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Metrics of social curiosity: The WhatsApp case

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ABSTRACT

A number of recent studies have explicitly introduced curiosity models into the analysis of online information consumption, most notably in the design of recommendation systems. However, most prior efforts have neglected the role of social influence as a component of the curiosity stimulation process, which has been referred to as *social curiosity*. In this paper, we propose a number of metrics to quantify social curiosity applying them to WhatsApp, a widely used communication platform. We show that our metrics capture aspects that are complementary to other variables priorly related to curiosity stimulation and use them to offer a broad characterization of user curiosity as a driving force behind communication in WhatsApp.

1. Introduction

Curiosity has been characterized as an important trait of our personality, influencing one's behavior in positive and negative ways at all stages of life [1]. According to [2,3], an individual's curiosity is essentially driven by external stimuli: an individual repeatedly receives stimuli from the environment and selectively responds to those that induce pleasure. This selection process has been explained by means of *collative variables*, notably novelty, complexity, uncertainty and conflict, which capture different external factors that govern how one's curiosity is stimulated [2]. In essence, each stimulus is indeed a combination of various collative variables, instantiated by different metrics, and the response to a stimulus depends on the particular individual upon whom it is imposed. A number of studies have explored models of human curiosity, relating an input stimulus to the curiosity induced in an individual, in the design of personalized and enhanced systems [4–8].

In the particular domain of online information dissemination, there have been recent efforts to formally introduce curiosity models into the design and evaluation of recommendation systems [9–13]. However, most of them have used metrics related to a single collative variable, and have neglected one important factor that may impact one's curiosity: social influence. Social influence has been widely studied as a key component in various behavioral phenomena, from information dissemination to opinion adoption (e.g., [14,15]). Yet, the focus has been mostly on those who have more influence on the community [16,17] and their impact on the phenomenon under study [18,19], and do not explicitly analyze the impact of such influence on individual behavior. Other studies have explored principles derived from social influence to design recommendation systems (e.g., [20–22]), but we are aware of only one recent effort to explicitly apply metrics related to social influence as part of a curiosity model, which in turn is used in the design of a recommendation method [11].

In contrast, some other studies have already discussed the concept of *social curiosity*, a facet of curiosity, which has been defined as the general interest in gaining new social information motivating exploratory behaviors [23–25]. Specifically, social curiosity entails two different aspects: a general interest in obtaining new information about how others think, behave or act as well as an interest in interpersonal information that is obtained through exploratory behavior. As such, social influence can be seen as yet another collative variable that stimulates one's curiosity and ultimately drives one's behavior.

In this context, our present effort is driven by three research questions:

> **Research Question 1 (RQ1):** *How to quantify social influence as a stimulus to one's curiosity driving the information dissemination process?*
>
> **Research Question 2 (RQ2):** *How does social influence relate to other collative variables priorly associated with curiosity stimulation?*
>
> **Research Question 3 (RQ3):** *How are users characterized in terms of social stimulation to curiosity?*

We tackle these questions using WhatsApp as case study. WhatsApp is a free messaging app that has surpassed the mark of 2 billion users

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[1] https://www.whatsapp.com/about/.

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worldwide in 2020.[1] It connects users in end-to-end as well as group conversations, and the latter has been shown to be an effective vehicle for information dissemination at large [26]. Thus, we here propose to *model the social stimulus to the curiosity that drives users to share content (thus communicating with each other) in WhatsApp groups.*

To that end, we start by proposing a set of novel metrics to quantify such stimulus (RQ1). Towards deriving these metrics, we follow the seminal work by Berlyne [2], which proposes a methodology to quantify collative variables related to curiosity stimulation based on information theoretical metrics. Berlyne applied these concepts to the derivation of metrics related to more traditional collative variables (e.g., novelty, conflict). We here follow his arguments, as well as similar ones by other authors [27], and apply his methodology to derive metrics capturing the effects of social influence as a component of curiosity stimulation.

Moreover, following the same methodology and building on our prior experience [28], we also adapt metrics capturing other collative variables related to curiosity stimulation, notably novelty, complexity, conflict and uncertainty to the particular domain of WhatsApp groups. These variables have been studied before in other domains [9,11,28,29] but not in a platform of group communication, such as the one provided by WhatsApp.

Our study is carried out in a dataset consisting of over 2 million messages shared by more than 7.5 thousand users in 335 publicly accessible groups in Brazil during a one-month period. By correlating the two sets of metrics – metrics related to social curiosity and metrics related to the other collative variables – we show that our social curiosity metrics do indeed capture novel aspects of one's curiosity stimulation which are not represented by the other (priorly studied) collative variables (RQ2).

Finally, we use our metrics to characterize the social curiosity stimulation of users when sharing content in WhatsApp groups (RQ3). Our characterization is performed at three levels of aggregations: we quantify social curiosity stimulation driving the sharing of individual messages, the overall behavior of individual users as well as WhatsApp groups.

Our main contributions can be summarized as follows:

- We propose four new metrics to capture social influence as a component of curiosity stimulation at the user level, as well as one metric to capture the same aspect at the group level. We instantiate the proposed metrics for the specific context of content sharing in WhatsApp groups, but they are general enough to be applied to other platforms of online group communication. Additionally, we also propose seven metrics that capture other traditionally studied collative variables, namely novelty, complexity, conflict and uncertainty, to the same context. To our knowledge, this is the first effort to propose metrics to quantify components of curiosity stimulation in such environment.
- We offer an extensive evaluation of social influence as a component of the curiosity stimulation driving content sharing in WhatsApp groups. Our study reveals that social influence, as captured by our proposed metrics, is complementary to the other traditionally analyzed collative variables, thus reflecting a novel and important component of the curiosity stimulation process. Also, we found great diversity and dynamics in social curiosity stimulation in WhatsApp, at the message, individual and group levels. Specifically, we found three profiles of social curiosity stimulation driving user behavior when sharing individual messages, and used them to uncover five different profiles describing how the social curiosity of a user in a given group evolves over time. We also found evidence that the social curiosity stimulation of a particular user may be quite different depending on the group she participates in, which hints at a role the group has on its members. Yet, different groups may exhibit quite different and very dynamic group-level social curiosity stimulation, as such dynamics results from the aggregation of the behavior of those users that are more actively sharing content at each time.

The remaining of this article is organized as follows. Section 2 presents background information. Our novel metrics of curiosity are introduced in Section 3. Our characterization results, including the dataset used, are discussed in Section 4. We discuss some limitations of our study and their implications in Section 5. Finally, conclusions and future work are offered in Section 6.

2. Background

2.1. Curiosity modeling: Basic concepts and prior studies

Curiosity is a basic element of our cognition, functioning as a motivator for learning, and being influential to decision-making as well as crucial for healthy development [1]. Our curiosity is driven by a stimulus selection process: our organism receives several stimuli from the environment and selectively responds to those that induce pleasure and arise our curiosity [3].

According to Berlyne [2], different *collative variables* govern the curiosity stimulation process, notably: (a) novelty, which is inversely related to frequency and dissimilarity in the stimulus pattern; (b) uncertainty, which is related to the difficulty in deciding how to respond to a stimulus; (c) conflict, which occurs when the same stimulus triggers multiple incompatible responses; and (d) complexity, which refers to the diversity in a stimulus pattern. These variables refer to different external factors that govern how curiosity is stimulated, and can be instantiated by various metrics, depending on the target environment. Thus, a stimulus is indeed a combination of multiple collative variables.

In his seminal work, Berlyne argues that properties of such collative variables can be discussed in an information-theory related language, and proposes a methodology to quantify such variables based on information theoretical metrics. Following a similar argument, Silvia [27] states that, with some mathematical manipulation, all collative variables associated with curiosity stimulation can be expressed by formulations using metrics from information theory. As we discuss in the next section, these arguments inspired some recent studies [9–11,30,31] in Computer Science to propose metrics capturing different collative variables, notably those originally investigated by Berlyne (i.e., novelty, conflict, uncertainty and complexity).

The theory of *optimal level of stimulation* establishes a relationship between the stimulus intensity and the pleasure response, also referred to as Wundt's curve [2,29,32]. A Wundt's curve follows a bell shape, indicating that too-little or too-much stimuli will respectively lead an individual to relaxation (i.e., boredom) or anxiety. Moderate stimulation, in turn, triggers curiosity. The exact stimulus thresholds that define these regions of operation and the (moderate) level of stimulation leading to maximum curiosity vary across individuals.

We here argue that, in addition to the four aforementioned collative variables, social influence should also be considered as part of the stimulus to one's curiosity, especially in online social networks and social media applications, where, to a large extent, one's behavior is driven by connections, common interests with others and social observation. This argument is aligned with the concept of *social curiosity*, recently introduced in [33], as a key component of a five dimensional curiosity model. The proposed five dimensions, namely joyous exploration, deprivation sensitivity, stress tolerance, thrill seeking and social curiosity are related but independent and can be distinguished by links to personality, emotion and well-being. According to the authors, social curiosity denotes the individual skills to tackle the interpersonal world, that is, the arising of interest in obtaining new information about how others think, behave or act as well as an interest in interpersonal information that is obtained through exploratory behavior. More recently, the authors distinguished between *overt* and *covert* social curiosity [34]. The former refers to being curious about how others think, behave or act, and is related to healthier outcomes (e.g. interpersonal competencies). The latter refers to observing others in a indirect and secretive way to obtain new information and regards to unhealthy outcomes (e.g. gossiping and social anxiety).

The two aforementioned studies [33,34] were based on surveys with real people. Here, we are interested in proposing quantifiable measures of social curiosity as a driving force behind online behavior. Specifically, we propose different metrics to quantify the impact of social influence as a component of curiosity stimulation driving users to share content on WhatsApp. To our knowledge, prior attempts to operationalize the concept of social curiosity by proposing quantitative metrics to estimate it are quite scarce and mostly limited [9,11,28]. This is probably due to the challenges to capture, quantitatively, the aspects associated with such a highly subjective concept, as argued by several recent studies in the Psychology and Neuroscience domains [33–38]. The derivation of our metrics, discussed in Section 3, follows the rationale on Berlyne's original arguments and his proposed methodology, here adapted to capture social curiosity. Specifically, we explore metrics from information theory to estimate how such highly subjective concept can compose the curiosity stimulation process in the particular setup of interest, i.e., group communication on WhatsApp. To our knowledge, we are the first to operationalize Berlyne's ideas to estimate social curiosity, especially in the selected domain.

2.2. Curiosity models in online information systems

Curiosity has had a great range of applications in computational models [29] including artificial creativity [39,40], adaptive mechanisms for robotics [6], multi-agent systems [7], learning algorithms for autonomous systems [5], artificial intelligence in education [4], text analysis [31], among others. In the domain of online information consumption, a number of recent efforts have exploited curiosity models in the design of information systems, notably recommendation methods [9,10,30]. For example, Zhao et al. [9] developed a recommendation system framework that considers that each recommended item denotes a stimulus to the user. However, only the item's novelty was used to compose such stimulus, which, in turn, was related to curiosity scores using the Wundt's curve. The authors showed that the integration of this curiosity model into different recommendation mechanisms provides personalized recommendations with improved accuracy. More recently, Mohseni et al. [30] also exploited a novelty-based curiosity model to recommend sequences of papers with increasingly more novel content. Chen et al. [10], in turn, reported results on the importance of considering serendipity, another facet of curiosity, for recommendation purposes, whereas Niu and Abbas [31], instead, focused on *surprise* as a component of curiosity stimulation.

There have been a few recent attempts to explore multiple collative variables in the study of online behavior in information systems. For example, we have proposed ten different metrics to capture traditional collative variables, notably novelty, uncertainty, conflict and complexity, using them as components to model curiosity in online music consumption [28]. However, we have not tackled any aspect related to social curiosity.

To our knowledge, the only prior effort to *explicitly* model social influence as a curiosity driver behind online information consumption was that of Xu et al. [11]. The authors extended the work developed in [9] by introducing another collative variable, referred to as *social conflict*. This variable was represented by the nearness to equality in the competing strengths [2] between positive and negative responses on the same item received from close social peers. The authors found that the use of both novelty and social conflict in the composition of curiosity's stimulus helps maximizing the diversity of recommendations.

The main research gap we address in this article with respect to the aforementioned studies is the modeling of a novel collative variable associated with curiosity stimulation, namely social curiosity. Thus, the closest study to ours is that by Xu et al. [11]. However, unlike this prior work, we do not aim at improving item recommendation. Rather, our primary focus is on modeling user behavior, with particular interest in how users' decisions to share content is driven by social curiosity. Moreover, we explore a completely different setting — content sharing in a group communication application, where curiosity most probably is stimulated differently. We here must capture how the curiosity that drives one to communicate (by sharing content) is impacted by the other members participating in the group. To that end, we propose several new metrics that help uncovering important components of (social) curiosity stimulation. As such, our work is completely orthogonal to [11].

2.3. WhatsApp

WhatsApp has become one of the main communication platforms in many countries [26]. It allows for one-to-one and group conversations, both encrypted. Groups are, by default, private spaces limited to 256 simultaneous users, although a user may join and leave a group at any time. Yet, as shown in [26], group administrators can make a group publicly accessible by sharing an invitation link in public websites, since anyone with the link can join the group. By gathering a large number of such publicly available invitation links, researchers were able to join the groups automatically and, once a member, gather data for posterior analysis.

For example, some researchers developed automatic tools to expose, in an anonymized fashion, the content being shared in publicly accessible groups [41,42], whereas others analyzed properties of such content [43] with notable focus on pieces of information that had been previously checked as fake by fact checking agencies [26,44–46]. Orthogonally, Melo et al. analyzed whether limiting message forwarding could mitigate misinformation spread on WhatsApp [41]. They found that, though effective in slowing down the process, such approach would not stop misinformation from being widely distributed.

In a complementary directions, a few prior studies focused on exposing the importance of the underlying networks that connect users across different WhatsApp groups to information spread [26,47]. In [26], the authors analyzed the structural properties of the network built from connecting users belonging to the same group, finding that this network has several properties, often observed in other online social networks, that had been associated with content virality. More recently, Nobre et al. focused on the media co-sharing network, built by connecting users who shared the same content, revealing the presence of strongly connected user communities that consistently help speeding up information spread [47].

Despite the recent surge of interest in analyzing content properties and user sharing patterns in WhatsApp, we are not aware of any prior attempt to investigate how to model social aspects of curiosity in this platform, as we do here. We believe that understanding the drivers behind users' sharing actions is key to proper modeling and understanding information dissemination on the platform. We take a step in that direction by proposing metrics to quantify one such driver — social curiosity.

2.4. Social influence analysis

Despite the scarcity of works on modeling social influence as a component of user curiosity, the literature has a rich body of prior analyses of social influence in social media platforms [48–52]. These studies can be broadly grouped into two major collections: those that aimed at quantifying social influence, often aiming at identifying the most influential users on the system [53–56], and those that proposed models of social influence diffusion (such as epidemic models [57], cascade models [58,59], linear threshold model [60,61] and complex contagious models [62–66]).

Our present effort is closer to the former group. Thus, we review studies in that category in this section.

Some early attempts to quantify social influence relied only on network properties such as degree distributions, diameter, clustering coefficient, community aspects and small world effect, often considering a single network model capturing all explicit connections among users (e.g., friendship links) [67]. However, the limitations of considering only topological measures to estimate user influence have already been pointed out by prior studies [68,69]. For instance, Zhang et al. argued that node degree (e.g., number of followers on Twitter) cannot be used alone to assess user influence as users with more connections (i.e., larger degrees) may not be the ones who more often forward content [68]. Steeg and Galstyan [69] also argued that structural measures of influence can lead to misleading assessments of influence. For instance, higher popularity does not imply necessarily higher influence. Moreover, topological properties are inherently dynamic [70], which implies that their temporal evolution, which cannot be captured by a single overall network structure, must be considered.

