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May I have your Attention, please? An eye tracking study on emotional social media comments

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ABSTRACT

Emotions are essential in today's complex information environments, as they catch readers' attention and impact the depth of information processing. In online interactions - such as user comments on social media platforms - emotions are increasingly present. We performed a preregistered eye-tracking study to understand the effects of emotional user comments on attention. Participants ($N = 155$) in our study read a series of user comments with different emotional tones. We measured the effects of emotions on information processing and visual attention by comparing the dwell times of participants of two experimental groups: a heuristic processing group and a systematic processing group. Our results revealed differences in visual attention towards comments with a negative versus positive valence and between the discrete emotions of anger and fear. These findings led to a discussion about emotions' role in information processing when individuals read user comments on social media.

People are increasingly consuming and commenting on news via social media (Newman, Fletcher, Kalogeropoulos, Levy, & Nielson, 2018; Ziegele Springer N., Jost, & Wright, 2017). On Facebook, for instance, 510,000 comments are posted every minute (Noyes, 2019). When people comment on news online, they often express incivility (Oz, Zheng, & Chen, 2018; Humprecht, Hellmueller, & Lischka, 2020; Saldaña & Rosenberg, 2020) and particular negative emotions, such as anger and sadness (Ben-David & Soffer, 2018). Emotional comments can lead to attitude extremity (Asker & Dinas, 2019), decrease trust in the news source (Graf, Erba, & Harn, 2016), and affect opinion formation, participation in deliberative debates, and decision-making (Schweiger, 2017).

While we know that negative comments may have an unfavorable impact, we know little about the users' attention to these comments. In order to be affected by comments, readers need to see (i.e., attend to) the information amongst a potential other information in the first place. Previous work has revealed that emotions play an essential role in information processing, as they may draw attention (Yiend, 2010). People unconsciously attend more to emotional information and process these with less effort than non-emotional information (Reeck & Egner, 2015; Yiend, 2010).

Although there is a high prevalence of emotionally-loaded user comments on social media, relatively little is known about the visual attention people pay towards these comments, nor the extent to which they may be better stored and recognized. This paper examines how much attention participants pay to emotional comments and whether emotional comments are better remembered compared to non-emotional comments. We argue that users pay more attention to negative comments, which are, in turn, selected for encoding. We further distinguished this encoding process into *attention* and *memory* on the assumption that emotional information attracts more attention, receives higher priority in processing, and persists longer in working memory (Ferré, 2002). Finally, we compare attention towards and recognition of (a) emotional vs. non-emotional comments, (b) positive vs. negative comments, and (c) two prominent discrete emotions: anger vs. fear. We applied an eye-tracking design in a laboratory experiment to measure attention. We preregistered this study's hypotheses, design, and analysis strategy (see https://osf.io/dbgst). This research contributes to the understanding of the role of emotions in user comments as a gateway for information transmission, news perception, and opinion formation in the digital era.

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1. Theoretical framework

1.1. Processing emotional user comments

What do we consider emotional content? We follow Bolls, Lang, and Potter (2001) in defining emotional content as verbal, nonverbal, and paraverbal emotional language. User comments are labeled as emotional when they contain an expression of an emotional state, such as "I feel worried about the news." Emotional content affects how people process messages, which we will discuss below.

Human cognitive resources are limited; individuals cannot fully process all aspects of their environment (Lang, 2000, 2006). To reduce the complexity of environments, individuals use strategies that allow them "to select and focus on particular input for further processing while simultaneously suppressing irrelevant or distracting information" (Stevens & Bavelier, 2012, p. 30). This selective processing is referred to as *selective attention*. According to selective attention theory (Yiend, 2010), the salient nature of emotional information, with its "inherent value and biological or personal relevance to an individual" (Reeck & Egner, 2015, p. 269), makes it attract more attention than non-emotional information. In other words, people are more likely to be attracted by emotional content.

As a consequence of selective attention, readers attend to certain information, and according to Kensinger and Corkin (2003), this attention results in an enhanced likelihood of processing. Moreover, successful information processing leads to storing information in memory (Ferré, 2002), a fundamental knowledge source that contains essential information for building opinions or perceptions. Therefore, both attention and information stored in memory are underlying processes of knowledge generation, which, in turn, is the basis for one's perception, judgment, and evaluation of, for example, the news.

Recognition is a subcategory of declarative memory and refers to the association of an event with one previously experienced. In other words, recognition entails remembering information and linking these back to when one was exposed to similar information. Recognizing information is largely an unconscious process and refers to a memory measurement and an encoding process (Tajika, 2001). In this study, we follow the work of Kruikemeier, Lecheler, and Boyer (2018), who distinguished *visual attention* towards news from *recognition* of news. They concluded that "visual attention to news content is an observable predecessor and likely predictor of news processing and learning" (p. 76). Thus, measuring recognition will allow us to observe how well emotional content is stored in memory.

