JBA.2.2013.003.

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors, 64*, 287–293. https://doi.org/10.1016/j.addbeh.2016.03.006.

Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological Reports, 110*(2), 501–517. https://doi.org/10.2466/02.09.18.Pr0.110.2.501-517.

Baccarella, C. V., Wagner, T. F., Kietzmann, J. H., & McCarthy, I. P. (2018). Social media? It's serious! Understanding the dark side of social media. *European Management Journal, 36*(4), 431–438.

Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological Science, 26*(10), 1531–1542. https://doi.org/10.1177/0956797615594620.

Ben-David, A., & Matamoros-Fernandez, A. (2016). Hate speech and covert discrimination on social media: Monitoring the Facebook pages of extreme-right political parties in Spain. *International Journal of Communication, 10*, 1167–1193. https://ijoc.org/index.php/ijoc/article/view/3697.

Bolton, R. N., Parasuraman, A., Hoefnagels, A., Migchels, N., Kabadayi, S., Gruber, T., et al. (2013). Understanding generation Y and their use of social media: A review and research agenda. *Journal of Service Management, 24*(3), 245–267.

Brady, W. J., Wills, J. A., Jost, J. T., Tucker, J. A., & Van Bavel, J. J. (2017). Emotion shapes the diffusion of moralized content in social networks. *Proceedings of the National Academy of Sciences, 114*(28), 7313–7318.

Broderick, R., & Grinberg, E. (2013). 10 people who learned social media can get you fired. Available at: http://edition.cnn.com/2013/06/06/living/buzzfeed-social-media-fired/ Accessed 5 January 2019.

Buckels, E. E., Trapnell, P. D., & Paulhus, D. L. (2014). Trolls just want to have fun. *Personality and Individual Differences, 67*, 97–102.

Carter, M. A. (2013). Protecting oneself from cyber bullying on social media sites—a study of undergraduate students. *Procedia-Social and Behavioral Sciences, 93*, 1229–1235. https://doi.org/10.1016/j.sbspro.2013.10.020.

Chen, B. X. (2018). Want to purge your social media timelines? Can you spare a few hours?. https://www.nytimes.com/2018/03/28/technology/personaltech/social-media-timeline.html?login=email&auth=login-email Accessed 28 March 2018.

Churchill, G. A., Jr. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research*, 64–73.

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences* (Vol. 718). Hoboken, NJ: John Wiley & Sons.

Dommeyer, C. J., & Gross, B. L. (2003). What consumers know and what they do: An investigation of consumer knowledge, awareness, and use of privacy protection strategies. *Journal of Interactive Marketing, 17*(2), 34–51. https://doi.org/10.1002/dir.10053.

Dwyer, R. J., Kushlev, K., & Dunn, E. W. (2018). Smartphone use undermines enjoyment of face-to-face social interactions. *Journal of Experimental Social Psychology, 78*, 233–239. https://doi.org/10.1016/j.jesp.2017.10.007.

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication, 12*(4), 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.

Firozi, P. (2011). Law school admissions use Facebook, Google to screen applicants, study finds. https://dailynorthwestern.com/2011/10/30/campus/campusarchived/law-school-admissions-use-facebook-google-to-screen-applicants-study-finds/ Accessed 5 January 2019.

Flaxman, S., Goel, S., & Rao, J. M. (2016). Filter bubbles, echo chambers, and online news consumption. *Public Opinion Quarterly, 80*(S1), 298–320. https://doi.org/10.1093/poq/nfw006.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (Vol. 7). Upper Saddle River, NJ: Pearson Prentice Hall.

Hardaker, C. (2010). Trolling in asynchronous computer-mediated communication: From user discussions to academic definitions. *Journal of Politeness Research, 6*, 215–242. https://doi.org/10.1515/JPLR.2010.011.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of Interactive Marketing, 28*(2), 149–165. https://doi.org/10.1016/j.intmar.2013.12.002.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons, 54*(3), 241–251.

Konus, U., Verhoef, P. C., & Neslin, S. A. (2008). Multichannel shopper segments and their covariates. *Journal of Retailing, 84*(4), 398–413. https://doi.org/10.1016/j.jretai.2008.09.002.

Krasnova, H., Günther, O., Spiekermann, S., & Koroleva, K. (2009). Privacy concerns and identity in online social networks. *Identity in the Information Society, 2*(1), 39–63. https://doi.org/10.1007/s12394-009-0019-1.

Kristensen, S. M., & Smith, P. K. (2003). The use of coping strategies by Danish children classed as bullies, victims, bully/victims, and not involved, in response to different (hypothetical) types of bullying. *Scandinavian Journal of Psychology, 44*(5), 479–488.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of Marketing, 80*(1), 7–25. https://doi.org/10.1509/jm.14.0249.

Kushlev, K., & Dunn, E. W. (2017). Smartphones distract parents from cultivating feelings of connection when spending time with their children. *Journal of Social and Personal Relationships*. https://doi.org/10.1177/0265407518769387.

Lin, L. Y., Sidani, J. E., Shensa, A., Radovic, A., Miller, E., Colditz, J. B., et al. (2016). Association between social media use and depression among US young adults.