Also, most prior studies assume that user influence propagates over explicit links that connect users on the platform of analysis (e.g., friendship links) [71–73]. However, in a group communication platform, such as WhatsApp, no such explicit links exist. Similarly, some prior analyses of user influence rely on explicit models such as epidemic models [74], topic models [67], probabilistic graphic models [75] and statistical models [76]. Instead, we adopt a more general *model independent* approach, grounded on information theory metrics. Indeed the metrics we propose are measured in bits, which facilitates straightforward comparisons between systems [77]. Moreover, prior model-based studies of user influence often rely on linear models [67,78]. However, online social networks are known to present *non-linear* relationships influencing information spread [79,80]. In that sense, our information-theoretic metrics are more robust as they are capable of capturing linear and *non-linear* interactions [77,81,82].

Another body of studies relied on statistical or machine learning models to estimate user influence. For example, Goyal et al. [78] proposed models of probabilistic influence among users and developed algorithms for learning the parameters of these models. Luceri et al. in turn, proposed a deep neural network based model to estimate social influence by exploiting the history of user actions propagated among friends [83]. Li and Xiong [84] presented measures to capture the social influence at both microscopic (based on explicit user actions such as comments and mentions) and macroscopic (based on number of followers) levels, while Zhang et al. [85] used regression techniques to study the role of triadic patterns in user behavior prediction. Kumar et al. [86], in turn, analyzed the probability of an individual to be socially influenced based on several machine learning approaches and a rich set of features including personal network exposure, structural diversity, locality, retweet time delay as well as size and path length of cascades.

In contrast to the aforementioned studies, Bonchi et al. [76] adopted a *causal* approach to the analysis of social influence from propagation data. Their goal – retrieving a minimal causal topology from the data – is somewhat complementary to ours. Instead, we here want to estimate how a user's curiosity may be stimulated by others in a group communication platform. Other studies of social influence relied on topic modeling to assess the social influence between users in specific topics [75] and factor graphs, a probabilistic graphic model to learn the effects of social influence, action correlation between users and time-dependency of user's actions [67].

Finally, the work by Steeg et al. [69,87] is arguably the closest to our present effort. They also proposed to estimate social influence based on information theoretical measures, but they used a different metric — information transfer,[2] which is based on mutual information. They used information transfer to measure the *direct* social influence between users on Twitter and identify influential users based on their capacity to predict the behavior of other users. Though with a similar goal, our work differs from Steeg et al.'s by considering a completely different platform — WhatsApp, using somewhat different metrics, and considering both direct and indirect influence.

More broadly, our work has some key differences in purpose from the aforementioned prior efforts, and, as such, has a complementary goal compared to them. Whereas most prior studies discussed above aimed at quantifying the influence of a user on others in general, often over a particular time window and focusing on the user who influences the others (origin of influence), we here aim at estimating how social influence from others may be driving a user towards sharing content (i.e., focus on the destination of influence). As such, social influence has to be computed at much finer granularity, i.e., each time a user shares a piece of content, since human curiosity is considered highly dynamic and contextual (see discussion in Section 3.1.1).

Table 1 presents a direct comparison of our work and the aforementioned prior studies on social influence along several dimensions. Some of these dimensions, such as whether the proposed solution is based on a *non-linear method* and whether it is *model independent*, refer to the level of generality of the proposed approach. For example, as mentioned, a non-linear model, as ours, should be more robust to capture non-linear effects impacting information diffusion in online social networks [80]. Similarly, by not exploring any specific model, as done by others [67,74–76], we offer a more general approach, where the result is not a model parameter but rather a number quantifying some relationships that exist in the data [77], and free from particular assumptions and specificities that may constrain such models. Also, our study, unlike some others, does explicitly consider the *temporal dynamics* of social curiosity, and by doing so, recognizes that this is a highly transient, dynamic and contextual human behavior trait [3,34,37].

Other dimensions listed in Table 1 relate to the particular domain under study — WhatsApp groups. As the first to propose metrics of curiosity stimulation to such environment, we had to address several challenges. For example, a *network free approach* was chosen due to the absence of explicit links connecting users. Instead, all group members may interact with each other at any time, unlike in other setups where there are explicit links connecting users through which social influence may propagate. This implies that, in the absence of such explicit links, a strategy to capture the heterogeneity and the dynamics of social influence in our metrics is required. Moreover, by developing a network free approach, we offer a more general solution that does not rely on existing links to estimate social influence and thus may be adapted to other setups.

Similarly, the target environment motivates the development of metrics to capture other effects of social influence, in addition to the often studied direct influence of one user on others. On one hand, we propose a metric to estimate *social curiosity at the group level*, which can be used to characterize human behavior in different groups. Since WhatsApp allows only for small groups (at most 256 members simultaneously), and these often target specific topics of discussion (as defined in the group name or description) [26,46], characterizing the curiosity of such small user populations over time may offer useful insights into social behavior (much more than in more open and unconstrained spaces like Twitter and Facebook). Moreover, inspired by prior analyses of WhatsApp [89,90], we also propose metrics to explicitly capture the *indirect effect* of strong influencers that may emerge in such constrained spaces.

In sum, we here propose to quantify social influence from a novel perspective – curiosity stimulation – offering a more general approach that is inspired by arguments available in the Psychology literature [2, 27], and that addresses particular challenges of a currently very popular communication platform, namely WhatsApp groups.

[2] Information transfer is also called of transfer entropy, information transfer between two stochastic process characterizes the reduction of uncertainty in a process due to knowledge of the other process [81].

Table 1
Comparison of our work with prior studies of social influence estimation.

Features	Goyal et al. [78]	Luceri et al. [83]	Li and Xiong [84]	Zhang et al. [85]	Bonchi et al. [76]	Tang et al. [75]	Tan et al. [67]	Kumar et al. [88]	Steeg et al. [69,87]	This work
Social network free									✓	✓
Model independent									✓	✓
Non-linear		✓							✓	✓
Temporal dynamics	✓	✓			✓		✓	✓	✓	✓
Indirect influence										✓
Group activity										✓
Platforms of study	Flickr	Plancast, Foursquare	Tencent Weibo	Weibo, CrossFire	Flixster, Twitter, LastFM	Arnetminer, Wikipedia Films	Twitter, Flickr, Arnetminer	Sina Weibo	Twitter	WhatsApp

3. Novel metrics of user curiosity

In this section, we present our novel metrics of curiosity stimulation driving user participation in group communication. Although we use WhatsApp as case study, the metrics are derived to be applicable to group communication in general. We consider that group membership is naturally dynamic, as members join or leave the group at their will. However, it is expected that (a subset of) members remain interacting with each other, exchanging opinions and content in general, for some time. We here are interested in quantifying the extent to which the bond created by such interactions can stimulate a member's curiosity towards carrying on the conversation. Specifically, we focus on quantifying stimuli to participating in such group conversations by *sharing content*. In other words, we propose metrics that capture different aspects of the stimuli one is driven by when choosing to share a piece of content with the group. As mentioned before, our derivation of the proposed metrics follows Berlyne's arguments and his proposed methodology [2]. Specifically we make use of measures from information theory to derive metrics that aim to capture different collative variables associated with curiosity stimulation.

In the following, we first present the preliminary concepts and notation used to define our metrics (Section 3.1). We then introduce our novel metrics of social curiosity, which aim to capture social influence as a stimulus to curiosity and constitute a key contribution of this work (Section 3.2). Next, we present metrics that instantiate other traditionally studied collative variables to the particular context of WhatsApp groups (Section 3.3). The latter are inspired by the metrics introduced in [28], originally developed for the context of online music consumption, and here adapted to a very different domain, notably content sharing in a group communication platform. They are used in this work for comparison purposes, so as to emphasize the complementary role of social influence as a component of curiosity stimulation. We defer to Section 5 a discussion on limitations introduced by some of our assumptions and design decisions and their implications to the study.

3.1. Preliminaries

We consider a universe of analysis consisting of sequences of messages shared by a number of users in various (independent) groups. A message is composed of pieces of content in any of four different media types, namely text, image, audio or video. Fig. 1 illustrates the case of a sequence of 12 messages shared by 4 user members of a given group in the interval between 1:00 pm and 3:00 pm. The left part of the figure shows the sequence as seen by user 3, with the messages shared by her highlighted in green. Note that the figure shows, for each message, the user who shared it, the message identifier, the content's media type and the time of sharing. In the following, as in the next sections, we will use this example to illustrate the main concepts behind our metrics.

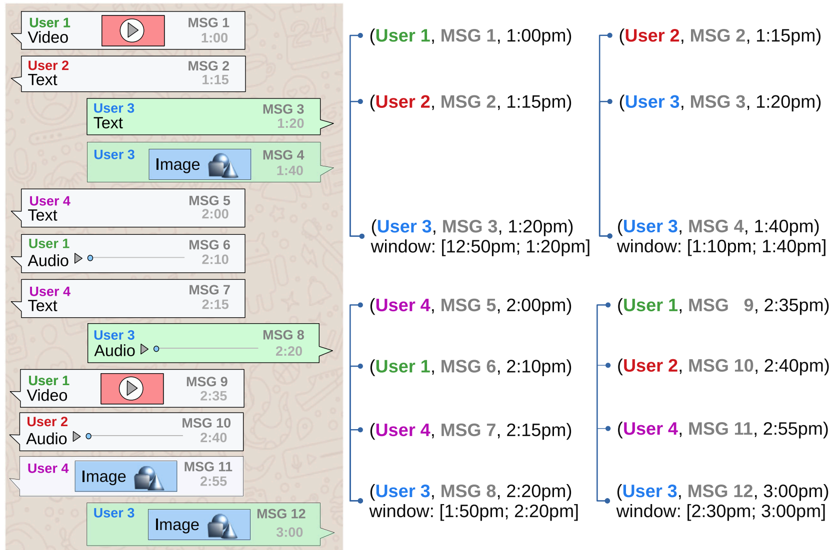
We first present the main assumptions behind the design of our proposed metrics. Then, we introduce the notation that will be used to derive these metrics.

3.1.1. Assumptions

Before moving forward, we first present three main **assumptions** behind the design of all proposed metrics. While deriving our metrics, we assume that:

1. The curiosity of a user may be triggered differently depending on the people with whom the user is interacting and the ongoing discussions among them [24,91]. In other words, one's curiosity stimulation may vary depending on the particular group the individual is participating in. More yet, if a person participates in multiple groups at the same time, her curiosity stimulation may vary across these groups. Thus, as illustrated in Fig. 1, our metrics will be computed and our analyses will be performed for different groups separately, considering only the messages shared in each group at a time.
2. The way one's curiosity reacts to a given stimulus may change over time, as observed in [28]. A stimulus that triggers great curiosity in a person may later be mostly innocuous, or fall into other regions of the stimulation process (i.e., boredom, anxiety). Thus, the proposed metrics should be quantified each time a user shares a message. This is illustrated in the right side of Fig. 1, which shows user 3's curiosity stimulation being analyzed (and metrics computed) each time user 3 shares a message (specifically at times 1:20, 1:40, 2:20 and 3:00, for the sequence shown in the left side of the figure). We note that this is indeed performed each time a message is shared by *any* user. Yet, to improve readability, Fig. 1 illustrates this process only for messages shared by user 3.
3. The curiosity driving the sharing of a message by a given user u at a given time t has a period of activation δ_T, that is, a time interval preceding the user's action (i.e., the sharing of the message) during which messages shared in the group (including messages shared by u herself) may contribute to stimulate u's curiosity. We refer to this period as a *window of interaction* to reflect the set of interactions stimulating u's curiosity at time t. Thus, a sharing event at time t defines a window of interaction $[t - \delta_T; t]$. Messages shared before $t - \delta_T$ are assumed to be too old to have any effect on u's curiosity at time t.
   We illustrate this assumption in the right side of Fig. 1. Assuming $\delta_T = 30$ min, the figure shows the window of interaction, notably the messages and users that fall within such window, defined for each message shared by user 3. The messages (and users) in a window will be used as input to compute the metrics of curiosity stimulation for user 3 at each given time. For example, user 3 shares a textual message (*msg 3*) at 1:20 pm. The stimulus to user 3's curiosity driving this particular action will be computed based on the messages shared in the interval [12:50 pm; 1:20 pm]. That is, we must consider *msg 1* shared by user 1 at 1 pm, *msg 2* shared by user 2 at 1:15 pm, and, depending on the specific metric of curiosity being derived,[3] even *msg 3* shared

[3] The message shared at the time curiosity stimulation is computed is taken into account for computing the metrics of curiosity stimulation related to



(a) Messages Shared by 4 members of a group.

(b) Windows of interaction for messages shared by user 3 ($\delta_T = 30$ min).

Fig. 1. Example of sequence of messages shared in a group. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

by user 3 at 1:20 pm, as these are the messages shared during the window. Similarly, the stimulus to user 3's curiosity when sharing the audio message at time 2:20 pm (*msg 8*) will be (re-) computed based on *msgs 5, 6, 7* and, depending on the metric, *8* shared within the window [1:50 pm; 2:20 pm]. Prior messages, which do not fall within the defined window of interaction, are disregarded.

Two other assumptions, specific to the design of the metrics related to social curiosity presented in Section 3.2, are:

4. One's *social curiosity* when sharing a message at time t is stimulated by the *user(s)* who shared content in the same group during the window of interaction. We do acknowledge that the content shared itself as well as characteristics of the target user whose curiosity is under analysis may also stimulate one's curiosity. However, when modeling *social* aspects of curiosity, we disregard such characteristics, focusing rather only on all the other *users* who shared content during the window of interaction. Properties of the content and of the target user are exploited to derive metrics related to other collative variables in Section 3.3.
The right side of Fig. 1 shows the users considered as stimulating user 3's curiosity each time she shares a message. These are all users included in the defined window of interaction *but user 3*. For example, users 1 and 2 are considered to compute the stimulus at time 1:20 pm, when user 3 shares her first message. Note that, although user 3 herself is also included in the window of interaction (due to *msg 3* shared at time 1:20 pm), only the other users in the window are considered for the sake of analyzing *social* curiosity driving user 3's behavior. Message *3*, shared at time 1:20 pm, will be taken into consideration to derive metrics related to other collative variables, as will be presented in Section 3.3. Similarly, only user 2 is considered as stimulating user 3's curiosity when she shares *msg 4* at time 1:40 pm.
5. The extent to which one's social curiosity is stimulated by other users can be estimated by historical patterns. Specifically, the influence of user u_1 on user u_2, which relates to the curiosity stimulus triggered on u_2 by u_1, is proportional to the frequency at which a message shared by u_1 is followed by a message by u_2 within an interval not greater than δ_T (that is, u_1 falls in the window of interaction defined for a message shared by u_2). This frequency is estimated based on the message sharing patterns prior to the current window of interaction (thus, historical patterns).
For example, in the right side of Fig. 1, the influence of user 1 on user 3 at the time she shares *msg 12* is based on the frequency at which user 3 shared content after user 1 (within a 30 min maximum interval), *before* the beginning of the current window of interaction, i.e., before 2.30 pm. This implies that we will look at all messages shared by user 1 before 2:30 pm and check how often user 3 shared a message after it, with a maximum delay of δ_T. In the particular scenario depicted in the figure, it happened twice: *msg 1* at 1:00 pm was followed by *msg 3* at 1:20 pm, and *msg 7* at 2:10 pm was followed by *msg 8* at 2:20 pm.

