

## Social Psychology

# Unveiling the Positivity Bias on Social Media: A Registered Experimental Study on Facebook, Instagram, and X

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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 used a mixed design to examine the positivity bias on Facebook, Instagram and Twitter/X. After recalling a personal event, 312 participants were randomly assigned to imagine telling this event to a group of friends and sharing it on social media (Facebook vs. Instagram vs. Twitter/X). Several characteristics were examined through repeated measures ANCOVAs including the texts' valence and the usage of emoji. Contrary to the pilot results, we found no significant differences in how events were reported. We, however, found significant differences between platforms. Specifically, messages posted on Twitter/X had a more negative valence than those posted on Instagram and Facebook. The positivity bias, often associated with social media, may therefore not necessarily represent a bias per se, but only a form of positive self-presentation that is consistent across contexts. These findings highlight the importance of focusing on platform characteristics, such as architecture, affordances, and socio-cultural context. This study advances our understanding of the positivity bias across multiple platforms through a pre-registered experimental approach.

### 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 (previously Twitter). In the subsequent section, we will delve deeper into our theoretical argument.

#### 1.1. The Positivity Bias on Social Media

##### 1.1.1. The Positivity Bias, a Form of Positive Self-Presentation

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).

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Social media impression management can be 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). This tendency towards positivity on social media can be rooted in a general desire for positive image and social approval (Pounders et al., 2016; Spottsworth & Hancock, 2016). Indeed, the *face theory* postulates that individuals strategically manage their self-presentation to maintain their social identity and uphold their reputation in the eyes of others (Goffman, 1959). However, while positive self-presentation is not exclusive to social media, these platforms tend to enhance and amplify it.

### **1.1.2. The Positivity Bias on Social Media, an Amplifying Context**

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 on social media. Firstly, these platforms offer users a level of control over self-presentation that surpasses real-life interactions (Merunková & Šlerka, 2019). A long line of research has shown that individuals can adapt their communication more easily in online environments, particularly as a result of asynchrony (Walther, 1996). Secondly, these platforms provide features that actively promote positivity, such as filters, and emoji. Emoji are small digital images used to express an idea, emotion, or concept in electronic communications. They can be used both as complementary cues in texts and as surrogates (Tandyomamanu & Tsuroyya, 2018). Emoji 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 (Spottsworth & Hancock, 2016).

However, one limitation in the literature is that research on positivity bias have primarily focused on Facebook alone (R. Lin & Utz, 2015; Spottsworth & 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 Twitter/X with 396.5 million users (Saquib, 2023). Although Facebook, Instagram, and Twitter/X are all classified as social media (El-

lison & 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., 2025).

### **1.2.1. Architecture**

Social media architecture refers to the underlying design and structural elements that govern functionalities, user interactions, and data flow within social media platforms. It includes various features that are crucial when examining the positivity bias (Bossetta, 2018). The most important is the connection mode, which pertains to the type of relationships that can be formed between users. Facebook operates on a bidirectional connection mode, where interactions occur mostly among users who are mutually recognized as "friends". This model promotes an intimate and reciprocal interaction environment, allowing users to control who sees their content (Vitak & Kim, 2014). In contrast, Instagram and Twitter/X employ a unidirectional connection mode, where one can follow another without requiring reciprocation. This type of connection fosters a dynamic where users often engage with a broader, less personal audience (Marwick & boyd, 2011). As a result, interactions on these platforms can be less about mutual exchange and more about broadcasting to followers, which may encourage users to present more curated, idealized versions of their lives to attract likes, shares, and new followers.

### **1.2.2. Affordances**

Affordances address not the objective features of platforms, but how users perceive them (boyd, 2010). They can be defined as "the perceived actual or imagined properties of social media, emerging through the relation of technological, social, and contextual, that enable and constrain specific uses of the platforms" (Ronzhyn et al., 2022, p. 3178). We suggest that two affordances are particularly relevant to positivity bias.

Visibility concerns the perceived degree of visibility of the published content (Treem & Leonardi, 2013). On Facebook, the visibility of content is generally lower compared to Instagram and Twitter/X due to its more enclosed, bidirectional nature. This might reduce the pressure to maintain a universally appealing image. In contrast, the higher visibility on Instagram and Twitter/X, driven by their unidirectional following system, amplifies the reach of posts and potentially the need to maintain a positive, attractive persona (Boczkowski et al., 2018).

Shareability pertains to the ease with which content can be shared across the platform and how suitable the content is perceived to be for different formats (Masciantonio et al., 2025). Facebook users often share a mix of text and images, which allows for more nuanced self-expression and personal storytelling (van Dijck, 2013). Instagram, being predominantly image-focused, encourages users to post visually appealing content, which often involves high levels of

stylization and impression management (Boczkowski et al., 2018). Twitter/X, known for its textual content, promotes brevity and wit, often leading to oversimplified or emphatic statements.

### 1.2.3. Socio-cultural Context

Finally, the last characteristic is the socio-cultural context (Masciantonio et al., 2025). 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/X and Facebook (Waterloo et al., 2018). These results are in line with sentiment analyses studies showing that Twitter/X posts are mainly related to negative content (Jiménez-Zafra et al., 2021; Naveed et al., 2011; Thelwall et al., 2011). Consequently, these socio-cultural norms can significantly amplify the positivity bias on platforms like Instagram and Facebook, as users adapt their content to align with platform-specific expectations. In contrast, the acceptance of more diverse emotional expressions on Twitter/X may help temper this bias, providing a more balanced portrayal of users' lives and perspectives.