Depression and Anxiety, 33(4), 323–331. https://doi.org/10.1002/da.22466.
MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly, 35*(2), 293–334. https://doi.org/10.2307/23044045.
Masyn, K. (2012). Latent class analysis and finite mixture modeling. In T. Little (Ed.), *The oxford handbook of quantitative methods in psychology* (Vol. 2, pp. 375–393). Oxford, UK: Oxford University Press.
McCutcheon, A. L. (2002). Basic concepts and procedures in single- and multiple group latent class analysis. In J. A. Hagenaars, & A. L. McCutcheon (Eds.), *Applied latent class Analysis* (pp. 56–87). Cambridge, UK: Cambridge University Press.
Miles, S. (2019). What is Apple Screen Time and how does it work?. https://www.pocket-lint.com/apps/news/apple/144733-what-is-apple-screen-time-and-how-does-it-work Accessed 22 August 2019.
Milne, G. R., Rohm, A. J., & Bahl, S. (2004). Consumers' protection of online privacy and identity. *Journal of Consumer Affairs, 38*(2), 217–232. https://doi.org/10.1111/j.1745-6606.2004.tb00865.
O'Keeffe, G. S., & Clarke-Pearson, K. (2011). The impact of social media on children, adolescents, and families. *Pediatrics, 127*, 800–804. https://doi.org/10.1542/peds.2011-0054.
Pai, P., & Arnott, D. C. (2013). User adoption of social networking sites: Eliciting uses and gratifications through a means-end approach. *Computers in Human Behavior, 29*(3), 1039–1053. https://doi.org/10.1016/j.chb.2012.06.025.
Patchin, J. W., & Hinduja, S. (2006). Bullies move beyond the schoolyard: A preliminary look at cyberbullying. *Youth Violence and Juvenile Justice, 4*(2), 148–169.
Pew Research Center. (2018). Social media use in 2018. http://www.pewinternet.org/2018/03/01/social-media-use-in-2018/ Accessed 5 January 2019.
Radovic, A., Gmelin, T., Stein, B. D., & Miller, E. (2017). Depressed adolescents' positive and negative use of social media. *Journal of Adolescence, 55*, 5–15. https://doi.org/10.1016/j.adolescence.2016.12.002.
Rutherford, M. J., Cacciola, J. S., Alterman, A. I., McKay, J. R., & Cook, T. G. (2000). Contrasts between admitters and deniers of drug use. *Journal of Substance Abuse Treatment, 18*(4), 343–348.
Sabate, F., Berbegal-Mirabent, J., Cañabate, A., & Lebherz, P. R. (2014). Factors influencing popularity of branded content in Facebook fan pages. *European Management Journal, 32*(6), 1001–1011.
Sheehan, K. B., & Hoy, M. G. (1999). Flaming, complaining, abstaining: How online users respond to privacy concerns. *Journal of Advertising, 28*(3), 37–51. https://doi.org/10.1080/00913367.1999.10673588.
Shevlin, M., & Miles, J. N. (1998). Effects of sample size, model specification and factor loadings on the GFI in confirmatory factor analysis. *Personality and Individual Differences, 25*(1), 85–90. https://doi.org/10.1016/S0191-8869(98)00055-5.
Son, J. Y., & Kim, S. S. (2008). Internet users' information privacy-protective responses: A taxonomy and a nomological model. *MIS Quarterly, 32*(2), 503–529. https://doi.org/10.2307/25148854.
Swant, M. (2018). A breakdown of all the offensive content Facebook removed in the first Quarter of 2018. https://www.adweek.com/digital/a-breakdown-of-all-the-offensive-content-facebook-removed-in-the-first-quarter-of-2018/ Accessed 5 January 2019.
Tiku, N. (2018). How much sex, violence, and hate speech is on Facebook?. https://www.wired.com/story/how-much-sex-violence-and-hate-speech-is-on-facebook/ Accessed 8 January 2019.
Turel, O., Soror, A., & Steelman, Z. (2017). The dark side of information technology: Mini-track introduction. In *Proceedings of the 50th Hawaii international conference on system sciences*. Honolulu: University of Hawaii at Manoa.
Turkle, S. (2016). *Reclaiming conversation: The power of talk in a digital age*. New York, NY: Penguin Press.
Turkle, S. (2017). *Alone together: Why we expect more from technology and less from each other*. New York, NY: Basic Books.
Valkenburg, P. M., Peter, J., & Schouten, A. P. (2006). Friend networking sites and their relationship to adolescents' well-being and social self-esteem. *CyberPsychology and Behavior, 9*(5), 584–590. https://doi.org/10.1089/cpb.2006.9.584.
Vermunt, J. K., & Magidson, J. (2002). Latent class cluster analysis. In J. A. Hagenaars, & A. L. McCutcheon (Eds.), *Applied latent class analysis* (pp. 89–106). Cambridge, UK: Cambridge University Press.
Vermunt, J. K., & Magidson, J. (2013). *Technical guide for latent GOLD 5.0: Basic, advanced, and syntax*. Statistical Innovations inc.
Wang, C. W., Ho, R. T., Chan, C. L., & Tse, S. (2015). Exploring personality characteristics of Chinese adolescents with internet-related addictive behaviors: Trait differences for gaming addiction and social networking addiction. *Addictive Behaviors, 42*, 32–35. https://doi.org/10.1016/j.addbeh.2014.10.039.
Wedel, M., & Kamakura, W. A. (2012). *Market segmentation: Conceptual and methodological foundations* (4th ed.). Boston, MA: Kluwer Academic Publishers.
Youn, S. (2009). Determinants of online privacy concern and its influence on privacy protection behaviors among young adolescents. *Journal of Consumer Affairs, 43*(3), 389–418. https://doi.org/10.1111/j.1745-6606.2009.01146.
Young, K. S. (1999). Internet addiction: Symptoms, evaluation, and treatment. In L. Vande Creek, & T. Jackson (Eds.), *Innovations in clinical practice: A source book* (Vol. 17, pp. 19–31). Sarasota, FL: Professional Resource Press.

Please cite this article as: Sands, S et al., Seeing light in the dark: Investigating the dark side of social media and user response strategies, European Management Journal, https://doi.org/10.1016/j.emj.2019.10.001