Emotions Trump Facts: The Role of Emotions in on Social Media: A Literature Review

Abstract

Emotions are an inseparable part of how people use social media. While a more cognitive view on social media has initially dominated the research looking into areas such as knowledge sharing, the topic of emotions and their role on social media is gaining increasing interest. As is typical to an emerging field, there is no synthesized view on what has been discovered so far and – more importantly – what has not been. This paper provides an overview of research regarding expressing emotions on social media and their impact, and makes recommendations for future research in the area. Considering differentiated emotion instead of measuring positive or negative sentiment, drawing from theories on emotion, and distinguishing between sentiment and opinion could provide valuable insights in the field.

1. Introduction

Social media has become an increasingly important part of our private and professional lives. It is used for various purposes, the main motivations being maintaining and creating connections with other users, sharing and obtaining information and enjoyment [1–3]. There has been a fair bit of research within Information Systems (IS) on the usage of social media in general [4, 5], focusing on aspects like knowledge exchange [6], knowledge acquisition [7], and organizational benefits [8]. Although some promising work regarding emotional drivers in online behavior exists, we still know little with respect to how feelings are communicated on social media.

Emotions are connected with various types of success both in our private and professional lives. Happy people are healthier and have better relationships [9]. The organizational climate is strongly related to employee happiness [10], and happy people are more productive [11] as well as creative [12] at work. Emotions are also a key factor in knowledge exchange [13].

As in all communication, emotions play an important role in how we interact with other people online, whether it be about excitement prior to an event [14], a retweeting decision [15, 16], or the perceived usefulness of an online review [17]. Emotions have been shown to be contagious [18], which also applies in an online environment [19, 20], and they are linked to rumor spreading behavior [21].

Understanding better how individuals express emotions on social media has relevance not only for the providers of leisurely social media such as Facebook or Twitter, but also for companies using social media platforms for internal communication as well as organizations using social media as a customer relationship management channel.

Although there is evidence of the relevance of emotions in online communication, many yet unanswered questions remain, and the field seems to not yet have established internal coherence. The results of our literature review show that not many studies draw from theories on emotions, and some concepts could use clarification. An additional challenge in researching social media is that it is a moving target: previous research indicates that the way people communicate online seems to have changed markedly during the last decade [22], although we know little about how and how much, exactly. This means that some of the previous findings in the field may no longer apply and should not be relied on blindly.

Research on expressing emotions on social media seems to be off to a promising start, but still somewhat scattered. This paper aims to consolidate extant research on the topic, charting out what kinds of topical domains have been represented in research so far and what kinds of emotional theories and categorizations have been used. Using a structured literature review approach, this work sets out to answer the following research questions:

1. In which areas within social media research have expressions of emotion been studied?
2. Which theories on emotions from reference fields does the research rely on?
3. How are emotions categorized in the research?

Based on our analysis of the literature, we identify three helpful guidelines for future research. To our knowledge, a review covering research on how users express emotions on social media has not been conducted before in spite of increasing interest in the topic.

The remainder of the paper is structured in the following manner. We begin by discussing existing knowledge about emotions. In the Methodology section, we describe our approach in conducting a structured literature review. We report what we learned in the Findings section and reflect on it in the Discussion section, after which we present our concluding remarks and suggestions for future research.

2. Related Work in Other Disciplines

There has been extensive research in the field of psychology on whether emotions and moods are distinct concepts or different points on the same continuum [23]–[25]. Although some research has made a distinction between the concepts, they seem to be often used interchangeably.

In this manuscript, the affective vocabulary is used according to the following definitions. *Affect*, or *core affect*, is a constant, underlying state of emotion or feeling, and can be experienced as free-floating (*mood*) or related to a specific event or cause (*emotion*) [25, 26]. This review focuses on literature about expressed or enacted emotion in the context of social media. Emotion expressions online are typically researched using *sentiment analysis.* In the context of sentiment analysis, *sentiment* can refer to either a feeling or emotion, or an attitude or opinion.

