Trends in Cognitive Sciences

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Review

Digital Emotion Contagion

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People spend considerable time on digital media, and are thus often exposed to expressions of emotion by other people. This exposure can lead their own emotion expressions becoming more similar to those of others, a process we refer to as 'digital emotion contagion'. This article reviews the growing literature on digital emotion contagion. After defining emotion contagion, we suggest that one unique feature of digital emotion contagion is that it is mediated by digital media platforms that are motivated to upregulate user emotions. We then turn to measurement, and consider the challenges of demonstrating that digital emotion contagion has occurred, and how these challenges have been addressed. Finally, we call for a greater focus on understanding when emotion contagion effects are likely to be strong versus weak or nonexistent.

Highlights

People are spending increasing time on digital media, during which time they are exposed to the emotion expressions of others. This can lead their own emotion expressions becoming more similar to those of others.

One distinction between digital and nondigital emotion contagion is that digital emotion contagion is mediated emotion contagion. The goals of digital media companies – to increase the frequency and intensity of user emotions – likely increase emotion contagion.

Another distinction between digital and nondigital contagion is that the size and the character of digital networks may amplify contagion. However, increased exposure may also contribute to habituation and fatigue, which may serve as a counterweight, thus decreasing emotion contagion.

Given that many factors contribute to changes in the emotion of a person from moment to moment, and the typical absence of information regarding user exposure to emotional content produced by others, it is challenging to determine when digital emotion contagion has occurred.

The Ubiquity of Digital Emotion Contagion

A study published in *Proc. Natl. Acad. Sci. U. S. A.* in 2014 sought to demonstrate emotion contagion on social media using an experimental design [1]. In this study, the content that Facebook users saw was manipulated without their knowledge to be either less negative or less positive. User emotions were evaluated with a dictionary-based program that counts the number of positive and negative words used [2]. Results indicated that those who were exposed to fewer negative or fewer positive emotions produced fewer of these emotions themselves. This is the only published study that manipulated user emotions without their knowledge on a digital media platform.

Perhaps fittingly, the emotional response of the general public to this article seemed to illustrate its thesis because intense emotions became increasingly intense as they spread over social media, bringing more and more users to express their outrage and anxiety about the possibility that their emotions were being manipulated without their explicit consent [3]. The growing outrage expressed by the public eventually led the scientist who authored the report to apologize in a public Facebook post and admit that the potential benefits may not have outweighed the costs.

The controversy surrounding this study has drawn increased attention to digital emotion contagion. Growing research on this topic highlights the idea that digital emotion contagion occurs in response to a variety of situations, both public and private, and that emotion contagion can play a key role in determining the emotions and behavior of users in a variety of domains. For example, it seems that the digital era we live in has given rise to a large number of online social movements, all highly driven by emotions [4–6], and that emotion contagion plays a crucial role in the spread of these emotions [7]. People also seem to share their personal emotions online in a way that affects not only their own well-being [8] but also the well-being of others who are connected to them [9]. Given the tremendous exposure to the emotions of others on digital media, the contagious spread of digital emotions seems to be having a powerful impact on user emotions and behavior.

In this article we review the growing literature on digital emotion contagion while making two central points. The first point is that digital emotion contagion should be understood as mediated emotion contagion, and that the goals of the digital media companies that serve as its mediators

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may influence the way digital emotion contagion unfolds in important ways. After providing a general review of emotion contagion in the first section, we dedicate the second section to examining whether and how the mediating role of digital media companies can affect contagion. The second point that we make is that, despite its apparent impact on emotional dynamics online, proving that digital emotion contagion has occurred is more difficult than one might expect. This point in discussed in later sections which focus on the challenges of measuring digital emotion contagion, and the ways these challenges have been met thus far. Finally, we conclude with a section that reviews central findings in this domain and, in light of existing findings, offers new questions and directions for future research on digital emotion contagion.

Emotion Contagion

Emotion contagion has long been recognized as a central driver of individual and collective behavior, as reflected in the writings of philosophers such as Hegel [10] and social scientists including Le Bon and Durkhein [11,12]. Within experimental psychology, a seminal book on emotion contagion [13] helped to initiate a wave of empirical research that has sought to specify the nature of emotion contagion and clarify its driving mechanisms [14–16]. Building on previous research, we define emotion contagion as the process by which the emotions of a perceiver become more similar to those of others as a result of exposure to these emotions. Importantly, we see emotion contagion as a process that can either be conscious or unconscious, the only necessary condition being that it contributes to increased similarity in emotions between two or more individuals.