1.2. Heuristic and systematic processing of emotional content

The idea that people are more likely to attend to and recognize emotional comments is based by the specific characteristics of social media's information environment. The overwhelming amount of content on social media platforms led Koroleva, Krasnova, and Günther (2011) to conclude that Facebook users mainly engage in heuristic processing. Heuristic processing refers to a quick and efficient way of processing information with low mental effort. Under heuristic processing, people rely upon cues, such as emotional content (Arceneaux & Vander Wielen, 2017), that are salient and easy to comprehend (Todorov, Chaiken, & Henderson, 2007). In contrast, people engage in systematic processing when enough cognitive resources are available to process information (Chaiken, 1980). The resources necessary and what the information effectively requires to be processed should be balanced (Kao, 2011). Systematic processing is relatively more effortful and time-consuming than heuristic processing (Chaiken, 1980; Griffin, Neuwirth, Giese, & Dunwoody, 2002).

We argue that if people have fewer cognitive capacities due to media environments that can be informationally overwhelming, such as Facebook, they are more likely to engage in heuristic processing. Emotions might draw more attention in this overwhelming environment than in a media environment with less information. Readers are more likely to rely on systematic processing in a media environment that is less overwhelming. We hypothesize that emotions draw more attention than non-emotional content, particularly under heuristic processing circumstances. Moreover, when people engage in heuristic processing, they might focus more on emotional comments than non-emotional comments. Therefore, we propose the following hypothesis:

H1. Under heuristic processing, compared to systematic processing, (a) user comments with emotional tone receive more (visual) attention and (b) can be better recognized than comments without emotional tone.

1.3. Differentiation of emotions

Comments on social media are often multi-dimensional; they can be negative or positive and contain specific emotions, such as anger, hope, happiness, or fear. Furthermore, comments vary in valence and arousal level; therefore, they can affect attention and memory differently. For this reason, we used a dimensional and a discrete approach to distinguish emotions. In Russell's (1980) circumplex model, emotions vary in their *arousal* (intensity from low to high) and *valence* (negative or positive). Yet, Izard (1993) defined emotions as *discrete*—specifying distinctions between interest, joy, surprise, sorrow, anger, disgust, contempt, fear, shame, and guilt. The following section will formulate two hypotheses about the attention paid to positive emotional comments versus negative and angry comments versus discrete, fearful comments.

The extent to which positive or negative information attracts attention is debated. Positivity bias literature claims that the presentation of positive aspects is favored over negative aspects (Reinecke & Trepte, 2014), while negativity bias literature claims that negative information draws more attention and is more arousing (Soroka, Fournier, & Nir, 2019). The idea that negative information attracts more attention (compared to neutral and positive information) may result from a tendency to attend to negative and threatening situations compared to positive and safe situations (Rozin & Royzman, 2001). Negative stimuli carry greater informational value than positive stimuli and attract more attention (Soroka et al., 2019). Compared to positivity bias, negativity bias is the more widely accepted psychological principle. Online research has shown that negativity leads to stronger effects on cognition, perceptions, and attitudes than positivity. For example, Waddell and Bailey (2017) found that individuals are more likely to attend to, recall, and be persuaded by negative rather than positive tweets. Similarly, Unkel and Kümpel (2019) found a stronger effect of negative user comments than positive comments on individuals' perceptions of quality. Winter (2019) showed that negative comments led to more negative attitudes and thoughts about news articles, while Rösner, Winter, and Krämer (2016) found that uncivil comments increased readers' hostile cognitions. Based on these considerations, we formulated the following hypothesis:

H2. Under heuristic processing (compared to systematic processing), (a) user comments with a negative emotional tone receive more (visual) attention and (b) can be better recognized than user comments with a positive emotional tone.

According to Izard (2009), different manifestations also exist of negative valence emotions, including sadness, anger, and fear. In this study, we focuse on anger and fear to better understand how people process emotional comments. Anger is considered an *approach* emotion, which means that anger "mobilize[s] and sustain[s] high levels of energy for the purpose of defending oneself, defending one's loved ones, or correcting some appraised mistakes" (Nabi, 1999, p. 298). Anger has an action tendency; it is an energizer and organizer of behavior. Consequently, it might lead more to deliberative actions than negative emotions, such as fear. Fear is considered an *avoidance* emotion that stems from perceptions of imminent physical danger and causes people to "fight" information rather than confront it. Nabi (2003) found that fear differentially affected selective attention (compared to anger), and asserted that humans are more likely to encode attributes indicative of a threatening emotion to recognize danger warning signs. Anger also promoted deeper information processing than fear (Nabi, 2003). Therefore, we expect that:

H3. Under heuristic processing (compared to systematic processing), (a) user comments with an angry emotional tone receive more (visual) attention and (b) can be better recognized than comments with a fearful emotional tone.

2. Methods

We preregistered the hypotheses, design, and planned analyses on the Open Science Framework one day before data collection was concluded on September 27, 2019 (see https://osf.io/dbgst). Our OSF page contains the survey, data, and code to reproduce the results reported in this paper. This study was approved by the university's ethics review board (#2019-CS-11020).