## 2. The Present Research

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 in terms of architecture, affordances and socio-cultural context. For instance, on image-oriented platforms like Instagram, the positivity bias might be more pronounced. The opposite could be true on platforms like X, 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.

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 was pre-registered, meaning that the study's hypotheses, methodology, and analysis plan were reviewed and publicly documented prior to data collection through the Peer Community In Registered Reports (PCI RR) initiative, ensuring greater transparency and

rigor in the research process. The link to the Stage 1 recommendation can be accessed at: <https://rr.peercommunityin.org/articles/rec?id=666>. The link to the Stage 2 recommendation can be accessed at: <https://rr.peercommunityin.org/articles/rec?id=908>.

The University of Geneva's Committee for Ethical Research attested ethical aspects of the research (CUREG-2022-10-110).

## 3. Data Availability Statement

The coding manuals, data, and analyses scripts can be accessed at this link: <https://osf.io/akgdj/>.

## 4. Pilot Study

### 4.1. 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/X), and the dependent variables were the texts' valence and the number of emoji. This pilot study was designed to address three research questions<sup>1</sup>:

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

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

**Pilot 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:

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

### 4.2. Method

#### 4.2.1. 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 follow the experimental instructions ( $n = 22$ ). The final sample was composed of 279 participants: 218 women,

<sup>1</sup> Some of the research questions were revised during the registered report Stage 1 review.

48 men, seven non-binary individuals, one person with another gender identity, and five people who chose not to disclose ( $M_{age} = 20.83$ ,  $SD_{age} = 3.09$ ).

#### 4.2.2. 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/X).

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/X) 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 three 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.

#### 4.2.3. Measures

Participants were asked which device they conducted the study on. They were also asked how often they used Facebook, Instagram and Twitter/X 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/X] 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][Twitter/X] mainly...” (1 = very negative; 7 = very positive). Internal consistency was satisfactory for injunctive norms ( $\omega$  for Facebook = .94,  $\omega$  for Instagram = .89,  $\omega$  for Twitter/X = .92) as well as for descriptive norms ( $\omega$  for Facebook = .78,  $\omega$  for Instagram = .62,  $\omega$  for Twitter/X = .76).

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

### 4.3. Results

Analyses were conducted using JASP software version 0.16.4.0.

#### 4.3.1. Preliminary Analyses

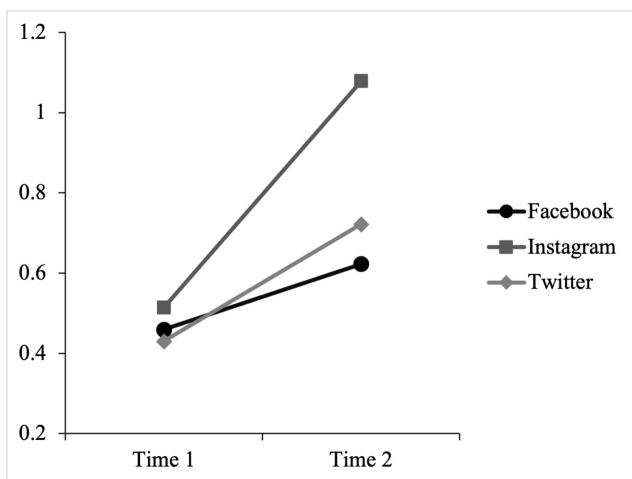
We performed a preliminary analysis to check the randomization. The valence of the text at time 1 did not differ significantly between the type of social media attributed at time 2,  $F(2, 276) = 0.04$ ,  $p = .959$ ,  $\eta^2 = 0.0003$ . We also found that the number of words at time 2, for texts written on social media, did not change between Facebook, Instagram and Twitter/X,  $F(2, 276) = 0.28$ ,  $p = .755$ ,  $\eta^2 = 0.002$ .

#### 4.3.2. The Positivity Bias on Social Media (Pilot RQ1 and Pilot 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) X 2 (Time: Narrative of the event vs. Narrative of the event on social media) repeated measures ANCOVA. We used as covariates age, gender<sup>2</sup>, 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 ( $p > .05$ ). The valence of texts at time 1 ( $M = 0.46$ ,  $SD = 1.58$ ) was less positive than

<sup>2</sup> Gender was 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.



**Figure 1. Text Valence at Time 1 and 2 by Social Media (Pilot Research)**

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/X ( $M = 0.72$ ,  $SD = 1.39$ ) and Facebook ( $M = 0.62$ ,  $SD = 1.44$ ). Pairwise comparisons with the Holm correction were, however, not significant ( $p.\text{adj} > .05$ ). The Cohen's d for the pairwise comparisons were  $d = -0.130$  for Facebook vs. Instagram,  $d = -0.102$  for Facebook vs. Twitter/X, and  $d = 0.028$  for Instagram vs. Twitter/X.

In reply to Pilot 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 answers negatively to Pilot RQ2.

#### 4.3.3. The Use of Emoji and the Positivity Bias (Pilot 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,  $F(2, 247) = 0.02$ ,  $p = .98$ ,  $\eta^2 < 0.001$ . 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 Pilot RQ3.