3.1.2. Notation

Having defined the main assumptions behind our proposed metrics, we now introduce the notation used to derive them in the following sections. We start by defining the sets of users, groups, and types of media used to compose the sequence of messages under analysis as $\mathcal{U}$, $\mathcal{G}$, $\mathcal{M}$, respectively. We do not assume access to message content, as it may not be available. Instead, we use the different types of media used to compose the message content as a representation of it, that is, we define $\mathcal{M} = \{$"text", "image", "audio", "video", "URL"$\}$.[4] Each message under analysis is then a tuple (u, C_m, g, t) indicating that it was shared by user $u \in \mathcal{U}$ in group $g \in \mathcal{G}$ at time t. Set $C_m \subseteq \mathcal{M}$ includes all media types used to compose the message's content. We refer to such media types as the *categories* of the message. Note that the same message may contain content in different medias (e.g., a text and an image), thus a message may have multiple categories captured in set C_m.[5]

traditional collative variables of novelty, uncertainty, conflict and complexity (Section 3.3), but not for computing metrics related to *social* curiosity (Section 3.2), as the latter depend solely on the messages shared by other users during the window of interaction.

[4] Other possible categories include emojis, stickers and gifs. However, these are not available in our dataset, and thus are not explored in this work.

[5] The same media type used multiple times to build a message's content (e.g., multiple images associated with it) is counted only once as part of C_m.

Table 2
Main notation used to derive the curiosity stimulation metrics.

Notation	Description
$\mathcal{U}$	Set of all users (individual user indicated by u)
$\mathcal{G}$	Set of all users (one group indicated by g)
$\mathcal{M}$	Set of all media types (i.e., categories) used as content representation ($\mathcal{M}$ = {"text", "image", "audio", "video", "URL"})
C_m	Set of categories associated with a given message (one category indicated by c)
$\mathcal{U}_g$	Set of user members of group g
$t_{i\|u,g}$	Timestamp of the ith message shared by user u in group g
δ_T	Duration of window of interaction
d	Destination user whose curiosity we are analyzing
o	Origin user who may stimulate the curiosity of a destination at a given time
$\rightarrow$	Quantity computed for current window of interaction
$\leftarrow$	Quantity computed for historical windows
$\mathcal{U}^{\rightarrow}_{t,g}$	Set of (distinct) users sharing content in group g during window of interaction $[t-\delta_T;t]$
$\mathcal{O}^{\rightarrow}_{t_{i\|d,g}}$	Set of (distinct) origins for destination d in group g at time $t_{i\|d,g}$ (all users, except for d, who shared content during the window $[t_{i\|d,g}-\delta_T;t_{i\|d,g}]$)
$\mathcal{C}^{\rightarrow}_{t,g}$	Set of (distinct) message categories shared during window $[t-\delta_T;t]$
$\mathbf{S}^{\leftarrow}_{t,g}$	Contingency table with historical patterns computed for group g at time t (see Fig. 2)
$n^{\rightarrow}_{u\|t,g}$	Number of times user u shared content in group g during window $[t-\delta_T;t]$
$n^{\rightarrow}_{c\|t,g}$	Number of messages of category c shared in group g during window $[t-\delta_T;t]$
$n^{\leftarrow}_{o,d\|t,g}$	Number of times o and d shared content in group g (in that order) within a δ_T time interval *before* the window $[t-\delta_T;t]$
G	Random variable associated with groups
O	Random variable associated with origin users
D	Random variable associated with destination users
C	Random variable associated with the categories of messages
$P^{\leftarrow}_{t,g}(X)$	Probability of random variable X computed based on historical patterns within group g before window of interaction $[t-\delta_T;t]$
$PMI^{\leftarrow}_{t,g}(D=d,O=o)$	Pointwise mutual information between the destination d and origin o in group g, measured at time t (Eq. (1))
$socInf^{\leftarrow}_{t,g}(D=d,O=o)$	Social influence from origin o on destination d in group g, measured at time t (Eq. (2))
$MI^{\leftarrow}_{t,g}(D,O=o)$	Mutual information of all destinations conditioned on an particular origin o in group g, measured at time t (Eq. (5))
$indSocInf^{\leftarrow}_{t,g}(D,O=o)$	Indirect social influence from origin o on all destinations (users in D) in group g, measured at time t (Eq. (6))
$H^{\leftarrow}_{t,g}(D \mid O=o)$	Entropy of destinations conditioned on a particular origin o in group g, measured at time t (Eq. (9))
$groupEntropy(t=t_{i\|d,g},g)$	Group-level entropy of destinations conditioned on all origins in group g, measured at time t (Eq. (10))
$H^{\leftarrow}_{t,g}(D)$	Entropy of destinations in group g, regardless of any social influence, measured at time t (Eq. (11))

We also note that, even though URLs are presented in textual format, we do consider them a separate category because URLs refer to external content (e.g., a post in another platform), which is not immediately visible to the user. Thus, from the perspective of curiosity stimulation, we speculate they may have a different impact compared to the rest of the textual content (which is immediately visible). More broadly, the use of media types as message categories is based on the assumption that different media types require different amounts of effort from the user to see and process the content, which should impact how the user curiosity is stimulated by it. We further elaborate on this point and discuss the implications of our choice of media types as categories in Section 5.

We use notation $t_{i|u,g}$ to refer to the timestamp of the ith message shared by user u in group g. We assume time is continuous starting at 0. Thus, no two messages can be shared at exactly the same time in a group. Each group is composed by a set of users $\mathcal{U}_g \subseteq \mathcal{U}$, with size $|\mathcal{U}_g|$. Moreover, let the groups be associated with the random variable G.

These definitions illustrate the basis of our notation. Variables are represented as small letters (e.g., user u and group g), random variables as capital letters (e.g., G), and sets are represented as calligraphic letters (e.g., $\mathcal{G}$ and $\mathcal{U}$). We employ subscripts to determine subsets (e.g., users in a group $\mathcal{U}_g$), and the Bayesian notation to define constraints/dependencies (e.g., $t_{i|u,g}$ is the time of the ith message shared by a given user u in a given group g). The complete set of notation, including those used above as others introduced in the following sections, is listed in Table 2.

3.2. Social curiosity

Having presented the general concepts, notation and assumptions, we proceed by zooming in the novel metrics that capture the impact of social influence as a driver to user curiosity (or simply social curiosity [33]). Recall that these metrics are meant to capture the influence that a set of users have on a particular (distinct) target user, as stimuli to this user's curiosity towards sharing content. Thus, in order to distinguish between the user whose curiosity we are analyzing, i.e., user u who shared a message in group g at time $t_{i|u,g}$, and the other users who may stimulate u's curiosity through social influence at time $t_{i|u,g}$, we refer to the former as the *destination* and the latter as *origins* (of social influence).

In the following, we use notations d to refer to a particular destination user and o to refer to one of his origins. We also define $\mathcal{O}^{\rightarrow}_{t_{i|d,g}}$ as the *set* of all origins for the destination user d sharing a message at time $t_{i|d,g}$, i.e., the set of all other users who shared content in the window of interactions $[t_{i|u,g} - \delta_T;\ t_{i|u,g}]$ and thus may stimulate d's curiosity at time $t_{i|u,g}$. Note that, by definition, the destination d herself does not belong to $\mathcal{O}^{\rightarrow}_{t_{i|d,g}}$, regardless if she also shared content during that period. In other words, we are interested in looking into the *other* users stimulating d's curiosity. Also, as a set, multiple occurrences of the same origin in the window of interaction count as one.

Given our assumption that influence is estimated based on historical patterns (assumption 5), we must distinguish between the *current* window of interaction and previous/historical windows (always with duration δ_T) which occurred before the current window initiated. Historical windows are used to estimate the influence of each origin o in d's content sharing at time $t_{i|d,g}$. We make such distinction by adopting notation $^{\rightarrow}$ (as in $\mathcal{O}^{\rightarrow}_{t_{i|d,g}}$) to refer to the current window of interaction and $^{\leftarrow}$ to refer to historical windows. Moreover, since we assume social influence may change over time, it must be recomputed using all available historical interactions up to (the beginning of) the current window of interaction.

For each window of interaction defined by a message sharing at time $t = t_{i|d,g}$, historical interactions are captured by a contingency table $\mathbf{S}^{\leftarrow}_{t,g}$. Each cell in the table determines the number of times origin o and destination d shared content in group g (in that order) within a maximum time interval of δ_T *before* the current window of interaction started (i.e., before time $t-\delta_T$), with $o,d \in \mathcal{U}_g$ and $o \neq d$. We use notation $n^{\leftarrow}_{o,d|t,g}$ to refer to this number. Note that, by definition,

$$
\begin{array}{cc|c}
 & \overbrace{\begin{array}{cccc} u_1 & u_2 & u_3 & u_4 \end{array}}^{\text{Destination of influence}} & \text{Total of rows:} \\
\text{Origin of influence} \left\{ \begin{array}{c} u_1 \\ u_2 \\ u_3 \\ u_4 \end{array} \right. & \begin{bmatrix} 0 & 1 & 2 & 1 \\ 0 & 0 & 2 & 0 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 2 & 0 \end{bmatrix} & \begin{array}{c} 4 \\ 2 \\ 2 \\ 3 \end{array} \\
\hline
\text{Total of columns:} & \begin{array}{cccc} 2 & 1 & 6 & 2 \end{array} & \text{Total:}\ 11
\end{array}
$$

Fig. 2. Contingency table $\mathbf{S}^{\leftarrow}_{t,g}$ computed when user 3 shares message 12 in Fig. 1.

$n^{\leftarrow}_{d,d|t,g} = 0$, i.e., self-influence (diagonal) is not considered. For the general case of a group with $|U_g|$ users, table $\mathbf{S}^{\leftarrow}_{t,g}$ has size $|U_g| \times |U_g|$.

Fig. 2 shows the contingency table computed for the example in Fig. 1 at 3:00 pm, when user 3 shared *msg 12*. All messages shared up to the beginning of the window of interaction defined for *msg 12* should be considered. Thus, *msgs 1–8*, shared before 2:30, are taken into account to compute the table. The column representing user 3 as destination is shown in red. For example, we can see that user 3 followed a message by user 1 within $\delta_T = 30$ min twice in the past (specifically when user 3 shared *msgs 3* and *8*). Similarly, user 3 followed messages by user 4 within that interval also twice in the past: *msg 8* by user 3 follows *msgs 5* and *7* by user 4. The figure also shows the joint count of the number of messages for each origin (row), each destination (column) and the overall total.

Now, let O and D be random variables associated with origins and destinations, respectively. Given the contingency table computed for a message shared at time t by destination d, we define the following probabilities for a group g, computed based on historical patterns (note the use of $^{\leftarrow}$):

(a) Probability of an origin o on group g:

$$P^{\leftarrow}_{t,g}(O = o) = P^{\leftarrow}(O = o \mid t_{i|d,g} = t, G = g) = \frac{\sum_d n^{\leftarrow}_{o,d|t,g}}{\sum_{o,d} n^{\leftarrow}_{o,d|t,g}};$$

(b) Probability of a destination d on group g:

$$P^{\leftarrow}_{t,g}(D = d) = P^{\leftarrow}(D = d \mid t_{i|d,g} = t, G = g) = \frac{\sum_o n^{\leftarrow}_{o,d|t,g}}{\sum_{o,d} n^{\leftarrow}_{o,d|t,g}};$$

(c) Probability of a destination given an origin:

$$P^{\leftarrow}_{t,g}(D = d \mid O = o) = P^{\leftarrow}(D = d \mid O = o, t_{i|d,g} = t, G = g) = \frac{n^{\leftarrow}_{o,d|t,g}}{\sum_d n^{\leftarrow}_{o,d|t,g}}.$$

(d) Joint probability of a destination and an origin:

$$P^{\leftarrow}_{t,g}(D = d, O = o) = P^{\leftarrow}(D = d, O = o, t_{i|d,g} = t, G = g) = \frac{n^{\leftarrow}_{o,d|t,g}}{\sum_{o,d} n^{\leftarrow}_{o,d|t,g}}.$$

Note that all probabilities are conditioned on the group and timestamp of the current message. Thus, to simplify notation we drop these two conditions, using subscripts instead. That is, we define $P^{\leftarrow}_{t,g}(\cdot) = P^{\leftarrow}(\cdot \mid t_{i|d,g} = t, G = g)$ as exemplified above.[6] We make the same simplification in the notation used below to improve readability.

Taking the contingency table shown in Fig. 2 as input, we can make, for example, the following computations at the time when user 3 shares *msg 12*:

(a) Probability of origin 3: $P^{\leftarrow}_{t,g}(O = u_3) = \frac{2}{11}$;

(b) Probability of destination 3: $P^{\leftarrow}_{t,g}(D = u_3) = \frac{6}{11}$;

(c) Probability of destination 3 given origin 2:

$$P^{\leftarrow}_{t,g}(D = u_3 \mid O = u_2) = \frac{2}{2} = 1;$$

(d) Probability of destination 3 given origin 4:

$$P^{\leftarrow}_{t,g}(D = u_3 \mid O = u_4) = \frac{2}{3};$$

(e) Joint probability of destination 3 and origin 4:

$$P^{\leftarrow}_{t,g}(D = u_3, O = u_4) = \frac{2}{11}.$$

Having defined these probabilities, we are ready to define our new metrics of social curiosity. In total, we propose four new metrics of the stimulation a user is exposed to by social influence from others in the group. All metrics are based on the concept of *mutual information* [92]. In essence, the Mutual Information (MI) of two random variables is a measure of the mutual dependence between them. Specifically, it quantifies the reduction in the *uncertainty* (or entropy [93]) associated with one variable as we observe the other random variable.

Our first two metrics are based on the concept of Pointwise Mutual Information (PMI), which is computed for a pair of outcomes x and y belonging to discrete random variables X and Y. In our case, we define the pointwise mutual information of a particular destination d and a particular origin o as [94]:

$$PMI^{\leftarrow}_{t,g}(D = d, O = o) = \begin{cases} \log_2\left(\dfrac{P^{\leftarrow}_{t,g}(D = d \mid O = o)}{P^{\leftarrow}_{t,g}(D = d)}\right), & \text{if } P^{\leftarrow}_{t,g}(D = d) > 0. \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The PMI of d and o measures the reduction in the uncertainty of destination d sharing a message due to the knowledge that o also shared a message (within the window of interaction).[7] This reduction comes from the social influence that o has on d, which in turn stimulates d's curiosity. It means that, based on historical patterns (social influence estimate), the behavior of (i.e., sharing of a message by) user d in the group is influenced by recent behavior of user o. Naturally, we set the PMI value to 0 if there is no history of messages shared by d (i.e., $P^{\leftarrow}_{t,g}(D = d) = 0$).

Note that, for the sake of estimating the social influence of o over d as a stimulus to d's curiosity, we are interested in *positive values* of PMI. However, there are cases in which Eq. (1) returns non-positive values. For example, $P^{\leftarrow}_{t,g}(D = d \mid O = o) = P^{\leftarrow}_{t,g}(D = d)$ suggests that the actions of d and o are independent, i.e., o has no influence of d's behavior. In that case, the PMI value is equal to 0. Similarly, if $P^{\leftarrow}_{t,g}(D = d \mid O = o) = 0$, there is no historical evidence of messages shared by o and d within a maximum interval δ_T, and, as defined, there is no evidence of social influence from o on d. In this case, the PMI value is negative. More generally, the PMI value will be negative whenever $P^{\leftarrow}_{t,g}(D = d \mid O = o) < P^{\leftarrow}_{t,g}(D = d)$. This case implies that the particular pair of destination d and origin o occurs less frequently than would be expected under the assumption of independent behavior, which might reflect unreliable statistics. Regardless, in all such cases, there is clearly no evidence of social influence of o on d. Thus, as in prior studies [95], we choose to clip negative values of PMI at 0, thus

[6] In other words, unless otherwise noted, whenever t is used we refer to time $t_{i|d,g}$ when the ith message of the target destination d was shared in group g.