Contagion has been shown to occur via at least three mechanisms. The first is mimicry, in which an emotional expression activates synchronous behavior on the part of the perceiver, which in turn activates affective processes [13,17]. Mimicry represents a family of synchronous behaviors that primarily include facial expressions, but also include body postures, eye movements, speech gestures, and laughter [15,18]. The second mechanism is category activation, in which exposure to emotional expressions primes an emotion category, which in turn leads to activation of specific emotional processes [14,19]. Activation is differentiated from mimicry because it does not necessarily involve behavioral copying of an emotional expression, and therefore can result from exposure to emotional cues via other forms of communication such as text. Finally, the third mechanism is social appraisal, in which individuals use the emotions of others as a guide for their own emotion appraisals, leading to similar emotional experiences [20,21]. These three mechanisms are not mutually exclusive and can occur in tandem.

Driven by these three mechanisms, emotion contagion can occur as a result of many types of exposures to the emotions of others. These include face-to-face interactions [13], exposure to emotions through text [22,23], and even information gleaned about what other people feel in response to a particular stimulus [24,25]. The variety of mechanisms by which contagion can develop means that it occurs in many different contexts and situations, ranging from interpersonal relationships [26,27] to large collectives [28,29].

For our purposes here, it is useful to limit the scope of emotion contagion and distinguish it from related phenomena. First, emotion contagion may be differentiated from contagion of other, longer-term, affective processes such as moods by focusing on short-term changes in emotions lasting for seconds or minutes [30]. Second, emotion contagion is intended to capture cases in which exposure to the emotions of other people leads to similarity in their emotions. This is in contrast to cases in which exposure to the emotions of others leads to different or complementary emotions [31–34], which is especially frequent when individuals are exposed to the emotions of people from rival groups [35].

Emotion Contagion on Digital Media

When people interact face-to-face or by phone, their emotional responses are directly perceived by others in an unmediated way. This makes most nondigital interactions different from interactions on digital media, which are almost always mediated by companies who control and manipulate both the content that users see and how they respond to each other. Even on platforms in which there is relatively less management of user exposure to information, such as online forums, digital news outlets, and video communication platforms, the nature of interactions is guided by top-down design decisions that maximize some behaviors over others. We argue that digital media companies are generally motivated to increase user engagement, and that to do so they often upregulate user emotions, leading to an amplification of the frequency and intensity of user exposure to emotions, and therefore of emotion contagion (Figure 1). These effects may be further amplified by the size and character of digital social networks. Despite exposure to more frequent and more intense emotions, however, it is not yet clear whether and to what degree other processes such as habituation and fatigue act to reduce the strength of digital emotion contagion.

Exposure to emotions produced by other users helps to keep users engaged. One of the strongest pieces of evidence for this claim can be seen in the Facebook contagion article [1], which reports on the 'withdrawal effect' in which users have a tendency to produce less content if they are exposed to fewer emotions. If exposing users to the emotions of others keeps them engaged, and if engagement is a key outcome for digital media, digital media companies may try to upregulate user emotions by increasing the frequency and intensity of expressed emotions (particularly positive emotions; Box 1). This is likely to magnify emotion contagion online.

Although the decision to maximize user emotions is implemented through algorithms that may not have a direct goal of increasing user exposure to emotional intensity, in practice, because increasing exposure to emotions leads to increased engagement, emotional content is likely to be promoted. Increased frequency and intensity of emotion expressions are not only achieved by selectively showing participants more emotional posts but also by creating an incentive structure that motivates participants to express emotions. Digital media platforms usually incentivize competition for attention and positive reinforcement in the forms of likes or shares [36]. Expressing emotions is an extremely useful way to attract attention and receive likes [4,37–39]. As seen in