Various categorizations for emotions have been proposed. Some of them include distinct states, like Ekman's five core emotions *enjoyment, sadness, anger, fear, and disgust* [27]. Others conceptualize emotions situated along dimensions like *pleasure* (also referred to as *valence*), *arousal* (also referred to as *activation*), and *dominance*, such as the Pleasure-Arousal-Dominance (PAD) emotional state model [28] or Russell's circumplex model of affect [29] (used e.g. in [14]). Yet others combine elements from both of the abovementioned approaches. Plutchik's wheel of emotions defines basic emotions as well as milder variants of them, and describes how they relate to each other [30] (used in e.g. [31, 32]), and Ekkekakis defined a hierarchical structure of the affective domain, combining the idea or core emotions and dimensions [25] (used in e.g. [33]).

Sentiment analysis is, as defined by Pang and Lee [34], "computational treatment of opinion, sentiment, and subjectivity in text". Traditionally, sentiment analysis has measured the positive and negative sentiment of a sentence or longer text, but there are recent examples of using more fine-grained approaches based on emotion categories such as the ones mentioned above (e.g. [32, 35]). There are two main methodological approaches. Lexicon based methods utilize a dictionary of words and their sentiment values – most often positive and negative – to assign a sentiment score to an input text [36, 37], whereas machine learning approaches classify documents into sentiment categories based on training data [38]. Some recent studies combine the two by using lexicon scores as input for a classifier [39].

3. Methodology

Our literature review process consisted of deciding the inclusion criteria, searching for relevant work, and finally analyzing the discovered articles. It was conducted following the recommendations of Webster and Watson [40] and vom Brocke et al. [41]. The structured literature analysis had five phases. The first step was to determine the scope of the review. The second phase was searching through the most important journals in IS, the *basket of eight* (http://aisnet.org/?SeniorScholarBasket), as well as collecting and testing potentially useful search phrases. The third step was to search through scientific databases, and the fourth to conduct backwards and forwards searches for the articles identified as relevant in the previous phases. As the final step, we analyzed the articles, categorizing them according to topic, theory usage, and emotional categorization.

3.1. Phase I: Deciding the Scope of the Literature Review

This literature review was conducted to map out the current knowledge regarding expressions of emotion in social media environments. The main focus is on IS, but other fields – such as computer science and social sciences – are taken into account as well. The criteria for including articles were that they be (1) peer reviewed, (2) in English, (3) published in 2006 or more recently, and (4) on the topic of how sentiment is expressed on social media. For both quality assurance and time management reasons this work focuses mainly on journal articles in the first two phases.

The year 2006 was deemed a reasonable cut-off, as it was around that time social media started emerging as a result of Web 2.0. Most of the articles discovered during our search were published after 2010, which confirmed that limiting the review to after 2006 is a rather safe choice with regard to including important previous work.

In deciding what counts as social media, we followed Kaplan and Haenlein's [42] definition: "Social Media is a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of User Generated Content". The term sentiment is used in a broad sense in this scoping – as is typical with sentiment analysis – and covers emotion, mood, and in some cases opinion.

3.2. Phase II: Searching the Top Journals and Identifying Search Terms

The first phase of the search was finding the relevant articles published in the basket journals. As they are of particular interest thanks to the overall high quality of the publications, we decided to search through them with particular care and use them as testing ground for various search phrases in order to avoid the failure to detect seminal works on the topic.

Several search words and search word combinations were tried out in order to ensure the discovery of as many relevant articles as possible and to get an overall idea of which search phrases work best. The search phrases tested include e.g. *"social media" + emotions*, *"social networking sites" + "sentiment analysis"*, and *"computer mediated communication" + sentiment*. Whenever a discovered article would contain a new potentially helpful key word or key word phrase, the list of search words was expanded. As a preparation for the next phase, search phrases were tested and compared to find a satisfactory balance between precision (i.e. how many of the articles in the search results were relevant) and recall (i.e. how many of the relevant articles we knew existed in the database the search would list).

The searches yielded some hundreds of results in all. Based on the titles and abstracts, 26 articles were chosen for closer inspection, out of which 13 were deemed relevant after reading.

