Real-time assessment of motives for sharing and creating content among highly active Twitter users

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Abstract

What motivates people to share and create content online? In real time, we linked each of $N = 2,762$ individual posts (retweets and newly created content) with the self-reported motives from a sample of $N = 137$ highly active US Twitter users over the course of one week. We also captured their total activity of $N = 48,419$ posts over 10 weeks (March-May 2022). Our results reveal that sharing (retweeting) political content stemmed mostly from motives related to expression and identity. When creating content, participants were more likely to be motivated by the goals of informing and persuading others, for which they used negative language and expressed outrage. In contrast, entertaining content and positive language was used for socializing and attention. Original and political content featuring outrage and anger was more likely to be subsequently retweeted by others. These findings may denote adaptive strategies in the incentive structure of social media that rewards such content.

Introduction

Online—–and on social media in particular—content is to a large extent shared and created through self-organized behaviour. As a result, individual decisions to share and create various types of content can drive the overall spread of information, thereby collectively influencing societal opinion formation [1–3]. As a consequence, a question that is becoming increasingly important is: What motives are behind sharing and creating content, and do they link to expressions of outrage or negative emotionality?

While the sharing and creation of information has long been considered an integral part of cultural evolution beyond social media [4–6] their processes and roles have undergone considerable changes in the digital age [7, 8]. So far, there is little insight into why people choose to share or create certain content online. We therefore investigated in depth the motives of people who are very active on social media and how they relate to the modes of interaction on the platform and the content itself. We focused on Twitter (prior to its rebrand as X) and used the survey platform formr [9] to implement a novel paradigm for ecological momentary assessment (EMA) that connects actual behavior with small survey questionnaires in real time, using the Twitter API (see Fig. 1A for an illustration). Our sample of active U.S. Twitter users allowed us to quantify various aspects of the content creation and sharing process, such as the actual content being created and the extent to which it was subsequently shared by others.

Ideally, for public discourse and accurate opinion-formation, people would share and create information on social media primarily because they consider the information to be important and true and follow the seemingly rational motive of disseminating correct information. But sharing and creating information may be disconnected from accuracy [10] and may instead serve a variety of other goals and functions [11, 12]. Qualitative interviews have found a plethora of motives behind posting on social media, including social interaction, entertainment, and expressing one's opinion [13, 14]. Various surveys have found similar motives, including enjoyment, self-efficacy, social engagement, reputation-building [15], socializing and status seeking [16–21], and political engagement [22]. Moreover, sharing conspiracy theories specifically has been linked to motives such as fostering in-group beliefs and a need for chaos [23, 24].

Another line of research investigating the dynamics of content dissemination has made use of platform data. For instance, studies have found that posts that are moral–emotional [25, 26] or derogatory [27] tend to receive more engagement and shares (but see also [28]). In addition, controlled experiments have shown that emotional content [29] and interesting-if-true content [30] can lead to subsequent sharing. Similarly, antagonistic social content seems to provoke replies [31]. Yet none of these studies examined the specific motives driving users' behaviors.

Two recent studies did make the connection between motives and content. Namely, Osmundsen at al. linked survey data about motives with observational data from social media [32] and found that political polarization and pushing one's political agenda were the primary motives for sharing true as well as false news. However, motives were aggregated for individuals without examining whether different content was associated with different motives within individuals. Finally, another study, Marie and Petersen, that built on the same method and combined observational data with a controlled experiment suggested that posting on social media may be also driven by the desire to garner positive reactions from a politically like-minded audience. However, it is important to note that the experiments were based on hypothetical content and sharing intentions [33]. These studies show impressively how important the interplay of motives, content and context is, but do not yet reach the level of the individual posting decision in an ecologically valid setting.

In summary, the available evidence suggests a plethora of motives for information-sharing behavior on social media, comprising informational, social, and attention-directing goals. The connections between motives and actual online behavior, however, have rarely been studied. Past research has rarely taken into account that the motives for sharing and creating content on social media can depend on both context and content, and an individual may act on the basis of multiple motives. The existing evidence exhibits the strengths and weaknesses of each methodology. On one hand, retrospective surveys rely on participants' memory of past behaviors, and more controlled experimental studies rely on hypothetical rather than actual posting behaviors [33, 34]. On the other hand, observational data allow for measuring actual behavior, but the motivational drivers behind the behaviors are unknown. Combining ecologically valid digital trace data with self-reported survey responses on the level of individual posts therefore provides the best of both worlds [35, 36]. In addition, using EMA establishes a temporally closer link between behavior and self-report.

Our goal is to reveal and describe the multitude and complexity of the motives at play, as well as their context dependency. Understanding the motivational drivers behind posting behavior and the resulting dynamics is necessary for designing effective interventions and regulations for social media [12]. Although several behavioral interventions are based on the implicit assumption—supported by self-reports on the importance of accuracy [37]—that people share information on social media in order to accurately inform others [10, 38], other motives may play an important role (e.g., when sharing misinformation [39]).

In this study, we aim to understand motives behind active posting behavior on Twitter [40] by linking actual posts on Twitter with small survey questionnaires sent via private message in real-time response to each post (see Fig. 1A for an overview of the procedure; for a more detailed timeline and description see the Methods section and Fig. 5). We generally distinguish *sharing* content as retweets that merely forward an existing message and *creating* content as original tweets, quotes, and replies. By investigating actual posted content, we were able to not only connect participants' personal attributes with their motives, but also with the content and context of their individual posts. To analyze posts, we collected features from meta-data (e.g., number of followers, tweet type) and inferred others from the content itself using the ChatGPT API (e.g., topic, sentiment [41]; see Methods for details). This process resulted in three categories of variables: motives, person features, and content features (for details, see Methods and Fig. 1B). The Twitter API allowed us to automate our survey to react to activity and type of tweet in real time, gauging motives for sharing with almost no delay. We used this approach to investigate the following research questions: What are people's self-reported motives for creating content and sharing content on Twitter and how do they vary between and within individuals?

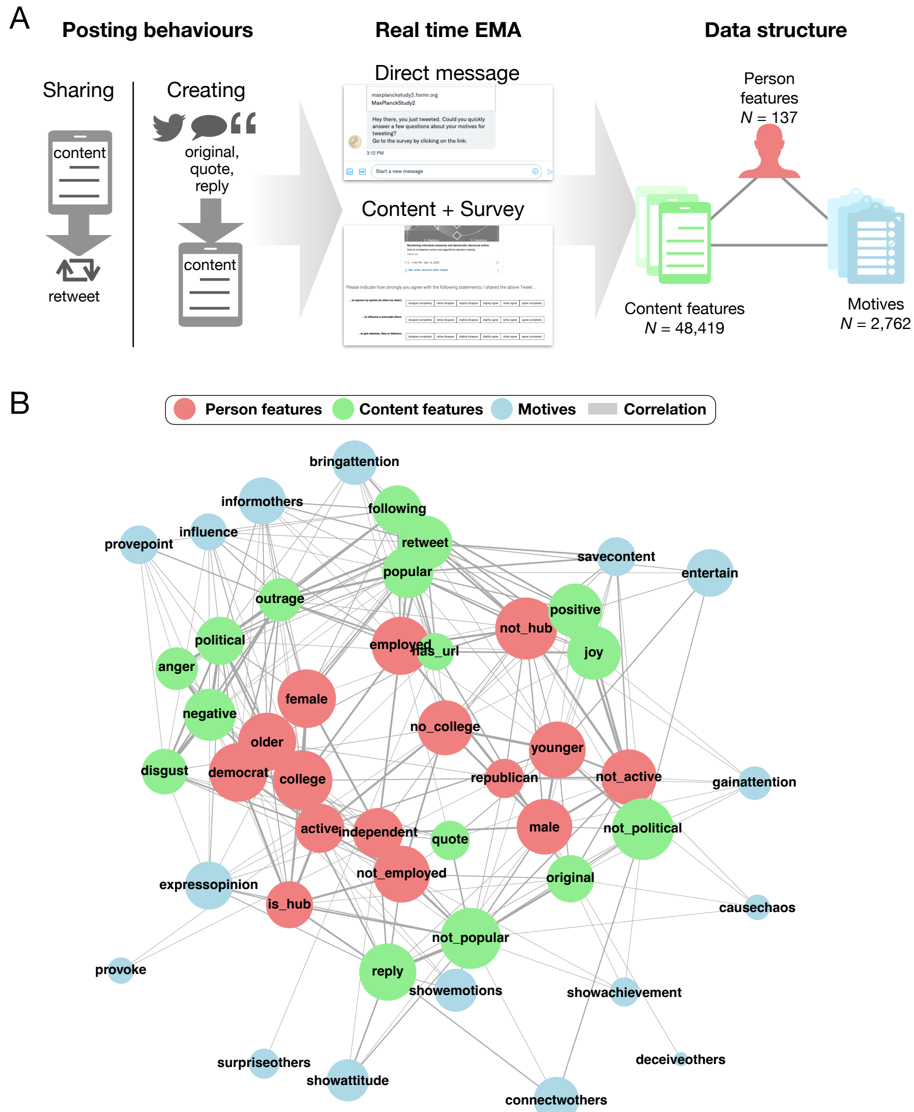

Figure 1: Overview of experimental setup, data structure, and correlational network of variables. **A:** General data-collection procedure for sharing and creating content. Shared content (content not created by the participant) is recorded via the API and a real-time survey about the motives for sharing it is sent via direct message. In the survey the respective content is repeated and the motive ratings are collected. The resulting three-dimensional data structure, where person features are collected once for each participant in the onboarding survey, motives are collected via multiple real-time survey for each post within the observation period (1 week), and content features are recorded from all content posted during the extended period (9 weeks). **B:** Network of positive Spearman's rank correlations between person features, content features, and motives. Weighted links represent the correlation coefficient within the $2,762$ posts recorded in the active period of data collection.