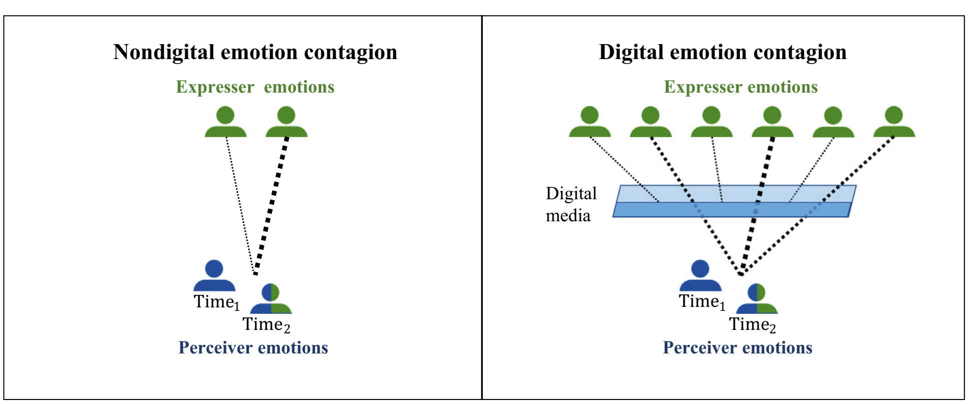

Figure 1. Digital versus Nondigital Emotion Contagion. In both digital and nondigital emotion contagion, the emotions of perceivers change as a result of exposure to the emotions of others (depicted by the change in color from Time$_1$ to Time$_2$). However, in digital emotion contagion, exposure occurs with great frequency and is often mediated by digital media companies that try to maximize the emotional content observed by participants (depicted by the width of lines connecting the expressers and the perceivers).

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Box 1. Positive Emotions on Digital Media

People express all manner of emotions on social media, but overall they seem to express more positive emotions than negative emotions. For example, in the Facebook contagion article, 46.8% of all analyzed posts contained positive words whereas 22.4% contained negative words [1], and the same is true for other digital media platforms [64,81,85]. The tendency to express more positive emotions is thought to arise both as a result of user internal motivations and as a result of top-down regulation by digital media platforms.

In general, people tend to prefer to feel (and therefore express) positive emotions because it feels better and because, in most social interactions, expressing positive emotions is more helpful in advancing the individual social goals both online and offline [86]. Congruent with this idea is the finding that expression of positive emotions is generally perceived as more appropriate than the expression of negative emotions [81]. For example, a recent study that showed that users perceived the positive emotions of joy and pride to be the most appropriate emotions on Facebook, Twitter, Instagram, and WhatsApp, and perceived the negative emotions of sadness and anger to be the least appropriate emotions. Second, digital media interactions are often driven by social comparison [87], and expressing positive emotions proves one's success and therefore helps the individual to positively compare themselves with others.

In addition to the internal motivations of users to express positive emotions, digital media companies are also motivated to increase user engagement, and hence to increase user positive emotions. Users produce more content when they are exposed to positive versus negative emotions [1]. Therefore, the design of many digital media platforms contributes to a positive bias in emotion expression. In most social media platforms, participants can express their enjoyment or gratitude in response to content by 'liking' it [88], but there are no 'unlike' buttons, which leads to more positive than negative feedback. In addition to these explicit design features, and with the evidence that digital media companies wish to maximize user emotions, some suggest that digital media algorithms selectively promote content with positive emotions. For example, some have suggested that Facebook chose to bury posts from the Ferguson unrest, a social movement that grew after the death of Michael Brown in Ferguson, Missouri, in favor of more positive posts [6]. However, providing empirical evidence for such claims is extremely challenging because digital media algorithms remain a black box for external researchers.

Figure 2, the intensity of emotional expression predicts the amount of both likes and retweets users receive on Twitter, and this effect is stronger for positive compared with negative emotions (Box 1). The rewards that users receive for expressing emotions create an incentive system that