[7] Alternative information theory-based metrics, such as transfer entropy [81,87] could also be used. We here chose PMI, instead, as it refers to single events, i.e., a single message shared by a user. Transfer entropy, instead, being based on mutual information, is meant to capture an aggregate relationship between two processes — specifically, the amount of directed transfer of information between them.

defining the following estimate of the social influence of origin o on destination d:

$$socInf^{\leftarrow}_{t,g}(D=d,O=o)=\max\Big(PMI^{\leftarrow}_{t,g}(D=d,O=o),0\Big). \quad (2)$$

Given that the current window of interaction may have multiple origins stimulating the curiosity of destination d, we need to aggregate the mutual information computed for each origin o that appears in set $\mathcal{O}^{\rightarrow}_{t_{i|d,g}}$. We do so by computing the average and maximum social influence for all origins o on d. We thus build two metrics capturing the average and the maximum *direct influence* of the origins on a destination d, *based on historical patterns*:

$$avgDirInf(d,t=t_{i|d,g},g)=\frac{\sum_{o\in\mathcal{O}^{\rightarrow}_{t_{i|d,g}}} socInf^{\leftarrow}_{t,g}(D=d,O=o)}{|\mathcal{O}^{\rightarrow}_{t_{i|d,g}}|} \quad (3)$$

$$maxDirInf(d,t=t_{i|d,g},g)=\max_{o\in\mathcal{O}^{\rightarrow}_{t_{i|d,g}}}\Big(socInf^{\leftarrow}_{t,g}(D=d,O=o)\Big) \quad (4)$$

In addition to direct influence, we argue that some users may have a natural ability to influence others. This is not a novel concept, neither in general nor in the particular case of WhatsApp, although we are the first to propose a metric to quantify it as a component of curiosity stimulation. Indeed, Guo et al. [50] made a distinction between direct and indirect influence, emphasizing that the latter may not have an obvious manifestation and may have gradual consequences on user behavior. Caetano et al. [89], in turn, identified the presence of (what they called) activists in public WhatsApp groups, i.e., users who often share content and, in doing so, keep the discussion going by driving others to also share content. This latter observation, in particular, motivated us to include metrics to capture such *indirect* influence: in a constrained (i.e., limited to 256 simultaneous users) and often focused space of communication, such as a WhatsApp group, it is reasonable to expect that these very active users (and activists) may indeed influence others much more often than it would occur in other unconstrained environments. That is, we consider that, even in the absence of prior experiences (i.e., $P^{\leftarrow}_{t,g}(D=d\mid O=o)=0$), such influencers may still stimulate the curiosity of a user (e.g., a newcomer) in the group.

We identify these *indirect* influencers by searching for origins o that tend to have *strong* influence towards some destinations d. Given this rationale, we propose two other metrics of social curiosity to capture the impact of such indirect influencers on destination d at time $t_{i|d,g}$. These metrics are based on the *mutual information of the destinations conditioned on an particular origin*, that is:

$$MI^{\leftarrow}_{t,g}(D,O=o)=\sum_{d'\in\mathcal{U}_g} P^{\leftarrow}_{t,g}(D=d',O=o)PMI^{\leftarrow}_{t,g}(D=d',O=o) \quad (5)$$

We note that, as done in Eq. (2), in order to capture *indirect social influence*, we clip non-positive values of mutual information at 0 as a reflection of no social influence from origin o on any destination $d\in D$. We thus define:

$$indSocInf^{\leftarrow}_{t,g}(D,O=o)=\max\Big(MI^{\leftarrow}_{t,g}(D,O=o),0\Big) \quad (6)$$

The random variable of interest in Eqs. (5) and (6) is D, conditioned on a particular origin o. Smaller values of $indSocInf^{\leftarrow}_{t,g}(D,O=o)$ suggest weaker and no clear influence of o over any user $d\in D$. Take, for example, the case when $P^{\leftarrow}_{t,g}(D=d'\mid O=o)$ is roughly uniform for all destinations d'. Based on the values of $P^{\leftarrow}_{t,g}(D=d'\mid O=o)$, origin o does not strongly influence any particular destination d. The mutual information is this case is minimum. In contrast, larger values of $indSocInf^{\leftarrow}_{t,g}(D,O=o)$ imply that the influence of origin o tends to be concentrated and stronger on fewer destinations. These are the cases we are searching for. That is, the higher the value of $indSocInf^{\leftarrow}_{t,g}(D,O=o)$, computed based on historical patterns, the higher the *indirect* influence that o may have over the target destination d under analysis, i.e., the user whose curiosity stimulation is being quantified.[8]

Table 3
Computing the metrics of social curiosity for destination user 3 at time $t=3$ pm (reference: Fig. 2).

Metric	Value
$PMI^{\leftarrow}_{3:00,g}(D=u_3,O=u_1)$	−0.13
$PMI^{\leftarrow}_{3:00,g}(D=u_3,O=u_2)$	0.87
$PMI^{\leftarrow}_{3:00,g}(D=u_3,O=u_4)$	0.29
$socInf^{\leftarrow}_{3:00,g}(D=u_3,O=u_1)$	0.00
$socInf^{\leftarrow}_{3:00,g}(D=u_3,O=u_2)$	0.87
$socInf^{\leftarrow}_{3:00,g}(D=u_3,O=u_4)$	0.29
$avgDirInf(d,t=t_{i\|d,g},g)$	0.39
$maxDirInf(d,t=t_{i\|d,g},g)$	0.87
$MI^{\leftarrow}_{t,g}(D,O=u_1)$	0.42
$MI^{\leftarrow}_{t,g}(D,O=u_2)$	0.87
$MI^{\leftarrow}_{t,g}(D,O=u_4)$	0.48
$indSocInf^{\leftarrow}_{t,g}(D,O=u_1)$	0.42
$indSocInf^{\leftarrow}_{t,g}(D,O=u_2)$	0.87
$indSocInf^{\leftarrow}_{t,g}(D,O=u_4)$	0.48
$avgIndInf(d,t=t_{i\|d,g},g)$	0.59
$maxIndInf(d,t=t_{i\|d,g},g)$	0.87

Again, we aggregate the above metric for all origins in the window of interaction via the average and maximum functions, referring to them as average and maximum *indirect* influence:

$$avgIndInf(d,t=t_{i|d,g},g)=\frac{\sum_{o\in\mathcal{O}^{\rightarrow}_{t_{i|d,g}}} MI^{\leftarrow}_{t,g}(D,O=o)}{|\mathcal{O}^{\rightarrow}_{t_{i|d,g}}|}, \quad (7)$$

$$maxIndInf(d,t=t_{i|d,g},g)=\max_{o\in\mathcal{O}^{\rightarrow}_{t_{i|d,g}}}\Big(MI^{\leftarrow}_{t,g}(D,O=o)\Big). \quad (8)$$

As mentioned, the indirect social influence metrics are particularly useful to capture the influence that an origin may exhibit on a destination she has not interacted with yet. If this is a recurring pattern, the direct influence metrics, computed based on $P^{\leftarrow}_{t,g}(D=d\mid O=o)$, will rise as time passes.

Going back to the example in Fig. 1, let us estimate the metrics of social curiosity applied to user 3 at the time $t=$ 3:00 pm, when *msg 12* was shared. To that end, we will use the contingency table shown in Fig. 2. The computation of all metrics are shown in Table 3. Note that users 1, 2 and 4 are origins of influence for user 3 at this time (i.e., they shared content during the window of interaction). Using Eqs. (1)–(4), we compute the average and maximum direct social influence of these origins on user 3 as $avgDirInf(u_3,t=3{:}00,g)=0.39$ and $maxDirInf(u_3,t=3{:}00,g)=0.87$, respectively. Also, using Eqs. (5)–(8), we compute average and maximum indirect social influence of the origins on user 3 as $avgIndInf(d,t=3{:}00,g)=0.59$ and $maxIndInf(d,t=3{:}00,g)=0.87$, respectively.

Before moving forward, we note that mutual information can also be used to quantify how social influence drives curiosity of a group of users. As such, it may offer an aggregate view of (social) curiosity stimulation in the ecosystem of a particular group g up to time $t_{i|d,g}$ when a member d shares a message. Towards defining such a metric, we start by introducing the entropy of destinations conditioned on a particular origin o [93], given by:

$$H^{\leftarrow}_{t,g}(D\mid O=o)=-\sum_{d'\in\mathcal{U}_g} P^{\leftarrow}_{t,g}(D=d'\mid O=o)\log_2\Big(P^{\leftarrow}_{t,g}(D=d'\mid O=o)\Big). \quad (9)$$

[8] We note that it may seem at first that Eqs. (5) and (6) lack this target destination d. Yet, recall that, as the metrics in Eqs. (1)–(4), it is conditioned on the time $t=t_{i|d,g}$ that the target destination d shared her ith message in group g. This condition was omitted from the equations simply to improve readability.

We then aggregate the conditional probability in Eq. (9) over all origins in the group to build a group-level metric:

$$groupEntropy(t = t_{i|d,g}, g) = \sum_{o \in \mathcal{U}_g} P^{\leftarrow}_{t,g}(O = o) H^{\leftarrow}_{t,g}(D \mid O = o). \tag{10}$$

The $groupEntropy$ metric should be analyzed in light of the entropy of destinations D *regardless of social influence*, defined as follows:

$$H^{\leftarrow}_{t,g}(D) = -\sum_{d \in \mathcal{U}_g} P^{\leftarrow}_{t,g}(D = d) \log_2 \left(P^{\leftarrow}_{t,g}(D = d) \right). \tag{11}$$

Based on Eqs. (10) and (11), we introduce the group-level mutual information between destinations and origins to capture the reduction in uncertainty associated with *destinations* due to the knowledge of the social influence from other users (origins) in the group. Specifically, we define:

$$groupMutInf(t = t_{i|d,g}, g) = H^{\leftarrow}_{t,g}(D) - groupEntropy(t = t_{i|d,g}, g). \tag{12}$$

The higher the mutual information, the greater the influence of origins over the destinations in group g. This may happen because either there are some highly influential origins or group curiosity is often stimulated by many group members.

Going back once again to our example, we also estimate the group-level social curiosity at the time user 3 shared *msg 12* as follows. We first compute the entropy of destinations $H^{\leftarrow}_{3:00,g}(D) = 1.91$ and the group-level entropy of destinations conditioned on origins $groupEntropy(t = t_{i|d,g}, g) = 1.39$. Based on these two values, we compute $groupMutInf(t = 3{:}00, g) = 1.91 - 1.39 = 0.52$ which corresponds to only 27% of the original entropy of destinations in the group. Thus the knowledge of the social influence from the origins causes a reduction of only 27% $\left(\frac{0.52}{1.91}\right)$ on the entropy of destinations. We could say that, up to this time, the group is not very strongly stimulated by social influence.

A summary of all user/individual and group level metrics of social curiosity is presented in the top part of Table 4. Unless otherwise noted, all metrics should be interpreted as: *the larger the value, the greater the curiosity stimulation*.

Table 4
Metrics of curiosity stimulation for content sharing in WhatsApp groups.

Collative variable	Metric	Definition
Social curiosity (individual)	$avgDirInf(d,t,g)$	Average direct influence of all origins on destination d at time t in group g (Eq. (3))
Social curiosity (individual)	$maxDirInf(d,t,g)$	Maximum direct influence of any origin on destination d at time t in group g (Eq. (4))
Social curiosity (individual)	$avgIndInf(d,t,g)$	Average indirect influence of all origins on destination d at time t in group g (Eq. (7))
Social curiosity (individual)	$maxIndInf(d,t,g)$	Maximum indirect influence of any origin on destination d at time t in group g (Eq. (8))
Social curiosity (group)	$groupMutInf(t,g)$	Mutual information between destinations and origins in group g at time t (Eq. (12): large values imply many strong curiosity stimulators in group)
Novelty	$userNovelty(d,t,g)$	Novelty associated with destination d sharing message in group g at time t (Eq. (13))
Novelty	$catNovelty(C_m,t,g)$	Novelty associated with set C_m of categories of the message shared by destination d in group g at time t (Eq. (14))
Uncertainty	$userUncertainty(t,g)$	Uncertainty associated with users in group g, measured at time t (Eq. (15))
Uncertainty	$catUncertainty(t,g)$	Uncertainty associated with categories of messages in group g, measured at time t (Eq. (16))
Conflict	$userConflict(t,g)$	Conflict associated with users sharing content in group g, measured at time t (Eq. (17))
Conflict	$catConflict(t,g)$	Conflict associated with categories of messages shared in group g, measured at time t (Eq. (18))
Complexity	$catComplex(t,g)$	Complexity associated with categories of messages in group g, measured at time t (Eq. (19))

3.3. Other collative variables

Having introduced our metrics of social curiosity, we now present 7 metrics that instantiate other collative variables, notably novelty, uncertainty, conflict and complexity, priorly associated with curiosity stimulation. We build on metrics originally proposed to the context of online music consumption [28], adapting them here to the domain of content sharing in group communication. Based on assumption 3, we assume once again that user curiosity is triggered based only on what happens (*who* shares *what*) during the window of interaction[9] (thus the use of notation $^{\rightarrow}$ throughout this section). Therefore, the metrics are computed based solely on properties of the *user* who is sharing the content (i.e., the destination user) and of the content being shared, as captured by the media types (i.e., categories) associated with it. A summary of these metrics is presented in the bottom part of Table 4.

We here propose two metrics that instantiate the *novelty* component of the stimulus imposed on destination d at time $t_{i|d,g}$. The first one – $userNovelty$ – captures the novelty related to the user sharing the content, i.e., user d. The idea is that the experience of sharing content is less novel to users who share more often, which ultimately affects the curiosity driving the action. This claim is inspired by arguments by Loewenstein [3], who states that novelty is determinant of exploratory behavior in the individual's curiosity, and by Kashdan [33,34], who argues that social curiosity may also be stimulated by novelty. Thus, we propose user novelty as a means to capture possible effects that a novel experience may have as a factor driving a user to participate in a group by sharing content. To our knowledge, we are the first to propose a novelty metric related to users, but we believe that in the specific domain of investigation – group communication – this variable may be a relevant component of curiosity stimulation. Indeed, as we will show in Section 4, the proposed metric is indeed complementary to the others in many cases, which is an indication that, to some degree, the metric does capture new information.

The $userNovelty$ metric is defined as the *surprisal*[10] associated with destination d:

$$userNovelty(d, t = t_{i|d,g}, g) = \begin{cases} -\log_2 \left(P^{\rightarrow}_{t,g}(D = d) \right), & \text{if } P^{\rightarrow}_{t,g}(D = d) > 0 \\ -\log_2 \left(1/|\mathcal{U}^{\rightarrow}_{t,g}| \right), & \text{otherwise} \end{cases} \tag{13}$$

where $P^{\rightarrow}_{t,g}(D = d)$ is the probability of d sharing content in group g during the current window of interaction, being thus defined as $n^{\rightarrow}_{d|t,g} / \sum_{u \in \mathcal{U}_g} n^{\rightarrow}_{u|t,g}$. Note that $P^{\rightarrow}_{t,g}(D = d) = 0$ corresponds to the maximum surprisal associated with destination d. In such case, we set

[9] This was also a guideline for deriving the social curiosity metrics. However, for those metrics in particular, we used historical patterns to estimate the social influence of origins and destination identified in the window of interaction.

[10] *Surprisal* is also called of *Shannon information content* [93].

the surprisal to its maximum value possible, which corresponds to a uniform distribution of destinations, i.e., $-\log_2(1/|\mathcal{U}^{\rightarrow}_{t,g}|)$, where $\mathcal{U}^{\rightarrow}_{t,g}$ is the *set* of distinct users sharing content in group g during the current window of interaction $[t-\delta_T;t]$.