How do people's motives change depending on the type of post (retweet, original, quote, reply)? How are different content features associated with the motives behind sharing (retweets)? How are different motives associated with the features of content that is created (original tweets, quotes, replies)? And finally, how do these motives and associated content features relate to a post's success?

Results

We conducted an exploratory field study on Twitter over 10 weeks (March–May 2022) to assess people's motives for posting behavior in real time (see Methods for details). We used a stepped-wedge design to average out the influence of external events on posting behavior (see Fig. 5, top row). Participants were recruited in 10 waves, each consisting of 1 week of active data collection. Of the $n = 2,762$ posts collected, $n = 907$ were shared (retweets) and $n = 1,855$ were created (original tweets, quotes, and replies). Participants allowed us to collect their posts for 4 weeks before and 4 weeks after the active observation, resulting in a total of $n = 48,419$ posts (see Fig. 5 for an overview). Overall, this resulted in an average of 39 posts per participant per week. This rate puts our sample in the ballpark of the 10% most active Twitter users—who, as a group, are responsible for 96% of the content on the platform [43]. The behavior of highly active users is of particular interest, given that "supersharers" of misinformation fall in this category [44].

As an initial analysis and to provide an overview, Fig. 1C shows Spearman's rank correlations between all variables as a network visualization. The structure of the network suggests that motives cluster around features of content. For instance, motives related to informing and persuading were linked to political and negative content as well as retweets, while motives linked to expression and identity were more connected to original tweets and replies. Higher education and older age were more connected to political content and its associated motives, whereas younger age was more connected to nonpolitical content and motives related to socializing.

General Distributions of Motives

To examine the self-reported motives for content sharing and creation, we asked participants to indicate the extent to which each of 16 preselected motives (see the methods section for a full list) captured the motives behind their posting behavior. Fig. 2A shows their average motive ratings, separately for two time points: at the beginning of the study (onboarding survey) and in real time, after they had posted on Twitter (EMA). Participants rated the motives of expressing their opinion, connecting with others, drawing attention to a topic, and informing others as most important at both time points. The rank order of motives was fairly consistent between the retrospective and the real-time surveys, with some notable discrepancies. In real-time, motives consistently drew lower average levels of endorsement. Presumably, when reflecting on a specific tweet, participants identified a few motives and excluded the rest, whereas reflecting on their general tweeting behavior made them more likely to endorse multiple motives. In the onboarding survey, participants also seemed to underestimate the importance of motives related to expression and identity, while overestimating the importance of motives related to socializing and attention, relative to the EMAs. Correlations on the level of individual participants between the general and real-time motives were all positive, ranging from .18 (showing achievement) to .67 (deceiving others; see Supplementary Table 1). Lower correlations may have been due to memory error or to the observed week being unrepresentative.

A multilevel structural equation model of the 16 motive real-time ratings suggested that they could be subsumed into four categories (see Supplementary Material for details): motives related to informing and persuading others, to expression and identity, to socializing and attracting attention, and to provocation (see additional labels in Fig. 2). The correlation matrix in Supplementary Fig. 3 further supports the notion that there are clusters of motives at play.

Fig. 2B shows the distributions of the average ratings per participant over the real-time surveys, split by political views. Although the sample of Republican participants consistently gave lower agreement ratings than the samples of Democrats or Independents, the general patterns of agreement were largely similar between all groups. Agreement differences were largest for motives related to socializing and attracting attention, which were more important for Democrats, and for motives related to expression and identity, which were more important for both Independents and Democrats. The ratings of all three groups were similar for the motive of 'proving a point.' Other sociodemographic

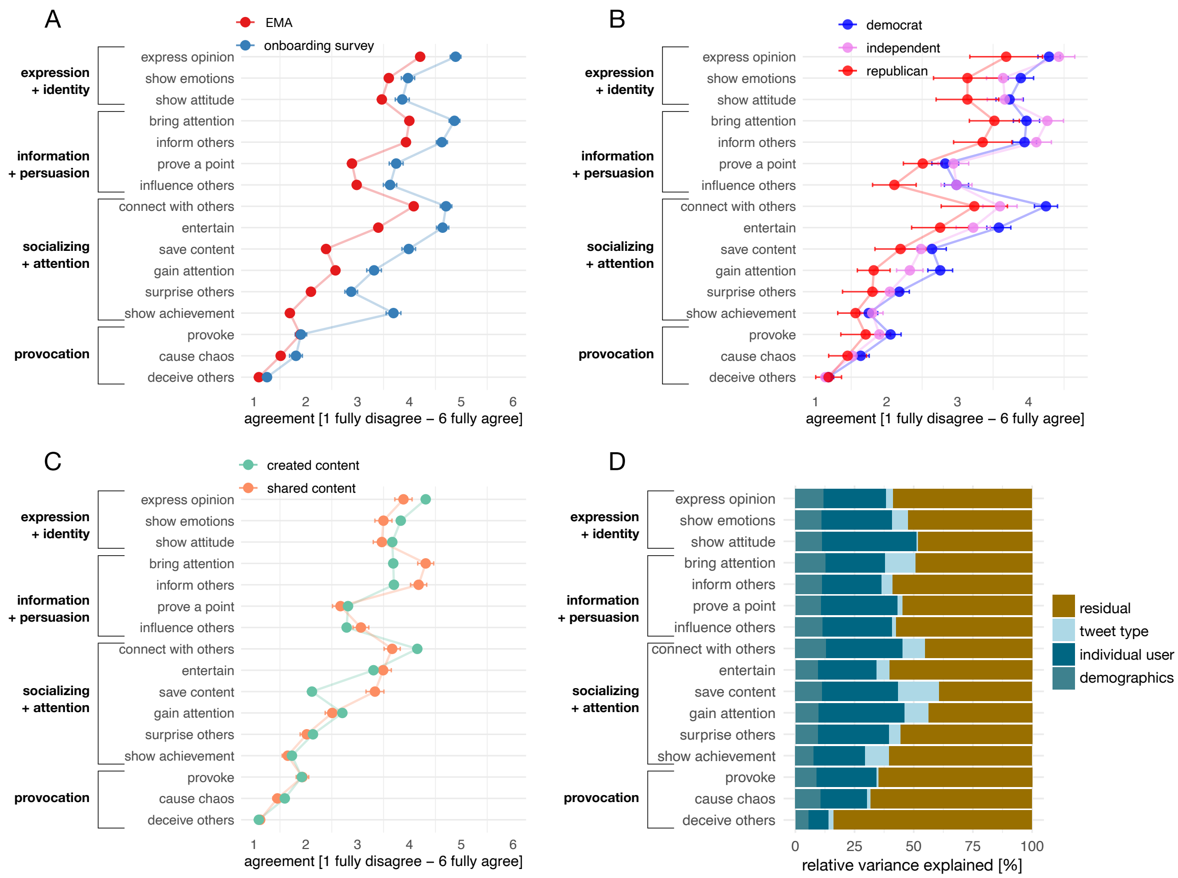

Figure 2: Person features and posting type and their relation to motives. **A:** Average agreement ratings for all 16 motives in the onboarding survey (blue) and for the per-participant averaged ratings over all their EMA real-time surveys (red). **B:** Distributions of average agreement ratings averaged for each participant over the real-time surveys, split across shared and created content. **C:** Distributions of average agreement ratings, split across Republicans, Democrats, and Independents. **D:** Explained variance R^2 [42] for the Bayesian regression model 1 for the model components: sociodemographic variables (age, political orientation, employment status, gender, and education), random intercept for each individual participant, type of tweet (original, retweet, quote, and reply), and the within-subject residual that remains unexplained.

variables did not yield large differences in the agreement distributions (see Supplementary Fig. 4). The most notable difference can be seen as a function of age: Younger participants agreed more strongly that they posted content for motives related to expression and identity, whereas older participants agreed more strongly that they posted for motives related to informing and persuading. Also, female participant agreed more strongly that they posted to 'show their emotions' than male participants, who identified more with the motive of 'showing their attitude'.

Motives for Sharing Versus Creating Content

We next examined whether motives for sharing or creating content differed. Fig. 2C shows the average motive ratings per participant, split between shared and created content. While the distributions of motives are similar, small differences can be discerned. Motives of information and persuasion were the dominant motives for sharing content, whereas motives related to expression and identity topped the list of motives to create content. In addition, compared to sharing content, creating content was more strongly associated with the motive of connecting with other. This suggests that, notwithstanding the similar motivational landscape, people create content more out of a desire for personal expression, and share content more to inform others and draw attention to issues.

These results also shed light on an important property of individuals' motivational repertoire: Participants invoked multiple motives, not just a single one. To analyze further how motives vary not only between, but within individuals, we conducted a simple linear regression model for each motive rating (model 1, see Methods for details). The model permits for variations via random intercepts for individual participants as well as for the type of tweet (retweet, original, quote, reply) and includes fixed effects for the following demographic variables: education, employment, age, gender, and political stance. We used the R^2 for Bayesian regression models [42] to calculate the relative contributions of the components of this model to the variance explained, for all 16 motive ratings in the real-time surveys. Fig. 2D shows that demographic variables only explained a small fraction of the variance in the data; individual differences unrelated to demographic variables accounted for a bigger part of the variance the model captures. However, for almost all motives the biggest part of variance was the within-participant residual that remained unexplained by the model. This suggests that other factors may shape people's motives for posting content on Twitter, although it should be noted that the residual also includes noise. This picture is corroborated by descriptive data in Supplementary Fig. 5, which shows the within-subject variability in the top-rated motives. On average, participants reported over five different motives within a week as being the most important for posting a particular content. Almost all participants had a clearly positive Shannon entropy of the distribution of motives they reported in that time, suggesting heterogeneity in an individual's motives over time.