2.1. Procedure

To test the preregistered hypotheses, we relied on an experimental eye-tracking design. The data were collected at the Behavioural Science Laboratory of the University of Amsterdam between September 5 and September 28, 2019. Participants were placed in front of an eye tracker and exposed to three social media news posts with manipulated comments of different emotional tones (emotional versus non-emotional, positive versus negative, angry versus fearful). The participants were randomly assigned to either a heuristic processing or a systematic processing group; those in the former were only given 30 seconds to read the posts and comments, while those in the latter were given as much time as they needed to read the content carefully (Rand, 2016).

The eye movements of each participant were measured using a SMI Red 500 eye tracker during the experiment. After a short distraction task using two questions from the cognitive reflection test (Frederick, 2005), we measured recognition using multiple-forced-choice recognition questions in a subsequent survey.

2.2. Participants

The participants were 169 students recruited via a website at the university. We aimed to arrive at a larger sample than those reported in previous publications that used eye-tracking; we relied upon the review by King, Bol, Cummins, and John (2019), who collected all of the studies that employed eye-tracking published between 2005 and 2015 in the top 25 communication science journals. King et al. (2019) showed that the average study relied upon 82 participants (min = 10, max = 248), while the total number for this study was conditional upon the resources and availability of the participants in the lab during the period in which we conducted our study. One hundred sixty-nine participants (78.4% female; mean age 20.21 years, SD = 4.32) participated in the study—approximately twice as many as the average eye-tracking study in communication science (King et al., 2019).

We did not conduct an a priori power analysis. Instead, we conducted a post-hoc sensitivity analysis (Perugini, Gallucci, & Costantini, 2018). With a sample of 169 participants, we could reliably (power of .8, alpha set a 0.05) detect an effect size of f = 0.1, which is considered a small effect size. As most effect sizes in the social sciences are small (Camerer et al., 2018), it is reasonable to assume that population effect sizes in the eye-tracking studies will also be small.

The students received either €7,50 or two research credits for their participation in the study. We preregistered the following exclusion criteria: insufficient data quality, if eye problems occurred (e.g., if the participant was cross-eyed), or if unexpected distractions occurred during the experiment (e.g., when a third individual entered the lab). In addition, the data were considered insufficient if the horizontal and/or vertical deviation of the calibration was larger than 1.50° or if more than 33% of the complete record was missing. Participants were also excluded if they reported having either Attention Deficit Disorder or dyslexia. After the exclusions, our study had a sample of 155 participants (we excluded 14 respondents). The average age of the participants in our analysis was 20 years (SD = 4.3) and 81% of the participants were female – for the full descriptives see Table 1.

2.3. Design

For the research, we experimentally manipulated heuristic and systematic processing conditions. In the heuristic processing condition, the participants were given a maximum of 30 seconds to read each news post. Reducing the amount of time to read shortens the time for cognitive processing (Rand, 2016). The Heuristic-systematic model of information processing (HSM) proposed by Chaiken (1980) predicts that time pressure affects information processing. When individuals are motivated and have sufficient time to process information, they are likely to process information systematically. When the motivation to process information is low or if the time allowed for processing information is constrained, individuals are expected to apply heuristic processing (Suri & Monroe, 2003). Building upon the work of Rand (2016), we set the time limit to 30 seconds so that the participants would have slightly less time than one would need to read the posts. The systematic processing condition had no time limit, and the participants were asked to read everything carefully. The treatment assignment was coded as dummy variables with 1 (heuristic processing group) and 0 (systematic processing group).

Table 1
Sample description in %.

Variables	Percentage of Total Sample
Gender	
Female	81.3
Male	18.7
Age	
17–20	74.2
21–30	23.2
>30	2.4
Educational attainment	
High School Graduate	85.8
Bachelor Degree	11.6
Master Degree	1.9
Nationality[a,b]	
The Netherlands	35.5
Germany	12.9
Italy	5.2
Romania	3.2
Peru	2.6
Belgium	2.6
China	2.6
Native Language [a,c]	
Dutch	37.4
German	16.8
French	7.8
Chinese	5.7
English	4.5
Italian	5.2
Spanish	4.5

Note. This table describes the sample regarding gender, age, educational attainment, nationality and native language. Percentages missing to 100 are "others" and missing values, N = 155. [a] Multiple answers were possible., [b] 40 different countries were mentioned in total., [c] 31 languages were mentioned in total. The study was performed in English. Participants were mostly students that stated that they understood the messages they read.

3. Stimuli

Both of the treatment groups were exposed to the same stimuli (see stimuli on our OSF page). The stimuli were two artificial news posts of the online newspaper "The Independent" ("Stimulus 1" and "Stimulus 2") presented in the layout of a Facebook post. Each post contained four emotionally manipulated comments: "Stimuli 1" contained a positive, a negative and two neutral comments, "Stimuli 2" an angry, a fearful and two neutral comments. The length of the Facebook articles and comments was comparable (articles were six, comments three lines long). The participants viewed the posts singularly and successively on a desktop screen. To get used to the lab situation, the participants were first shown an additional social media news post ("Stimulus 0") that was not part of the analysis.