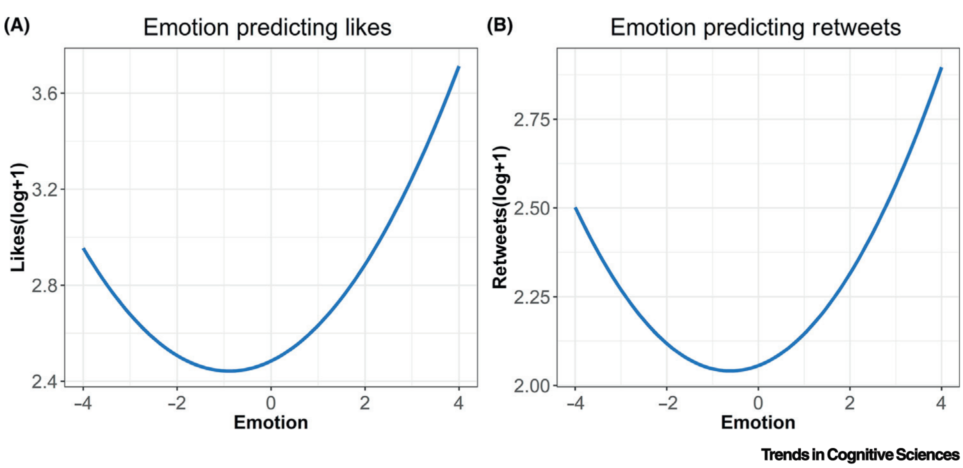

Figure 2. Emotions Predict Likes and Retweets. The number of likes and retweets (log+1 transformed) as a function of the emotions expressed in the tweets (very negative to very positive). We downloaded ~1.5 million random tweets from Twitter API (application programming interface). We then conducted sentiment analysis of the tweets using SentiStrength [112]. The analysis of each text using SentiStrength provides two scores (discrete numbers) ranging from 1 to 5, one score for positive intensity and one score for negative intensity. We combined the two to generate a scale from −4 (very negative) to 4 (very positive). Because most tweets do not receive any likes or retweets, we conducted a log+1 transformation of the likes and retweets data. The data were then fitted to both linear and quadratic functions. The results suggested that the quadratic function was a better predictor of the data (depicted), indicating not only that participants tend to like and retweet emotional tweets compared with nonemotional ones, but also that likes and retweets tend to be higher for positive than for negative emotions.

further perpetuates subsequent expression of emotions and therefore contributes to further emotion contagion [40].

The overarching goal to increase engagement by increasing the frequency and intensity of emotion expressions is combined with the structure of social networks in online platforms in a way that increases digital emotion contagion. Because digital social networks encourage users to connect and interact with as many people as possible, users tend to have larger social networks online than offline, and can be exposed to content produced by users who are more distant in their network [41,42]. This often leads to online emotions spreading to a larger number of users and more distant populations [41]. Consider, for example, the spread of emotions in response to the death of Khaled Mohamad, a 28-year-old Egyptian man from Alexandria who was beaten to death by the Egyptian police in June 2010. Mainstream media did not report the death. However, the Facebook page dedicated to Khaled's death became an occasion for Egyptians to express their frustration to each other. This frustration reached so many people, and increased the intensity of their anger to such a degree, that it led to mass demonstrations in Tahrir Square which contributed to the collapse of the Egyptian government and the initiation of the Arab Spring [43]. As this example suggests, as a result of the mediating role of digital media companies, there is an increase in the number and size of social movements which are driven by the exchange of emotions, both online and offline [6,36] (Box 2).

On the face of it, it seems that digital emotion contagion should be more intense, more frequent, and more far-reaching than nondigital contagion. However, this may not always be the case. This is because frequent exposure to emotions can also lead to habituation [44] or fatigue [4], making each exposure to emotional expression online less impactful on the emotions of the perceiver. Considering that people spend ample amounts of time online, they may learn to ignore, at least at some level, the tremendous volume of emotion expressions around them. Furthermore, online social connections tend to be less intimate and valuable to users than offline relationships [45,46], and this may also mean that people are less influenced by the emotions of their online friends. Therefore, even though digital emotion contagion is likely to be a much more frequent and intense than nondigital emotion contagion, it is also possible that each such exposure to the emotions of others on digital

Box 2. Digital Media, Emotion Contagion, and Social Movements

Increased use of digital media, especially social media, has transformed the way in which social movements unfold. In particular, the large number of social connections that each user can have, and the high frequency of social interactions, are leading to more frequent online social movements [6,89]. It is almost impossible to imagine movements such as the Arab Spring or the Black Lives Matter without digital media.

One important driver for social movements is the exchange of emotions between users, particularly anger [4,5,90]. Anger tends to spread faster than other emotions on social media [50] and to cascade to more users by shares and retweets, enabling quicker distribution to a larger audience [37,58]. Users are also motivated to share their anger because they wish to signal their social network about their morality [4,7] and to convince them to join the movement [31].

Despite the obvious impact of digital media on online social movements, the translation of online activity to collective action outside social media is often surprisingly limited. For example, although the Save Darfur Facebook campaign – designed to increase awareness and donations to the war in Sudan – was able to recruit 1.2 million members to the movement, the amount and quality of activism that resulted from the campaign was relatively modest because most users did not donate money for the cause [91]. A similar example can be seen in the viral Ice Bucket Challenge, which was designed to raise awareness of amyotrophic lateral sclerosis (ALS) and donations to ALS research. Over 28 million users joined the challenge, and $115 million were raised. Nevertheless, donations were not sustained and fell back to pre-campaign levels the year after [38]. Furthermore, one of four users who completed the challenge did not mention ALS in their videos, and only one of five mentioned a donation, suggesting that much of the public interest was not translated into actual action. These examples show that, although it is clear that digital media greatly contribute to online social movements, the question of how much these movements translate to action in the real world remains open.

media has less impact on the emotions of an individual. Further work will be necessary to test whether and under what conditions the activating factors outweigh the inhibiting factors.