Our approach also allowed us to consider a variety of content features of posts within participants. We collected several features of the content itself, namely, topic, sentiment, emotions being expressed, and the inclusion of an external URL. To consider social context, we collected the follower relationship between the original author of content that was retweeted by our participants. For original tweets, quotes, and replies, we collected the subsequent number of retweets our participants' posts received (see Methods for a full list of content features). Furthermore, when considering the connection between motives and content, the type of posting behavior is crucial [45]. For original tweets, quotes, and replies, motives can be conceptualized as triggers of the tweet's content. For retweets, however, the content in all likelihood triggers motives for sharing. To account for differences in the triggering process, we split the following analysis between pre-existing content that our participants shared (retweets) and content that they themselves created (original tweets, quotes, and replies).

Predictors of Sharing Motives

When someone retweets, they are sharing another person's content with their own followers. To investigate whether this choice is driven by a distinct set of motives, we focused on retweets only, annotated with motive ratings. This resulted in 907 data points that we used in the following linear regression model (in modified Wilkinson notation):

model 1: Predictors of sharing motives

```
motive_rating ~ outrage + category + sentiment + following + url_type + emotion + (1 | user)
```

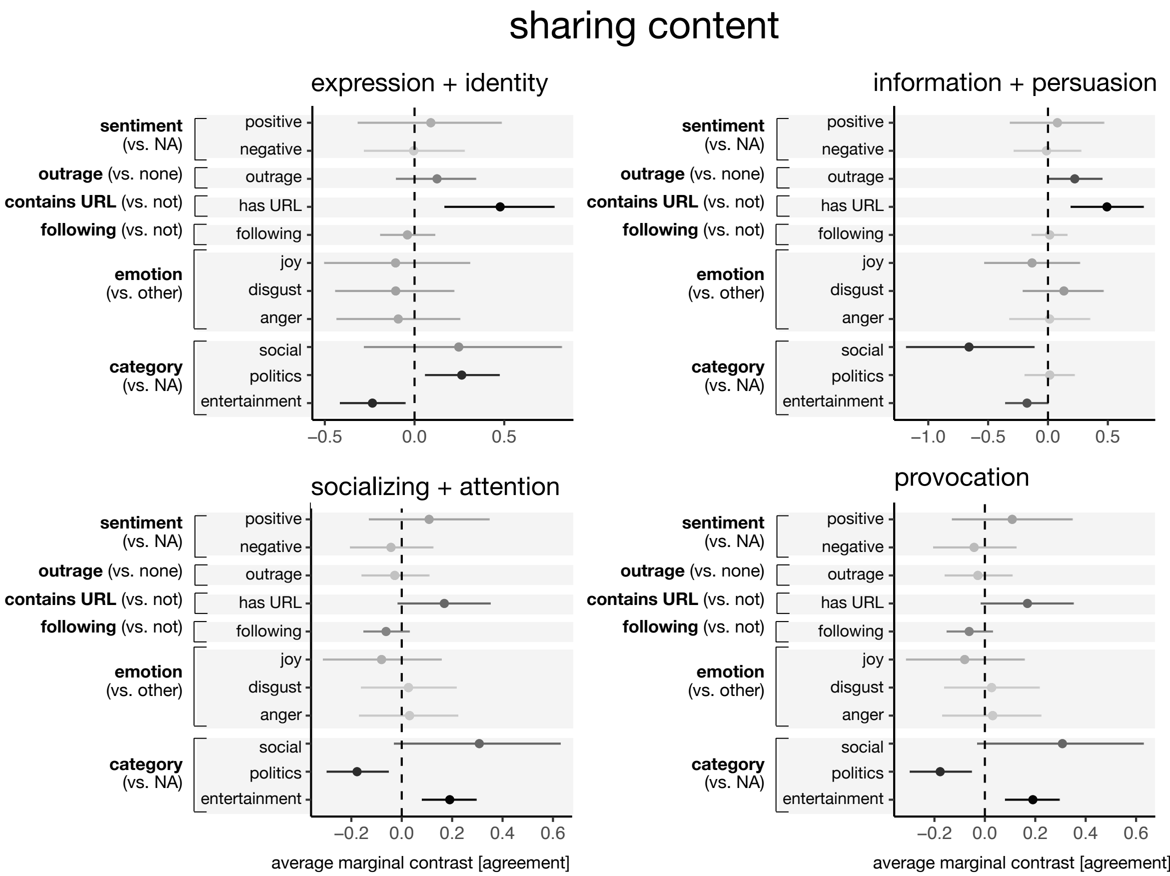

Figure 3: Marginal effect comparison of model estimates for content-feature variables on motive ratings for retweets only, using a linear regression model (see Methods for details). The four dependent variables are the averaged motive ratings of the factors determined by the factor analysis: expression and identity, informing and persuading, socializing and attention, and provocation. Independent variables and their levels are listed in the Methods section. Average marginal contrasts on the x-axes are shown in the units of ratings from the original Likert scale. Values describe the change in response to changing one of the predictor variables listed on the y-axes, relative to the baseline level listed in parentheses. Darker colors represent marginal contrasts further from zero and divided by the width of the confidence interval (95%).

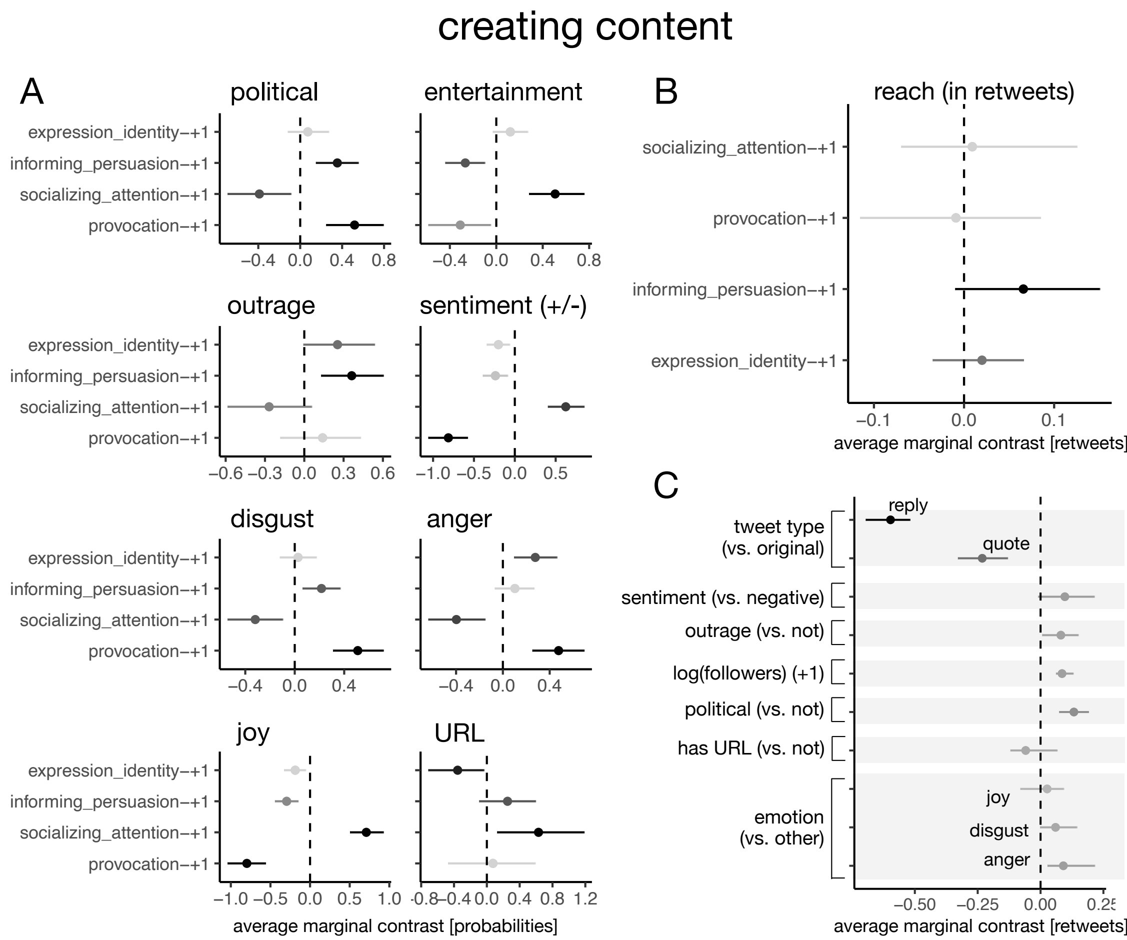

Figure 4: Marginal effect comparison of model estimates for content-feature variables of created (original tweets, replies, and quotes) posts. **A:** Results of the logistic regression model 2 for political and entertainment content, outrage, sentiment (coded negative to positive), the top three emotions, and presence of an external URL. **B:** Resulting marginal effects of the hurdle lognormal model 3 for subsequent retweets per category of motive. **C:** Resulting marginal contrasts from the hurdle lognormal model for the full sample of posts containing original content.

, where the dependent variables are the four categories of motive ratings: informing and persuading, expression and identity, socializing and attention, and provocation. Fig. 3 shows the resulting marginal contrasts of the content-level variables on motive ratings (expressed in their original units). The results reveal several associations. For example, the presence of external links was generally an important factor for retweeting across most motives, but in particular for motives related to expression and identity as well as to informing and persuading. Furthermore, political content was mostly shared for motives related to expression and identity, but not for motives related to socializing and attention or provocation. Outrage content was retweeted to inform and persuade. Content showing the emotions of joy, anger, and disgust, as well as positive sentiment, seemed to have no pronounced relationship with motives. Whether the tweet's original author was someone the participant followed also had no strong relationship with any motive.