The comments were artificially developed as reactions to the posts and were expressed in varying emotional tones: neutral, positive, and negative. Neutral comments were designed as non-emotional evaluations of the article, negative comments included negative emotional evaluations, and the positive comment a positive emotional evaluation.

Based on these definitions, the stimuli were manipulated in three steps (Kalch & Naab, 2017; Krämer et al., 2019; Sung & Lee, 2015). First, we selected sentences that contained story details from the news articles; these served as a neutral basis for the comments. Second, the comments were emotionally manipulated using verbal (emotion words and linguistic markers) and nonverbal cues (paralinguistic cues), based on the work of Harris and Paradice (2007). Attention patterns are driven by visual cues (Bucher & Schumacher, 2006), and therefore each comment contained two emojis to represent specific emotions—for instance, for positive, for fearful, for angry, and for neutral (Hauthal, Burghardt, & Dunkel, 2019). In the third step, we adjusted the layout of the comments so they were comparable in length, number of likes, and comment author information (e.g., all names were gender neutral, typically English and the profile pictures were blurry and shot from a distance).

We conducted a pre-test to test the intended emotional tone. In an online questionnaire, 57 participants who were not part of the eye-tracking study rated 50 manipulated user comments in terms of emotional arousal (from 1, "not emotional at all", to 7, "very emotional"), valence (from 1, "very negative", to 7, "very positive") and the degree of the discrete negative emotion (from 1, "angry", to 7, "fearful") on bipolar axes. The comments that were rated to present the intended emotions the most were chosen for the current study.

Besides the emotional manipulation of the stimuli, the news posts were designed to be less likely to influence the attention and memory outcome variables. We chose original news topics that were presumed to be of low personal interest and involvement from a British newspaper that is not typically consumed in The Netherlands.

To summarize, we developed internally valid stimuli with some degree of external validity. At the same time, we acknowledge that our design and stimuli do not one-on-one resemble the information environment on Facebook or social media in general. However, the goal of this study is to isolate the causal effects. To achieve this, we needed an internally valid study. We return to this issue and outline suggestions for future work in the discussion.

4. Measurements

Attention was measured as visual attention using eye-tracking. Using visual attention to measure one's cognitive attention is based on the eye-mind assumption that there is "a direct link between where one looks and what one cognitively attends" (King et al., 2019, p. 150). We used the dwell time—which is captured by the sum of all dwells, including fixations, saccades, and revisits—within the areas of interest (AOI). Dwell time is commonly used as indicator for visual attention (Orquin & Holmqvist, 2018). Areas of interest (AOI) are selected regions of a displayed stimulus. In this study, each stimulus contained five AOIs, one on each of the four comments and one on the social media posts themselves. The user comment AOIs were each the same size, and the news post AOI was the size of the sum of all comments with the aim that the dwell times would be comparable. We aimed to yield a ratio-level measure of attention allocation to an area of interest within a stimulus with this approach.

We used a SMI Red 500 eye tracker attached to a 22-inch computer screen to measure the participants' eye movements. The SMI Red 500 is a stationary eye tracker that uses a sample rate of 120 Hz. The data was recorded with iView X and SMI Experimental Center 3.7.60. The behavioral and gaze analysis software BeGaze 3.7 analyzed the data. Following settings were applied: the detection algorithm was dispersion based, the resolution was 1680 px horizontal and 1050 px vertical, the physical stimulation dimensions were 474 mm horizontal and 257 mm vertical, and the size of the AOI of the article was 474 px and for the comments 116 px.

We had the participants sit about 60 cm from the eye tracker to obtain optimal results. The calibration and validation were performed before the start of the experiment, and we kept a logbook for notes in order to exclude cases if the study procedure was interrupted. We provide pictures of the experimental setting on our OSF repository.

Recognition was measured as story detail. Every comment contained one key aspect of the news story. For each comment, the participants were asked to answer a multiple-forced-choice question with four possible answer items about the key aspect (eight questions in total for each comment in Stimulus 1 and Stimulus 2). The response to each question was scored as either 1 (correct) or 0 (wrong or don't know).

Table 2
Randomization check for baseline characteristics for treatment groups.

	Heuristic Treatment *Mean*	Systematic Treatment *Mean*	$\chi 2$/F	*P*-Value
Categorical variables				
Gender			1.97	.16
National Language			1.36	.51
Origin			.01	.91
Ordered Variables				
Age	19.92	20.38	.43	.52
Educational Degree	1.10	1.21	2.64	.11
Need for Cognition	4.30	4.45	1.29	.26
Facebook Use Frequency	3.97	4.32	1.49	.22
Familiarity with The Independence	1.50	1.51	.01	.94
Topic Interest Stimulus 1	1.88	1.97	.28	.60
Topic Interest Stimulus 2	3.92	3.21	7.90	.01
Topic Familiarity Stimulus 1	1.01	1.10	3.47	.10
Topic Familiarity Stimulus 2	1.59	1.52	.13	.72

Note. P-values are derived from Pearson $\chi 2$-tests for categorical variables and F-tests for the ordered variables, N = 155.

