

Running title: The Positivity Bias on Social Media

**Unveiling the Positivity Bias on Social Media: A Registered Experimental Study On
Facebook, Instagram, And X.**

This research was supported by Association for Disseminate the International Research in
Social Psychology.

Abstract

Social media has transformed how people engage with the world around them. The positivity bias on social media, in particular, warrants in-depth investigation. This is particularly true as previous research has concentrated on one specific platform, Facebook. Based on a pilot study of 279 university students, this pre-registered experimental research will use a mixed design to examine the positivity bias on various social media platforms. After recalling a personal event, participants will randomly imagine telling this event to a group of friends and sharing it on social media (Facebook vs. Instagram vs. X). Several characteristics will be examined through repeated measures ANCOVAs including the texts' valence and the usage of emoji. Data collection will take place via the Prolific platform, adhering to our required sample size of 300 participants. By focusing explicitly on Facebook, Instagram and X, this research aims to enrich the current understanding of the positivity bias on social media through an experimental and pre-registered approach.

Keywords: social media; cross-platform; valence; positivity bias; self-presentation; emoji.

Unveiling the Positivity Bias on Social Media: A Registered Experimental Study On Facebook, Instagram, And X.

1. Introduction

More than 4 billion people use social media every day (Patard, 2021). Ever since the arrival of these new technologies, the general public has expressed concerns, wondering if social media could “ruin our lives” (Appel et al., 2020). Many studies have subsequently delved into social media effects on mental health, alleviating some of these concerns (Valkenburg, 2022). Nonetheless, scrutinizing the nature of exchanges carried out within these platforms remains essential (Meier & Reinecke, 2021). This is precisely the case for the positivity bias, which can provide insights into how social media platforms shape our perceptions, emotions, and overall mental health (Schreurs et al., 2023). Despite the wealth of research conducted on Facebook, there is a notable gap in understanding how the positivity bias manifests across diverse social media platforms. The aim of this paper is therefore to address this gap through a pre-registered experimental study on Facebook, Instagram, and X. In the subsequent section, we will delve deeper into our theoretical argument.

1.1 The Positivity Bias on Social Media

The positivity bias on social media reflects users' tendency to present favorable aspects of themselves rather than negative ones (Schreurs & Vandenbosch, 2021), aligning with the concept of positive self-presentation (Utz, 2011). Numerous studies have demonstrated the prevalence of positive emotions over negative ones in social media content (R. Lin & Utz, 2015; Thelwall et al., 2010), as well as the predominance of positive emoji (Novak et al., 2015). Consequently, researchers have investigated the positivity bias on social media in relation to both users' authenticity and the overall tone of their self-representation (Reinecke & Trepte, 2014; Spottswood & Hancock, 2016; Utz, 2011).

This tendency towards positivity on social media reflects a desire for online positive image and social approval. Indeed, this bias is rooted in the *face theory*, which postulates that

individuals strategically manage their self-presentation to maintain their social identity and uphold their reputation in the eyes of others (Goffman, 1959). This impression management on social media is achieved in a variety of ways, through the selection of topics posted, the audience targeted and the way in which information is presented (Marwick & boyd, 2011; Merunková & Šlerka, 2019; Vitak & Kim, 2014).

As a result, the positivity bias on social media not only prompts users to highlight the favorable aspects of their lives but also encourages them to frame both positive and negative facets in a positive light. This phenomenon is propelled by several factors. Firstly, social media platforms afford users a level of control over self-presentation that surpasses real-life interactions (Merunková & Šlerka, 2019). Secondly, these platforms provide features that actively promote positivity, such as filters and emoji. Emoji, in particular, have become integral to self-expression, also contributing to the formation of users' identities (Huang et al., 2022). Users are more likely to post a message on social media when it contains an emoji (Daniel & Camp, 2020), and messages with an emoji are perceived as more positive than those without (Novak et al., 2015). Lastly, when users are posting publicly (e.g., Facebook), rather than privately through messaging application (e.g., Facebook Messenger), the potential audience is significantly larger, amplifying the pressure to maintain a positive image (Spottswood & Hancock, 2016).

However, one limitation in the literature is that research on positivity bias have primarily focused on Facebook alone (R. Lin & Utz, 2015; Spottswood & Hancock, 2016) or on social media overall (Reinecke & Trepte, 2014; Schreurs et al., 2023). With the increasing diversity among platforms, there is therefore a need to explore how positivity bias plays out on various social media (Masciantonio & Bourguignon, 2023).

1.2 The positivity Bias on Various Social Media

With 2.91 billion active users, Facebook remains the most widely used social media worldwide (Saquib, 2023). However, other platforms are also extremely popular such as Instagram with 2.35 billion users, and X (previously Twitter¹) with 396.5 million users (Saquib, 2023). Although Facebook, Instagram, and X are all classified as social media (Ellison & boyd, 2013), they differ in several aspects that significantly influence users interactions on the platform. The cross-platform approach suggests that social media can be differentiated according to three characteristics: architecture, affordances and social-cultural context (Masciantonio et al., 2024).