In summary, a multitude of motives were at play when content was retweeted, and these motives varied depending on the content. Political content, negative content, and content expressing outrage was shared for motives that had a public-facing end, such as informing and persuading and expression and identity. Social motives were more closely linked to sharing entertainment content than political content.

Motives predicting Created Content

We used a different set of models to examine the association between motives and the content people create. In these models, content features are the dependent variable and motives are the predictors. This results in a set of logistic regression models, where `content_feature` is the dependent variable, entailing several binary variables (e.g., whether the content expresses outrage, whether it is political, whether the sentiment is positive or negative), while the four categories of motives represent the predictor variables:

model 2: Motives predicting created content

```
content_feature ~ expression_identity + informing_persuasion + socializing_attention +
    provocation + (1 | user)
```

Filtering the data for creation (original tweets, quotes, and replies) resulted in $1,855$ data points. They are the basis of our regression model. Fig. 4A shows the resulting marginal contrasts in units of probability (0 to 1), highlighting that different motives clearly predicted different created content. For example, when people are motivated by informing, persuading, or provoking, it was much more likely that they had written political content. Relatedly, when participants wanted to provoke others, it was much more likely that their created content contained negative emotions like disgust and anger. Content that expressed outrage was mostly created to inform and persuade others, as well as for motives related to expression and identity. For motives related to socializing and gaining attention, participants created mostly nonpolitical content and entertainment content, incorporating positive sentiment and language expressing joy.

Predictors of Retweet Success

Why do social media users resort to negative emotions and outrage when aiming to spread their message, express themselves, and signal their identity? One possibility is that users who are active and experienced on the platform have learned to take advantage of emotions when their goal is to increase the reach of their messages on Twitter [46]. Here we investigate this issue in more detail.

To model a tweet's success (i.e., the likelihood of it being retweeted and the number of retweets it receives), we used a hurdle lognormal model with the dependent variable being the number of retweets. Only a few motives related to informing and persuading others predicted retweet success (Fig. 4B). This resonates with the public-facing nature of those motives.

We used another hurdle lognormal model to examine which content features in the full dataset of original content from our sample of created posts ($32,870$ data points) predicted subsequent retweets:

model 3: Predictors of retweet success

```
number_retweets ~ outrage + political + sentiment + tweet_type + emotion + log_followers +
    (1 | user)
```

Resulting marginal contrasts are shown in Fig. 4C. Structural factors such as being a hub (i.e., having more than 3,000 followers) and being original content (vs. quotes or replies) led to more retweets, as did content that was political and expressed outrage or anger.

Discussion

The current study aimed to understand motives behind active posting behavior on Twitter. A number of studies have shed light on what motivates people to share and create content online. However, due to methodological limitations they could not directly connect motives with content. We took a novel approach that combined the real-time elicitation of motives via EMA with the actual behavior in question—namely, sharing or creating content—on the level of individual posts. We observed five key results.

First, we found that people have a large variety of motives when posting content, beyond simply informing others. This rich repertoire can be collapsed into four categories: expression and identity, informing and persuading, socializing and attention, and provocation. In our 1-week observational window, participants selected more than five different motives as the "most important," thereby demonstrating the broad array of motives underlying posting behavior.

Second, even though the distributions of motives behind sharing and creating content were not strikingly different, the motives that participants invoked most were: Motives related to identity and expression were ranked top for creation, whereas motives related to informing and persuading were ranked top for sharing.

Third, people shared political content primarily for the purposes of expression and identity, and less so to socialize or attract attention. By contrast, people created political content to inform, persuade, or provoke. When provocation was the driving force, negative emotions such as anger and disgust permeated the content, whereas when people's motivations were related to informing and persuading, outrage was commonly displayed. Anger, disgust, and outrage were also predictors of the success of a tweet, alongside the number of followers a person has and whether the content is political.

Fourth, for motives related to socializing and gaining attention, people mostly posted entertaining rather than political content. These motives also tend to be linked to joyful content and positive sentiment, possibly because such positive interactions foster bonding and in-group interactions.

Fifth, our results align with previous findings that older adults are generally more interested in news and visit more news sites [47] than younger people. In our sample, older participants reported being more strongly motivated by informing and persuading than younger participants, who were more strongly motivated by expression and identity.

Limitations of our study revolve around the limited number of participants we were able to recruit due to the long and laborious participation for each individual. However, as a trade-off, the design gave us access to many data points on the content level. Our study is therefore not as well powered to detect associations with demographic variables as it is for content features. In future studies, the observation period could be shortened in order to reduce the burden on each participant and thereby be able to involve more participants. This trade-off during recruitment also resulted in some deviations from the preregistration that mostly regarded the data portioning approaches, which were not feasible with our small sample (see https://osf.io/n7wfm; see Methods for a detailed description). Another limitation of the study is rooted in the current lack of a coherent conceptual framework of the types of behaviors we observed and their dependency on platforms' technical affordances [48]. We had to refine our research questions along different types of posts in order to accommodate a phenomenon we had initially overlooked: There are mechanistically different relationships between motives and content depending on whether the content is shared or created. Based on our insights, future studies could focus more specifically on those mechanistic differences.

The use of negative and outraging language (also observed in other studies [26, 27]) for motives related to informing and persuading can be understood as behavior adapted to a platform's affordances and incentives. The engagement-based algorithms that curate content on platforms like Twitter have been shown to favor emotionally charged content [49], thereby increasing its reach. We believe that the negative language and outrage we observed may be a technique people use to reach their goal of spreading their message further. Using negative and outraging language may well be a strategy that our participants have learned through reward learning, with social feedback as the reward [46, 50]. It seems to work: Content that is created with the goal of informing and persuading others does receive more retweets than content created for other motives. Given that our sample belonged to the small group of highly active (and likely experienced) Twitter users, those results may be indicative of how the platform incentivizes the creation of such content by favoring it with social feedback and algorithmic selection.

Motives related to socializing also influence people's posting behavior. The clear differences between content posted for motives related to socializing and content posted for motives related to informing align with previous findings on the general differences between broadcasting versus narrowcasting [51]. Retweets geared at informing others and bringing attention to a topic represent broadcasting; these include more critical and political content. Replies, on the other hand, represent narrowcasting; in our study, these contained less political content and more positive language, and were posted for motives related to socializing.

In sum, our results confirm that motives vary on the level of individual tweets, and show how motives may drive people to share negative and outraging content. Our findings also highlight the importance of designing online environments that do not favor this potentially divisive content [52], of implementing interventions against sharing misinformation that shift people's motives further towards accuracy [53], and of employing algorithms that maximize metrics other than pure engagement [54, 55]. The interplay of motives, content, and platform affordances should be taken into account in all efforts to understand and improve public discourse online.

Methods

We recruited 195 consenting participants through Twitter advertisements in four different campaigns, each aimed at balancing age and gender. A total of $N = 137$ participants followed through the whole 1-week observation period and were actively tweeting during that time (see Supplementary Fig. 2 for a description of the sample).

The anonymized data (excluding the original text of posts, user names, exact timestamps, and other details; but including relevant derived content features, e.g., sentiment, topic, number of retweets) can be found at https://osf.io/gqfjs/ alongside the preprocessing and all analysis scripts. We used the survey platform formr [9] to implement an event-driven experience sampling approach during the active observation time, when our participants' Twitter accounts were continuously and automatically monitored. Within 2 minutes of tweeting during their 1-week period of observation, participants received a direct message containing a link to a short survey. The survey displayed the tweet that had just been posted and asked participants about their agreement with 16 statements, each corresponding to one motive for posting that content. The average response rate for the real-time surveys was 67%. See Fig. 5 for the detailed participant timeline, Supplementary Fig. 1 for screenshots of the procedure, and Supplementary Fig. 2 for details on the sample. The resulting data structure consisted of observational data of participants' activity on Twitter, including posts from before and after the active observation period, as well as survey-based data on their demographic and political variables and their self-reported general motives for sharing content on Twitter.

Our original preregistered research questions—which we needed to subsequently refine—were:

- RQ1: What are the main self-reported motives for sharing information on Twitter and how do they vary within and between individuals?
- RQ2: How do these self-reported motives differ for the type of content (e.g., web domain, topic, sentiment) being shared, its context (e.g., popularity, original author), and the type of sharing (tweet, retweet, quote tweet, reply)?
- RQ3: How does sharing behavior change if participants are repeatedly prompted to reflect on their motives for sharing content on Twitter?

To:

- What are people's self-reported motives for creating content and sharing content on Twitter and how do they vary between and within individuals?
- How do people's motives change depending on the type of post (retweet, original, quote, reply)?
- How are different content features associated with the motives behind sharing (retweets)?
- How are different motives associated with the features of content that is created (original tweets, quotes, replies)?
- How do these motives and associated content features relate to a post's success?

The preregistered data partitioning was not feasible due to smaller than expected sample sizes and the exploratory research questions. This combination did not allow for developing an analysis pipeline of a (very small) subset of the data, as further steps depended on the results in our inherently exploratory approach. Without explicit hypothesis, we needed the full data set for identifying the most important relationships in the data.

Preprocessing Pipeline

All preprocessing steps can be found in the 'Make public data' script at https://github.com/philipplorenz/real_time_motives.