#### 4.3.4. Test of the Socio-Cultural Context on Social Media (Pilot RQ4)

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

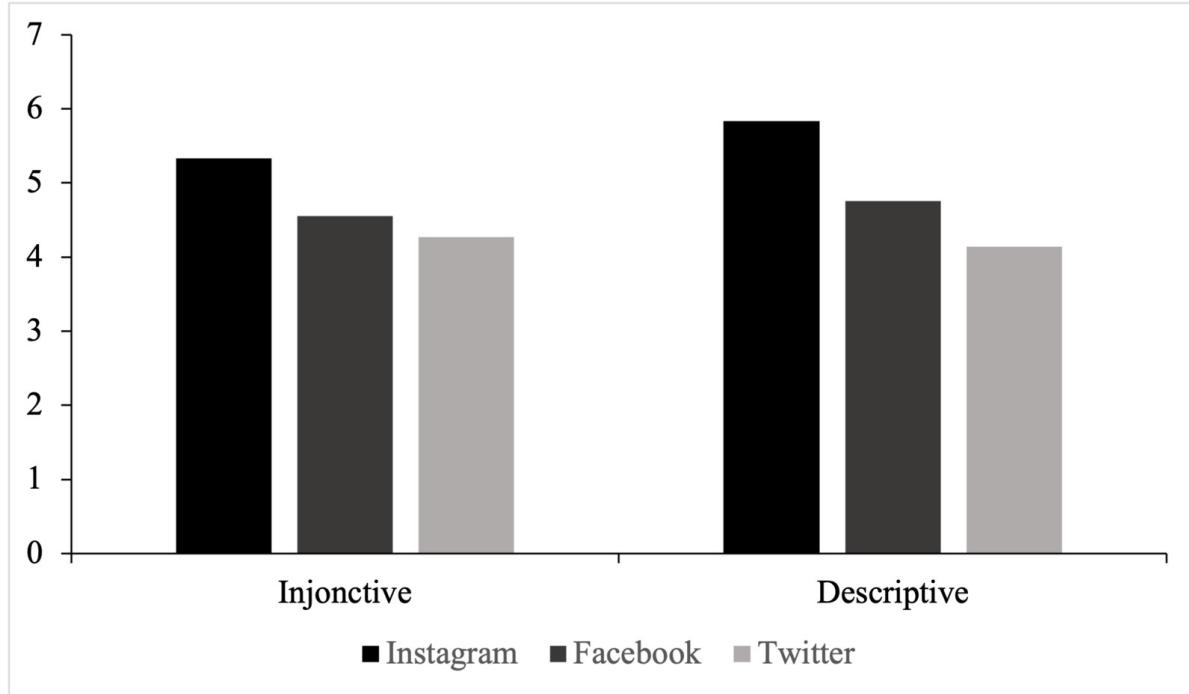
First, we have created a new variable depending on whether the event at time 1 was positive, negative or neutral. We then performed a chi-square to test the association between the text's valence at time 1 (positive vs. negative vs. neutral) and the question where participants could choose which of the three social media was most appropriate to share this event (Facebook vs. Instagram vs. Twitter/X). 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,  $\chi^2(4, N = 279) = 22.21$ ,  $p < .001$ ,  $V = .200$ . Regardless of valence, only 9.32% of the participants chose Facebook. Concerning Instagram and Twitter/X, 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,  $F(2, 132) = 40.179$ ,  $p < .001$ ,  $\eta^2 = .319$ . 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/X ( $p.\text{adj} < .05$ ). The Cohen's d for the pairwise comparisons for descriptive norms were  $d = -1.014$  for Facebook vs. Instagram,  $d = 0.573$  for Facebook vs. Twitter/X, and  $d = 1.588$  for Instagram vs. Twitter/X. For injunctive norms, Cohen's d were  $d = -0.572$  for Facebook vs. Instagram,  $d = 0.207$  for Facebook vs. Twitter/X, and  $d = 0.779$  for Instagram vs. Twitter/X.

Therefore, these analyses provide more information on the socio-cultural context of social media. The findings revealed that the norms for emotional expression do differ between Facebook, Instagram and Twitter/X (Pilot RQ4).

## 4.4. Discussion

The pilot study provides new empirical insights for the main research. Indeed, the results emphasized the positivity bias (Pilot 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 (Pilot RQ3). We also found no significant differences between the three platforms (Pilot RQ2). Still, the results revealed that the socio-cultural context differed between platforms (Pilot RQ4) (Masciantonio et al., 2025). Indeed, participants associated Instagram with more positive content than Twitter/X and Facebook, which is consistent with the literature (Waterloo et al., 2018).



**Figure 2. Emotional Injunctive and Descriptive Norms by Social Media (Pilot Research)**

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

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 or the video 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 network of individuals on Facebook, Instagram, and Twitter/X. 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.

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

## 5. Preregistered Main Research

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

### 5.1. Hypotheses and Research Question

The main research focused on understanding how the positivity bias manifests on social media and whether it varies depending on the type of 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., 2025). 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/X rather than on Instagram and Facebook, and conversely. Therefore, in line with the literature (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 Twitter/X and Facebook.
- H2b:** The posts' valence is more negative for Twitter/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. Similarly, the pilot study did not reveal any platform-specific differences in emoji use; nevertheless, the ability to accompany a post with a photo or video might influence emoji usage. We therefore additionally explored our previously stated research question:

- RQ:** Does positivity bias have an influence on emoji use?

## 5.2. Method

### 5.2.1. 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  $f = 0.216$ ). Based on these parameters, our power analysis for a repeated measures ANOVA indicated that we require at least 219 participants for Hypothesis 1 (within-subject effects), and 270 participants for Hypothesis 2 (interaction effects). Our study design is, therefore, statistically powered to detect an effect size of .21. If we observe an effect greater than .21, it will be informative, though not necessarily indicative of a meaningful effect. Conversely, if the effect size is less than .21, while we can rule out larger effects, smaller yet significant effects could still be theoretically and practically meaningful. To account for potential non-adherence to instructions by some participants, we also plan to oversample, aiming for a total of 350 participants.