Besides the sociodemographic controls (i.e., gender, age, education, nationality, and native language) used in this study, we also collected several other variables. These variables include Facebook use frequency, familiarity with the news provider (*The Independent*), the news reports shown in the stimuli, need for cognition (see Table 2 for the randomization check), and interest in the stimuli.

5. Results

5.1. Descriptive results of viewing patterns in different conditions

In this section, we describe the viewing patterns in the different conditions. Using the dwell times, we observed that those in the systematic processing group spent on average 69.4 seconds ($SD = 24.6$, min = 1.04, max = 133.5) reading the news post (see details in Table 3). This is more than twice as long as the induced 30 seconds given to those in the heuristic treatment group, which supports our expectation that individuals would read the posts more intensively when asked to (in the systematic processing treatment condition).

In the systematic processing condition, 66.7% of the participants successfully recognized the comments' story details, while in the heuristic processing condition 40.7% recognized the comments. An additional t-test revealed that those who had successfully recognized the comments had a higher dwell time ($M = 7.7$, $SD = 4.7$) compared to the participants who did not recognize the comments ($M = 5.2$, $SD = 3.8$, $t = 10.2$, $p < .000$, $n = 1240$, d = 0.58). In other words, we found that people who spent more time reading the comments were likely to remember them better.

The descriptive results suggest that our manipulation of the systematic versus heuristic processing was successful. In the next section, we turn to the preregistered test of the hypotheses.

6. Test of the preregistered hypotheses

To introduce the modeling strategy, we must discuss our data structure. In our experiment, we collected, in total, eight dwell times and eight recognition measurements on four comments in two social media posts per participant. The data we collected was thus nested as we have collected multiple observations per participant. Consequently, we used multilevel regression analyses for the dwell times as the outcome variable and multilevel logistic regression for recognition success.

The hypotheses we formulated predicted that the emotional (H1), negative (H2), and angry (H3) comments would (a) draw more visual attention and (b) would be more often successfully recognized than their opposed comments (non-emotional, positive, and fearful) in the heuristic versus the systematic processing condition. Therefore, we estimated the impact of emotions on visual attention and recognition by including emotional tone, processing mode (systematic vs. heuristic), and the interaction between the emotional tone and the processing mode as predictors in our analysis. Positive estimates for the interaction term thus indicate a higher likelihood that an individual would have more attention (e.g., dwell time) or better recognize a comment that contains the emotion of interest compared to the opposite emotion in the heuristic mode vs. the systematic condition. We also controlled for dwell time in the recognition analysis.

In Table 4 (attention) and Table 5 (recognition), the results of the multilevel regression analyses (attention) and multilevel logistic regression analyses (recognition) show the impact of emotional arousal (H1; Model 1), valence (H2; Model 2), and discrete negative emotions

Table 4
Multilevel regression analyses predicting dwell times of emotional compared to non-emotional, negative compared to positive, and angry compared to fearful comments.

	Model 1: Arousal *b (SE)*	Model 2: Valence *b (SE)*	Model 3: Discrete Negative *b (SE)*
(Constant)	9.82*** (.39)	8.55*** (.38)	9.82*** (.49)
Heuristic[a]	−6.50*** (.54)	−5.83*** (.53)	−5.70*** (.68)
Emotional[b]	−.20 (.26)		
Emotional*Heuristic	.37 (.36)		
Negative[c]		−.13 (.35)	
Negative*Heuristic		1.33** (.49)	
Anger[d]			1.85*** (.43)
Anger*Heuristic			−2.79*** (.60)
Log Likelihood	−3362.40	−778.51	−850.39
Num. Obs.	1240	310	310
Num. Groups:	155	155	155

Note. Adjusted ICC = 0.649; Dwell Time is measured in seconds (min = 0, max = 23.44, SD = 6.54; [a] Processing style is dummy coded (1 = heuristic, 0 = systematic), [b] Emotional Arousal is dummy coded (1 = emotional, 0 = non emotional), [c] Emotional Valence is dummy coded (1 = negative, 0 = positive), [d] Discrete Negative Emotions is dummy coded (1 = angry, 0 = fearful), ***p < .001; **p < .01, *p < .05.

Table 3
Mean dwell times and recognition success scores for treatment groups (heuristic and systematic) and stimuli (social media news posts; Stimuli 1 and Stimuli 2).