Firstly, social media architecture comprises several features (Bossetta, 2018). The connection mode is the most essential to consider when studying positivity bias, as it relates to the type of relationships between users. Facebook has a bidirectional connection mode (e.g., friends) whereas Instagram and X have a unidirectional connection mode (e.g., followers). This implies that Facebook users partly know their friends on the platform, which is not necessarily the case for Instagram and X. Secondly, affordances address not the objective features of platforms, but how users perceive them (boyd, 2010). Two affordances are especially relevant in the context of positivity bias. Shareability relates to the content shared on platforms (Masciantonio et al., 2024): Facebook is perceived as suitable for posting text and image, Instagram is mainly associated with image content and Twitter with textual content (Pittman & Reich, 2016). Image-oriented social media are associated to the most stylization from users, and thus impression management (Boczkowski et al., 2018). The visibility affordance can also be at play, focusing on the perception of the degree of visibility of the published content (Treem & Leonardi, 2013). For example, it is lower on Facebook due to its bidirectional nature, and higher on Instagram and Twitter. Finally, the last characteristic is the socio-cultural context (Masciantonio et al., 2024). Users are aware that according to specific social media, certain actions are more accepted by others – the injunctive norms – or more done by others – the descriptive norms (Cialdini et al., 1991; Cialdini & Trost, 1998). These social norms guide user

behavior and appropriate contents for each platform (Boczkowski et al., 2018; Tandoc et al., 2019). Waterloo et al. (2018) found that positive emotions were perceived as more appropriate on Instagram and Facebook, while negative emotions were perceived as more appropriate on Twitter and Facebook (Waterloo et al., 2018). These results are in line with sentiment analyses studies showing that Twitter posts are mainly related to negative content (Jiménez-Zafra et al., 2021; Naveed et al., 2011; Thelwall et al., 2011).

Despite the relevance, there remains a dearth of knowledge concerning the positivity bias when examined in the context of various social media platforms. While the positivity bias should appear across all social media platforms, its prevalence and manifestations may vary depending on the platform's unique characteristics. For instance, on image-oriented platforms like Instagram, the positivity bias might be more pronounced. The opposite could be true on platforms like Twitter, known for textual concise messages. By delving into how the positivity bias operates within the distinct contexts of various social media platforms, we can gain a more comprehensive understanding of its influence on user behavior.

2. The Present Research

The aim of the present research is to examine the manifestation of the positivity bias on various social media. Given the paucity of existing research, a pilot study was first conducted to refine the research questions and the protocol. The main research is intended to be pre-registered and will be carried out under the condition of acceptance of the manuscript as a registered report.

The University of Geneva's Committee for Ethical Research attested ethical aspects of the research (CUREG-2022-10-110). In support of open science, the research will be pre-registered on OSF. The coding manual, data and analyses for the pilot study can be accessed at this link: https://osf.io/akgdj/?view_only=42142acd518a42cf99b33f5ebec1c780. The coding manual and power analysis script for the main study can be accessed at the same link. The data and the analyses for the main study will also be deposited on the same OSF project.

3. Pilot Study

3.1 Research Questions

As no research has directly tested the positivity bias on various social media, we conducted a pilot study to test an original protocol: participants were asked to remember an event and write a text about it (time 1), they were then asked to imagine sharing this event on a particular social media by writing a text again (time 2). The type of social media was the independent variable (Facebook vs. Instagram vs. Twitter), and the dependent variables were the texts' valence and the number of emoji. This pilot study was designed to address three research questions:

RQ1: How does the positivity bias manifest on social media?

RQ2: Does the positivity bias vary according to the type of social media?

RQ3: Does positivity bias have an influence on emoji use?

In addition, while architecture and affordances can be approximated by comparing the platforms, the socio-cultural context is more difficult to estimate. Therefore, on an exploratory basis, we addressed another research question related to the norms of emotional expression on the three platforms:

RQ4: How does the socio-cultural context around emotional expression differ across Facebook, Instagram, and Twitter?

3.2 Method

3.2.1 Participants

Four hundred thirty seven university students took part in the pilot study. Among these, we removed those who did not give their informed consent or who did not fully complete the study ($n = 136$). We also removed participants who did not understand the experimental instructions ($n = 22$). The final sample was composed of 279 participants: 218 women, 48 men, seven non-binary individuals, one person with another gender identity, and five people who chose not to disclose ($M_{age} = 20.83$, $SD_{age} = 3.09$).

3.2.2 Experimental Manipulation

From Talarico et al. (2004), participants were presented with the experimental instruction: *“You are asked to recall an event from your personal past. It is usually a specific, dateable event in which you were personally involved. It is usually a snapshot of a specific scene rather than a movie of a time period or an extended event. There is usually a plot, a setting and characters. However, not all of these characteristics need to be present in each individual memory. Memories can be about any period of your life, from early childhood to what you did just before you came here today. Autobiographical memories are not facts and are not about events that will happen in the future. Now write a short text (max. 5 lines) summarizing this event”*.

They were right after asked on which social media they would share this event (Facebook, Instagram, or Twitter).

Finally, they were randomly assigned to one of the three experimental conditions through Qualtrics' randomization tools: they had to imagine sharing this event on a particular social media (Facebook vs. Instagram vs. Twitter) by writing a text again.

For each text written by the participants, the number of words and the number of emoji were counted. In addition, three researchers qualitatively analysed all the texts to estimate their valence on a 7-point scale (-3 = Very negative; 3 = Very positive). Coders proceeded to code 50 of the same texts independently, and they then exchanged on the existing disagreements to reach a consensus. Finally, they all evaluated the set of texts. In order to verify inter-rater reliability, Intra Class Correlation Coefficient was used. The latter shows a sufficient agreement between the tree coders: $ICC = .93$, 95% CI[.91; .94], $F(576, 1152) = 13.58$, $p < .001$. A valence score for each text was therefore calculated by averaging the evaluation scores of the three coders.