Recall that we assume users may share messages with content in the following categories, defined based on media type: $\mathcal{M}$ = {"text", "image", "audio", "video", "URL"}. Given a particular message shared at time t, let C be the random variable associated with category, c be a category associated with the given message (i.e., $c \in C_m$) and $C^{\rightarrow}_{t,g}$ be the *set* of media types associated with all messages shared within the window of interaction $[t-\delta_T;t]$. Similarly to what was done for users, we define a novelty metric related to the message categories, based on the surprisal associated with that variable:

$$catNovelty(C_m, t = t_{i|d,g}, g) = \begin{cases} -\log_2\left(\bar{P}^{\rightarrow}_{t,g}(C_m)\right), & \text{if } \bar{P}^{\rightarrow}_{t,g}(C_m) > 0 \\ -\log_2\left(1/|C^{\rightarrow}_{t,g}|\right), & \text{otherwise} \end{cases} \quad (14)$$

where $\bar{P}^{\rightarrow}_{t,g}(C_m)$ is the average probability of categories associated with the message (categories in C_m), defined as:

$$\bar{P}^{\rightarrow}_{t,g}(C_m) = \frac{1}{|C_m|}\sum_{c\in C_m} P^{\rightarrow}_{t,g}(C=c).$$

The probability of a specific category is estimated as $P^{\rightarrow}_{t,g}(C=c) = n^{\rightarrow}_{c|t,g}/\sum_{k\in C} n^{\rightarrow}_{k|t,g}$, where $n^{\rightarrow}_{c|t,g}$ is the number of messages with category c shared in group g in the window of interaction $[t-\delta_T;t]$.[11] This metric captures how surprising it is that the message shared at time $t = t_{i|d,g}$ has category c.

Taking the example of user 3 sharing *msg 12* at 3:00 pm, illustrated in Fig. 1, we find that a total of four messages were shared during the current window of interaction, defined as [2:30,3:00]. The destination, user 3, shared only once. Thus, the novelty associated with the destination is computed as: $P^{\rightarrow}_{3:00,g}(D=u_3) = 1/4$, hence $userNovelty(u_3, t = 3{:}00, g) = 2$. Similarly, during this window, two images, one audio and one video were shared. In particular, *msg 12* contains only an image (i.e., $|C_m| = 1$). Thus, the novelty associated with the category of this message can be computed as: $\bar{P}^{\rightarrow}_{3:00,g}(C_m = \{\text{"image"}\}) = 2/4$, which results in $catNovelty(\{\text{"image"}\}, t = 3{:}00,\ g) = 1$. Thus, the curiosity driving user 3 to share *msg 12* is more stimulated by the novelty the user herself experiences with this action than by the novelty of (the category of) the content shared.

Note that both novelty related metrics focus on a single element: the destination user or the (categories of the) message shared. The aggregation of either metric for all elements in the window of interaction, using entropy, captures the *uncertainty*. Thus, we define metrics of uncertainty related to user and categories as:

$$userUncertainty(t = t_{i|d,g}, g) = -\sum_{d\in\mathcal{U}_g} P^{\rightarrow}_{t,g}(D=d)\log_2\left(P^{\rightarrow}_{t,g}(D=d)\right), \quad (15)$$

$$catUncertainty(t = t_{i|d,g}, g) = -\sum_{c\in C^{\rightarrow}_{t,g}} P^{\rightarrow}_{t,g}(C=c)\log_2\left(P^{\rightarrow}_{t,g}(C=c)\right). \quad (16)$$

The idea behind these metrics is that the curiosity of the destination may be more/less stimulated by the greater/less diversity in the users sharing messages (and in the categories of these messages) during the window of interaction.

For the sake of illustration, let us compute the stimulus related to user uncertainty experienced by user 3 when sharing *msg 12*. We first calculate the probability of each user sharing a message in the current window of interaction, which is equal to 1/4 for all four users in the window. The user uncertainty is then computed as $userUncertainty(t = 3{:}00, g) = 2$. Turning to the stimulus related to the uncertainty associated with message categories, we compute probabilities $P^{\rightarrow}_{3:00,g}(C = \text{"video"}) = 1/4$, $P^{\rightarrow}_{3:00,g}(C = \text{"audio"}) = 1/4$ and $P^{\rightarrow}_{3:00,g}(C = \text{"image"}) = 2/4$, which leads to an uncertainty equal to $catUncertainty(t = 3{:}00, g) = 1.5$. Thus, at time 3:00 pm, the diversity (uncertainty) in users sharing content is greater than the diversity in content category. Thus, user 3's curiosity is more stimulated by the former.

According to Berlyne [2], *conflict* occurs when the same stimulus triggers multiple incompatible responses, being positively related to the strengths of the competing responses. To operationalize the concept of conflict, we follow the same approach in [29]. The basic idea is that the different elements (categories/users) that appear in the window of interaction represent the potentially incompatible responses stimulating the curiosity of the destination user, and the strength of each response is captured by the probability of occurrence of each element (category/user). We instantiate this variable by first computing the average probability of users (categories) over all users (message categories) in the window of interaction, and then taking the surprisal of the result. This procedure leads to two new metrics, one related to users and the other to categories:

$$userConflict(t = t_{i|d,g}, g) = -\log_2\left(\frac{1}{|\mathcal{U}^{\rightarrow}_{t,g}|}\sum_{d\in\mathcal{U}_g} P^{\rightarrow}_{t,g}(D=d)\right), \quad (17)$$

$$catConflict(t = t_{i|d,g}, g) = -\log_2\left(\frac{1}{|C^{\rightarrow}_{t,g}|}\sum_{c\in C^{\rightarrow}_{t,g}} P^{\rightarrow}_{t,g}(C=c)\right). \quad (18)$$

Again, we use the example in Fig. 1 to exemplify how the metrics of conflict are computed for user 3 sharing *msg 12*. We first take the average probabilities across all users and categories which are 1/4 and 1/3, respectively. We then compute $userConflict(t = 3{:}00,\ g) = 2$ and $catConflict(t = 3{:}00,\ g) = 1.59$.

Finally, an alternative form of capturing the diversity of message categories in the current window of interaction is by exploiting the unique occurrences of the media types. This metric, also based on surprisal, captures the *complexity* associated with the categories of messages shared during the current window of interaction, which is also a collative variable associated with curiosity stimulation. It is defined as:

$$catComplex(t = t_{i|d,g}, g) = -\log_2\left(\frac{|C^{\rightarrow}_{t,g}|}{|\mathcal{M}|}\right). \quad (19)$$

Note that, unlike uncertainty and conflict, which captures the diversity of message categories considering only those included in the window of interaction, complexity captures a somewhat different notion of diversity that takes into account all possible categories (included in set $\mathcal{M}$). Once again, we compute the complexity of message categories at time 3:00 when user 3 shared *msg 12* as follows. The current window of interaction includes 3 types of media (notably, "video", "audio" and "image") out of a total of 5 different types possible. Thus, the complexity associated with message categories is computed as $catComplex(t = 3:00, g) = -\log_2\frac{3}{5} = 0.74$.

As a final remark, we note that the metrics defined in Eqs. (13)–(19) are always non-negative and should be interpreted as: the greater the value the higher the stimulus to the curiosity of the destination user. Having introduced the novel metrics of curiosity stimulation, we applied them to study curiosity stimulation behind content sharing in Whatsapp groups. We discuss the main results from our investigation next.

4. Curiosity stimulation in WhatsApp groups

In this section, we use the metrics introduced in the previous section to characterize user curiosity in WhatsApp groups. Our goal is to both show the applicability of the metrics and uncover behavioral traits in a widely used communication platform.

[11] Note that since messages may have multiple categories, the same message may be counted multiple times in the numerator and in the denominator of $P^{\rightarrow}_{t,g}(C=c)$.

To that end, we rely on a dataset gathered by the WhatsApp Monitor[12] [41], a system for collecting shared messages in publicly accessible WhatsApp groups. The dataset consists of a sequence of messages posted in a number of publicly accessible groups in Brazil over a period of great social and political turmoil in the country (April 1st 2018 to April 30th 2019) which includes the 2018 general elections in the country. The monitored groups are themed around political topics.

Each entry in the dataset consists of posting time, anonymized user identifier, group identifier and message categories (media types).[13] We note that even though WhatsApp currently allows users to reply to a particular message, thus creating an explicit link between messages, this feature was not available at the time our dataset was collected.[14] As such, any possible link must be inferred from the available data, notably from the time when the messages were shared, since message content is not accessible.

To avoid issues with data sparsity, for each group, we only consider users who shared at least 30 messages during the whole period, and we only compute the metrics for sharing events with at least 10 messages in the window of interaction.[15] These lower bounds were imposed so as to be able to compute reliable values for the metrics, following the arguments in prior work [96] that state that that samples with fewer than 10 elements often lead to estimations with low statistical power. We also ran some preliminary experiments with other bounds and based on observations from these experiments as well as our own prior experience with curiosity stimulation on LastFM [28], we found that fewer data points often lead to unreliable measures. After applying these filters, the resulting dataset, which is used in our study, is composed on 2,054,302 messages posted by 7584 distinct users in 335 groups.

4.1. Relationships among collative variables

We start by quantifying the relationships among different collative variables, namely social influence, novelty, uncertainty, conflict and complexity, as captured by the proposed metrics. We aim at assessing the extent to which different metrics, notably the four novel metrics related to (individual-level) social influence (Eqs. (3), (4), (7) and (8)) are able to capture aspects related to curiosity stimulation which are not covered by the other (more traditional) variables (Eqs. (13)–(19)). To that end, we classify the metrics into *redundant* or *complementary* as to whether their effect on curiosity stimulation is mostly captured by the others (thus being redundant) or not.

Specifically, we first compute, for each user u in a group g, all metrics (11 in total) for each message shared by u in g. We then use these values to compute the Spearman correlation coefficient between each pair of metrics, for each (u, g) pair. Next, as in [28], we employ a heuristic to identify redundant metrics: two metrics are considered redundant for a given (u, g) pair if their correlation falls in the $(-1, -0.5)$ or $(+0.5, +1)$ ranges, which can be considered moderate-to-strong correlations. Otherwise, the correlation is deemed weak and the metrics are taken as *complementary*.

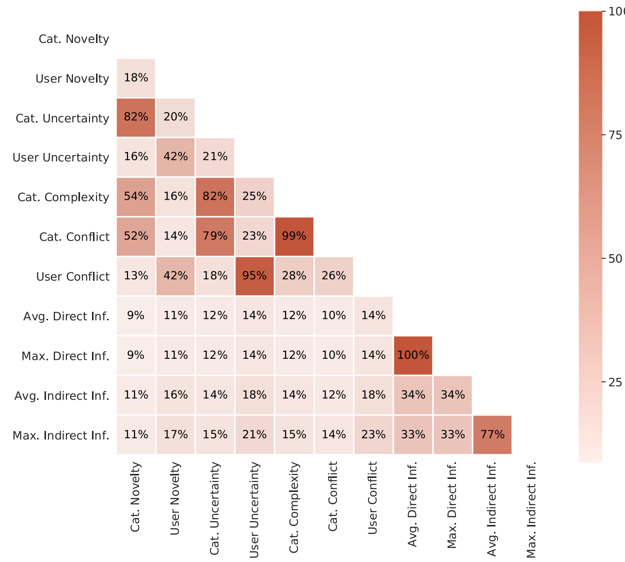


Fig. 3. Fraction of redundant (user, group) cases for each pair of metrics.

Fig. 3 shows a matrix with the fractions of cases, i.e., (user, group) pairs, for which each pair of metrics was considered redundant. One key result is that the four social influence metrics, shown in the last four rows (and columns), are *complementary* when compared to the metrics related to the other collative variables for most (more than 77%) of the cases. Thus, these metrics indeed capture relevant aspects of curiosity stimulation which are not covered by traditionally studied metrics. We also observe that direct and indirect social influence do often capture distinct effects, as their related metrics cannot be considered redundant for a large fraction of the cases (67% for the metrics of maximum influence). Yet, given the same general effect (i.e., direct or indirect social influence), taking either the average or maximum across all origins of influence is quite similar, as the corresponding metrics are redundant with respect to each other in most cases.

We can also note great redundancy between several traditional metrics, such as between uncertainty and novelty and between uncertainty, conflict and complexity, all related to message categories, as well as between uncertainty and conflict related to users. These redundancies are consistent with those observed in [28] for curiosity in online music consumption, and reflect the similar effects captured by those related metrics.

In the following, given our goal to study social influence as a component of curiosity stimulation, we focus our analyses on the two social influence metrics – maximum direct influence and maximum indirect influence – identified as complementary to each other in most cases.

4.2. Diversity and dynamics of social curiosity

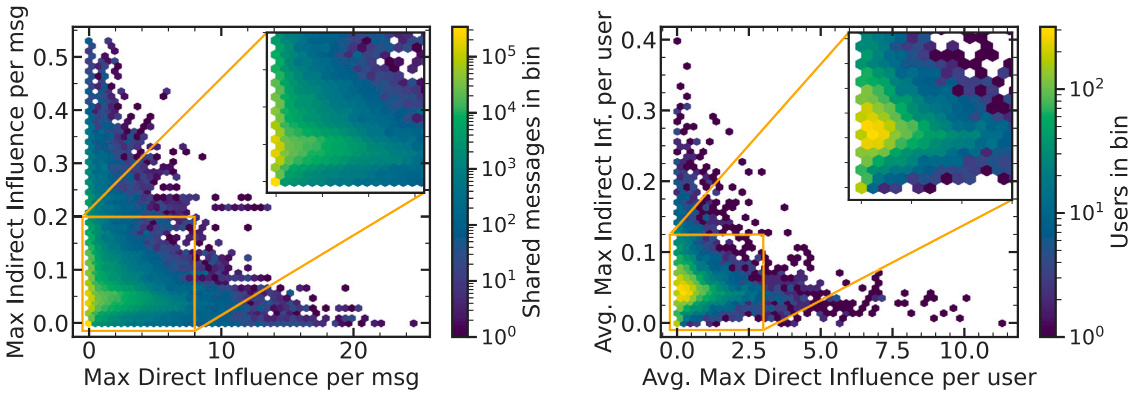
As a first analysis, we focus on how diverse user curiosity stimulation is in terms of the two complementary metrics of social curiosity. Recall that both metrics are computed for each *message sharing* event, performed by a user d in a group g at time $t_{i|d,g}$. Fig. 4 shows results of the two metrics for individual messages (Fig. 4a) as well as averages across all messages shared by the same user d (Fig. 4b), both computed for specific groups (i.e., the same user in different groups appear separately). Each graph in the figure shows the number of elements (messages or users) with specific values of *maximum direct influence* (x-axis) and *maximum indirect influence* (y-axis). For both graphs, we

[12] WhatsApp Monitor is available online at http://www.monitor-de-whatsapp.dcc.ufmg.br/.

[13] All user identifiers are indeed anonymized phone numbers as we are not able to identify multiple phone numbers belonging to the same person. Moreover message content, though collected by WhatsApp Monitor, cannot be made publicly available and, as such, was disregarded.

[14] Yet, our metrics might still be used (with some adjustments) when replies are available. In that case, we argue that, even though the original message was the primary source of curiosity stimulation on the user sharing the reply, other messages shared recently could also compose the stimulus driving the user behavior, perhaps with a lower intensity. Thus, a weighting scheme could be employed to combine all signals, favoring the message being replied. Exploring such scheme is an interesting subject for future work.

[15] For the sake of research reproducibility, we make our anonymized data as well as our code publicly available at https://zenodo.org/record/5790153#.Yb0Osb_MJE4.



(a) Stimuli associated with messages. (b) Average stimuli for users.

Fig. 4. Diversity of social curiosity stimuli across message sharings and users.

zoomed in a specific region of the graph and inset it to the graph. We highlight that the regions zoomed in correspond to 97% and 92% of all messages and users, respectively. The graphs are meant to contrast the values of both social curiosity metrics for each message and user. As such, they also show the ranges of the values observed for both metrics considering individual messages as well as aggregated across all messages shared by the same user.