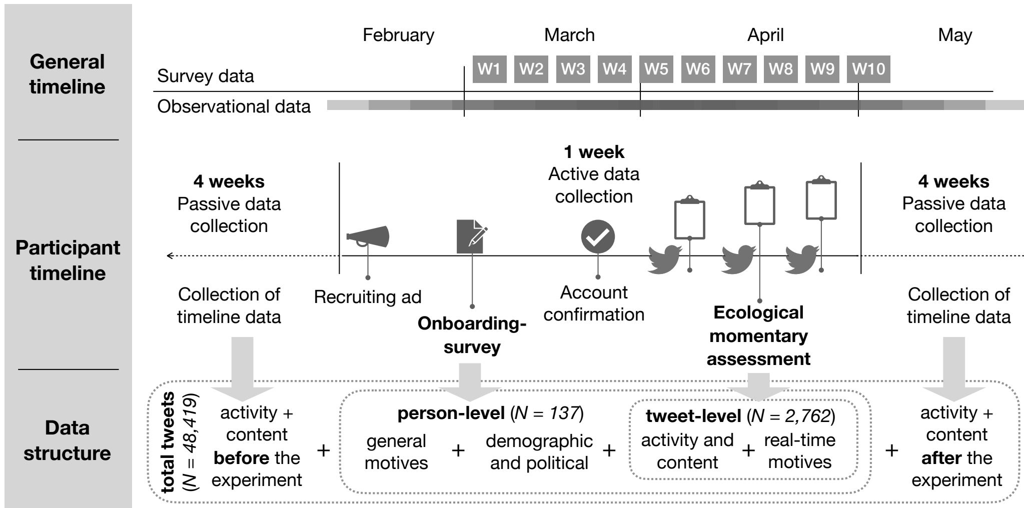

Figure 5: Overview of the study timeline and setup. The general timeline included 10 waves of recruitment in a stepped-wedge design. The participant timeline spanned 4 weeks of passive data collection (after consent, collected in hindsight via the API), 1 week of active data collection (including recruitment via advertisement, the onboarding survey, and the real-time surveys automatically triggered through the API by on-platform activity), and another 4 weeks of passive data collection. The resulting nested data structure from all phases of the study is shown in the bottom row.

Variables Collected

Participants were asked to rate their agreement with the statement "I shared the above tweet ..." followed by 16 predefined motives on a 6-point Likert scale ("strongly agree" to "strongly disagree") derived from the literature [11, 13–23, 25, 29, 30, 32, 56, 57]. The following 16 items were presented in randomized order:

- to inform.
- to entertain.
- to express my opinion (to share my views)
- to provoke others.
- to save the content to my timeline.
- to show my emotions.
- to connect with others (start a conversation).
- to show an achievement.
- to show my attitude.
- to deceive others.
- to gain attention, likes, or followers.
- to prove a point.
- to cause chaos.
- to bring attention to the topic.
- to influence or persuade others.
- to surprise.

We collected the following participant features through the onboarding survey and the Twitter API:

- age
- gender (male, female, other)
- political affiliation (Democrat, Republican, Independent)
- education (no college degree, some college degree or higher)
- employment status (full- or part-time employment; not employed, including students and others)
- number of followers (hub = more than 3,000 followers; no hub = fewer than 3,000 followers)
- activity on Twitter (active = more than 10 posts per day; not active = fewer than 10 posts per day).

We also collected features of individual posts:

- tweet type (original, retweet, quote tweet, reply)
- URL types (entertainment, mainstream news, alternative news)
- number of retweets (number).

Content Coding With ChatGPT

For summaries of the content itself we used a simple ChatGPT pipeline, which can be found in the preprocessing script (https://github.com/philipplorenz/real_time_motives), including all exact prompts. We used this method to infer the following features of individual posts from the text:

- topic (political, social, entertainment, others)
- sentiment (positive, negative)
- outrage (present, not present)
- emotion (anger, joy, disgust, other)

The results were cross-checked with a human coder (100 random posts) who received the exact same instructions. The interrater reliability was 0.72 for sentiment, 0.76 for outrage, 0.77 for political vs. not and 0.46 for the type of emotion.

Reactivity to EMAs

Another unique feature of our dataset is the data we were able collect historically through the API, which had been created by participants even before they joined the study. With participant consent, we collected data from 4 weeks of their timeline both before and after the study. This allowed us to quantify whether and how participants changed their behavior during and after our study. Fig. 6A shows the descriptive results and indicates that slightly fewer original tweets, quotes, and replies were created during the study period than prior to it. This change in behavior could be due to the feeling of being observed (especially given the direct messages they received after each tweet). Participants may also have tweeted less so as to avoid the burden of responding to more real-time surveys. The results of modelling different content features as dependent on the study period (before, during, and after the active observation period) indicate that the type of content did not change credibly during our study (Fig. 6B). Slightly more negative sentiment, outrage, and disgust were observed after the study, but this could also be due to exogenous events that were not averaged out by the stepped-wedge design.

Data availability: The data is stripped of details that would make it possible to re-identify participants in terms of user names, original text, or exact timing. All individual data points, including all variables used in this manuscript, can be found at https://github.com/philipplorenz/real_time_motives.

Code availability: All code used for preprocessing and anonymizing the data, as well as for analysis and plotting, can be found at https://github.com/philipplorenz/real_time_motives.

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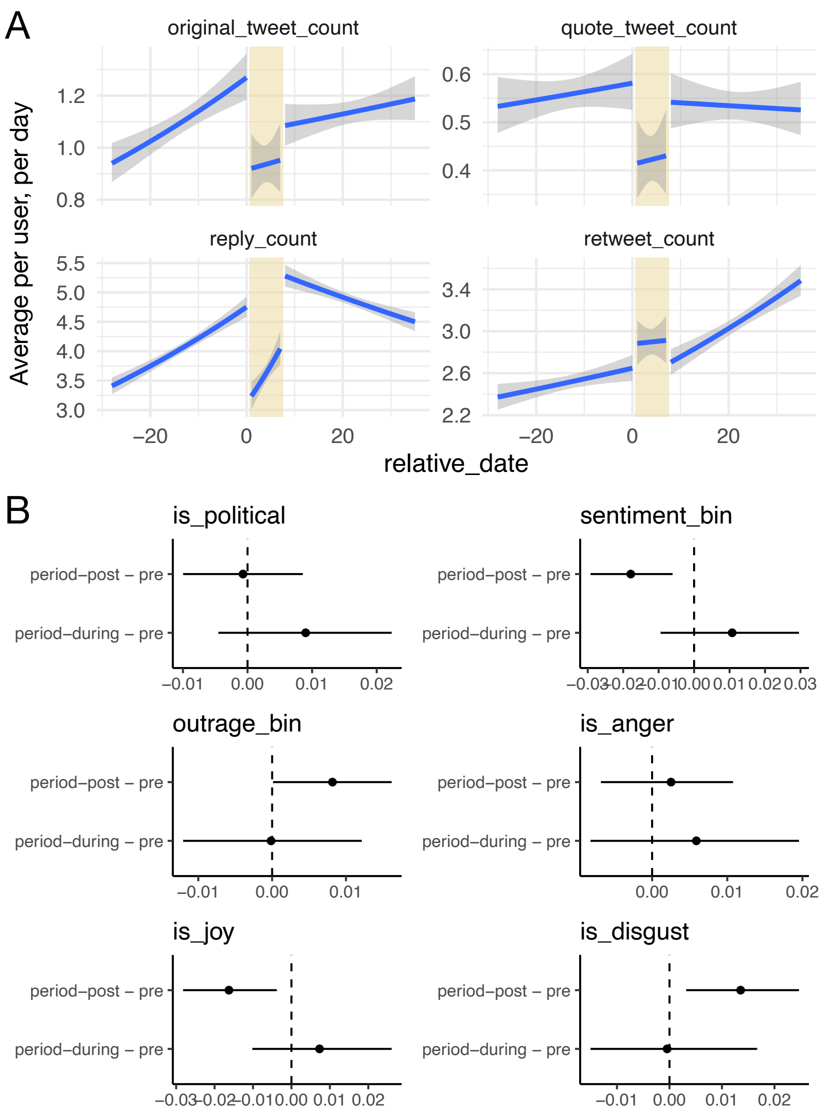

Figure 6: Reactivity analysis to the ecological momentary assessment (EMA) approach. **A:** Descriptive average activities per user, per day, of the different types of posting behavior: retweet, original, quote, and reply. **B:** Resulting marginal contrasts in units of probability (0–1) of the logistic regression model `content_feature ~ period + (1 | user)`, with ‘period’ representing a categorical variable that distinguished between pre-, during, and post-EMA treatment.

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Author Contributions: Conceptualization: P.L.-S., A.K., B.S.-T., M.G., S.M.H., and R.H. Data curation: P.L.-S. Formal analysis: P.L.-S., R.C.A., and S.M.H. Funding acquisition: S.M.H. and R.H. Investigation: P.L.-S. Methodology: P.L.-S., R.C.A., A.K., B.S.-T., and S.M.H. Project administration: P.L.-S. Software: R.C.A. Supervision: S.M.H. and R.H. Visualization: P.L.-S., R.C.A., and S.M.H. Writing - original draft: P.L.-S. Writing - review & editing: P.L.-S., R.C.A., A.K., B.S.-T., M.G., S.M.H., and R.H.

Ethics Declaration: Informed consent was obtained from all participants, and the study was conducted in accordance with relevant guidelines and regulations. The Institutional Review Board of the Max Planck Institute for Human Development approved the study

Competing Interests Statement: The authors declare no competing interests.