3.2.3 Measures

Participants were asked which device they conducted the study on. They were also asked how often they used Facebook, Instagram and Twitter on a 7-point scale (never, rarely, once a month, several times a month, once a week, several times a week, daily).

Since social media use is highly dependent on individual characteristics (Valkenburg & Peter, 2013), we measured emotional intelligence in an exploratory way (WEIS, Wong et al., 2007). Our assumption was that positivity bias might depend on how users perceive their own emotions and those of others. The Wong's Emotional Intelligence Scale consists of four dimensions: appraisal and expression of emotion in the self ($\omega = .82$), appraisal and recognition of emotion in others ($\omega = .82$), use of emotion to facilitate performance ($\omega = .78$) and regulation of emotion in the self ($\omega = .88$).

Regarding the socio-cultural context on social media, we measured injunctive and descriptive norms of emotional expression on the three platforms (Masciantonio & Bourguignon, 2023). Injunctive norms were measured for each platform with three items; for example “The people who influence my behavior expect me to post content on [Facebook][Instagram][Twitter] mainly...” (1 = very negative; 7 = very positive). Descriptive norms were also measured for each platform with three items; for example, “The people who influence my behavior post content on [Facebook][Instagram][Instagram] mainly...” (1 = very negative; 7 = very positive). Internal consistency was satisfactory for injunctive norms (ω for Facebook = .94, ω for Instagram = .89, ω for Twitter = .92) as well as for descriptive norms (ω for Facebook = .78, ω for Instagram = .62, ω for Twitter = .76).

Finally, three socio-demographic questions were asked related to participants' age, gender and current situation.

3.3 Results

3.3.1 Preliminary Analyses

We performed a preliminary analysis to check the randomization. The valence of the text at time 1 did not differ significantly between the type of social media attributed at time 2, $F(2, 276) = 0.04, p = .959$. We also found that the number of words at time 2, for texts written on social media, did not change between Facebook, Instagram and Twitter, $F(2, 276) = 0.28, p = .755$.

3.3.2 The Positivity Bias on Social Media (RQ1 and RQ2)

We first examined the impact of social media on the texts' valence with a 3 (Type of social media: Facebook vs. Instagram vs. Twitter) X 2 (Time: Narrative of the event vs. Narrative of the event on social media) repeated measures ANCOVA. We used as covariates age, genderⁱⁱ, emotional intelligence, and social media frequencies of use.

As we can see in Figure 1, the repeated measures ANCOVA revealed an interaction effect between time and social media, $F(2, 247) = 3.63, p = .028, \eta^2 = .004$. There was no significant effect of covariates. The valence of texts at time 1 ($M = 0.46, SD = 1.58$) was less positive than the valence of texts at time 2 ($M = 0.82, SD = 1.39$), with valence highest for Instagram ($M = 1.08, SD = 1.37$), followed by Twitter ($M = 0.72, SD = 1.39$) and Facebook ($M = 0.62, SD = 1.44$). Pairwise comparisons with the Holm correction were, however, not significant ($p.adj > .05$).

In reply to RQ1, the results highlighted that the valence of self-expression is more positive on social media, which is consistent with the positivity bias (Reinecke & Trepte, 2014). However, we found no significant differences between the three social media, which does not allow us to answer RQ2.

[Insert Figure 1]

3.3.3 The Use of Emoji and the Positivity Bias (RQ3)

Since previous analyses have highlighted the existence of a positivity bias, we wondered in what way the use of emoji might play a role in it.

We first checked that the number of emoji used did not depend on the type of social media assigned to the participants. We performed an ANCOVA with the same covariates mentioned previously. Results did not reveal a significant effect of the type of social media on the ratio number of emoji per word, $F(2, 247) = 0.02, p = .98$. We, however, found an effect of the covariate frequency of Facebook use, $F(1, 247) = 4.60, p = .052; \eta^2 = .018$.

We then tested the association between the valence of the text at time 1 and the ratio number of emoji per word. We found a positive association, meaning that the more the text valence at time 1 was positive, the more participants used emoji to write a text on social media at time 2; $r(277) = 0.13, p = 0.03$. We also performed a multiple regression analysis to adjust for the previously mentioned covariates. Text valence was no longer significantly associated with the ratio of number of emoji per word ($\beta = 0.12, t(247) = 1.81, p = 0.072$); however, frequency of Facebook use was ($\beta = 0.14, t(247) = 2.09, p = 0.038$). This partially answers RQ3.

3.3.4 Test of the Socio-Cultural Context on Social Media (RQ4)

Finally, we used two methods for examining the socio-cultural context on Facebook, Instagram, and Twitter.

First, we have created a new variable depending on whether the event at time 1 was positive, negative or neutral. We then performed a chi-square to test the association between the text's valence at time 1 (positive vs. negative vs. neutral) and the question where participants could choose which of the three social media was most appropriate to share this event (Facebook vs. Instagram vs. Twitter). In this way, we were able to determine whether, depending on the valence of an event, users will turn to one social media platform rather than another to express themselves. Results showed that the social media chosen by participants is significantly associated with text's valence at time 1, $\chi^2(4, N = 279) = 22.21, p < .001$, Cramer's $V = .200$. Regardless of valence, only 9.32% of the participants chose Facebook. Concerning

Instagram and Twitter, they were chosen in the same way to share negative events (44.94% and 46.07% of participants respectively). However, when the events were positive, 71.35% of the participants chose Instagram.