The graphs reveal great diversity in values of both metrics across messages and users. On one hand, there is a major concentration in smaller values for both metrics, highlighted in the insets. Smaller values suggest that, based on the historical patterns, the behavior of the destination user (in terms of content sharing actions) is only weakly influenced (if influenced at all) by how the others in the current window of interaction (origins) behave. That is, the small amount of information (in terms of bits) about the interactions between these users suggest weaker social influence. In contrast, a fraction of the messages as well as a fraction of the users exhibit very large values of both metrics (two to four times larger than the majority), suggesting that, in those cases, the behavior of the destination user is strongly influenced by past behaviors of the origins. As a consequence, this produces more information (in terms of bits) about the interactions between those users, offering stronger evidence of social influence between them. Also, as the axes of both graphs show, direct influence is clearly spread over larger values, as a result of how the metric is computed (i.e., based on pointwise mutual information).

Moreover, by comparing the spreading of values (especially in the x-axis) on both graphs, we can infer that the diversity is great even if we look at the same user over time, i.e., over all the messages the user shared. In other words, the (social) curiosity of a user is stimulated quite differently for different users and even for the same user, considering different messages shared by her (potentially in different groups), which is consistent with some of our key assumptions presented in Section 3.1.1.

Given these observations, we delve deeper into the analysis of the diversity and dynamics of social curiosity by considering three levels of aggregation. First, we focus on individual messages shared by users in the groups (Section 4.2.1). Next, we consider all messages shared by the same user in a given group (Section 4.2.2). Finally, we look at social curiosity at the group level (Section 4.2.3). We discuss our results next.

4.2.1. Social curiosity at the message level

Aiming at identifying common patterns of social stimulation driving the sharing of a message, we clustered the message sharing events based on the values of both metrics – $maxDirInf$ and $maxIndInf$. To that end, we employed the Mini-Batch K-means algorithm [97], a widely used parallel version of K-means adequate for large datasets, to cluster the values of curiosity stimulus (computed by the two metrics) associated with the messages shared by all users (over 2 million messages in total). We varied the number of clusters k from 2 to 18 and, for each value, we repeated each experiment 10 times and computed the Silhouette index [98] of the clustered results. This is a measure of how similar an element is to its own cluster (cohesion) compared to other clusters (separation). Larger values indicate better matching of elements into clusters. Using the results of Silhouette index, we set $k = 3$ as the best number of clusters, as it led to the highest Silhouette index among all values analyzed (equal to 0.55, which suggests that a reasonable clustering structure was obtained [99]).

Table 5
Message-level social curiosity stimulation profiles.

Cluster	% msgs	Max. Dir. Influence (average ± 95% C.I.)	Max. Ind. Influence (average ± 95% C.I.)
Independent	72.6%	0.26 ± 0.000750	0.04 ± 0.000044
Indirect	14.4%	0.43 ± 0.002320	0.15 ± 0.000210
Dependent	13.0%	3.52 ± 0.006623	0.05 ± 0.000099

Table 5 shows a description of the three identified clusters in terms of average values (and associated 95% confidence intervals) of both metrics as well as fraction of messages in each cluster. Note that the confidence intervals are quite tight, implying that the average values of both metrics are very representative of the elements in each cluster. By comparing these values for each metric,[16] we label the clusters as:

- (Socially) Independent: both metrics tend to assume the smallest values among the three clusters, implying less frequent co-occurrence of destination and origins, and suggesting that social influence plays a less important role in curiosity stimulation. This occurs in 73% of the messages;
- Indirect (Social Influence): compared to the other clusters, the maximum direct social influence tends to assume moderate values, whereas the maximum indirect influence assumes the largest values of the three clusters. Thus, in comparison to the other two clusters, indirect social influence seems to have a particularly important role on the curiosity stimulation in this case. This occurs in 14% of the messages;
- (Socially) Dependent: this cluster exhibits, by far, the largest values of direct social influence, suggesting more frequent co-occurrences of destination and origins, and thus much stronger social stimuli as captured by this metric. This happens in 13% of the messages.

[16] Note that we do not compare values of different metrics as they cover very different intervals. Rather, we analyze differences across the three clusters by looking at the values of each metric at a time.

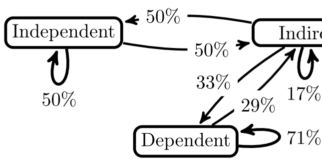


Fig. 5. Example UBMG for a user u with a sequence of message-level stimulation pattern equal to PPIDDDIPPIPIIDDDDIPP in a group g (P for independent, I for indirect and D for dependent).

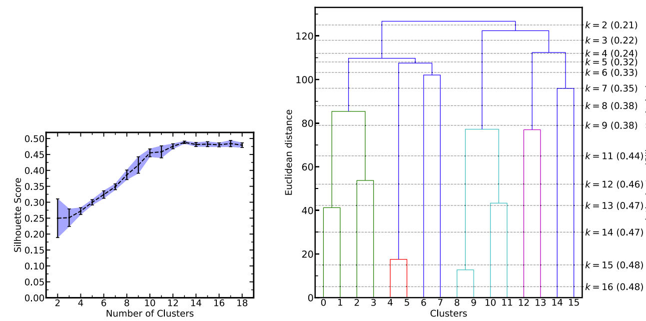
4.2.2. Social curiosity at the user level

Having identified patterns of social stimulation associated with individual messages, we now use them to cluster users in terms of their social stimulation profiles. Given our assumption, supported by the results in Fig. 4b, that social curiosity stimulation may vary across time for the same user, our goal is to build a user profile representation that reflects such dynamics using the patterns of social stimulation at specific messages as building blocks. We do so by first representing each user u by the sequence of social stimulation patterns (independent, indirect or dependent) associated with the sequence of messages shared by u. We then model such sequence using a User Behavior Model Graph (UBMG) [100]. A UBMG is a graph where each node represents a pattern of social stimulation (state) and edges denote the transitions between patterns from a message to the next one, by the same user. Edge weights are the probabilities of such transitions. One UBMG is used to model a user in *a given group*. Thus, the same user in different groups are represented by multiple (possibly distinct) UBMGs, one for each (user, group) pair.

We illustrate the UBMG representation by considering a fictitious user u who shared 20 messages in a group g. Given the social stimulation pattern associated with each message shared by u in g – P for independent, I for indirect and D for dependent – we first build a representation of (u, g) as a temporally-ordered sequence of stimulation patterns. Let us say such representation is PPIDDDIPPIPIIDDDDIPP. That is, u's curiosity stimulation in g is associated with the independent (P) pattern in the first two messages, then changes to the indirect (I) pattern in the third message, changing once again to the dependent (D) pattern, and so on. The corresponding UBMG is shown in Fig. 5. Note that once in the *independent* state, user u has 50% of chance of remaining in this state in the next message and 50% of chance of changing to *indirect*. Once in the *indirect* state, u either goes back to the *independent* state, with 50% of chance, changes to *dependent*, with 33% of chance, or remains in the same state (17% of chance).

Having built the UBMGs for all (user, group) pairs, we then clustered these UBMGs to uncover patterns of user curiosity stimulation. To that end, we employed once again the Mini-Batch K-Means algorithm, using the Silhouette index to select the best number k of clusters. Fig. 6a shows the average Silhouette index (computed for 10 runs) along with 95% confidence intervals as a function of k. Note that the average Silhouette increases greatly with k until reaching a rough plateau for $k \geq 13$. Also, the wider confidence intervals for small values k indicate higher variability of the results. Yet, the intervals become quite tight for larger values of k.

Based solely on the Silhouette index results, one would choose a value of k around 13 (or just above this mark) as the number of clusters. However, such large number of clusters makes it difficult to identify distinguishing characteristics. Indeed, by manually analyzing the centroids of these clusters, we found great similarities among many of them. Thus, in the interest of obtaining a more interpretable set of UBMG profiles, we applied the Agglomerative Hierarchical clustering algorithm [101], which seeks to build a hierarchy of clusters. The method starts with n clusters and sequentially combines pairs of similar clusters (the most similar ones first) until a single cluster is obtained.



(a) Silhouette index. (b) Dendrogram

Fig. 6. Determining the number of UBMG clusters.

We applied the algorithm starting with $n = 16$ clusters.[17] Fig. 6b exhibits the dendrogram for these clusters where the sixteen labels are shown along the x-axis. Pairs of similar clusters are linked, and the height of the line connecting two clusters represents the Euclidean distance between them, shown in the y-axis. The right side of the figure shows decreasing values of k (from 16 down to 2), as the most similar clusters are merged together, along with the corresponding Silhouette index (within parentheses).

Based on these results, along with a manual analysis of the centroids of all 16 initial clusters, we chose to set k equal to 5 clusters, as it delivers the best trade-off between clustering quality (i.e., Silhouette index) and interpretability of the properties characterizing each identified cluster.[18] On one side, the Silhouette index for $k = 5$ is 0.32, which, despite lower, is still indicative of an existing clustering structure [99]. On the other side, we observed that larger values of k led to mostly variants of the same clusters identified with $k = 5$.

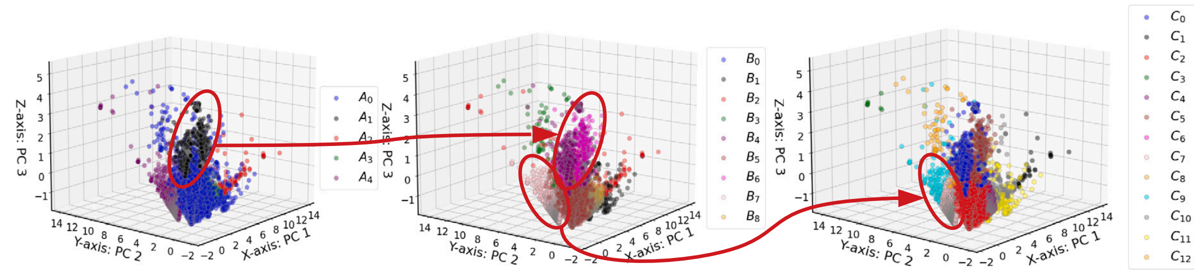
We illustrate the latter point by applying Principal Component Analysis (PCA) to identify the three most important components for three different values of k, notably $k = 5$, $k = 9$ and $k = 13$. Results are shown in Fig. 7. By comparing Fig. 7a and b we can see that increasing the number of clusters from $k = 5$ to $k = 9$ simply led to splitting some of the clusters into multiple ones, but those are quite similar to each other. Note for example cluster A_1, identified in black in Fig. 7a. It is basically split into two closely related variants, clusters B_4 and B_6 shown in pink and purple, respectively, in Fig. 7b. Similarly, by comparing results for $k = 9$ and $k = 13$, we note that cluster B_7 (in light pink in Fig. 7b) is mostly split into two variants, clusters C_7 and C_9 (cyan and light pink, respectively) in Fig. 7c.

Fig. 8 shows the five user-level profiles, referred to as $U_0 \ldots U_4$, identified by the centroids of the five UBMG clusters obtained. For each profile, the figure also shows the number of (user, group) pairs in the cluster, and the average number of messages per such pair. To help interpreting the UBMGs, Table 6 shows, for each profile, the average fraction of all messages sent by the user in the given group characterized by each message-level curiosity stimulation profile.

As shown in Fig. 8a, profile U_0, including almost 30% of all (user, group) pairs in our dataset, is characterized by a general trend of repeatedly staying in the same state of social stimulation (strong self-transitions). In other words, users in this profile tend to experience a rather stable curiosity stimulation process, being consistently driven by one of the three patterns over time, with occasional changes to a different pattern. In particular, as shown in Table 6, this user profile is dominated by the *independent* state, which characterizes over 65% of

[17] This starting point was selected as it is one of the values of k in the plateau of maximum Silhouette index shown in Fig. 6a.

[18] We found that restricting to 5 clusters facilitates interpretation of the results as the identified clusters are more clearly distinct and refer to different patterns.

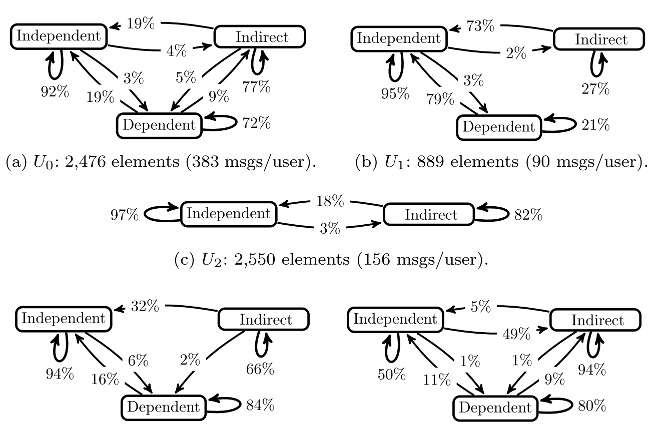


(a) $k = 5$. (c) $k = 9$. (b) $k = 13$.

Fig. 7. Results from Principal Component Analysis applied to $k = 5$, 9 and 13 clusters.

Table 6
User-level social curiosity stimulation profiles: percentage of messages in each UBMG state.

UBMG	User-level profiles				
State	U_0	U_1	U_2	U_3	U_4
Independent	65.73%	87.72%	80.17%	70.25%	8.66%
Indirect	20.88%	6.23%	19.80%	0.20%	84.49%
Dependent	13.39%	6.06%	–	29.54%	6.85%



(a) U_0: 2,476 elements (383 msgs/user). (b) U_1: 889 elements (90 msgs/user).

(c) U_2: 2,550 elements (156 msgs/user).

(d) U_3: 2,156 elements (283 msgs/user). (e) U_4: 235 elements (67 msgs/user).

Fig. 8. User-level social curiosity stimulation profiles: state transition diagrams (UBMGs), each element is a (user, group) pair.

the messages, on average. In other words, users with this profile, who are the most active ones in terms of the average number of messages shared, tend to be mostly insensitive to social influence around two thirds of the time. Yet, social influence does take a more important role as a component of curiosity stimulation, either directly or indirectly, in roughly 35% of the messages shared by those users.

Users in profile U_1, shown in Fig. 8b, may also experience the three states, but changes towards the independent state are much more frequent, which, in turn, tends to dominate the overall profile. In other words, compared to U_0, users in U_1 tend to have less diversity in terms of social curiosity stimulation patterns, suffering little impact from social influence most of the time (87% of the messages). They also tend to be much less active than users in U_0. This cluster includes 11% of all (user, group) pairs.

Profile U_2, shown in Fig. 8c, is characterized by a mixture of independent and indirect states, though being also greatly dominated by the former (80% of the messages, as shown in Table 6). Unlike users in the other clusters, users in U_2 do not experience the dependent state. In other words, the curiosity stimulation of these users is mostly insensitive to *direct* social influence. Moreover, the strong self-transitions imply that users often remain repeatedly in the same state of curiosity stimulation. Around 31% of the (user, group) pairs in our dataset fall into this cluster.

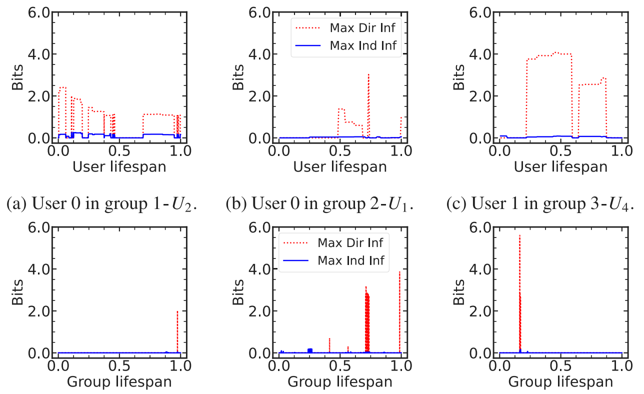
Profile U_3, shown in Fig. 8d, exhibits a distinguishing characteristic compared to the others. There are no transitions into the indirect state from the other states (only the self-transition). Users in this cluster either start in the indirect state and possibly move towards the other states or never experience it. Compared to users in U_0, U_1 and U_2, users in U_3 tend to fall in the dependent state more often (in roughly 30% of the messages), being thus more sensitive to direct social influence as a driver to curiosity stimulation. These users tend to be very active, falling behind only users in U_0. This cluster includes almost one third of all (user, group) pairs (26%).