In order to have an older and more gender-balanced sample, the data collection was conducted on the paid platform Prolific. First, a selection study was carried out to en-

sure that participants used the three social media (Facebook, Instagram, and Twitter/X) at least once a month to interact with users (post and/or comment). As pre-registered, as soon as 350 persons have completed the study in full, the collection was stopped. As with the pilot study, participants who did not follow the instructions were also removed from the study. The participant flow is presented in [Figure 3](#). The final sample consists of 312 participants, with 102 assigned to the Facebook condition, 108 to Instagram, and 102 to Twitter/X. The average age of participants was 31.23 years ( $SD = 9.74$ ), with 157 women, 149 men, and six participants identifying as another gender or opting not to disclose. The majority of participants were employed full-time ( $n = 225$ ), 42 were students, 18 were unemployed, and the rest reported being in other situations ( $n = 27$ ). On average, participants' frequency of use of Instagram was higher ( $M = 6.22$ ,  $SD = 1.27$ ) than their frequency of use of Facebook ( $M = 5.58$ ,  $SD = 1.76$ ) and Twitter/X ( $M = 5.42$ ,  $SD = 1.77$ ).

### 5.2.2. Experimental Manipulation

Regarding the experimental manipulation, as for the pilot study, the participants had to think about an event, but this time they were asked to write a text to describe it. The recalling instruction was 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 was added at the end: "Please choose an event that is not too much painful".

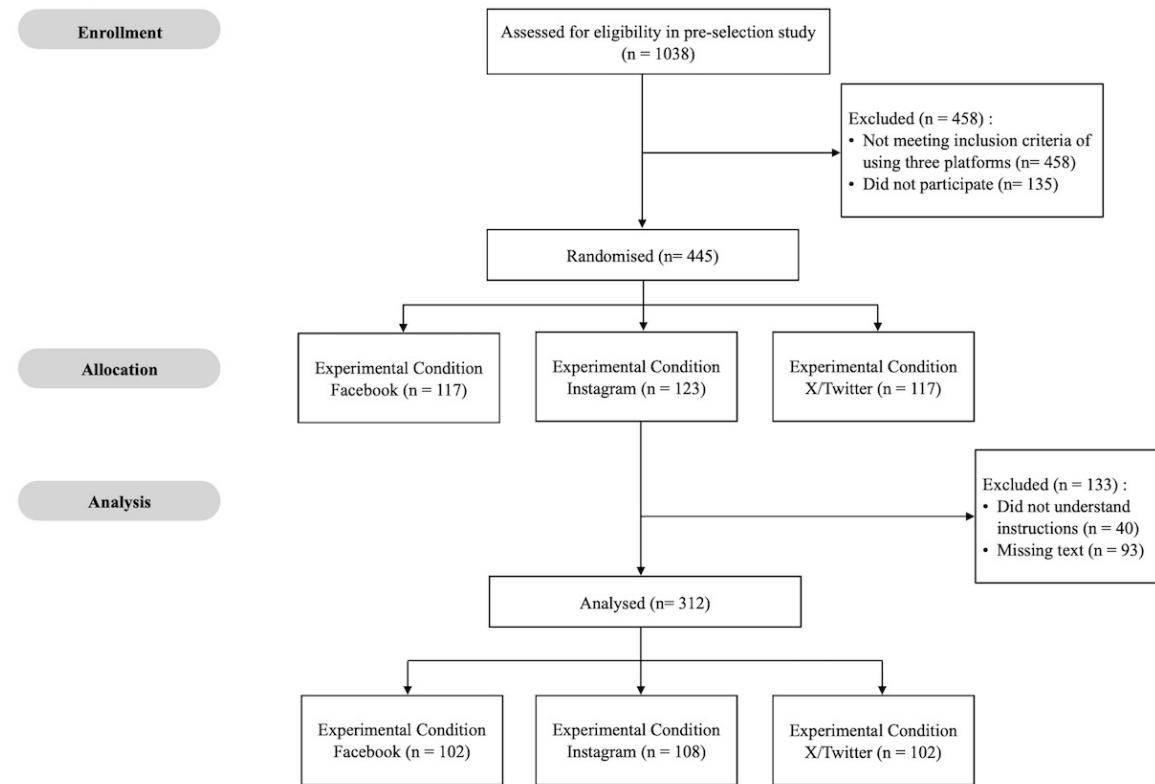
Participants were then randomly assigned to tell this event to a group of friends and to share it on social media (Facebook vs. Instagram vs. Twitter/X) using the Qualtrics platform. They were asked to "imagine sharing this event with a group of friends as if you were recounting it in person. Write down below what you would tell them, without thinking too much, naturally". In addition, for the social media conditions, they were asked to "imagine sharing this event on [Facebook][Instagram][Twitter/X]. Write a post below as you would in real life. Please note that this must be a post, and not a story.". To reflect the fact that Instagram is an image-oriented social media, they were also asked an optional question: "If you plan to use an image or a video to accompany this post, please describe it briefly here".

### 5.2.3. Measures

The measurement of frequencies of use of Facebook, Instagram, and Twitter/X were the same as the pilot study. We also asked participants on which devices they most often use social media (computer, tablet or smartphone). In addition, we added several measures, one concerning the number of relations on Facebook, Instagram and Twitter/X: "How many friends do you have on Facebook?", and "How many followers do you have on [Instagram][Twitter/X]". Another one regarding how well they know these relations in real life: "How well do you know your [Facebook][Instagram][Twitter/X] [friends][followers] in real life?" from 1

**Figure 3**

### *Participant Flow Diagram*



**Figure 3. Participants Flow (Main Research)**

(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 were counted. Three researchers analyzed qualitatively all the texts and image descriptions to estimate their valence on a 7-point scale (-3 = Very negative; 3 = Very positive). To assess inter-rater reliability, we calculated the Intra-Class Correlation Coefficient (ICC), which indicated a high level of agreement among the three coders for both the text and image evaluations (ICC = .75, 95% CI [.73; .77],  $F(944, 1888) = 10.11$ ,  $p < .001$ ).