The second method compared the norms of emotional expression on the three social media. A repeated measures ANOVA revealed that injunctive norms differed across platforms, $F(2, 132) = 30.95, p < .001, \eta^2 = .319$. We found the same result for descriptive norms, $F(2, 170) = 62.98, p < .001, \eta^2 = .433$. As can be seen in Figure 2, pairwise comparisons with the Holm correction showed that injunctive and descriptive norms were most positive for Instagram, followed by Facebook and Twitter ($p_{adj} < .05$).

[Insert Figure 2]

3.4 Discussion

The pilot study provides new empirical insights for the main research. Indeed, the results emphasized the positivity bias (RQ1): when individuals imagined themselves sharing an event on social media, they tended to accentuate the positive aspects (Reinecke & Trepte, 2014). Results were more mixed for emoji use, since with the addition of covariates, the significant association between event valence and the number of emoji did not persist (RQ3). We also found no significant differences between the three platforms (RQ2). Still, the results revealed that the socio-cultural context differed between platforms (Masciantonio et al., 2024). Indeed, participants associated Instagram with more positive content than Twitter and Facebook, which is consistent with the literature (Masciantonio & Bourguignon, 2023; Waterloo et al., 2018).

The pilot study also provides additional methodological perspectives for the main research. First, the proposed protocol was maybe not the most appropriate to answer the research questions. On the one hand, we have to take into account the fact that Instagram is an image-oriented platform. This is one of the limitations most often encountered in media studies (Griffioen et al., 2020). One solution might be for participants not only to write the text for the

social media, but also to describe the image they would like to associate with it. This would lead to greater ecological validity. Nevertheless, it will also be necessary to ensure beforehand that participants regularly use all three social media, which was not done in the pilot study. On the other hand, comparing the valence of an event with that of its expression on social media may not be the most informative. Indeed, to demonstrate the existence of a positivity bias specific to social media, it is necessary to establish that this bias is not equivalent in face-to-face social contexts (Goffman, 1959). For this reason, one solution would be to ask participants to imagine themselves narrating this event to a group of friends, and then ask them to share it on one of the three social media.

Second, the choice of the variables measured can also be improved. We found no effect of emotional intelligence in any of the analyses. Furthermore, although we found differences in the perception of socio-cultural context between platforms, we only had very little information regarding the environment of individuals on Facebook, Instagram, and Twitter. The literature highlighted at least two key variables to consider, the number of relations on each social media, and to what extent users know about these relations in real life (H. Lin et al., 2014). These variables could provide further insight into platforms architecture and affordances (Masciantonio et al., 2024).

Taking these considerations into account, the main research should provide a more accurate and complete test of our assumptions.

4. Preregistered Main Research

In order to address the limitations of the pilot study, we will use a mixed design: participants will think about an event, they will then be asked to imagine telling this event to a group of friends, and sharing it on social media (Facebook vs. Instagram vs. X). The dependent variables will be the texts' valence and use of emoji.

4.1 Hypotheses and Research Question

The main research will therefore aim to address the following fundamental question: how does the positivity bias manifest on social media, and does it vary depending on the type of social media platform?

The literature suggests the existence of a positivity bias on social media (Reinecke & Trepte, 2014), which was also observed in the pilot study. We can therefore expect the valence of the written texts for the three social media to be more positive than the valence of the written text as if they were telling the event to a group of friends:

H1: The social media post's valence are more positive compared to the valence of the event recounted to friends.

Furthermore, the literature has highlighted that social media differ from one another in terms of architecture, affordances and socio-cultural context (Masciantonio et al., 2024). While we did not detect significant differences in positivity bias between platforms in the pilot study, we did observe similar results as Waterloo et al. (2018) for emotional expression norms. People perceived it as more acceptable to post negative content on Twitter rather than on Instagram and Facebook, and conversely. Therefore, in line with the literature (Masciantonio et al., 2024; Waterloo et al., 2018), our hypotheses point to a variation in positivity bias across social media:

H2: The posts' valence is dependent on the social media.

H2a: The posts' valence is more positive for Instagram compared to X and Facebook.

H2b: The posts' valence is more negative for X compared to Instagram and Facebook.

Finally, little is known regarding the relationship between emoji use and the positivity bias. The pilot study showed that the more positive the event, the more emoji participants used. However, when adding covariates, the association did not persist. We therefore restate our research question:

RQ1: Does positivity bias have an influence on emoji use?

4.2 Method

4.2.1 Participants

To determine the sample size, we carried out an a-priori power analysis (Lakens, 2014), using the package ‘WebPower’ (Zhang & Yuan, 2018). We set the alpha level to 0.05, and aimed for a power of 80%. Regarding the effect size, we identified the Smallest Effect Size of Interest (Lakens, 2022). We used a subjective justification based on prior meta-analyses (Lakens et al., 2018). As there is no meta-analysis directly comparing positive self-presentation in person and on different social media, we relied on Ruppel et al. (2017) meta-analysis examining the difference between computer-mediated and face-to-face self-disclosure. Their findings indicated an average meta-analytic effect size of $r = .211$ (equivalent to $f = 0.216$). For a repeated ANOVA, power analysis indicated a minimum required sample size of 219 for H1 (within-subject), and of 270 for H2 (interaction). We have rounded the required sample size to 300 participants. The R script for the power analysis is available at this link: https://osf.io/akgdj/?view_only=42142acd518a42cf99b33f5ebec1c780.

In order to have an older and more gender-balanced sample, the data collection will be conducted on the paid platform Prolific. As soon as 300 persons have completed the study in full, the collection will stop. As with the pilot study, participants who will not give consent to take part in the study, who will not respond to the entire study, or who will not understand the instructions, will be removed from the study.