Finally profile U_4, shown in Fig. 8e, shows the distinguishing characteristic of much stronger transitions (including self-transition) to the indirect state, leading to profiles that are dominated by this state, which characterizes 85% of the messages, on average. The independent state, in turn, is much less prevalent compared to the other profiles, as can be noted by the much lower self-transition probability. Indeed, as shown in Table 6, the independent state happens in only 8% of the messages shared by users with this profile, on average. These are users whose curiosity stimulation tends to be often influenced by social factors but by *indirect* means, possibly because the lack of frequent activity prevents the formation of strong social ties that could influence user curiosity. Indeed users in U_4, which account for only 3% of all (user, group) pairs in our dataset, are the least active ones in terms of message sharing, on average.

The results in Fig. 8 show great diversity in social curiosity stimulation profiles across different users and, for many users, very dynamic profiles. To further illustrate this point, we show in Fig. 9 the time series of both social curiosity metrics – $maxDirInf$ e $maxIndInf$ – for six selected (user, group) pairs. These curves illustrate how the social curiosity of particular users in specific groups evolve over time, as captured by both metrics. To facilitate visualization, the x-axis of Fig. 9a–f represent the normalized *lifespan* of the particular user in the given group, that is, the time interval between the first and last message shared by this user in the group, normalized to fall between 0 and 1.

Overall, we can see some important fluctuations over time, notably in terms of the maximum *direct* influence.[19] Such fluctuations follow the natural dynamics of user participation in the group. Fig. 9a and b

[19] As already shown in Fig. 4b, the values of $maxDirInf$ tend to be much larger than those of $maxIndInf$.



(a) User 0 in group 1-U_2. (b) User 0 in group 2-U_1. (c) User 1 in group 3-U_4.

(d) User 2 in group 4-U_2. (e) User 3 in group 4-U_0. (f) User 4 in group 4-U_0.

Fig. 9. Time series of both metrics of social curiosity for different (user,group) pairs.

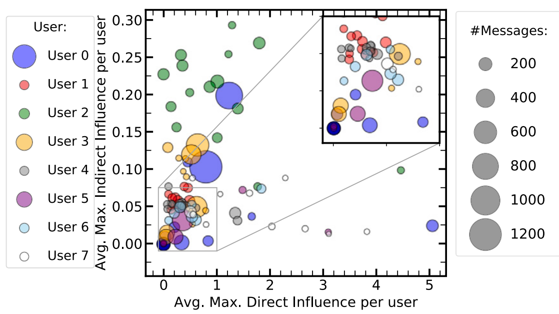


Fig. 10. Diversity of social stimulation of selected users in different groups: the same user in different groups is represented by the same color. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

show the time series of the social curiosity of the same user (identified as user 0) in two different groups she participates in (identified as groups 1 and 2). We note very different patterns, temporally and on average. Indeed, the dynamics captured by these two sets of curves fall into two very different profiles, identified by UBMGs 2 and 1, respectively. This observation hints at the validity of one of our key assumptions, that is, that user curiosity stimulation varies depending on the group. Fig. 9c shows the time series of another user in a different group. As illustrated in the figure, this user's social curiosity fluctuates greatly over time, with alternating behavior of greater and lower stimulation.

Fig. 9d–f shows the time series of three different users, members of the same group. For that reason, the x-axes of these three graphs represent the normalized lifespan of the given *group* (i.e., identified as group 4), that is the time interval between the first and the last message shared by any user in the group, normalized to fall between 0 and 1. This group was selected as one among those with the largest number of distinct users during the monitoring period. Once again, we see that user social curiosity fluctuates greatly over time (notably user 3, shown in Fig. 9e). Most importantly, we see very different patterns across the three users, even though they are members of the same group. This observation hints at the idea that the impact of the group on the curiosity of individual members may be different for distinct users. We further elaborate on this point in the following section, as we present our key results on group-level social curiosity stimulation.

4.2.3. Social curiosity at the group level

To analyze social curiosity at the group level, we focus on two aspects, notably: (1) the role of the group on the curiosity stimulation of its members and (2) the overall social curiosity of each group. For the latter, we use the group-level social curiosity metrics defined in Section 3.

Table 7
Test of statistical difference of social stimulation metrics of the same user on different groups (users 0–7 refer to selected users in Fig. 4b).

User	Total # Msgs	# Groups	# Pairwise Comparisons	# (%) Pairs of Groups with Different Metrics	
				Max. Dir. Influence	Max. Ind. Influence
0	4361	17	136	71 (52.21%)	70 (51.47%)
1	1210	13	78	15 (19.23%)	11 (14.10%)
2	1736	15	105	75 (71.43%)	75 (71.43%)
3	2459	12	66	13 (19.70%)	25 (37.88%)
4	1168	15	105	32 (30.48%)	31 (29.52%)
5	976	6	15	4 (26.67%)	5 (33.33%)
6	803	7	21	5 (23.81%)	11 (52.38%)
7	558	11	55	14 (25.45%)	3 (5.45%)

To investigate the role of the group on the curiosity of its members, we selected the 8 users who shared the largest number of messages in multiple groups, and computed the *average* values of both social influence metrics for each (user, group) pair. Fig. 10 shows the results as a scatter plot where each circle is a (user, group) pair. The same user (in different groups) is shown in the same color and the circle's diameter represents the number of messages shared by the user (in the given group). Visually, there are great distinctions on both metrics (in terms of average values) for the same user depending on the group she is participating in.

Such distinctions were confirmed by pairwise statistical tests of difference of averages for each of the two metrics. Specifically, for each user u, we used a Kruskall-Wallis Honestly Significant Difference (HSD) test [102] (with $\alpha = 0.05$) to test for the difference between the averages of maximum direct influence for pairs of groups u participates in. We did the same for the maximum indirect influence. The results are reported in Table 7, which shows, for each selected user u, the total number of messages shared by u, the number of groups u participates in, the total number of pairs tested and the number (and percentage) of pairs for which there is a statistical difference in each metric (two rightmost columns). As shown, the differences are statistically significant for a large fraction of the cases for several users. Thus indeed the social stimulation of the same user may be quite distinct depending on the group she participating in, as already suggested by the results in Fig. 9a and b. Indeed, we note that user 0 in Table 7 refers to the same user 0 shown in those two figures.

As a final analysis, we use the group-level social curiosity stimulation metric, defined in Eq. (12), to characterize the groups in our dataset. Recall that this metric captures a reduction in uncertainty associated with destinations, defined in Eq. (11), due to the knowledge of the social influence from other users (origins) in the group. Thus, to facilitate analysis, Fig. 11 shows a scatter plot with the values of these two metrics – group mutual information ($groupMutInf$) and destination entropy – computed for each of the 335 groups at the time of the last message sharing in each group.

The figure shows great diversity in social curiosity also at the group level. Many groups have a value of $groupMutInf$ (x-axis) very close to the destination entropy $H^{\leftarrow}_{t,g}(D)$ (y-axis), suggesting that a large fraction of the total uncertainty associated with the destinations in those groups can be captured by social influence. In other words, social influence is a key component of curiosity stimulation in the group. This happens for groups with distinct profiles in terms of number of users and level of activity of these users, which ultimately lead to groups with distinct values of destination entropy. On the other hand, a number of groups have values of $groupMutInf$ much smaller than the total uncertainty associated with the destinations. In those cases, social influence plays a less important role on curiosity stimulation at the group level.

For illustration purposes, Fig. 11 also highlights (in blue) the groups in which one selected user – user 0 in Fig. 10 – participates. As shown,

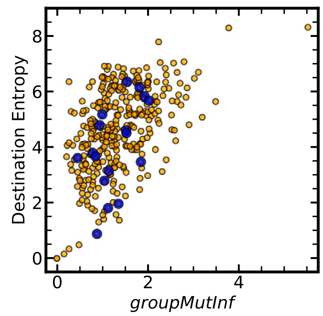
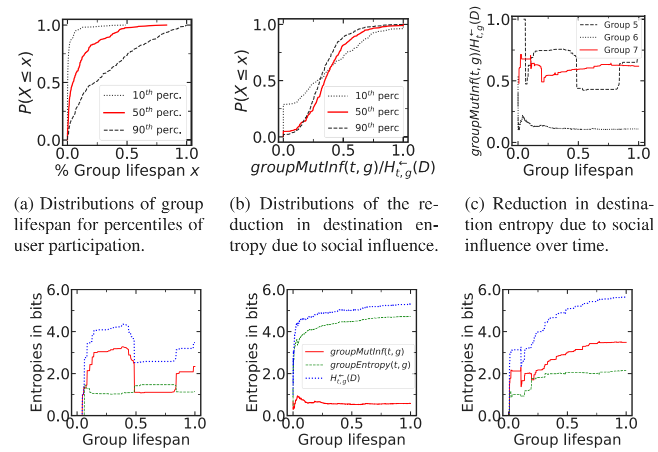


Fig. 11. Social curiosity stimulation across groups: group mutual information versus destination entropy, measured at the time of the last message in the group (groups of user 0 in blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)



(a) Distributions of group lifespan for percentiles of user participation.

(b) Distributions of the reduction in destination entropy due to social influence.

(c) Reduction in destination entropy due to social influence over time.

(d) Group 5.

(e) Group 6.

(f) Group 7.

Fig. 12. Group-Level Social Curiosity Stimulation: CDFs of (a) group lifespan and (b) reduction in destination entropy due to social influence, measured when group reaches 10th, 50th and 90th percentiles of user participation; (c) Time series of reduction in destination entropy due to social influence of 3 example groups; (d)–(f) Time series of group-level metrics for the same 3 groups. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the diversity in user 0's social stimulation shown in Fig. 10 follows the diversity present also in his groups. We measured the correlation between group-level social curiosity and individual-level social curiosity (as captured by both metrics considered) for the selected 8 users in a few selected time windows but found not clear pattern: some cases of positive correlation, several cases of negative correlation and some cases of no-correlation at all. Thus, even though user curiosity stimulation does indeed vary depending on the group, we found no consistent indication that a more socially stimulated group always translates into the same behavior on all its members. Indeed, as shown in Fig. 9d–f, different members of the same group may exhibit quite distinct patterns of social curiosity. More broadly, it might be the case that different users dominate the overall group-level curiosity stimulation pattern at different time windows.

Recall that Fig. 11 shows results for a specific time window, that is, the time of the last message sharing in each group. We finish our discussion by showing the dynamics of the group-level social curiosity metric over time. Naturally, one key component of social curiosity at the group level is user participation in the group. Thus, we analyze social curiosity in each group in different points in time defined based on user participation. Specifically, for each group g, we looked at the total number of *distinct users* who shared some message in g *since the first message until the last message shared during the monitoring period*, and considered the time when g reached the ith percentile of user participation.[20] We then looked at the lifespan of each group, and measured the time when each group reached the ith percentile of user participation, as a fraction of its total lifespan.

Fig. 12a shows the Cumulative Distribution Functions (CDFs) of the fractions of group lifespans associated with the 10th, 50th and 90th percentiles of user participation in each group. Whereas some groups reach all three percentiles quickly, others take much longer to attract greater diversity in user participation, reaching the 90th and even the 50th percentiles very later on during monitoring. For instance, roughly 40% of the groups take more than 50% of their lifespans to reach the 90th percentile of user participation. In light of this dynamics and heterogeneity, Fig. 12b shows the CDFs of the reduction in destination entropy due to social influence (defined as the ratio $groupMutInf(t,g)/H^{\leftarrow}_{t,g}(D)$), measured at the same points in time (same three percentiles). Recall that the greater the reduction in destination entropy the more important the role of social influence on curiosity stimulation at the group level. Once again, there is great diversity across groups, here shown over time. Roughly 30% of the groups have reductions of at least 50% at the time they reach the 10th percentile of user participation. In contrast, around 70% of the groups have the same amount of reduction (or less) by the time of the 50th percentile.

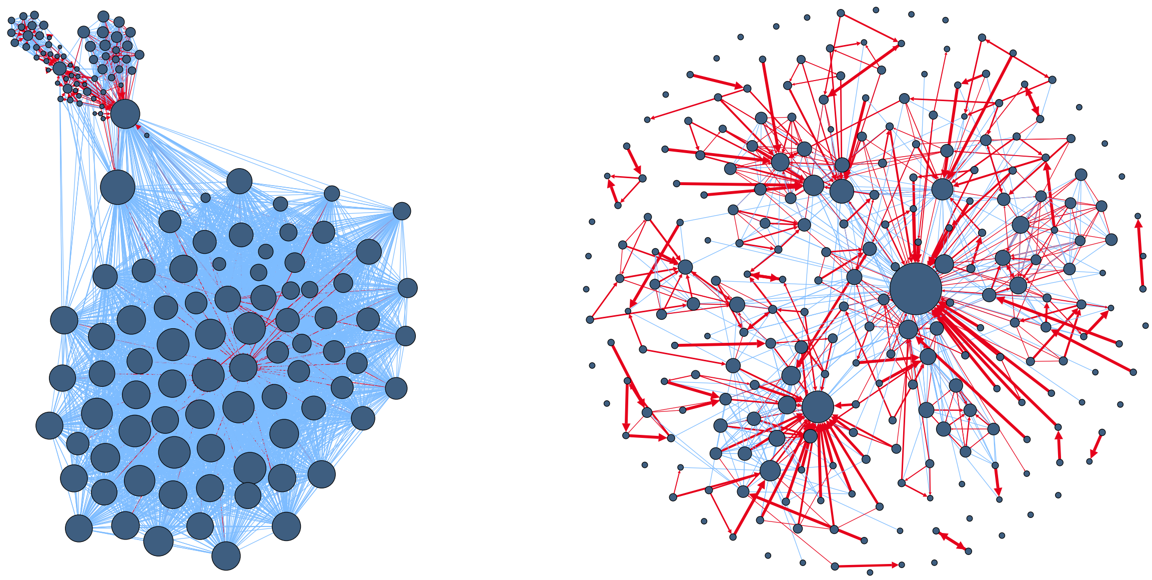
Moreover, groups may experience quite dynamic social curiosity stimulation, evolving over time according to different patterns for distinct groups, as an aggregation of the individual patterns of the current group members (which, as discussed in the previous section, is also quite dynamic and heterogeneous). This is illustrated in Fig. 12c, which shows the time series of the reduction in destination entropy due to social influence for three selected groups. Such patterns illustrate the very dynamic role of social influence as a driving force behind curiosity stimulation in the group: in some cases, social influence starts as an important component of group-level curiosity and continuously decreases over time (e.g., group 6 in the figure); while in other cases, the importance of social influence fluctuates over time (e.g., group 5), possibly reaching rough stability (e.g., group 7).