Measuring Digital Emotion Contagion

Emotion contagion occurs when the emotions of a perceiver become more similar to those of others as a result of exposure to these emotions. However, given that many factors contribute to changes in someone's emotion from moment to moment [47], and given the typical absence of crucial information regarding these other factors when using data from digital media, it is by no means clear when emotion contagion has occurred. It is therefore important both to discuss the challenges that digital emotion contagion researchers face, and to consider the ways in which these challenges have been addressed.

Defining the Challenges

To have confidence that emotion contagion on digital media has occurred, we must be able to successfully address three challenges. The first challenge is to estimate the emotion expressions of a perceiver in response to a situation, ideally at two timepoints – before ($Time_1$) and after ($Time_2$) the perceiver is exposed to the emotions of others. The second challenge is to accurately estimate the exposure of a perceiver to the emotions of an expresser or expressers between these two timepoints. The third challenge is to show that the emotion expression of the perceiver was actually influenced by the emotions of the expressers as opposed to other sources of influence (such as concurrent changes in the situation itself). Addressing these three challenges can be difficult based on the nature of data available to researchers from social media. In the following section we discuss each of these challenges in turn, with an eye to how they have been addressed, while recognizing there is no ideal approach and solutions at one level introduce problems at another.

Meeting the Challenges

When measuring contagion on digital media, the most basic challenge is to estimate the emotions of perceivers based on their digital traces. Importantly, assessing such emotions involves capturing user expressions of emotions, which may be very different from their emotional experiences, especially on digital media (Box 3). In the past few years technology has tremendously improved our ability to estimate emotions by looking at the facial expressions, vocal responses, and written text of users (Box 4). The challenge of assessing emotion based on digital traces is compounded by the need to assess the emotion of a perceiver at two timepoints – before and after exposure to the emotion of an expresser. In laboratory experiments, such baseline measurement is relatively easy. However, on digital media it becomes much more challenging, both because finding multiple expressions of emotions by the same user to the same situation is difficult, and because at every timepoint users are already exposed to some emotions by others. In practice, researchers often ignore perceiver emotions at $Time_1$, and measure perceiver emotions at $Time_2$, in light of different emotions expressed by others (an approach taken also in laboratory experiments [25]). For example, in a recent study that examined digital emotion contagion of negative emotions in response to rain, researchers showed that decreases in positive and increases in negative emotions spread to other users who did not experience rain [48], and this was done without examining user baseline emotional responses. In a recent attempt to establish a pre-exposure measure, researchers estimated user emotions at $Time_1$ by looking at emotions expressed in an earlier content they produced in response to the same situation [7], and this seems to produce stronger estimates of contagion compared with only measuring changes at $Time_1$.

Once perceiver emotions have been estimated, the second challenge is to estimate the emotional content that perceivers observed before expressing their own emotions. It is seldom clear what users have encountered. Whereas some users may have been surfing the web for hours, others

Box 3. Emotion Experience versus Expression on Digital Media

To what extent do emotion expressions on digital media reflect the true emotional experiences of the expressers? After all, we know that emotion experience and expression are imperfectly correlated in everyday life [92], and there are factors that might either increase or decrease the gap between experience and expression in digital versus nondigital contexts.

The prevailing assumption is that communication on digital media allows more opportunities for positive self-presentation than in nondigital contexts [93–95]. If so, we might assume that expression–experience differences are larger online, such that online users either upregulate or downregulate emotional expressions to fit with self-presentation goals [96]. This can be supported by a few arguments. First, communication on digital media is asynchronous, such that users do not need to respond to each other in real time [97,98]. A longer response time provides more opportunity for expression regulation, which may increase the difference between experience and expression. Second, digital communication also involves a larger audience [95], which often leads to an increase in self-presentation motivations [99]. Finally, digital communication allows for less information richness [80,97,100], which means that users must amplify their expressions to make sure that perceivers understand their emotions.