	Part A: Dwell Time in Seconds[a]		Part B: Recognition Success Score[b]	
	Heuristic Treatment	Systematic Treatment	Heuristic Treatment	Systematic Treatment
(1): Means (SD) for Stimuli 1				
Total	29.0 (9.7)	67.9 (25.9)	.40 (.27)	.68 (.28)
News Article	15.7 (5.8)	32.7 (14.1)	–	–
Neutral	4.7 (3.6)	10.1 (5.1)	.32 (.47)	.61 (.49)
Negative	3.9 (2.6)	8.4 (3.1)	.50 (.50)	.65 (.48)
Positive	2.7 (2.6)	8.6 (4.6)	.44 (.50)	.77 (.42)
Neutral	2.0 (2.5)	8.1 (4.4)	.40 (.49)	.70 (.46)
(2): Means (SD) for Stimuli 2				
Total	29.3 (11.2)	70.9 (26.0)	.41 (.30)	65 (.26)
News Article	15.4 (5.4)	28.3 (12.1)	–	–
Neutral	5.0 (3.4)	10.8 (5.9)	.63 (.48)	.82 (.39)
Fearful	4.1 (3.8)	9.8 (4.7)	.36 (.48)	.48 (.50)
Angry	3.2 (2.9)	11.7 (5.2)	.34 (.48)	.77 (.42)
Neutral	1.6 (3.2)	10.3 (6.8)	.27 (.44)	.55 (.50)
(3) Mean (SD) for Combination Stimuli 1 und Stimuli 2				
Emotional[c]	3.5 (2.5)	9.6 (3.5)	.41 (.32)	.67 (.30)
Non-emotional[d]	3.3 (2.6)	9.8 (4.5)	.40 (.26)	.67 (.29)

Note. N ranges from 77 (systematic treatment) to 78 (heuristic treatment), [a] Dwell Times ranges from 0 (min) to 266.9 (max) seconds, [b] Recognition Success Score ranges from 0 (wrong answer) to 1 (correct answer), [c] Emotional is the mean of the positive, negative, fearful and angry comments, [d] Non-emotional is the mean of all neutral comments.

Table 5
Multilevel logistic regression analyses predicting the likelihood for recognition success for emotional compared to non-emotional, negative compared to positive, and angry compared to fearful comments.

	Model 1: Arousal *b (SE)*	Model 2: Valence *b (SE)*	Model 3: Discrete Negative *b (SE)*
(Constant)	−.14 (.24)	−.46 (.44)	−1.41* (.57)
Heuristic[a]	−.65* (.25)	−.39 (.42)	.03 (.52)
Dwell Time[b]	.10*** (.02)	.22*** (.05)	.13** (.05)
Emotional[c]	−.02 (.19)		
Emotional*Heuristic	.03 (.26)		
Negative[d]		−.71 (.38)	
Negative*Heuristic		.71 (.50)	
Anger[d]			1.58*** (.46)
Anger*Heuristic			−1.54* (.62)
Log Likelihood	−769.93	−186.83	186.29
Num. Obs.	1240	310	310
Num. Groups:	155	155	155

Note. Adjusted ICC = 0.263; Recognition Success is dummy coded (1 = correct answer, 0 = wrong answer); [a] Processing style is dummy coded (1 = heuristic, 0 = systematic), [b] Dwell Time is measured in seconds (min = 0, max = 23.44, SD = 6.54) [c] Emotional Arousal is dummy coded (1 = emotional, 0 = non emotional), [d] Emotional Valence is dummy coded (1 = negative, 0 = positive), [d] Discrete Negative Emotions is dummy coded (1 = angry, 0 = fearful), ***p < .001; **p < .01, *p < .05.

(H3; Model 3) on (a) visual attention, and (b) recognition. We used margin plots to visualize the effects (Fig. 1 attention and Fig. 2 recognition).

Concerning arousal, our results showed no significant differences between (a) dwell times (Table 4, Model 1) or (b) recognition (Table 5, Model 1) on emotional comments compared to non-emotional comments conditional upon the processing modes. This result implies that arousal does not influence visual attention or recognition; see Fig. 1 (Panel A) and Fig. 2 (Panel A) for a visualization of the results. Thus, our data does not support hypotheses H1a and H1b.

Regarding the impact of valence on attention (a), we found a positive and significant interaction effect for the interaction of the negatively valenced comment and heuristic processing ($b = 1.33$, $p < .01$, Table 4, Model 2). The result indicates longer dwell times on the negative comment compared to the positive comment in the heuristic processing mode (Fig. 1, Panel B). In other words, when people had reduced time to read the comments, they were more likely to read the negative comment than the positive one. Turning to (b) the recognition scores, however, the estimate of the interaction effect was not statistically significant (Table 5, Model 2). Therefore, our results support hypothesis H2a, but not H2b, and thus indicate negativity bias for attention, but not for recognition.

Interestingly, the interaction between anger and heuristic processing showed a significant negative effect on both (a) dwell time ($b = -2.79$, $p < .001$, Table 4, Model 3) and (b) recognition ($b = -1.54$, $p < .001$, Table 5, Model 3). Contrary to our preregistered hypothesis, we found that participants in the systematic condition focused more on the angry