3.3. Phase III: Database Literature Search

Based on the search phrase comparison in phase II, the database search was conducted using the search phrase "social media" + emotion + analytics. The databases searched were the AIS electronic library (AISeL), ScienceDirect and Springer. As previously, a reading list of 116 potentially relevant articles was assembled by reading through the titles and abstracts of the results. In all, 35 relevant documents were identified during this search phase, including a selection of relevant conference papers. The database search yielded a large number of papers focused on sentiment analysis from a purely methodological standpoint, and were excluded from this review unless they communicated empirical findings on the expression of emotions on social media.

3.4. Phase IV: Refining Literature Results

The final search phase consisted of forward and backward searching the articles identified as relevant in the two previous phases. The original inclusion criteria were applied for the articles examined, including the cut-off at 2006. As in the previous phase, some conference proceedings were included in the collection of relevant papers.

All in all, 82 articles were identified as relevant during the search phase, and were included in the analysis. (See Table 1.)

Table 1: The number of articles identified for reading and deemed as relevant during the literature search

	Read through	Relevant
Basket (phase II)	26	13
Database (phase III)	116	35
Forward-backward (phase IV)	72	34
In all	**164**	**82**

3.5. Phase V: Literature Analysis

After the completion of the search, the articles were read and analyzed. Notes were made for each article on what the area or topic of interest is (in order to answer research question 1), whether they draw from some emotion related theory (research question 2), and what kind of categories they use for emotions (research question 3). The topics were manually coded by one author and a random sample of 25 % papers was coded by another author in order to ensure the coding categories and decisions were sound. (See Table 2 for categories.)

There seems to be a steadily increasing interest in the topic recently. Most of the work published is from 2011 onwards, and 10 out of 13 basket papers have been published in 2013 or later. Nine of the papers are method or design focused, i.e. the research questions were formulated in a way that is related to the design or method rather than the empirical results. Three of the articles are reviews, and the rest of them are empirical.

4. Findings of the Literature Review

Table 2 lists the articles sorted by their topic and choice of categorizing emotion. Both the topic and emotion categories are a result of manually coding the literature.

The most typical way of looking at emotions was measuring positive or negative affect. The *Positive/negative* column also contains the papers that classified neutrality or polarity in addition to valence. *Emotion/no* is a simpler version of this, where only the presence or absence of emotions is considered. *Differentiated* contains all papers that look at differentiated emotions or focus on a specific emotion (e.g. anxiety), whereas articles using partially differentiated emotions in combination with valence (e.g. positive, negative, anger, anxiety and sadness) were classified in *Partial*, which also contains looking into only one dimension (e.g. high or low activation). *N/A*, not applicable, is where the papers not using any emotional categorization – mainly literature reviews – were classified.

Collective sentiment contains articles on sentiment expression in a large group of people, such as Twitter users, football spectators or Chinese bloggers. Changes in sentiment levels can be detected online in relation to cultural, social, political or economic events.

Contagion refers to emotional contagion between users, which the articles unanimously confirm occurs on social media. People tend to have similar subjective well-being levels as their connections, although it is unclear whether this is due to contagion or other factors [43].

CRM/eWOM/OCR is a combination of *customer relationship management*, *electronic word of mouth* and *online customer reviews*. The three areas were merged into one category due to the topical overlap between them being very commonplace in the articles. Roughly one half of the papers focus on online reviews, and found sentiment to be connected to reviewer popularity and perceived helpfulness. Looking into differentiated emotions revealed that the perceived helpfulness of a review depends on which emotions the review contains [32, 35], which can be explained by the beliefs regarding the cognitive efforts of the reviewers [35].

Information diffusion contains research looking into how emotions affect people's decisions to pass on information in their network. The papers focus on the virality of news and retweeting behavior. In spite of similar data sets and publication times between studies, there are some contradicting findings in this category. A study examining NY Times articles found that the virality of a piece of news is connected to high arousal emotions, and that positive content is more likely to go viral than negative [88]. However, according to another paper, negative sentiment enhances virality in the context of news, but not in the context of tweets [89].