4.2.2 Experimental Manipulation

The study will be conducted using the Qualtrics platform. First, a selection study will be conducted on Prolific to ensure that participants use Facebook, Instagram, and Twitter at least once a month. In addition, the questionnaire will only be able to be answered on a smartphone to get as close as possible to a real-life situation.

Regarding the experimental manipulation, as for the pilot study, the participants will have to think about an event, but this time they will not be asked to write a text to describe it. The text-writing instruction will be almost identical to that of the pilot study (Talarico et al., 2004). However, to prevent participants from reporting traumatic experiences, in agreement with the Ethics Committee of the University of Geneva, a sentence will be added at the end: “Please choose an event that is neither very painful nor very positive”.

Participants will then be asked to “imagine sharing this event with a group of friends as if you were recounting it in person. Write down below what you would tell them, without thinking too much, naturally”.

After writing the text, participants will be randomly assigned to one of three experimental conditions (Facebook vs. Instagram vs. X): “Imagine that you are now sharing this event on [Facebook][Instagram][X]. Write a post below as you would in real life, using emoji if you like”. To reflect the fact that Instagram is an image-oriented social media, they will also be asked an optional question: “If you plan to use an image or photo to accompany this post, please describe it briefly here”.

4.2.3 Measures

The measurement of frequencies of use of Facebook, Instagram, and X will be the same as the pilot study. We will ask participants on which devices they most often use social media (computer, tablet or smartphone). We will also add several measures, one concerning the number of relations on Facebook, Instagram and X: “How many friends do you have on Facebook?”, and “How many followers do you have on [Instagram][X]?”. In addition, we will ask participants, “How well do you know your [Facebook][Instagram][X] [friends][followers] in real life?” from 1 (not at all known in real life) to 7 (completely known in real life).

As with the pilot study, the texts’ number of words and the number of emojis will be counted. Three researchers will qualitatively analyze all the texts to estimate their valence on a

7-point scale (-3 = Very negative; 3 = Very positive). We will use Intra Class Correlation Coefficient to verify inter-rater reliability. The same procedure will be used to assess the valence of the description of the images associated with the post.

4.3 Results

The study design template is presented in Table 1. For all analyses, results will be considered significant if the p-value is less than .05. The covariates that will be used are: frequency of use of Facebook, Instagram, and X; number of connections on Facebook, Instagram, and X; knowing these connections on Facebook, Instagram, and X; age; and gender.

[Insert Table 1]

As can be seen in Table 1, to test H1 and H2, we will perform a 3 (Type of social media: Facebook vs. Instagram vs. X) X 2 (Time: Narrative of the event to friends vs. Narrative of the event on social media) repeated measures ANCOVA. To test H2a and H2b, contrasts will be conducted in the direction of the hypotheses (see Table 1).

For the RQ1, exploratory analyses will be conducted. In particular, we will test the association between the valence of the event told to friends and the ratio of emoji used to share the event on social media using correlation, as well as multiple regression comprising the covariates.

For the other exploratory analyses that will be carried out, we will use the same covariates, the same decision threshold criterion, and if necessary, the pairwise comparisons will use the Holm correction. In particular, we will perform the same analyses as for text valence for image valence, however it is possible that not all participants will imagine adding an image to their post. We will also compare whether adding an image depends on the type of social media (Facebook vs. Instagram vs. X) using chi-square test.

As sensitivity analyses, we will repeat the analyses only on participants who responded that they would be ready to share the post they wrote on the three social media.

4.4 Discussion

Under the condition of acceptance of the manuscript as a registered report.

5. General Discussion

Under the condition of acceptance of the manuscript as a registered report.

References

- Appel, M., Marker, C., & Gnambs, T. (2020). Are Social Media Ruining Our Lives? A Review of Meta-Analytic Evidence. *Review of General Psychology, 24*(1), 60–74. <https://doi.org/10.1177/1089268019880891>
- Boczkowski, P. J., Matassi, M., & Mitchelstein, E. (2018). How Young Users Deal With Multiple Platforms: The Role of Meaning-Making in Social Media Repertoires. *Journal of Computer-Mediated Communication, 23*(5), 245–259. <https://doi.org/10.1093/jcmc/zmy012>
- Bossetta, M. (2018). The digital architectures of social media: Comparing political campaigning on Facebook, Twitter, Instagram, and Snapchat in the 2016 US election. *Journalism & Mass Communication Quarterly, 95*(2), 471–496. <https://doi.org/10.1177/1077699018763307>
- boyd, danah. (2010). Social network sites as networked publics: Affordances, dynamics, and implications. In Z. Papacharissi (Ed.), *A networked self* (pp. 39–58). Routledge.
- Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A Focus Theory of Normative Conduct: A Theoretical Refinement and Reevaluation of the Role of Norms in Human Behavior. In M. P. Zanna (Ed.), *Advances in Experimental Social Psychology* (Vol. 24, pp. 201–234). Academic Press. [https://doi.org/10.1016/S0065-2601\(08\)60330-5](https://doi.org/10.1016/S0065-2601(08)60330-5)
- Cialdini, R. B., & Trost, M. R. (1998). Social influence: Social norms, conformity and compliance. In D. T. Gilbert, S. T. Fiske, & G. Lindzey (Eds.), *The handbook of social psychology, Vols. 1-2, 4th ed* (pp. 151–192). McGraw-Hill.
- Daniel, T. A., & Camp, A. L. (2020). Emojis affect processing fluency on social media. *Psychology of Popular Media, 9*(2), 208–213. <https://doi.org/10.1037/ppm0000219>
- Ellison, N. B., & boyd, danah. (2013). Sociality through social network sites. In W. H. Dutton (Ed.), *The Oxford handbook of Internet studies* (pp. 151–172). Oxford University Press.