On the other hand, digital media also provide opportunities for self-disclosure and genuine expressions of emotion in ways that are difficult to achieve in nondigital contexts [95,97,101–103]. First, digital media allow people to express themselves in anonymity, which seems to promote self-disclosure [103–105]. Second, online users can receive a much a larger amount social support from their social environment, particularly in cases where their offline social environment does not support these emotions. This can sometimes lead to upregulation of emotion expression with the goal of obtaining more likes [4,40], but can also lead to genuine self-disclosure in ways that could not occur in face-to-face interactions [101]. Finally, some argue that, because of accountability and feedback provided by user social networks, digital media represent extensions of the real lives of the users and that people communicate their true selves [80,106,107]. These considerations suggest that experience–expression differences in digital contexts may be either smaller than or similar to face-to-face interactions.

may have just logged in. Previous studies have taken three different approaches to address this challenge (Table 1). One approach – referred to as the 'window of interest approach' – is to look at the content perceivers could have been exposed to and assume that it was perceived more or less equally across users. For example, in a recent study, researchers [49] estimated the content observed by Twitter users by looking at the average emotional content of tweets produced by the followees of a given perceiver during the hour preceding their posting [7,48,50]. A second approach is the 'overall emotional variance approach'. In this approach, researchers focus on macro-changes in emotional variance within a certain user community, with the implicit

Box 4. Estimating User Emotions from Digital Media

Digital media activity allows researchers to detect user emotions from different types of signals [108]. Facial expressions, produced in videos and photos, can be analyzed by image sentiment analysis software [109]. Audio can be analyzed in terms of pitch [110]. In addition, text produced by users can be analyzed used text-based sentiment analysis tools [111].

Of these response channels, text is the most commonly analyzed. For this reason, text-based sentiment analysis tools have received the most attention. These tools vary greatly in the way they process text. Some sentiment analysis tools, such as Linguistic Inquiry and Word Count (LIWC), count emotional words based on predetermined dictionaries [2], others add context rules for such dictionaries and include more complex word compositions [112,113], and some use sophisticated machine-learning algorithms [114]. Comparing these tools is challenging because outcomes may depend on the specific domain (product review, social media posts etc.), and the length of the text (Twitter posts versus blogs) [115]. It is likely that machine-learning algorithms that are trained to predict emotions in product reviews would be superior to other tools at predicting emotions in their pretrained domain, but in the absence of fine-tuning these algorithms may prove to be inferior to more basic tools in predicting emotions in a completely different domain. In general, however, there are many tools with good predictive power that correlate well with the emotion ratings of human raters. The sentiment analysis tool VADER (Valence Aware Dictionary and Sentiment Reasoner), for example, achieved a correlation of r = 0.88 with human raters in classifying tweets as positive, negative, or neutral.

One especially important component of emotions expressed in text is the use of emotion icons (emoticons, emojis), which are visual representations of various emotional states (and other states). Emoticons are extremely popular and are used by 92% of the online population [116]. The use of emoticons is extremely helpful from a communication perspective because it provides a relatively clear picture of the emotions that participants wish to express [97,117]. Emoticons are also perceived in a similar way to facial expressions [118]. Although some basic sentiment analysis tools do not incorporate emoticons in their analysis, most newer tools take them into account and this improves their ability to estimate user emotions from their texts [113].

Table 1. Summary of Approaches Designed to Estimate the Content Observed by the Perceiver

Name	Description	Advantages/disadvantages	Refs
Window of interest	Summarizes the emotional content produced by the digital community of a perceiver in a given timeframe before their expression of emotion at $Time_2$.	*Advantages:* relatively easy to implement. *Disadvantages:* we have no clear indication that perceivers actually saw any of the summarized content.	[7,48–50]
Overall variance approach	Measures changes in overall variance of emotions within a particular digital community over time.	Advantages: provides a view of contagion at the macro level. Disadvantages: other factors may lead to reduction in emotional variance within a community apart from contagion, such as changes in the nature of stimuli or the population within the community.	[51,52]
Emotional cascade approach	Compares the content produced by replies in relation with their related original post, or counting the number of likes and shares produced in response to a particular post.	Advantages: resolves the challenge of understanding what a particular perceiver saw. Disadvantages: increases ambiguity about the content that the perceiver produced.	Reply cascades: [7,54,55] Share cascades: [37,58,59]

assumption that what every perceiver saw was more or less similar [51,52]. A third approach – referred to as the 'emotional cascades approach' – focuses on the people who share or respond to a particular emotional content [53]. In this approach, the assumption is that exposure to emotions elicits similar emotions in perceivers, who then express their emotion by either replying [7,54–57] or further sharing the content [37,58–60]. Emotional cascades resolve the challenge of understanding what a given perceiver saw (although other content may also influenced their decision), but in the analysis of replies it is difficult to establish that a perceiver replying to the emotion of an expresser is reacting to the expresser and not to the situation itself [61]. In the case of shares, it is difficult to establish whether sharing an emotional content indicates that the perceiver is feeling similar emotions.