### 5.3. Results

Analyses were conducted using R version 4.2.1. The study design template updated is presented in [Table 1](#).

### *5.3.1. Preliminary Analyses*

We did not find differences in the number of words between Facebook, Instagram and Twitter/X,  $F(2, 309) = 1.03$ ,  $p = .360$ ,  $\eta^2 = 0.007$ .

### **5.3.2. The Positivity Bias on Social Media (H1 and H2)**

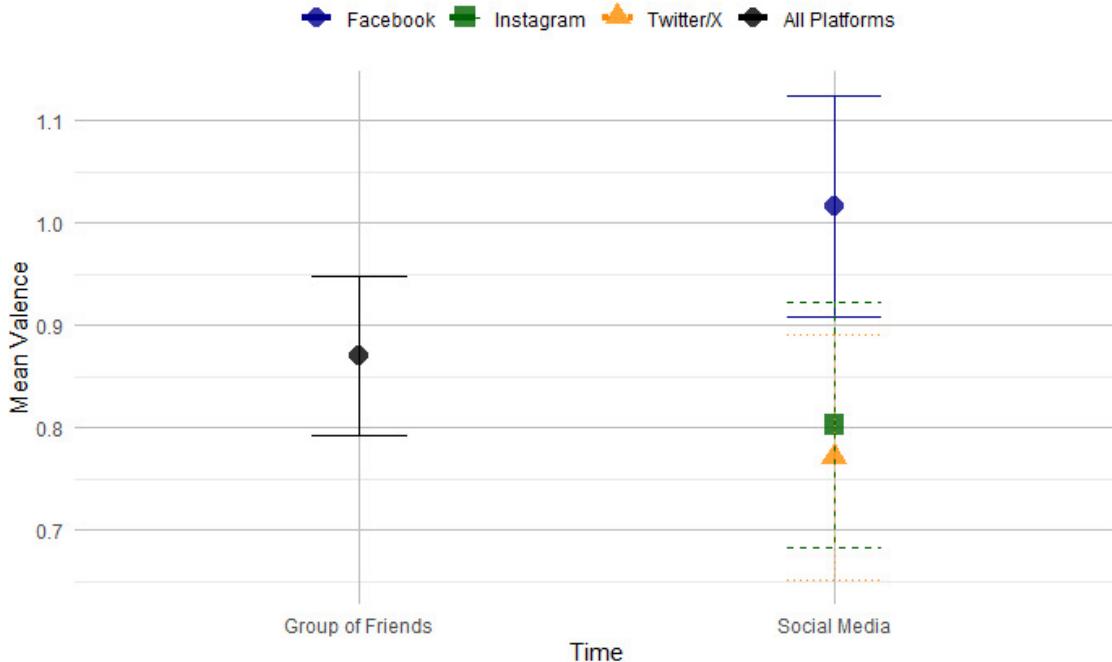
We examined the impact of social media type and time on the valence of texts using a 3 (Type of social media: Facebook vs. Instagram vs. Twitter/X) X 2 (Time: Narrative of the event to friends vs. Narrative of the event on social media) repeated measures ANCOVA. We used as covariates: frequency of use of Facebook, Instagram, and Twitter/X; number of connections on Facebook, Instagram, and Twitter/X; knowing these connections on Facebook, Instagram, and Twitter/X; age; and gender<sup>3</sup>. To test H2a and H2b, contrasts were planned in the direction of the hypotheses: Instagram versus Twitter/X and Facebook for H2a, and Twitter/X versus Instagram and Facebook for H2b.

As we can see in [Figure 4](#), the results did not reveal a significant main effect of time,  $F(1, 563) = 0.001, p = .982, \eta^2 = .010$ , nor of the interaction between time and social media,  $F(2, 563) = 0.436, p = .647, \eta^2 = .001$ . However, we found a significant main effect of the type of social media ( $F(2, 563) = 3.939, p = .020, \eta^2 < .001$ ). Regarding the contrasts, we did not find a significant effect of the first contrast (Instagram vs. other platforms),  $t(563) = 0.494, p = .622, d = .494$ ; but a significant effect was found for the second contrast (Twitter/X vs. other platforms),  $t(563) = -2.97, p = .003, d = -2.97$ .

<sup>3</sup> In the main research, gender was again treated as a dummy variable with "woman" as the reference category.