- Goffman, E. (1959). *The Presentation of Self in Everyday Life*. Anchor.
- Griffioen, N., Rooij, M. van, Lichtwarck-Aschoff, A., & Granic, I. (2020). Toward Improved Methods in Social Media Research. *Technology, Mind, and Behavior*, 1(1). <https://doi.org/10.1037/tmb0000005>
- Huang, V., Hu, Y., & Li, Y. (2022). A Systematic Literature Review of New Trends in Self-expression Caused by Emojis and Memes. *2021 International Conference on Social Development and Media Communication*, 75–79. <https://doi.org/10.2991/assehr.k.220105.016>
- Jiménez-Zafra, S. M., Sáez-Castillo, A. J., Conde-Sánchez, A., & Martín-Valdivia, M. T. (2021). How do sentiments affect virality on Twitter? *Royal Society Open Science*, 8(4), 201756. <https://doi.org/10.1098/rsos.201756>
- Lakens, D. (2014). Performing high-powered studies efficiently with sequential analyses. *European Journal of Social Psychology*, 44(7), 701–710. <https://doi.org/10.1002/ejsp.2023>
- Lakens, D. (2022). Sample Size Justification. *Collabra: Psychology*, 8(1), 33267. <https://doi.org/10.1525/collabra.33267>
- Lakens, D., Scheel, A. M., & Isager, P. M. (2018). Equivalence Testing for Psychological Research: A Tutorial. *Advances in Methods and Practices in Psychological Science*, 1(2), 259–269. <https://doi.org/10.1177/2515245918770963>
- Lin, H., Tov, W., & Qiu, L. (2014). Emotional disclosure on social networking sites: The role of network structure and psychological needs. *Computers in Human Behavior*, 41, 342–350. <https://doi.org/10.1016/j.chb.2014.09.045>
- Lin, R., & Utz, S. (2015). The emotional responses of browsing Facebook: Happiness, envy, and the role of tie strength. *Computers in Human Behavior*, 52, 29–38. <https://doi.org/10.1016/j.chb.2015.04.064>

- Marwick, A. E., & boyd, D. (2011). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society*, *13*(1), 114–133. <https://doi.org/10.1177/1461444810365313>
- Masciantonio, A., & Bourguignon, D. (2023). Too Positive to Be Tweeted? An Experimental Investigation of Emotional Expression on Twitter and Instagram. *Media Psychology*, *0*(0), 1–28. <https://doi.org/10.1080/15213269.2023.2236935>
- Masciantonio, A., Gugushvili, N., Wormley, A., Kross, E., & Verduyn, P. (2024). *Social Network Sites and Mental Health: A Cross-Platform Approach* [Manuscript submitted for publication]. Work and Social Psychology Department, Maastricht University.
- Meier, A., & Reinecke, L. (2021). Computer-Mediated Communication, Social Media, and Mental Health: A Conceptual and Empirical Meta-Review. *Communication Research*, *48*(8), 1182–1209. <https://doi.org/10.1177/0093650220958224>
- Merunková, L., & Šlerka, J. (2019). Goffman's Theory as a Framework for Analysis of Self Presentation on Online Social Networks. *Masaryk University Journal of Law and Technology*, *13*(2), 243–276.
- Naveed, N., Gottron, T., Kunegis, J., & Alhadi, A. C. (2011). Bad news travel fast: A content-based analysis of interestingness on twitter. *Proceedings of the 3rd International Web Science Conference*, 1–7. <https://doi.org/10.1145/2527031.2527052>
- Novak, P. K., Smailović, J., Sluban, B., & Mozetič, I. (2015). Sentiment of Emojis. *PLOS ONE*, *10*(12), e0144296. <https://doi.org/10.1371/journal.pone.0144296>
- Patard, A. (2021, January 27). 30 chiffres sur l'usage d'Internet, des réseaux sociaux et du mobile en 2021. *BDM*. <https://www.blogdumoderateur.com/30-chiffres-internet-reseaux-sociaux-mobile-2021/>

- Pittman, M., & Reich, B. (2016). Social media and loneliness: Why an Instagram picture may be worth more than a thousand Twitter words. *Computers in Human Behavior*, *62*, 155–167. <https://doi.org/10.1016/j.chb.2016.03.084>
- Reinecke, L., & Trepte, S. (2014). Authenticity and well-being on social network sites: A two-wave longitudinal study on the effects of online authenticity and the positivity bias in SNS communication. *Computers in Human Behavior*, *30*, 95–102. <https://doi.org/10.1016/j.chb.2013.07.030>
- Ruppel, E. K., Gross, C., Stoll, A., Peck, B. S., Allen, M., & Kim, S.-Y. (2017). Reflecting on Connecting: Meta-Analysis of Differences between Computer-Mediated and Face-to-Face Self-Disclosure. *Journal of Computer-Mediated Communication*, *22*(1), 18–34. <https://doi.org/10.1111/jcc4.12179>
- Saquib. (2023, May 31). How Much Time People Spend on Social Media? [2023 Stats]. *New Vision Theatres*. <https://www.newvisiontheatres.com/time-people-spend-on-social-media>
- Schreurs, L., Meier, A., & Vandenbosch, L. (2023). Exposure to the Positivity Bias and Adolescents' Differential Longitudinal Links with Social Comparison, Inspiration and Envy Depending on Social Media Literacy. *Current Psychology*, *42*(32), 28221–28241. <https://doi.org/10.1007/s12144-022-03893-3>
- Schreurs, L., & Vandenbosch, L. (2021). Introducing the Social Media Literacy (SMILE) model with the case of the positivity bias on social media. *Journal of Children and Media*, *15*(3), 320–337. <https://doi.org/10.1080/17482798.2020.1809481>
- Spottswood, E. L., & Hancock, J. T. (2016). The positivity bias and prosocial deception on facebook. *Computers in Human Behavior*, *65*, 252–259. <https://doi.org/10.1016/j.chb.2016.08.019>