Table 2: The reviewed articles grouped by their topic and choice of emotional categorization

Topics in the literature	**Categorization of emotions**					
	Differentiated	Partial	Positive/negative	Emotion/no	N/A	All
Affect on SM in general	[14]		[39][44][45][46] [47] [48][49][50] [51][52][53]			12
Collective sentiment	[54][55][56]	[57]	[58][59][60][61] [62]	[63][64]		11
Contagion	[31][65]	[66] [67]	[19][20][43] [68][69][70]			10
CRM/eWOM/OCR	[32][35]		[17][71][72][73] [74][75][76][77] [78][79][80][81] [82][83][84][85] [86]	[87]		20
Information diffusion	[21]	[88]	[15][17][89][90][91]			7
Literature review					[4][5][92]	3
Methods and tools			[93][94][95]		[96]	4
Negative behavior	[97]		[98]			2
Outcome prediction	[33][99][100]	[101]	[102][103][104] [105][106][107] [108]			11
Predicting user engagement		[109]	[110]			2
In all	**13**	**6**	**56**	**3**	**4**	**82**

All the studies based on Twitter data seem to agree on emotions increasing the likelihood of retweeting, but there are differences regarding how, exactly. Some report that positive messages get more retweets [16], [90], others find no significant difference between the propagation of positive and negative tweets [15]. There were also some mixed results on whether negative tweets spread more rapidly than positive ones [15, 90].

Outcome prediction papers predict some real-world effect based on social media data. Most of the articles address changes in the stock market based on social media sentiment. According to some, differentiated sentiment is necessary in order to obtain accurate results [33, 99]. Other work in this category found that measuring sentiment online can be a feasible substitute for or addition to political polls in predicting election results [101, 108].

The papers in *Predicting user engagement* found that the emotional content of a message affects how much users on social media engage with the message. In the case of political blog entries, elevated positive or negative sentiment led to a clearly increased the number of comments.

Affect on SM in general contains papers that investigate how affect is expressed on social media, but that do not fit into the other more specific categories. Findings include, among other things, that influential users online tend to use more affect in their messages [46, 50], that the levels of emotional expression are gender related [45] and that affect influences self-disclosure indirectly by adjusting the perceived benefits [48].

As social media research in general, the majority of the papers are rather data driven than theory driven [5]. Table 3 lists all the theories used in the analyzed literature. Even though most articles reference at least some psychological literature, it seldom goes beyond defining core emotions or phenomena on a general level. Out of all the reviewed work, 11 papers based their research questions or hypotheses on a theory about emotions, and no theory is mentioned twice. In contrast, some papers use multiple theories. Some of the largest topic groups, *CRM/eWOM/OCR* and *Outcome prediction*, contain no theories on emotion.

To synthesize, some domains are more extensively researched than others, and theories are not

Table 3: Theories on emotion used in the literature grouped by topic

Theories on emotion	Affect on SM in general	Collective Sentiment	Contagion	CRM/eWOM/OCR	Information diffusion	Literature review	Methods and tools	Negative behavior	Outcome prediction	Predicting user engagement
Affect heuristic theory	[48]									
Affect Infusion Model (AIM)										[100]
Affective events theory	[14]									
Affective response model	[14]									
Anthony's rumor theory		[64]								
Coping classification framework							[93]			
Direct causation theory	[48]									
Dissonance reduction theory	[51]									
Feedback process model	[51]									
Gross: 5 factors of emotion regulation			[70]							
Interpersonal theory of depression			[68]							
Mimicry			[66]							
Negativity bias					[15]					
Positivity bias					[90]					
Self-determination theory	[14]									
Social information processing theory			[68]							
Number of papers in topic category:	3	1	3	0	2	0	1	0	0	1

commonplace in any domain. Although there is evidence supporting the usefulness of analyzing emotions in a fine-grained manner, it is not a common approach thus far. In particular, domains like information diffusion, online customer reviews, and outcome prediction have focused primarily on bipolar sentiment.

5. Discussion of the Key Findings on Emotions in Social Media

During the past decade, social media has certainly claimed its place as a worthy area of interest, and the increasing amount of research regarding emotions in the domain is an indication of how essential they are in our online communication. The work done in the field so far has provided us with a lot of valuable insight, and now serves as a good basis for asking how we can do even better. Based on our literature analysis, we provide three concrete suggestions: using more theories on emotion to support the research, being more precise about the terminology, and considering whether looking at differentiated emotions provides better explanations than bipolar emotions.