**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	Observed outcome
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) $\times$ 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.	We will reject H0 if the effect of time on valence is significant ( $p < 0.05$ ) and exceeds the size that the study was designed to detect ( $r > .21$ ). However, it is important to note that if a significant effect is observed with an effect size less than .21, we will not reject H1. Instead, we will interpret this as an indication that while larger effects are unlikely, smaller yet significant effects could still have theoretical and practical relevance.	Positivity Bias (Reinecke & Trepte, 2014).	H1 is disconfirmed
H2: The posts' valence is dependent on the social media.  H2a: The posts' valence is more positive for Instagram compared to Twitter/X and Facebook.  H2b: The posts' valence is more negative for Twitter/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 contrasts: <u>Instagram vs Others (H2a):</u> • Instagram: 1 • Twitter: -1/2 • Facebook: -1/2 <u>Twitter vs Others (H2b):</u> • Instagram: -1/2 • Twitter: 1 • Facebook: -1/2	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.	We will reject H0 for hypothesis 2 if the interaction between 'Type of social media' and 'Time' is significant ( $p < 0.05$ ) and exceeds the size that the study was designed to detect ( $r > .21$ ). However, it is important to note that if a significant interaction is observed with an effect size less than .21, we will not reject H2. Instead, we will interpret this as an indication that while larger interactions are unlikely, smaller yet significant interactions could still have theoretical and practical relevance. Furthermore, for hypotheses H2a and H2b, we will accept them if the specific contrasts within the interaction are significant ( $p < 0.05$ ).	Cross-platform approach (Masciantonio et al., 2025)	H2 is disconfirmed, although the second contrast was significant.



**Figure 4. Text Valence told to Friends and on Social Media (Main Research)**

This result suggests that Twitter/X's valence is lower than the average valence on Instagram and Facebook.

Among the covariates, the frequency of Facebook use ( $F(1, 563) = 4.20, p = .041, \eta^2 = .007$ ), the number of followers on Instagram ( $F(1, 563) = 4.70, p = .031, \eta^2 = .008$ ) and Twitter/X ( $F(1, 563) = 5.01, p = .026, \eta^2 = .008$ ), and the knowledge of followers on Twitter/X ( $F(1, 563) = 5.05, p = .025, \eta^2 = .008$ ) had a significant association with the texts' valence. To compare with the significant associations of the number of followers on Instagram and Twitter/X, the results for the number of followers on Facebook were  $F(1, 563) = 0.538, p = .463, \eta^2 < .001$ . Additionally, age was a significant positive predictor ( $F(1, 563) = 5.99, p = .015, \eta^2 = .010$ ), and gender showed a significant negative effect ( $F(1, 563) = 9.86, p = .002, \eta^2 = .016$ ), with women reporting higher valence ( $M = .99, SD = 1.16$ ) than men ( $M = .73, SD = 1.21$ ).

### 5.3.3. The Use of Emoji and the Positivity Bias (RQ)

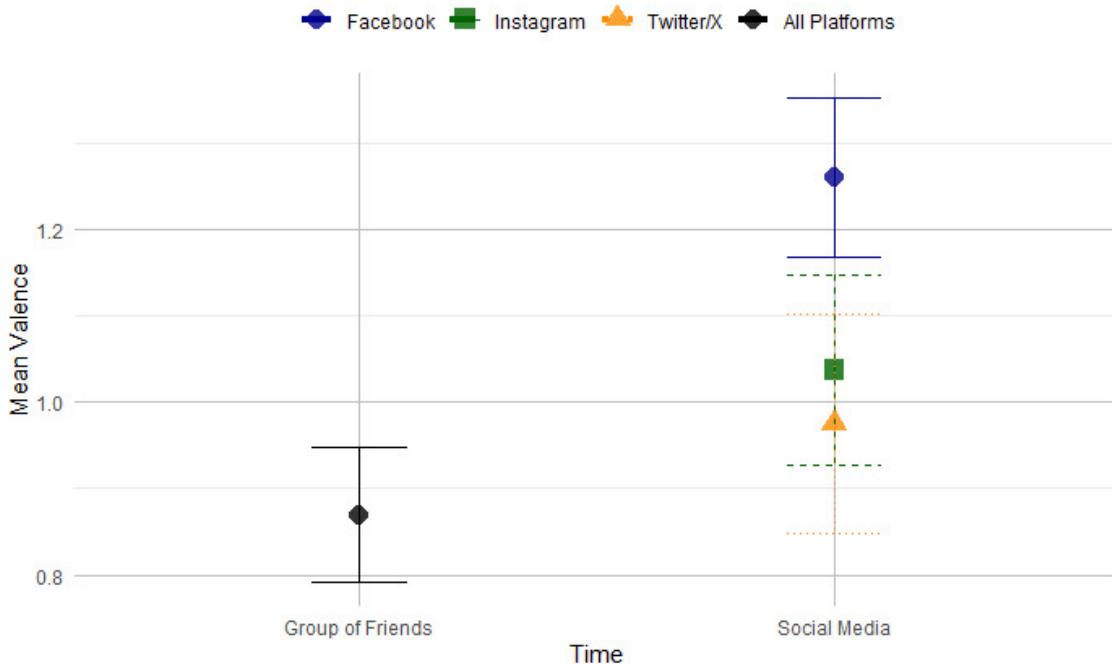
We checked that the number of emoji used varied across the social media platforms assigned to participants. We performed an ANCOVA with the same covariates mentioned previously. Results did not reveal a significant effect of the type of social media on the ratio number of emoji per word,  $F(2, 276) = 1.16, p = .316, \eta^2 = 0.007$ .

We then tested the association between the valence of the text at time 1 and the ratio number of emoji per word, but the results were non-significant;  $r(310) = -.001, p = .982$ . Finally, a multiple regression analysis was conducted to adjust for the previously mentioned covariates. The results were also non-significant;  $\beta = -.003, t(277) = -1.27, p = .205$ .

### 5.3.4. The Positivity Bias and the Use of Images (Exploratory Analyses)

First, using a chi-square test, we tested whether describing an image in addition to the text depended on the type of social media assigned to the participants (Facebook vs. Instagram vs. Twitter/X). The results showed a significant association between the type of social media platform and the description of an image;  $X^2(2, N = 301) = 8.76, p = .013, V = .15$ . Specifically, participants on Instagram (98 out of 103, 95.1%) were more likely to include an image description compared to those on Facebook (87 out of 99, 87.9%) and Twitter/X (81 out of 99, 81.8%).