Even if one can determine that the emotions of a perceiver have changed, and that the perceiver was exposed to the emotions of another user during the period in which his or her emotions changed, one is still left with the third challenge of determining that the emotions of another user played a causal role in that change. One concern is differentiating contagion from similarity-based responses [62]. In a similarity-based response, two or more users respond to a situation in a similar way not because they are influencing each other but merely because they are similar to each other.

Perhaps the most compelling way to establish causality is to randomly assign participants to experimental groups that are exposed to the exact same situation, but that differ in their exposure to the emotional expressions of other users. This has been done in many laboratory experimental paradigms measuring nondigital emotion contagion [24,25,63]. In field contexts, researchers have tried to address the issue of causal inference in various ways. For example, one recent study showed that seemingly similar perceivers responded differently to the same situation when exposed to emotions higher or lower in intensity than their own emotions at $Time_1$ [7]. Other studies have estimated individual and group-level influences within online communities and statistically controlled for similarity-based effects [64]. However, both methods cannot fully guarantee that we are able to capture contagion [65]. In fact, even the Facebook contagion article, which manipulated the perceived content of users, struggled with this issue because manipulating the perceived emotions of users may also have affected the content that they observed [1].

What Predicts the Degree of Emotion Contagion on Digital Media?

Perhaps because measuring the occurrence of emotion contagion on social media is still in its infancy, many studies are still trying to show that contagion exists in a specific platform or situation. To move this developing field forward, we believe it will be useful to shift the focus of the field toward predicting when emotion contagion will be stronger or weaker. In this section we summarize what the current literature suggests, and point to gaps in the literature, focusing in turn on the expressed emotion, the network connection, the perceiver, and the platform (see Outstanding Questions).

The strength of emotion contagion is first and foremost dictated by the nature of emotions expressed by the expresser. It is generally assumed that stronger emotion expressions lead to greater emotion contagion. However, there is very little consensus in the literature on what type of emotions lead to stronger contagion. According to the Facebook contagion article [1], contagion for positive and negative emotions seem to be similar in size, which fits some offline behavioral data [66], and even experiments that examined contagion using neuroimaging [25]. Other findings, however, suggest that positive emotions are more prone to contagion both online [48,49,59,67] and offline [68]. These results are somewhat surprising considering the negativity bias, which holds that people tend to pay more attention to negative stimuli [69,70]. We currently know of one study showing that negative emotions, and particularly anger, lead to stronger contagion on digital media [50]. Interestingly, the methods used in this study were similar to those of another research project that found stronger contagion for positive emotions [49]. One difference between the two studies is that they measured emotional tweets in different languages, and therefore in different cultural contexts which may differ in their emotion expressions [71]. Based on these conflicting findings, one pressing question concerns which contexts and cultures lead to more or less emotion contagion for particular, situationally relevant emotions.

The strength of emotion contagion depends not only on the emotions of the expresser (intensity and type) but also on the connection between the expresser and the perceiver. It is currently assumed that stronger ties between the expresser and perceiver (evaluated either by reciprocity or by degree of mutual connections) lead to stronger contagion [72]. Nevertheless, the relationship between the strength of network connection and contagion seems to depend on the type of expressed emotion [73]. In the first study that tested this question [50], researchers compared how contagion of anger and joy were influenced by the strength of network connection. They found that anger contagion was stronger in weaker ties whereas joy contagion was less pronounced. Furthermore, a recent study suggests that emotion contagion not only is influenced by network structure but also changes the structure itself [74]. Looking at the spread of negative emotions within an investment company after a drop in stock prices, results suggest that people have a propensity to share their emotions with stronger ties, making these ties even stronger. Future studies that examine the connection between emotion contagion and network structure may be especially important for advancing our understanding of the phenomena.