- Talarico, J. M., LaBar, K. S., & Rubin, D. C. (2004). Emotional intensity predicts autobiographical memory experience. *Memory & Cognition*, 32(7), 1118–1132. <https://doi.org/10.3758/BF03196886>
- Tandoc, E. C., Jr., Lou, C., & Min, V. L. H. (2019). Platform-swinging in a poly-social-media context: How and why users navigate multiple social media platforms. *Journal of Computer-Mediated Communication*, 24(1), 21–35. <https://doi.org/10.1093/jcmc/zmy022>
- Thelwall, M., Buckley, K., & Paltoglou, G. (2011). Sentiment in Twitter events. *Journal of the American Society for Information Science and Technology*, 62(2), 406–418. <https://doi.org/10.1002/asi.21462>
- Thelwall, M., Wilkinson, D., & Uppal, S. (2010). Data mining emotion in social network communication: Gender differences in MySpace. *Journal of the American Society for Information Science and Technology*, 61(1), 190–199. <https://doi.org/10.1002/asi.21180>
- Treem, J. W., & Leonardi, P. M. (2013). Social media use in organizations: Exploring the affordances of visibility, editability, persistence, and association. *Annals of the International Communication Association*, 36(1), 143–189. <https://doi.org/10.1080/23808985.2013.11679130>
- Utz, S. (2011). Social Network Site Use among Dutch Students: Effects of Time and Platform. *Networked Sociability and Individualism: Technology for Personal and Professional Relationships*, 103–125. <https://doi.org/10.4018/978-1-61350-338-6.ch006>
- Valkenburg, P. M. (2022). Social media use and well-being: What we know and what we need to know. *Current Opinion in Psychology*, 45, 101294. <https://doi.org/10.1016/j.copsyc.2021.12.006>

- Valkenburg, P. M., & Peter, J. (2013). The Differential Susceptibility to Media Effects Model. *Journal of Communication, 63*(2), 221–243. <https://doi.org/10.1111/jcom.12024>
- Vitak, J., & Kim, J. (2014). “You can’t block people offline”: Examining how facebook’s affordances shape the disclosure process. *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing, 461–474*. <https://doi.org/10.1145/2531602.2531672>
- Waterloo, S. F., Baumgartner, S. E., Peter, J., & Valkenburg, P. M. (2018). Norms of online expressions of emotion: Comparing Facebook, Twitter, Instagram, and WhatsApp. *New Media & Society, 20*(5), 1813–1831. <https://doi.org/10.1177/1461444817707349>
- Wong, C.-S., Wong, P.-M., & Law, K. S. (2007). Evidence of the practical utility of Wong’s emotional intelligence scale in Hong Kong and mainland China. *Asia Pacific Journal of Management, 24*(1), 43–60. <https://doi.org/10.1007/s10490-006-9024-1>
- Zhang, Z., & Yuan, K.-H. (2018). *Practical statistical power analysis using Webpower and R*. ISDSA Press. <https://doi.org/10.35566/power>

Table 1

Study Design Template for the Preregistered Main Research

Hypothesis	Sampling Plan	Analysis Plan	Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
H1: The social media post's valence are more positive compared to the valence of the event recounted to friends.	The power analysis for an alpha level of .05, a power of .80 and an effect size f of .216, indicated a required sample size of 219 participants.	3 (Type of social media: Facebook vs. Instagram vs. X) X 2 (Time: Narrative of the event to friends vs. Narrative of the event on social media) repeated measures ANCOVA. Covariates: Frequency of use of Facebook, Instagram, and X; number of connections on Facebook, Instagram, and X; knowing these connections on Facebook, Instagram and X; age; gender.	We determined the SESOI based on previous meta-analyses (Lakens et al., 2018). The meta-analysis of Ruppel et al. (2017) revealed an average effect size of $f = 0.216$ for the difference between computer-mediated and face-to-face self-disclosure.	If there is a significant effect of the variable "Time" on valence ($p < 0.5$), H1 will be accepted.	Positivity Bias (Reinecke & Trepte, 2014).
H2: The posts' valence is dependent on the social media. H2a: The posts' valence is more positive for Instagram compared to X and Facebook. H2b: The posts' valence is more negative for X compared to Instagram and Facebook.	The power analysis for an alpha level of .05, a power of .80 and an effect size f of .216, indicated a required sample size of 270 participants.	Same analysis that for H1, with three contrasts: First (H2a & H2b): • Instagram: +1 • Twitter: -1 • Facebook: 0 Second (H2a): • Instagram: +1 • Twitter: 0 • Facebook: -1 Third (H2b): • Instagram: 0 • Twitter: +1 • Facebook: -1	We determined the SESOI based on previous meta-analyses (Lakens et al., 2018). The meta-analysis of Ruppel et al. (2017) revealed an average effect size of $f = 0.216$ for the difference between computer-mediated and face-to-face self-disclosure.	If there is a significant interaction between "Type of social media" and "Time", H2 will be accepted. If the contrasts are significant ($p < 0.05$), H2a and H2b will be accepted.	Cross-platform approach (Masciantonio et al., 2024)