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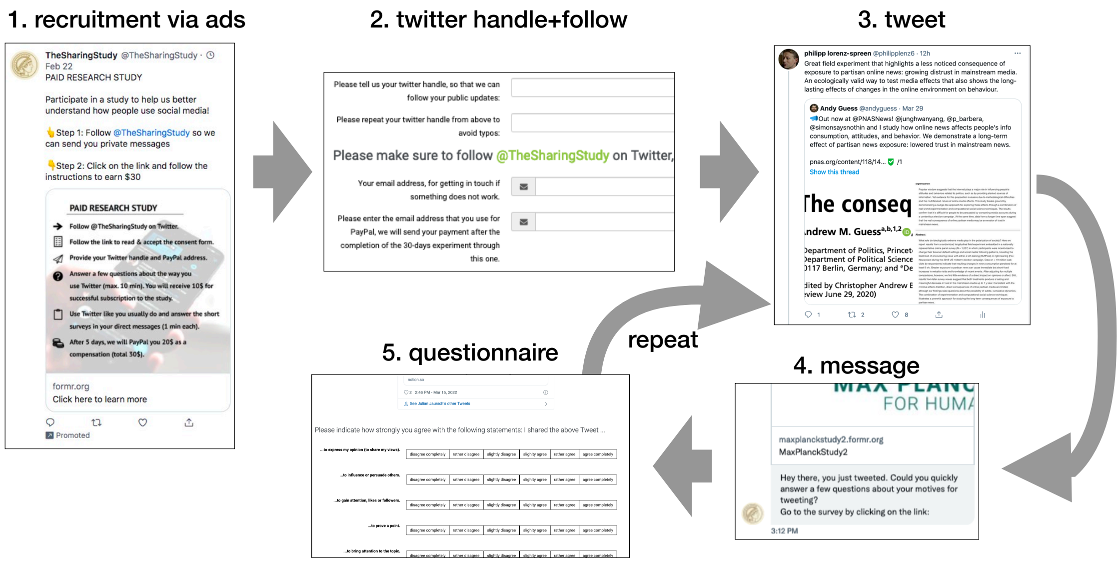
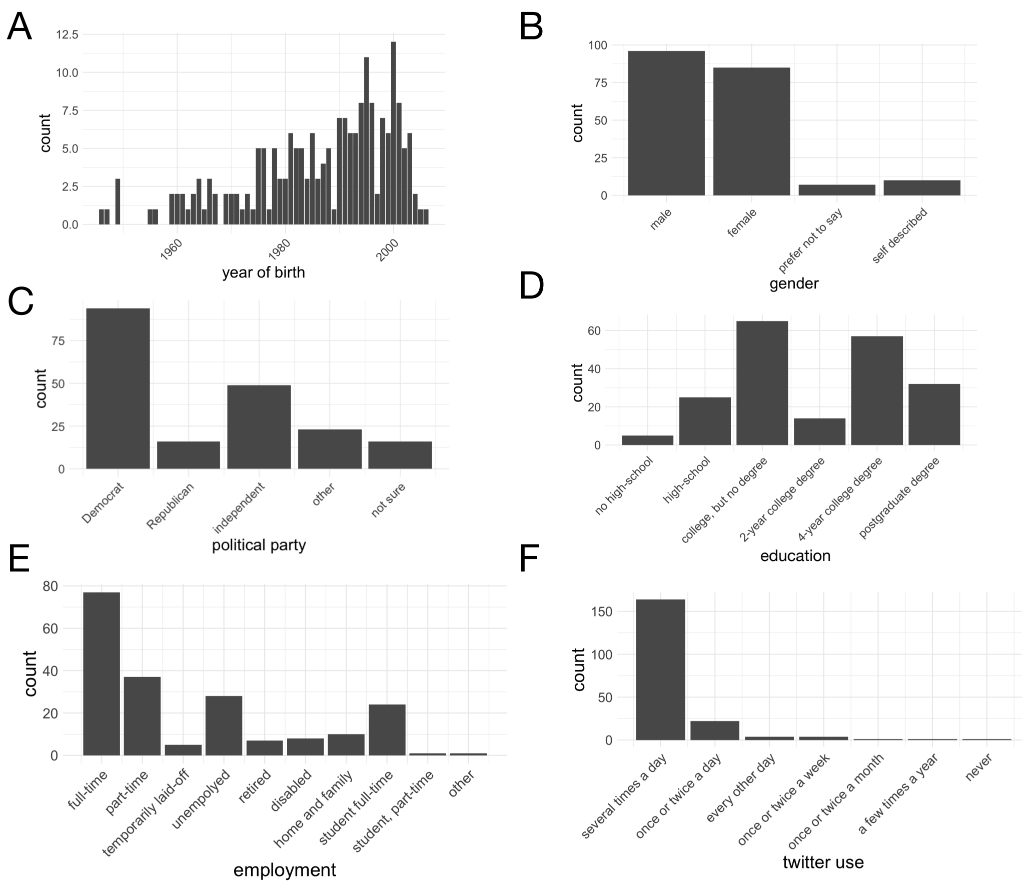
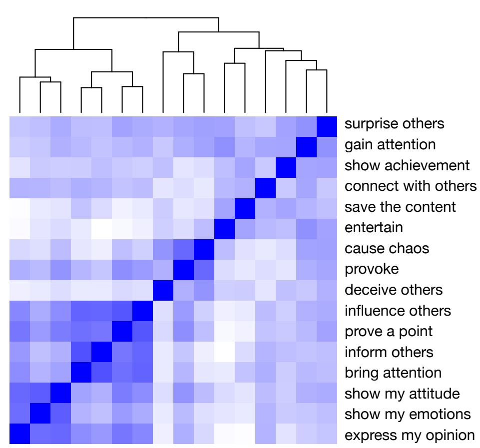
Supplementary Material for "Real-time assessment of motives for sharing and creating content among highly active Twitter users"



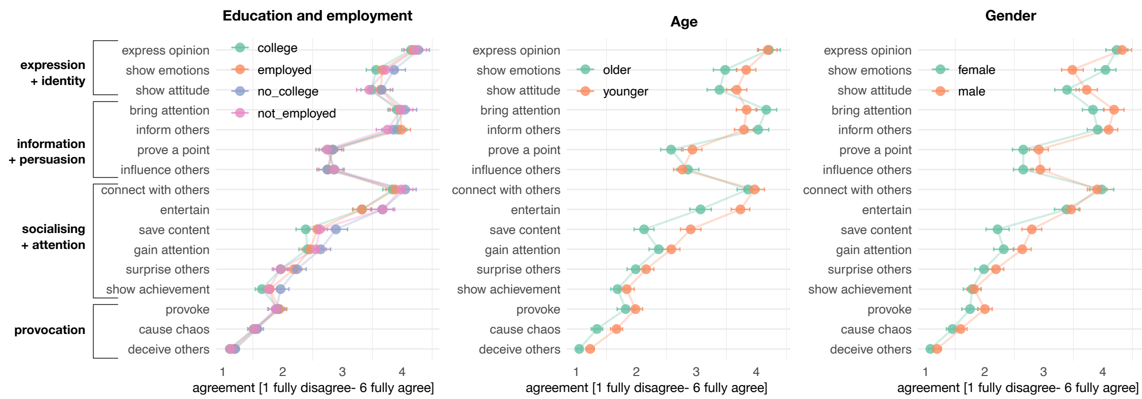
Supplementary Figure 1: Detailed procedure of the study setup with screenshots from the recruitment ad, questionnaire and other elements.



Supplementary Figure 2: Descriptive data of the final sample, with A the age distribution, B the gender, C the political affiliation, D level of education, E status of employment and F self-reported twitter use.



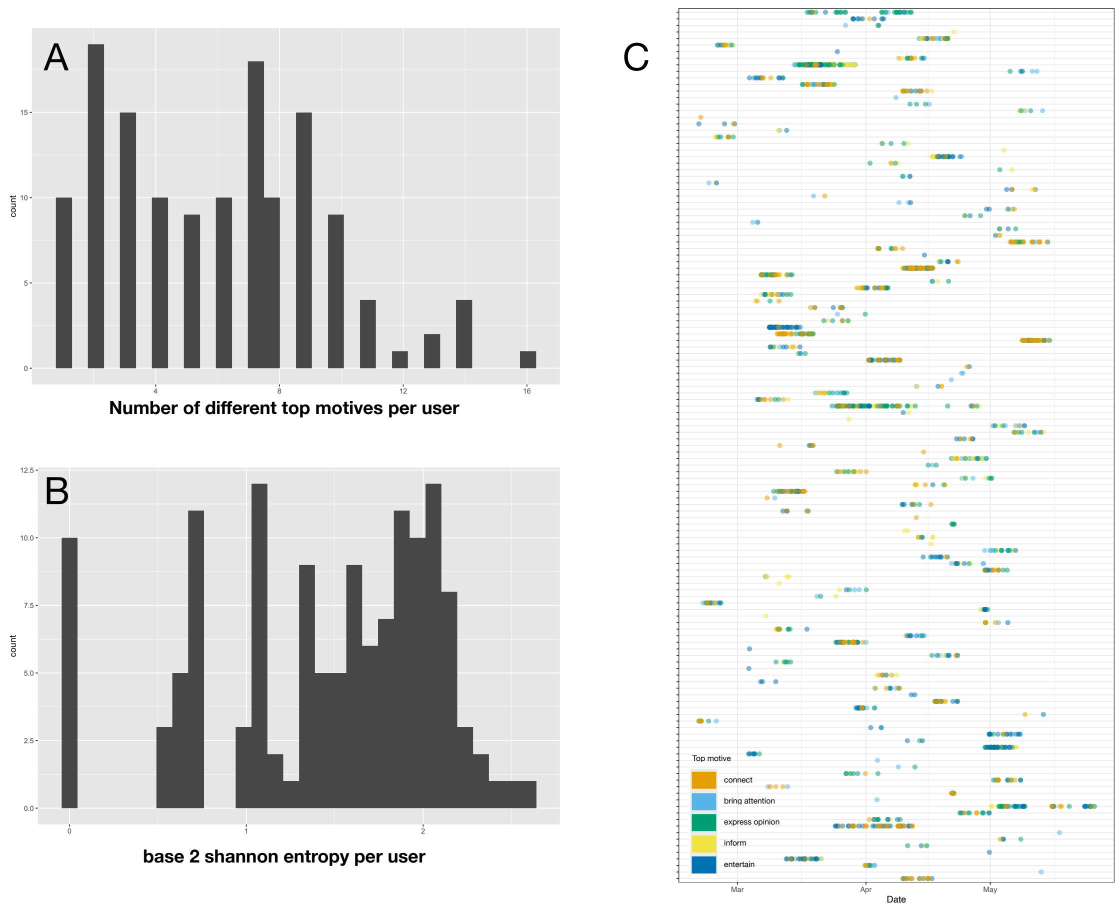
Supplementary Figure 3: Correlation matrix between motive ratings