5.1 Theories on Emotion in Social Media Research

One of the points of interest discovered in analyzing the literature was that although IS scholars are used to drawing from theories in other domains, it seems to not be a common practice when it comes to emotions in a social media context. The usage of theories explaining affect in the papers examined was sparse – little over 10% of the articles used a theory on emotion to guide their research questions or hypotheses – although emotions have been extensively researched within psychology for a long time.

It would be interesting to take a closer look at why such theories are not more commonly used. Could it be that most of the research on expressing emotions online so far has been focused on describing what happens instead of attempting to explain why it occurs? Theories on emotion serve as a good basis for explaining and reasoning about observed behavior, but might not be considered necessary for simply describing observations.

5.2 Distinguishing Sentiment, Emotion, and Opinion

The concepts of affect, emotion, and mood are not trivial to differentiate between, and even psychology scholars have varying views on how to define them [25], which makes it a challenge for social media researchers to be accurate with the terminology. Nevertheless, there is one particular case of unclear term usage that does not require extensive expertise in the psychology of emotions, and we would like to propose that it merits some attention.

There seems to be an implicit assumption about the concepts sentiment and opinion being interchangeable. However, sentiment can refer to either an emotion or an opinion. Both can be interesting and relevant topics for research, and sometimes the same tools may be good for measuring either of them. However, when we report findings, we should be clearer on which one is being discussed. Positive (or negative) opinion towards something does not necessarily equal positive (or negative) experienced emotion; in fact, they may even be opposite. For instance, imagine a hotel review saying *"I'm glad they're out of business!"*. The emotion – or sentiment – may be positive, but the opinion is most certainly not.

If we want to know how highly people value a service or product, opinion is of interest to us. If we want to know what drives people's behavior and communication, emotion is probably going to be of more interest. Applying what we know about opinions to emotions or vice versa is likely to not always be accurate. We would like to suggest that these two should be separated clearly when reporting findings, and treated as two distinct concepts.

5.3 From Bipolar to Differentiated Emotion

A further discovery from the literature is that analyzing sentiment has so far mainly happened on a bipolar scale. However, some recent papers indicate that differentiated emotions give us more insight than simply looking at valence [33, 35, 66, 100]. We know that the activation level of an emotion matters with respect to what kinds of behavior it triggers: anger – a high activation negative valence emotion – causes reactions very different from sadness, a low activation negative emotion [88]. Distinguishing between emotions in a more fine-grained way than before would be likely to increase our understanding of the phenomena we investigate. For instance, it would be interesting to investigate whether an analysis using differentiated emotions could explain the inconsistencies between the findings in the *Information diffusion* category regarding retweeting behavior and emotions.

Why are we, then, not looking at differentiated emotions more? It may well be that in some contexts a bipolar analysis approach is adequate for the purposes of the study. It is also possible that in spite of some findings pointing that way, the significance of differentiated emotion is not yet common knowledge in our field. Another possible contributing factor is that there is a much larger variety of tools readily available – or commonly known by researchers – for bipolar than differentiated sentiment analysis.

One useful thing to keep in mind regarding differentiated emotions is that the ways they are expressed may be context or culture dependent [27].

6. Conclusions and Avenues for Future Research

Emotions are an important part of how people communicate online, and there is much yet to be discovered in that realm. Looking at previous findings regarding emotions on social media helps us ask new questions and set new courses in our research. Based on the results of our literature analysis, theories on emotion are infrequently used to support the research, key terms – such as sentiment, emotion and opinion – are not always defined precisely, and sentiment analysis is mostly limited to measuring positivity and negativity instead of considering differentiated emotions. We argue that being better aware of the aforementioned observations will help scholars in the field make better informed choices regarding their research.

Possible future work avenues include looking into how differentiated emotion could bring further insight to e.g. how information diffusion works with respect to emotions, and what types of negative emotions cause certain types of antisocial behavior online. It would also be interesting to take a closer look at the studies where theories on emotion have been used; is there indeed a difference in what types of questions (e.g. what vs. why) are asked compared to the ones that do not draw from theories?

One limitation of this work is that although the literature search was structured and broad, and we used search term expansion as well as backward and forward searches in addition to covering the leading IS publication outlets, it is likely that some works will have evaded our attention in spite of our best efforts, since the nature of the topic is interdisciplinary and the publication outlets diverse.

7. References

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