We then used a 3 (Type of social media: Facebook vs. Instagram vs. Twitter/X) X 2 (Time: Narrative of the event to friends vs. Narrative of the event on social media) repeated measures ANCOVA. The same covariates and contrasts as those used in the analysis of texts' valence were applied. As we can see in Figure 5, the results did not reveal a significant interaction effect between time and social media,  $F(2, 521) = 0.172, p = .842, \eta^2 = .0006$ . We found a significant main effect of time on the valence of the images description,  $F(1, 521) = 4.078, p = .044, \eta^2 = .007$ , although it accounts for a relatively small portion of the variance in the data. Additionally, we found a significant main effect of the type of social media,  $F(2, 521) = 4.707, p = .009, \eta^2 = .020$ . Regarding the contrasts, no significant effect was found for the first contrast (Instagram vs. other platforms),  $t(521) = 0.380, p = .704, d = .380$ ; but a significant main effect was found for the second contrast (Twitter/X vs. other platforms),  $t(521) = -3.162, p = .002, d = -3.162$ . This result suggests that Twitter/X's image valence is lower than the average valence on Instagram and Facebook. Among the covariates, gender showed a significant negative effect ( $F(1,$



**Figure 5. Image Valence told to Friends and on Social Media (Main Research)**

$F(2, 521) = 14.949, p = .001, \eta^2 = .026$ , with women reporting higher valence of the image ( $M = 1.26, SD = .98$ ) than men ( $M = .89, SD = 1.25$ ).

### 5.3.5. Sensitivity Analysis

To assess the robustness of our findings, we conducted a sensitivity analysis that included only participants who indicated they would be willing to share the post they wrote on social media platforms (Facebook, Instagram, or Twitter/X). We again used a 3 (Type of social media: Facebook vs. Instagram vs. Twitter/X) X 2 (Time: Narrative of the event to friends vs. Narrative of the event on social media) repeated measures ANCOVA, as well as the same covariates used in the primary analysis (H1 and H2).

The model did not reveal a significant main effect of time ( $F(2, 447) = 0.907, p = .405, \eta^2 = .004$ ), nor a significant effect of the first contrast;  $t(447) = 1.333, p = .183, d = 1.332$ . However, consistent with the primary analysis, we found a significant negative effect for the second contrast (Twitter/X vs. Instagram and Facebook), suggesting that texts for Twitter/X had a lower valence compared to those for the other platforms;  $t(447) = -3.983, p = .001, d = -3.983$ .

Regarding covariates, knowing followers on Instagram ( $F(1, 447) = 5.602, p = .018, \eta^2 = .011$ ) and Twitter/X ( $F(1, 447) = 5.038, p = .025, \eta^2 = .013$ ) were significantly associated to the texts' valence. We also again found a significant effects of gender ( $F(1, 447) = 6.062, p = .014, \eta^2 = .012$ ) and age ( $F(1, 447) = 4.627, p = .032, \eta^2 = .009$ ).

## 5.4. Discussion

Our research aimed to test how the positivity bias manifests on social media and whether this bias varies depending on the type of social media platform used: Facebook,

Instagram and Twitter/X. To our knowledge, this is one of the first studies to experimentally examine how the positivity bias manifests across diverse social media platforms. Moreover, there is limited literature comparing this bias in real-life contexts versus on social media (Merunková & Šlerka, 2019). Finally, scholars have increasingly called for greater methodological rigor in media studies (Griffioen et al., 2020). In line with these calls, this research employed an experimental approach and was conducted as a registered report with a balanced gender sample and an older demographic. The findings revealed valuable insights into how the positivity bias operates on different social media platforms.

Contrary to our first hypothesis (H1), we did not observe significant differences in how events were recounted to a group of friends versus on social media. This is inconsistent with the pilot study. One possible explanation is that in the pilot study, participants described the event rather than recounting it to friends as they did in the pre-registered study. According to *face theory*, individuals tend to present themselves positively in real-life interactions (Goffman, 1959). Therefore, what is often referred to as a positivity bias on social media (Reinecke & Trepte, 2014; Spottswood & Hancock, 2016; Utz, 2011) may not necessarily represent a bias per se, but rather a consistent pattern of positive self-presentation and self-enhancement that occurs in both online and offline contexts. The literature findings may only reflect the increased control over self-presentation that social media conveys, compared to real-life interactions. On social media, users have access to features such as asynchronous communication (Walther, 1996), filters, and emoji (Novak et al., 2015), which allow for more curated self-presentation. In our study, participants were given equal control over how they presented themselves to friends and on

social media, which may have minimized differences in valence between these contexts. This emphasizes the importance of considering the degree of control individuals have in both online and offline communication environments.