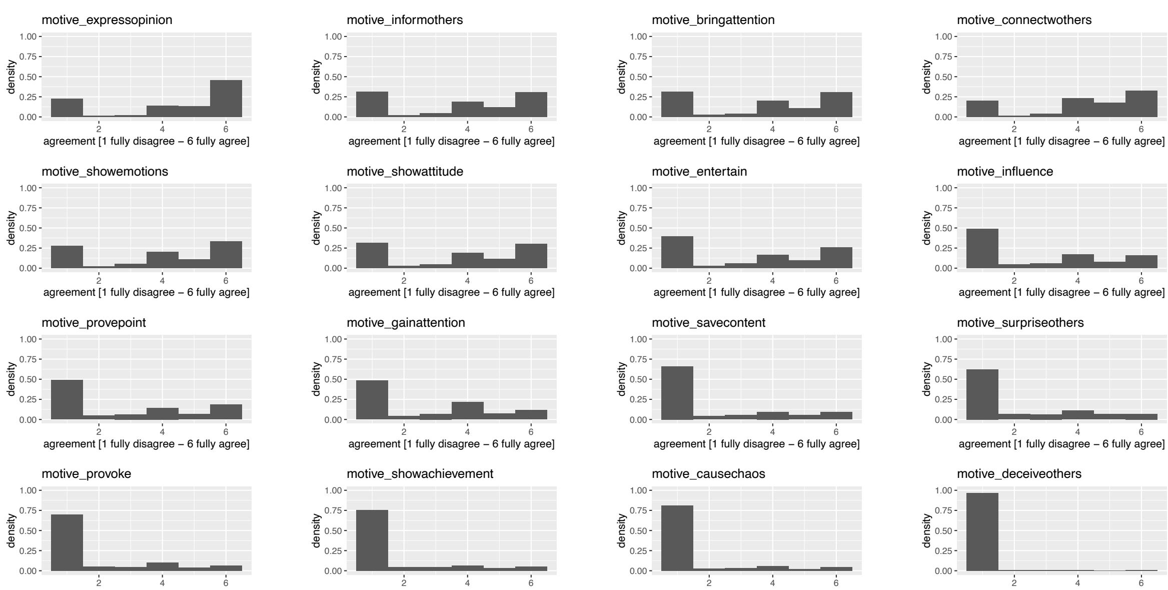
Supplementary Figure 4: The distributions of average agreement ratings (ranging from 1 "disagree completely" to 6 "agree completely") averaged for each participant over the real-time surveys, split across sociodemographic variables, namely, education and employment, age and gender, respectively.

motive	within-subject correlation
informothers	0.32
entertain	0.40
expressopinion	0.25
provoke	0.48
savecontent	0.50
showemotions	0.27
connectwothers	0.34
showachievement	0.18
showattitude	0.44
deceiveothers	0.67
gainattention	0.40
provepoint	0.42
causechaos	0.45
bringattention	0.31
influence	0.47
surpriseothers	0.36

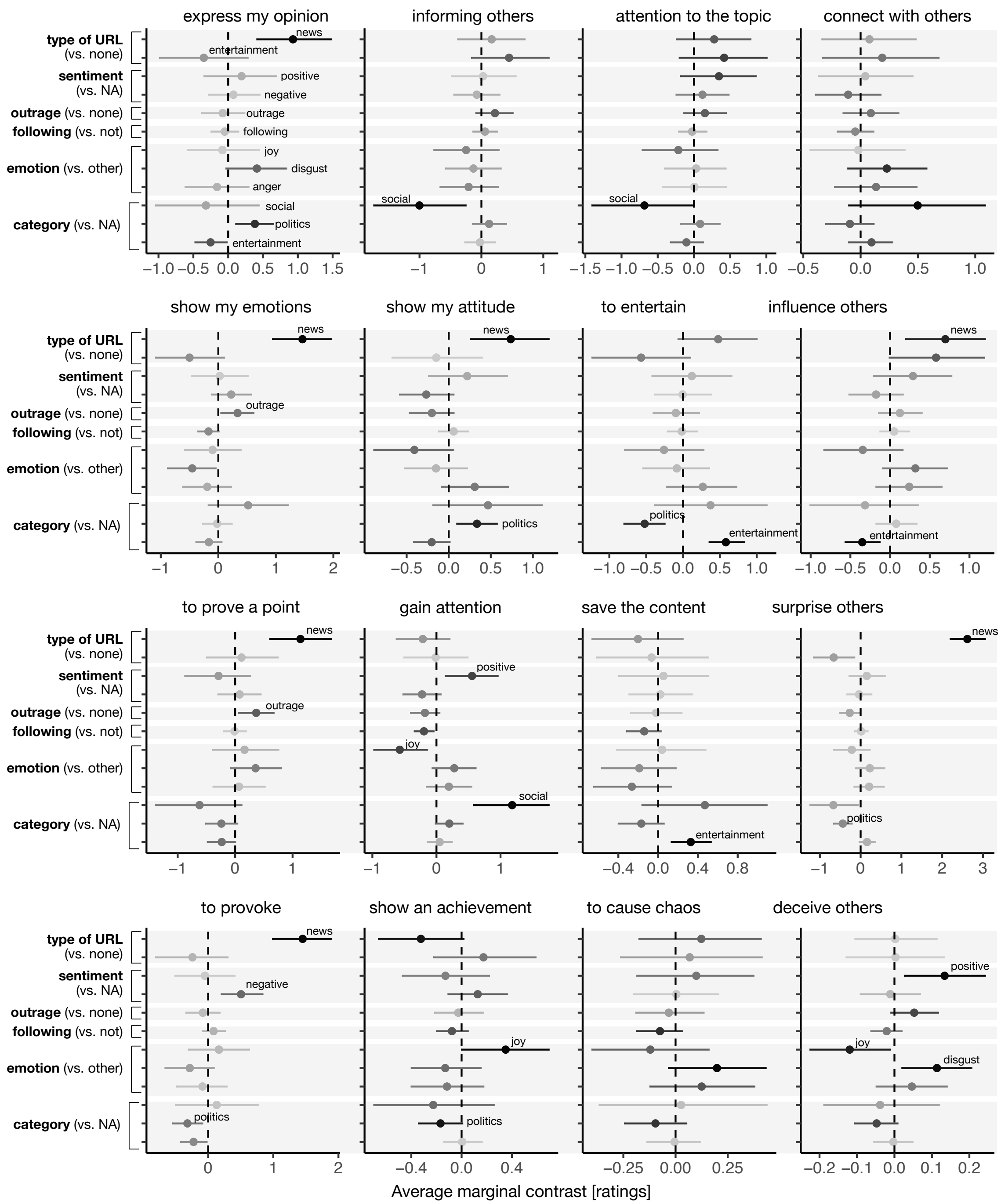
Supplementary Table 1: Correlation values of within-subject comparison between general motives stated in the onboarding survey and the average motives they report during the real-time surveys.



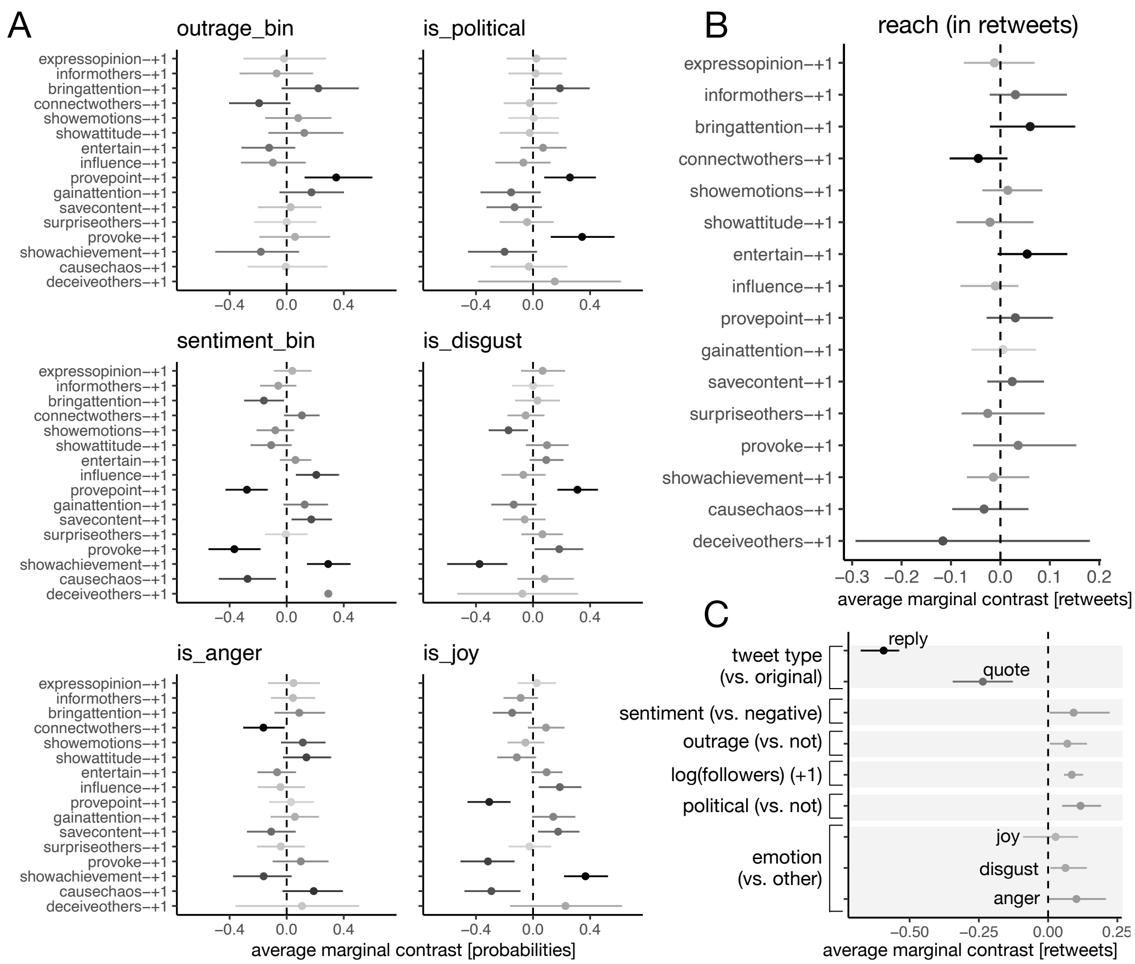
Supplementary Figure 5: Variance of motives within participants. A shows the number of different motives that were reported as the most important for each participant during the one week observation time. B shows the corresponding Shannon entropy and C the different categories of motives over time for each participant row-wise.