A third crucial factor to consider is the perceiver. However, we know little about how the attributes of perceivers predict contagion. We therefore wish to suggest a few important future directions. First, the degree of contagion might be influenced by factors such as personality [75,76], which can now be evaluated by user behavior on social media [77]. For example, it seems likely that people who are more extraverted and agreeable are more likely to be influenced by the emotions of others on digital media. It is also likely that users who are high on neuroticism are more likely to be more influenced by negative emotions in particular [78]. Other individual differences such as status (particularly online status), age, gender, and culture are also likely to influence the degree of contagion between users [51]. Finally, further research should be carried out on how user characteristics, such as time spent online and degree of activity versus passivity, affect digital emotion contagion. For example, a recent study examining emotions in online communities suggests that more active users tend to shift more quickly to express negative emotions [52]. Future work should further examine these questions.

Finally, the type of platforms that users employ, each with its slightly different set of motivations in relation to a desired level of user emotion, as well as the type of content they produce in these platforms, are also likely to influence the nature of contagion [79,80]. Different digital media platforms are characterized by different emotional baselines (Box 1), which may affect the degree of contagion of particular emotions. Social media platforms and video-sharing sites such as YouTube are often characterized by more positive emotions [1,48,64,81], although this depends on the specific content [82]. Online forums also tend to be more positive, but forums that are centered around well-being, depression, and anxiety are more likely to be negative, primarily reflecting the emotional baseline of the users who create the content [83]. Comments in responses to online newspaper articles tend to include a larger mix of emotions, and some of them tend to be negative [84] whereas others are more positive [67]. The emotional content of the situations that are common in digital spaces can play a role in emotion contagion. If negative situations are present in the vast majority of situations, users are more likely to be influenced by more negative emotions [7]. However, we must remember that, although the Facebook contagion study reported much stronger positive emotions, no differences in contagion effect sizes were found, suggesting that more research should be carried out to answer these questions [1].

Concluding Remarks

The goal of the current article has been to review the growing literature on digital emotion contagion while making two central points. The first point is that digital emotion contagion should be understood as mediated emotion contagion. The goals of digital media companies – to increase user engagement, and hence the frequency and intensity of user emotions – are likely to act as excitatory factors for digital emotion contagion. However, increased exposure may also contribute to habituation and fatigue, especially considering the fact that social connections on digital media are less meaningful [44], and therefore may inhibit digital emotion contagion. Future work should examine these different features of digital emotion contagion and their impact on the degree of contagion (see Outstanding Questions).

The second point that we make is that, despite its apparent impact on emotional dynamics online, proving that digital emotion contagion has occurred is more difficult than one might expect. For example, users can have similar emotional responses to similar situations without any contagion, but differentiating such cases of similar emotional responses from contagion is extremely challenging. It is therefore important to measure contagion in different ways, while recognizing the advantages and disadvantages of any measurement.

Because proving that digital emotion contagion has actually occurred is challenging, most existing studies have aimed to demonstrate that contagion exists. We believe that, with increasingly established methods, it is now time to shift the focus of the field toward predicting when emotion contagion will be stronger or weaker. Future studies should ask what type of expressed emotions, expressed by whom, to whom, and in what contexts, can predict stronger or weaker contagion. We are excited by the opportunities ahead in this growing field supported by ever-increasing data and use of digital media.

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Outstanding Questions

Is there greater exposure to the emotions of others in digital versus nondigital interactions? If so, how does this influence emotion contagion? In general, greater exposure to the emotions of others should lead to more emotion contagion. However, habituation and fatigue may at least partially offset the magnifying effect of greater exposure.

How do digital media platforms influence contagion? This is likely to depend on the goals of media companies in relation to user emotion. It is also likely to depend on the size and shape of the networks, and the type of content that users can produce to express their emotions (text, photos, videos).

What features of the expressed emotions (e.g., intensity, type) predict digital emotion contagion? The intensity of emotions is likely to play an important role in contributing to stronger contagion. However, the link between the type of emotion and degree of contagion may depend upon the situation, the platform, and the specific culture.

What features of the perceiver predict greater digital emotion contagion? It is likely that personality attributes that are associated with increased susceptibility to nondigital contagion are important. However, other more specific attributes such as time spent on a specific platform, overall smartphone use, and social hierarchy within digital media platforms are also likely to play a contributing role for increased contagion.

What role does network structure play in emotion contagion? Do more clustered networks lead to greater contagion, or are random networks more conducive to emotion contagion? Answers likely depend on the amount and type of exposure required for contagion. If mere exposure to the emotions of others is sufficient to elicit contagion, random networks may lead to more contagion. However, if users need to be exposed to a particular emotion multiple times, clustered networks are more likely to elicit stronger contagion.

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