Figure 1

Text valence at time 1 and 2 by social media

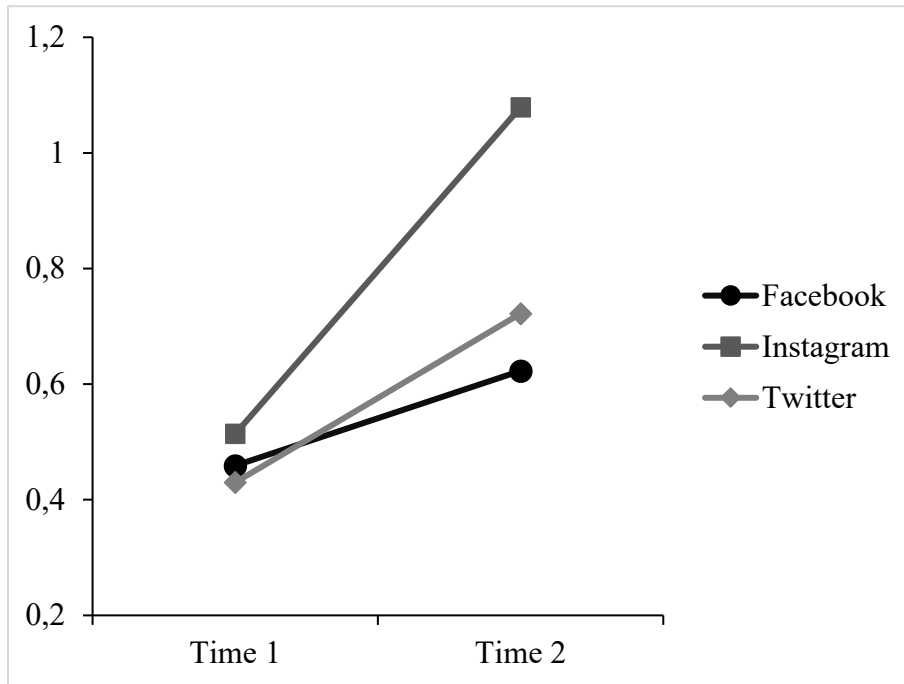
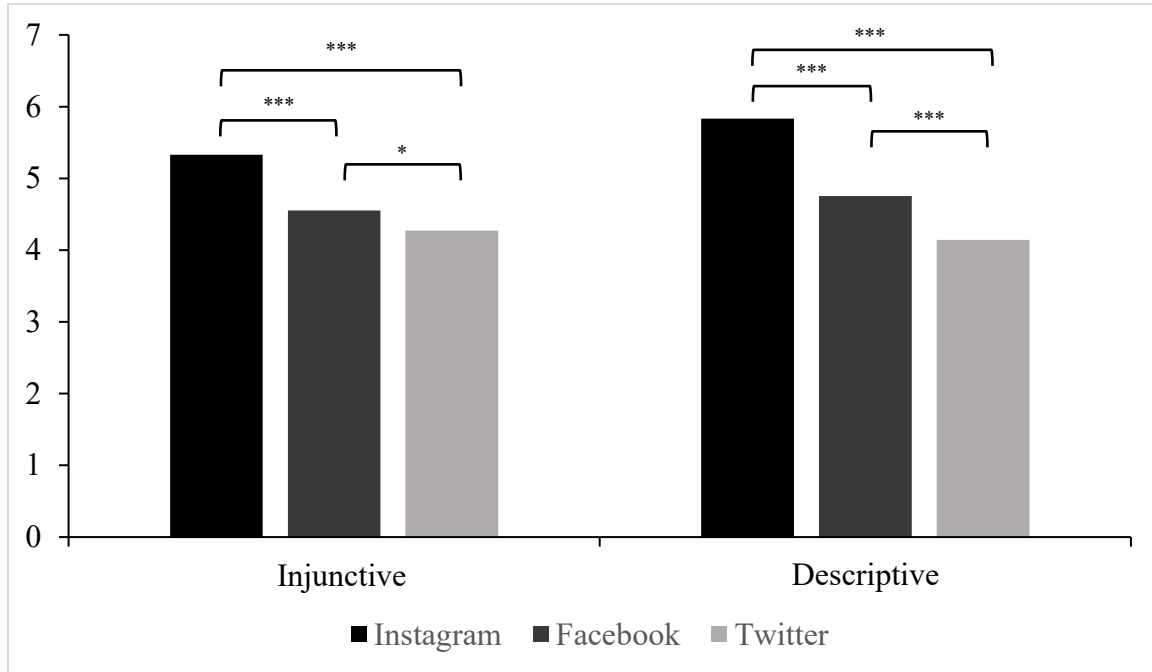


Figure 2

Emotional injunctive and descriptive norms by social media



Note. *** $p < .001$. * $p < .05$.

ⁱ It should be noted that the pilot study was conducted before the name change from “Twitter” to “X”. In doing so, we decided to leave “Twitter” when a study or the results were conducted before this change.

ⁱⁱ Gender is a nominal variable with four modalities: woman, man, non-binary and other gender identities. We grouped non-binary people with those with other gender identities since we had few participants in these categories, we then created two dummy variables with “woman” as the reference category.