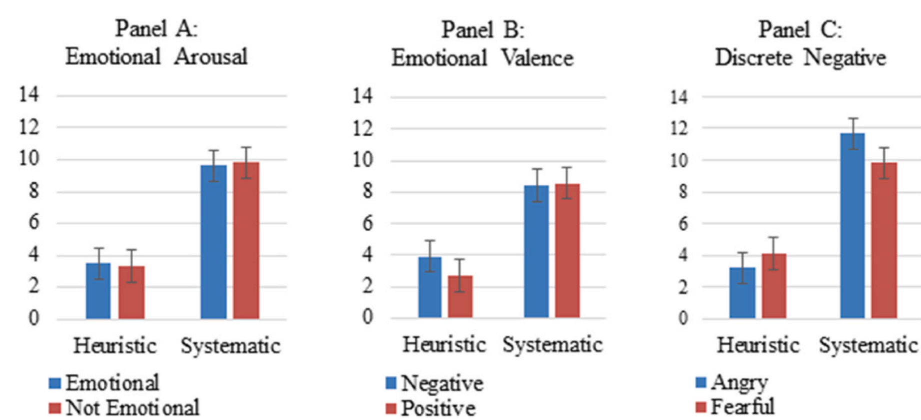

Fig. 1. Comparison of dwell times in seconds on different emotional comments in the heuristic and systematic experimental group *Note.* This figure illustrates margin plots with confidence intervals comparing dwell time in seconds by processing mode (heuristic and systematic) and emotion (arousal, valence and discrete negative emotions).

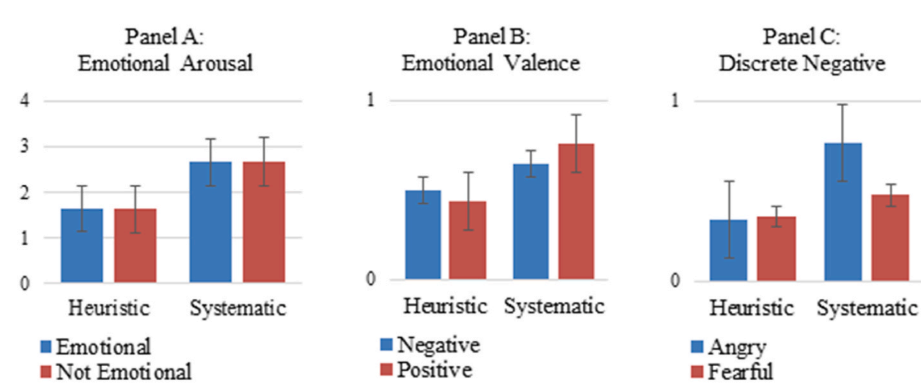

Fig. 2. Comparison of recognition success scores for story details of different emotional comments in the heuristic and systematic experimental group, *Note.* This figure illustrates margin plots with confidence intervals comparing recognition success by processing mode (heuristic and systematic) and emotion (arousal, valence and discrete negative emotions) ranking from 0 to 4 for emotional arousal; and from 0 to 1 for emotional valence and discrete negative emotion.

comment and recognized it better than the fearful comment. Thus, when the participants had more time, they were significantly more likely to read (see Fig. 1, Panel C) and recognize (see Fig. 2, Panel C) the angry comment compared to the fearful one. In sum, for H3, our results do not support our preregistered expectations that people under heuristic processing conditions focus more on angry than they do on fearful comments. Instead, we found support for the proposed effect in the systematic treatment condition.

7. Discussion

The aim of this study was to investigate how much attention is given to emotional comments on social media posts and the extent to which their content is memorized. With our methods, we did not find that people were more attracted to emotional comments compared to non-emotional comments under heuristic versus systematic processing. However, we found differences comparing emotional tones in comments. We found that people were more strongly attracted to negative than positive comments under heuristic processing conditions and that they showed significantly more attention and displayed better recognition of the story details of the angry comment compared to the fearful comment under systematic processing conditions. With that, our findings show that emotional comments grab attention and stimulate information processing in a different way. We will discuss the results and suggest further exploration in future work.

Our results showing that negative emotions attract more attention is align with previous research on negativity bias, which holds that negative information is more important (Rozin & Royzman, 2001) and captures attention (Soroka et al., 2019). Our results also nicely align with Soroka et al. (2019) who captured attention with heart rate variability. However, we did not find that the participants better recognize negative information. Perhaps attention to negativity does not translate into recognition. Another possibility is that they chose to turn attention away from the negative information. Literature in communication science has shown that in response to a pandemic (which is arguably negative) people choose to avoid consuming more information (de Bruin, de Haan, Vliegenthart, Kruikemeier, & Boukes, 2021). So one possibility is that people turn their attention to other – more positive thoughts and suppress the negative thoughts and, consequently, might not remember the stimuli later. We see a fruitful line of research that addresses how people regulate the feelings that negative information causes and whether this could explain some of the findings we outline here.

Compared to the heuristic condition, the angry, compared to the fearful comment, received more attention and were better recognized in the systematic condition. This finding supports the cognitive-functional model of the effects of discrete negative emotions, shown in the work of Nabi (1999), in which anger promotes deeper information processing of news stories than fear. However, this finding only applied to the systematic processing condition (compared to the heuristic condition) in the current study. It was, therefore, contrary to our preregistered expectation that in a heuristic processing mode, participants will give priority to angry comments.