Supplementary Figure 6: Distributions of ratings over motives.



Supplementary Figure 7: Full model results for content types predicting sharing motives as in model 1 and as shown in Fig. 3.



Supplementary Figure 8: Full model results for content types predicting sharing motives as in model 2 and model 3 and as shown in Fig. 4

Structural Equation Model

Model:

```
model <- '
  level: 1
    information_tw =~ motive_provepoint + motive_bringattention +
    motive_influence + motive_informothers
    expression_tw =~ motive_expressopinion + motive_showemotions +
    motive_showattitude
    provocation_tw =~ motive_provoke + motive_causechaos +
    motive_deceiveothers
    social_tw =~ motive_showachievement + motive_gainattention +
    motive_surpriseothers + motive_connectwothers + motive_entertain +
    motive_savecontent
  level: 2
    information_ind =~ motive_provepoint + motive_bringattention +
    motive_influence + motive_informothers
    expression_ind =~ motive_expressopinion + motive_showemotions +
    motive_showattitude
    #entertainment_ind =~ motive_entertain + motive_savecontent
    provocation_ind =~ motive_provoke + motive_causechaos + motive_deceiveothers
    social_ind =~ motive_showachievement + motive_gainattention +
    motive_surpriseothers + motive_connectwothers + motive_entertain +
    motive_savecontent
'
```

Results of a multilevel CFA (Confirmatory Factor Analysis):

```
lavaan 0.6.17 ended normally after 104 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        92

  Number of observations                          2762
  Number of clusters [session]                     137

Model Test User Model:

  Test statistic                              1807.125
  Degrees of freedom                               196
  P-value (Chi-square)                           0.000

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian


Level 1 [within]:

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)
  information_tw =~
    motive_provpnt     1.000
    motv_brngttntn     1.185    0.054   22.060    0.000
```

```
    motive_influnc     1.055    0.044   23.786    0.000
    motiv_nfrmthrs     1.092    0.053   20.444    0.000
  expression_tw =~
    motiv_xprsspnn     1.000
    motive_shwmtns     1.051    0.044   24.073    0.000
    motive_shwtttd     1.117    0.047   23.751    0.000
  provocation_tw =~
    motive_provoke     1.000
    motive_causchs     0.709    0.046   15.431    0.000
    motive_dcvthrs     0.138    0.013   10.512    0.000
  social_tw =~
    motv_shwchvmnt     1.000
    motive_gnttntn     2.196    0.219   10.013    0.000
    motv_srprsthrs     1.878    0.203    9.258    0.000
    mtv_cnnctwthrs     1.221    0.149    8.193    0.000
    motive_entertn     2.674    0.284    9.403    0.000
    motive_svcntnt     1.599    0.168    9.501    0.000

Covariances:
                     Estimate  Std.Err  z-value  P(>|z|)
  information_tw ~~
    expression_tw      0.443    0.035   12.533    0.000
    provocation_tw     0.307    0.035    8.772    0.000
    social_tw          0.082    0.012    6.568    0.000
  expression_tw ~~
    provocation_tw     0.377    0.035   10.645    0.000
    social_tw          0.083    0.013    6.643    0.000
  provocation_tw ~~
    social_tw          0.117    0.014    8.494    0.000

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .motive_provpnt    1.451    0.052   28.144    0.000
   .motv_brngttntn    1.358    0.056   24.261    0.000
   .motive_influnc    1.199    0.046   26.189    0.000
   .motiv_nfrmthrs    1.736    0.062   28.064    0.000
   .motiv_xprsspnn    1.555    0.058   26.869    0.000
   .motive_shwmtns    1.429    0.055   26.155    0.000
   .motive_shwtttd    0.964    0.050   19.096    0.000
   .motive_provoke    0.718    0.065   11.014    0.000
   .motive_causchs    0.579    0.035   16.471    0.000
   .motive_dcvthrs    0.186    0.005   34.129    0.000
   .motv_shwchvmnt    1.188    0.035   34.017    0.000
   .motive_gnttntn    1.100    0.044   25.120    0.000
   .motv_srprsthrs    1.323    0.046   28.788    0.000
   .mtv_cnnctwthrs    1.753    0.052   33.961    0.000
   .motive_entertn    2.091    0.078   26.884    0.000
   .motive_svcntnt    1.609    0.050   32.082    0.000
    information_tw    0.850    0.059   14.375    0.000
    expression_tw     1.052    0.070   15.085    0.000
    provocation_tw    1.011    0.076   13.338    0.000
    social_tw         0.102    0.018    5.551    0.000


Level 2 [session]:
```

```
Latent Variables:
                    Estimate  Std.Err  z-value  P(>|z|)
  information_ind =~
    motive_provpnt     1.000
    motv_brngttntn     0.889    0.084   10.573    0.000
    motive_influnc     0.966    0.068   14.242    0.000
    motiv_nfrmthrs     0.835    0.083   10.047    0.000
  expression_ind =~
    motiv_xprsspnn     1.000
    motive_shwmtns     0.926    0.089   10.354    0.000
    motive_shwtttd     1.047    0.106    9.848    0.000
  provocation_ind =~
    motive_provoke     1.000
    motive_causchs     1.037    0.152    6.842    0.000
    motive_dcvthrs     0.550    0.092    5.962    0.000
  social_ind =~
    motv_shwchvmnt     1.000
    motive_gnttntn     1.355    0.212    6.393    0.000
    motv_srprsthrs     1.349    0.176    7.685    0.000
    mtv_cnnctwthrs     0.969    0.219    4.424    0.000
    motive_entertn     0.972    0.205    4.734    0.000
    motive_svcntnt     1.177    0.218    5.398    0.000

Covariances:
                    Estimate  Std.Err  z-value  P(>|z|)
  information_ind ~~
    expression_ind     1.021    0.171    5.959    0.000
    provocation_nd     0.320    0.110    2.906    0.004
    social_ind         0.461    0.101    4.583    0.000
  expression_ind ~~
    provocation_nd     0.179    0.093    1.934    0.053
    social_ind         0.328    0.087    3.784    0.000
  provocation_ind ~~
    social_ind         0.287    0.070    4.075    0.000

Intercepts:
                  Estimate  Std.Err  z-value  P(>|z|)
   .motive_provpnt    2.805    0.117   23.945    0.000
   .motv_brngttntn    3.971    0.115   34.606    0.000
   .motive_influnc    2.862    0.113   25.270    0.000
   .motiv_nfrmthrs    3.872    0.110   35.303    0.000
   .motiv_xprsspnn    4.208    0.110   38.173    0.000
   .motive_shwmtns    3.717    0.115   32.231    0.000
   .motive_shwtttd    3.578    0.125   28.552    0.000
   .motive_provoke    1.954    0.090   21.732    0.000
   .motive_causchs    1.563    0.074   21.108    0.000
   .motive_dcvthrs    1.152    0.044   26.171    0.000
   .motv_shwchvmnt    1.783    0.082   21.720    0.000
   .motive_gnttntn    2.579    0.110   23.394    0.000
   .motv_srprsthrs    2.083    0.093   22.318    0.000
   .mtv_cnnctwthrs    4.009    0.116   34.510    0.000
   .motive_entertn    3.463    0.113   30.781    0.000
   .motive_svcntnt    2.622    0.123   21.327    0.000

Variances:
                  Estimate  Std.Err  z-value  P(>|z|)
```

.motive_provpnt	0.240	0.072	3.340	0.001
.motv_brngttntn	0.407	0.095	4.290	0.000
.motive_influnc	0.226	0.062	3.629	0.000
.motiv_nfrmthrs	0.366	0.097	3.760	0.000
.motiv_xprsspnn	0.173	0.077	2.233	0.026
.motive_shwmtns	0.471	0.100	4.716	0.000
.motive_shwtttd	0.547	0.123	4.436	0.000
.motive_provoke	0.429	0.083	5.158	0.000
.motive_causchs	0.134	0.050	2.699	0.007
.motive_dcvthrs	0.101	0.020	4.953	0.000
.motv_shwchvmnt	0.338	0.070	4.815	0.000
.motive_gnttntn	0.676	0.121	5.589	0.000
.motv_srprsthrs	0.232	0.070	3.311	0.001
.mtv_cnnctwthrs	1.168	0.184	6.336	0.000
.motive_entertn	0.953	0.159	5.991	0.000
.motive_svcntnt	1.214	0.187	6.478	0.000
information_nd	1.312	0.220	5.967	0.000
expression_ind	1.144	0.202	5.662	0.000
provocation_nd	0.433	0.122	3.558	0.000
social_ind	0.400	0.100	3.989	0.000