In support of our second hypothesis (H2), we found significant and meaningful differences between platforms. Specifically, we were not able to confirm H2a, but in line with H2b, posts on Twitter/X had more negative valence than those on Instagram and Facebook. This aligns with existing literature on Twitter/X (Jiménez-Zafra et al., 2021; Naveed et al., 2011; Thelwall et al., 2011; Waterloo et al., 2018). From a positive presentation perspective, a large body of literature shows that Instagram and Facebook are used for self-presentation purposes (Alhabash & Ma, 2017), particularly Instagram (Sheldon & Bryant, 2016). Twitter/X, on the other hand, is primarily used for informational rather than social needs (Johnson & Yang, 2009). Another explanation could lie in the affordances of the platforms (boyd, 2010). As explained in the introduction, shareability pertains to how suitable the content is perceived to be for different formats (Masciantonio et al., 2025). Our results showed that participants assigned to Twitter/X decided to add an image 82% of the time, compared with 88% for Facebook and 95% for Instagram. But, this result may also be related to the architecture of the platforms (Bossetta, 2018). For example, we found that the number of followers on Instagram and Twitter/X was associated with a more positive valence, but we did not find a significant association for Facebook. This is a significant finding because it demonstrates that Instagram and Twitter/X's unidirectional mode of connection fosters less intimacy and reciprocity, which could increase the need for positive self-presentation. Doing so, this finding highlights an important point: rather than focusing solely on the platforms themselves, it may be more valuable to examine specific features of these platforms. While we found differences in our main study, some studies with other designs, such as opinion mining, did not reveal differences between platforms (Avalle et al., 2024). As we discussed in the introduction, platform architecture, affordances, and socio-cultural context are important aspects to consider (Masciantonio et al., 2025). By focusing on these platform-specific characteristics, like the connection mode, researchers can move beyond merely noting differences between platforms to understanding the underlying mechanisms driving these differences. Such insights are crucial for informing regulatory policies, particularly those related to digital platform regulation (e.g., see the recent Digital Services Act; European Commission, 2024).

Regarding our research question (RQ) on emoji use, we did not observe significant differences across platforms, mirroring the results of our pilot study. This finding contrasts with prior research suggesting that users consider posts with emoji to be easier to understand and more credible than messages without emoji or with an emoji inappropriate (Daniel & Camp, 2020), and messages featuring emoji are often perceived as more positive than those without (Novak et al., 2015). However, our results may suggest that positive self-presentation on social media does not necessarily translate into increased emoji use. One possible

explanation is that emoji usage may depend on the context: emoji might be more commonly used in private, interpersonal exchanges (e.g. Facebook Messenger) rather than in social media posts (e.g., Facebook) (Cherbonnier et al., 2024). Additionally, emoji may be integrated into language to complement rather than directly express emotions. Finally, users might also adhere to platform norms, using emoji selectively based on the expectations of the platform and the online community to which they belong. For example, Huang et al. (2022) have shown that the use of emoji is used as a sign of belonging to specific social circles on social media, helping to create boundaries between these circles. In this sense, emoji usage on social media may reflect broader emotional display norms, similar to those observed in face-to-face interactions.

Despite the contributions of this research, it has several limitations. First, it lacks ecological validity, a common issue in social media research (Griffioen et al., 2020). Specifically, the analysis of images presents challenges when comparing Instagram with Facebook or Twitter/X, as Instagram is inherently an image-centric platform. Furthermore, the temporal structure of our study contrasts with the typical post-creation process, where users often respond to immediate emotional stimuli rather than selecting an event from memory. However, by experimentally testing the positivity bias across platforms in a controlled setting, our study offers valuable insights into how individuals may filter or adjust their emotional expression when recounting past events. Although real-time emotional stimuli were not used, the controlled design allowed us to isolate the effects of platform-specific norms and features. Future studies could build on this work by employing more ecologically valid methods, such as analyzing real-time social media interactions or using longitudinal designs to capture how emotional expression evolves over time.

Second, we selected an expected effect size of .21 based on prior meta-analyses (Ruppel et al., 2017), as a benchmark for powering our analyses. This value was chosen because it represents a theoretically plausible effect size in this domain, given the limited availability of direct comparisons across platforms. However, we acknowledge that this does not constitute a strictly defined Smallest Effect Size of Interest (SESOI). Instead, it reflects an expected effect size that was used for practical purposes in determining our sample size. The main positive effect on Twitter/X valence aligns closely with this SESOI, suggesting that our observed effects are within the range we deemed theoretically interesting at the outset. However, the meaningfulness of effect sizes, particularly in the context of social media research, depends on several factors beyond the magnitude of the observed effect. Various mechanisms could amplify or counteract the importance of effect sizes, such as repetition and scaling-up mechanisms (Anvari et al., 2023). Repetition mechanisms suggest that while the observed difference between platforms may be small, it could have a more significant impact over time, given that individuals spend hours on social media each day. Similarly, scaling-up mechanisms could amplify the effect, as billions of people are impacted by social media use. On the other hand, coun-

teracting mechanisms, such as habituation (Anvari et al., 2023), may dampen the effects, particularly as users may become desensitized to positive self-presentation on social media. Future research should focus on clarifying these mechanisms in the context of social media use.

In conclusion, this research provides important insights into how self-presentation and positivity bias manifest across different social media platforms. While we did not observe significant differences in valence between events shared with friends and those posted on social media, this might be explained by the fact that our design gave participants the same degree of control in both conditions, which is not a reflection of real-life situations. Moreover, the significant variation in valence across platforms, particularly the more negative expression on Twitter/X, highlights the importance of considering platform-specific features when studying online behaviors. This research therefore contributes to the ongoing conversation about the role social media plays in influencing mental health and emotional expression. As social media technologies continue to evolve, future research should expand on the nature of these exchanges, exploring how different platform features and evolving social norms influence not only self-presentation but also broader social and psychological outcomes. Only by addressing these questions, we can in the long term improve our understanding of the impact of these platforms on individuals and society as a whole.

## Competing Interests

The authors have nothing to declare.

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## Contributions

Contributed to conception and design: AM, NH, AC

Contributed to acquisition of data: AM, NH, AC

Contributed to analysis and interpretation of data: AM, NH, AC

Drafted and/or revised the article: AM, NH, AC

Approved the submitted version for publication: AM, NH, AC

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### Peer Review Communication

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