Additional factors might explain the importance of anger in the systematic processing mode. Tiedens and Linton (2001), for example, argued that emotions promote both heuristic or systematic processing, depending on certainty appraisals. They found that emotions associated with uncertainty resulted in greater reliance on the expertise of a source of a persuasive message than emotions associated with certainty. Thus, anger in user comments might be more associated with uncertainty than fear.

Compared to the heuristic processing condition, the unexpected effects of anger versus fear on information processing in the systematic processing condition calls for more research, theorizing, and testing, especially concerning people's emotional reactions to perceived emotions. This latter finding is, overall, the most intriguing of our findings. Moreover, we found that fearful comments draw the most attention when people have less time to read or are more distracted.

Every study, including ours, has limitations that we discuss here. Eye-tracking studies are always less ecologically valid in their research setting (King et al., 2019). In our design, we had to make hard decisions due to limited funds and the fact that adding more conditions can decrease the statistical power and increase the risk of type II errors. Therefore, we could not compare a broader range of emotions outside of positive versus negative and angry versus fearful, and we could only use one example comment for the comparison. Furthermore, we could not manipulate emotional triggers such as emojis, capital letters, and words (e.g., capital letters compared to emojis compared to only emotional words). We were limited to specific news topics. We also presented the stimuli only in the style of a Facebook post rather than employing other social media interfaces that could have revealed similar or different results. Therefore, our study must be regarded as a precursor in eye-tracking on emotional comment perception. We welcome future studies that will build upon our work to conduct well-powered, preregistered studies in which the limitations of our study are addressed.

An important additional limitation that should be discussed in more detail is that we could not change the order of the comments within the social media posts, as this would double the necessary number of participants – and we did not have the financial resources to do so this. This design choice might have influenced our first finding: people are more strongly attracted to negative than positive information (the negative comment was included above the positive comment). When we compare the dwell time on the comments in terms of their order in the posts (see Table 3), it becomes evident that in the heuristic processing condition, the dwell time was significantly lower for each comment when going from top to bottom. For example, the differences between the dwell time spent on the first and the second comment ($t = 12.68$, $p = .000$, $n = 1240$, $d = 0.36$), the second and the third ($t = 6.16$, $p = .000$, $n = 1240$, $d = 0.17$), and the third and fourth comment ($t = 6.66$, $p = .000$, $n = 1240$, $d = 0.18$) were significant for Stimulus 1. Thus, the participants were more likely to explore a post from top to bottom.

From previous research, we know that people usually do read texts, including posts, from top to bottom (Unkel & Kümpel, 2019). Therefore, this *order effect* might have influenced the comments to which the participants gave priority. It is important to note that we did not find this order effect among those in the systematic processing treatment group. We found that the dwell times did not support an order effect if people were asked to read carefully. The differences in the dwell times in the heuristic processing condition are not necessarily an indicator of order effects. Moreover, testing the influence of order on the results of post recognition did not reveal any evidence for an order effect; the participants remembered the comments on the bottom in the same way as those on the top. To conclude, we want to emphasize that we did not find consistent evidence that our findings were caused by the order. That said, future studies would be well advised to randomize the order of the treatments.

On an important note related to preregistration, it is common that experimental designs are used as they are necessary if we are to gain insight into the psychological processes that underlie media consumption. Null findings, however, are not often written up or reported (Franco, Malhotra, & Simonovits, 2014), and researchers will often formulate hypotheses after the results are known (Chambers, 2019). Preregistration is one way to tackle limitations that appear due to experimental design, which requires detailed planning and reporting of a study and supports a high level of research transparency (Yamada, 2018). Our study's preregistered documentation allowed us to think through and fix the analytical design before proceeding with the analysis, and it laid a strong foundation for other researchers at all levels to replicate and reproduce the work (Allen & Mehler, 2019). To the best of our knowledge, this study is among the first preregistered eye-tracking studies in media psychology. As our results ran, at times, counter to our preregistered expectations, and as some of our other findings were not statistically significant, we found that preregistering our study provided us with a clear framework for analyzing and reporting our preregistered results. Our study thereby illustrates the importance of preregistration. We hope that more researchers will report preregistered eye-tracking studies in the future.

8. Conclusion

To conclude, the results of this study reveal insights into the effects that negative emotional user comments can have on attention and information processing when individuals read news on social media. They also reveal the opportunity for a great spectrum of necessary follow-up research. First, we have shown that it is important to distinguish discrete negative emotions (e.g., anger versus fear), as they can affect readers in significantly different ways. Future research can build on our study by testing the effects of different emotions, emotional cues, and processing strategies as well as different news providers, formats, and topics. Second, future research should consider how emotionally invested people might get when reading (emotional) comments. Research in this field can help to better understand how information processing influenced by emotion can influence readers' perceptions of news stories in general.

Credit author statement

Susann Kohout: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Funding acquisition; **Sanne Kruikemeie**r: Conceptualization, Methodology, Validation, Supervision, Writing – review & editing; **Bert N. Bakker**: Conceptualization, Methodology, Validation, Supervision, Writing – review & editing

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