In order to explain such varied patterns, we plot in Fig. 12d–f the three metrics associated with group social curiosity, namely the $groupMutInf$ (red line), $groupEntropy$ (green line) and destination entropy, or $H^{\leftarrow}_{t,g}(D)$ (blue line) for the same three selected groups. For the groups shown in Fig. 12d and f, social influence plays an important role on the overall group curiosity over large periods of time, as the $groupMutInf$ curves represents a large fraction of the total destination entropy (over 60%, on average). For both groups, such importance decreases mostly when the $groupEntropy$ increases, that is, when the probabilities of the same *destination* conditioned on the same *origins* decrease. In that case, the chance of the same users co-occurring in the same window decreases. Thus, social influence loses relevance as a curiosity driver for the group. When this happens at the same time as an overall drop in destination entropy, possibly due to an increase in the number of distinct users sharing messages, the role of social influence on curiosity at the group level becomes even less important (e.g., group 5 at around 50% of its lifespan). In contrast, $groupEntropy$ is very high, dominating the total destination entropy for group 6 throughout its lifespan, as shown in Fig. 12e. Clearly, the curiosity of this group, in general, is very weakly impacted by social influence, as shown in Fig. 12c.

4.2.4. Some illustrative examples

In this section we discuss a few examples to further illustrate the use of our metrics. We start by looking at the participation of a particular

[20] Obviously, group activity prior to the monitoring period is disregarded. Thus, the analysis reflects group activity during this period only.



(a) Group: "We are all HADDAD!".

(b) Group: "Lula the father of prisoners".

Fig. 13. Graph representation of direct social influence among members of two selected groups (node diameters are proportional to out-degrees, red/blue edges refer to strong/weak social influence, thus strong/weak social curiosity stimulation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 8
Three example messages shared by the most active user in group "Science, Religion and Politics".

Msg id	Curiosity profile	Max. Dir influence	Max. Ind. influence	Window of interaction	
				# messages	# users
1	Dependent	6.78	0.03	28	6
2	Indirect	0.50	0.10	61	7
3	Independent	1.50	0.08	90	8

user, referred to as user u, in a group entitled "Science, Religion and Politics" (translated to English), which is one of the groups with the largest number of distinct members (353 users during the complete monitoring period) and messages shared (48,389). User u is the most active user in this group, having shared a total of 3787 messages. Also, u's curiosity stimulation follows profile U_0 which, as shown in Table 6, experiences all three states of message-level curiosity stimulation. Thus, we selected three messages shared by u, referred to by identifiers 1, 2 and 3, associated with each profile – dependent, indirect and independent, respectively.

Table 8 presents information associated with each selected message, notably its curiosity stimulation profile, the values of two social curiosity metrics (maximum direct and maximum indirect influences) as well as statistics of the window of interaction defined when the given message was shared. The latter includes the number of distinct users (i.e., origins of influence) and number of messages shared during the period.

We note that the number of potential sources of social influence on u when she shared message 1, i.e., the number of origins of influence, is the smallest among the three messages (6). The same holds for the total number of messages shared during the window of interaction (28). Yet, this message has the largest value of maximum direct influence (6.78), much larger than the other messages, and the smallest value of maximum indirect influence (0.03). Thus, despite in smaller number, the past behavior of these origins and of the destination u offer strong evidence of *direct* social influence driving u's content sharing decisions. This message is characterized by the *dependent* profile.

In contrast, when sharing message 2, user u's curiosity is not strongly stimulated by those sharing content during the window of interaction, at least not with respect to the stimulus triggered by direct influence estimated by prior interactions. In other words, the maximum direct influence is very small (only 0.5). Yet, compared to message 1, we do find more evidence of indirect influence from the origins stimulating u's curiosity at this time: the maximum indirect influence has the largest value of the three messages, and the message is characterized by the *indirect* profile. Indeed, some of these origins are among the top 10 most active users in the group. Also, we tracked these origins over successive windows, observing an increase in the *direct* influence from some of them on u, which suggests that, as mentioned in Section 3.2, sources of indirect influence may become stronger sources of direct influence as time progresses.

Finally, when sharing message 3, user u's curiosity is not strongly stimulated by neither direct nor indirect influence, despite the presence of large numbers of messages and users in the corresponding window of interaction (the largest ones out of the three messages). The message is characterized by an *independent* profile. Clearly the more intense user activity during the window does not translate into stronger curiosity stimulation on u: both social curiosity metrics have intermediate values.

To illustrate social curiosity at the group level, we build a graph representation of social influence based on the contingency table, which contains historical patterns (see definition in Section 3.2). In this graph representation, each node represents a group member and a direct edge from user u to user v is added to represent that u (origin) has influence on v (destination). Edge weights are given by the conditioned probability of a destination given an origin, i.e., $P^{\leftarrow}_{t,g}(D = d \mid O = o)$, computed based on values in the contingency table.

Fig. 13 shows the graphs built for two specific groups considering the complete history of user interactions in each group, that is, by the time the last message is shared in the group. In each graph, node diameters are proportional to out-degrees and edge colors denote the strength of the conditioned probabilities used as weights (and thus the strength of the social influence computed from such probabilities). Specifically, red edges are those whose weights are above 0.1, thus representing stronger social curiosity stimulation, and blue edges have weights below 0.1, suggesting weaker social curiosity stimulation.

Fig. 13a represents a group entitled "We are all HADDAD!", which had 147 distinct members who shared 3012 messages during the monitoring period. Fernando Haddad was a left-wing presidential candidate in the 2018 general elections in Brazil. Approximately 95% of the edges in the graph are blue, suggesting that social influence does not play an important role in the group. Indeed, the overall reduction of destination entropy due to social influence – $groupMutInf(t,g)/H^{\leftarrow}_{t,g}(D)$ – is below 6%. This happens despite the great number of edges connecting users, that is, there is some evidence of social influence, but in the vast majority of cases this evidence is very weak. Indeed, the authors are aware that most members of this group often shared news about the candidate's campaign, which did not generate much response or engagement from most members. The occasional user interactions resulting from such messages offer only weak evidence of influence (if any at all). However, there are a few cases of more responsive and intense discussions on specific political themes, often with the participation of particular users. These cases show up in the few red edges in the top part of the graph. Note that many of them are linked to a particular node, possibly a user who is frequently involved in the discussions.

Fig. 13b, in turn, shows the graph representation for the group entitled "Lula the father of prisoners", which had 221 distinct members and 935 messages shared during the monitoring period. Lula is a former president of Brazil and a charismatic representative of the left wing who was arrested during the period of the 2018 general elections. Unlike in Fig. 13a, this graph is very balanced in terms of the strength of social influence among users: 51% (49%) of the edges are blue (red). Overall, social influence is a much stronger component of curiosity stimulation, with a reduction of destination entropy due to social influence of 62%. This group is mostly driven by very passionate pro-right wing discussions, thus the group's title is a sort sarcasm or irony. As reflected in the graph, such discussions, often involving the same participants, do offer strong evidence of curiosity stimulation as a driver behind content sharing. Note also that, compared to the graph in Fig. 13a, the graph in Fig. 13b is much more sparse, suggesting that such strong curiosity stimulation occurs between specific pairs of users for whom the bond created by prior interactions offer greater evidence of social influence.

5. Limitations of our study and their implications

In the process of modeling such a highly subjective and complex concept such as social curiosity, we made a number of assumptions and simplifications so as to be able to derive metrics that are reasonably simple while still useful and informative. In the following, we discuss some of these limitations and their implications.

5.1. Lack of content representation

Message content is most probably an important factor influencing how one's curiosity is stimulated. Specifically, the contents of messages posted by others may indeed be a component of how *social* curiosity affects one's behavior. However, we chose not to exploit it in the derivation of our *social* curiosity metrics, focusing only on the primary factors, which, we argue, are related to who is sharing content in the group,i.e., users and their (inferred) social links. There are several reasons to do so:

1. Access to message content is not always available. Thus, by not using message content we assure that our metrics of social curiosity can be used even when content is not accessible (as is the case of our dataset).
2. As mentioned, by focusing only on the users sharing content, we aim at addressing a novel aspect of curiosity stimulation that is not captured by the other (traditional) collative variables. Thus, we complement these variables by proposing metrics related to a novel aspect.
3. By not including content in the social curiosity metrics, we are able to assess the extent to which the most primary component of social influence (i.e., people themselves) can drive one's curiosity.

We note however that, even though the content factor is not explicitly included in the proposed metrics, these metrics do exploit prior user interactions, which in turn, may have been influenced by the content shared by those users at those prior moments in time. Thus any content related effect that might impact social influence is being indirectly captured when we make use of such user interactions.

Having argued for not exploiting content to estimate social curiosity, we note that we did use message categories as a proxy for content properties when deriving metrics related to the traditional collative variables (see Section 3.3, acknowledging its importance as a component of curiosity stimulation in general — not only from a social perspective). Obviously, categories, as those used by us, offer only a very coarse approximation of content properties and their use as such is another a limitation of the study, as we further elaborate next.

5.2. Media categorization

Our choice of exploiting message categories in the derivation of the traditional collative variables follow prior work [9], including ours [28], which also used pre-existing content categories to derive metrics associated with content novelty, uncertainty, conflict and complexity. In our present context, there is no pre-existing categorization of content (as exists in platforms like LastFM [28]). Thus, we chose to use a coarse categorization (the only one available in our dataset) – media type. It is a simplification. However, by doing so, we make our metrics independent of any specific method to build such categorization. The multitude of strategies that could be applied to do so – e.g. topic models [103], text embedding strategies [104–106], exploring a finer grained categorization including memes, emojis, stickers and even more recently deployed WhatsApp features[21] – justifies a study on itself, which should be subject of future work.

Also, as mentioned in Section 3.1.2, a key assumption of ours is that since different media types typically require different levels of engagement of the user to access the content, they should have different effects on curiosity stimulation. For example, textual content is immediately visible, whereas URLs require the user to leave WhatsApp and go to another (Web) application, which is something that the user might feel inclined to defer to another time (or even not do at all). Also, reading a textual message (most often) requires much less effort and much less time than watching a video or listening to an audio. Again, the user may simply choose to defer watching the video or listening the audio to a later time, because she either does not feel like or cannot do it at the time she sees the message. Indeed, this assumption finds some evidence in recent studies of WhatsApp messages which revealed distinct properties in terms of propagation dynamics depending on the type of media [26,44,45,107].

To offer further evidence of the potential distinct effects of different media types in curiosity stimulation, we computed, for each category c ($c \in$ {"text", "image","audio", "video", "URL"}), the time interval between the sharing of a message with category c and the next message (regardless of its category) shared in the same group. This time interval is a (rough) estimate of the reaction time, i.e., the time it took for someone in the group to react (by sharing new content) to the first message. Shorter reaction times might suggest a greater impact on user behavior. Obviously, this should be considered only a coarse approximation of reality, as several other (internal and external) factors may have driven the user to share the new content. Yet, we found very different reaction times for the five categories analyzed. Specifically, average reaction times and corresponding 95% confidence intervals, computed for our entire dataset, are as follows: (a) 4.69 ± 0.02 minutes for text; (b) 7.73 ± 0.07 minutes for images; (c) 8.10 ± 0.18 minutes for audios; (d) 10.90 ± 0.10 minutes for videos; and (e) 11.61 ± 0.09 minutes

[21] https://faq.whatsapp.com/general/chats/about-forwarding-limits/?lang=en.

for URLs. Clearly, messages with textual content tend to have shorter reaction times, whereas URLs and videos tend to trigger much longer reaction times, which corroborates the assumption discussed in the last paragraph.

5.3. Focus on intra-group curiosity stimulation

As a first effort to quantify social curiosity in group communication, we chose to focus on each group separately, under the assumption that *intra-group social influence* is a primary factor driving user curiosity. Indeed, our results suggest that the curiosity of a user may be stimulated differently depending on the group (see, e.g., results in Fig. 9a and b as well as Fig. 10). By focusing on *intra-group* curiosity stimulation we are able to isolate (potentially secondary) *inter-group* effects, offering a foundation upon which follow-up studies can be developed. Moreover, we note that our dataset, as all datasets used in other analyses of WhatsApp [42,43,46,108], are collected from publicly accessible groups. These are essentially different from (private) family and friend groups where members have external (real-world) connections that may influence their curiosity stimulation. In publicly accessible groups, it is not possible to identify such external links among users.

5.4. Modeling of temporal dynamics

In the derivation of our metrics, we assume that the curiosity driving the sharing of a message has a period of activation δ_T determined by a fixed-duration time window. In other words, we assume that only messages shared within the specific time window stimulate the user's curiosity. This time window allows us to capture changes in the curiosity stimulation of a user over time. However, it is not possible to determine, from the data, whether indeed the user read all messages shared during a time window. Our assumption is thus a design choice to be able to capture the temporal dynamics of user curiosity.

Such choice, and in particular the window duration of 30 min, is based on observations in prior work [89], where authors used the same window duration to study collective attention in publicly accessible WhatsApp group. The authors experimented with several window durations (from 5 min to 2 h), selecting 30 min after manual investigation of the topics discussed in the analyzed groups during the defined windows. They argue that 30-min windows led to the best tradeoff between capturing small variations of attention over time and still approximating the duration of continuous conversations in WhatsApp. Given the close relationship between attention and curiosity, we chose to follow the same approach, especially because our work focuses on Whatsapp groups similar to those analyzed in [89], that is, publicly accessible political-oriented groups in Brazil.

As an alternative to fixed-duration time windows, one could consider windows with variable durations. For example, one might argue that the window duration should be adjusted based on the current level of activity (message sharing) in the group. However, we found very weak correlations between the number of messages shared during a window and the average user and group-level social curiosity, as estimated by the proposed metrics (Spearman correlation coefficients below 0.14). Nevertheless, investigating alternative approaches to model the temporal dynamics of user curiosity stimulation is an avenue worth pursuing in the future.

6. Conclusions and future work

In this article, we have investigated curiosity stimulation as a driving force behind content sharing in group communication, specifically in WhatsApp groups, focusing on a novel component of curiosity stimulation, namely social influence. To that end, we proposed novel metrics to quantify such component, as well as metrics that instantiate other traditionally studied collative variables related to curiosity stimulation (though not to social behavior). We used the proposed metrics to show that social influence is indeed a distinct component of curiosity stimulation, as compared to the other traditional variables, as well as to offer a broad characterization of social curiosity stimulation in a number of publicly accessible political-oriented WhatsApp groups in Brazil.

In the following, we first present a summary of our work as well as our main findings and how they relate to the three research questions introduced in the beginning of the paper (Section 6.1). In doing so, we also review the main challenges addressed so as to emphasize key design decisions. We then discuss possible directions of follow-up studies (Section 6.2).

6.1. Summary of main findings

Recall that, as presented in Section 1, we here aimed at addressing three research questions, which we repeat below:

RQ1: *How to quantify social influence as a stimulus to one's curiosity driving the information dissemination process?*

RQ2: *How does social influence relate to other collative variables priorly associated with curiosity stimulation?*

RQ3: *How are users characterized in terms of social stimulation to curiosity?*

Towards answering this RQ1, we proposed four new metrics to capture social influence as a component of curiosity stimulation driving individual users to communicate with each other by sharing content in a currently very popular group communication platform — WhatsApp. The derivation of our metrics is founded on the arguments of psychologist Daniel Berlyne on the modeling of human curiosity and its connection with information theory [2].

The challenges we faced while deriving these metrics relate to how to instantiate Berlyne's general methodology to quantify collative variables associated with curiosity stimulation to the particular context of social influence in group communication. Specifically, we had to make assumptions so as to be able to deal with the lack of explicit signals of user interactions in our dataset. Also, results from prior studies of WhatsApp [89] motivated us to derive metrics capturing not only the traditionally studied direct influence but also indirect influence reflecting the possible presence of some great influencers in the group. Similarly, we argued for the relevance of proposing metrics for both individual users and groups. Notably assessing group-level social curiosity may offer valuable insights into the dynamics of group members provided that groups are reasonably small and discussions are more focused on specific topics, as is the case of WhatsApp groups. This is in contrast to more open spaces of communication (e.g., Twitter, Facebook), where group membership is unlimited and often much larger, and, as such, curiosity stimulation driving the discussions might be more disperse and perhaps more fragmented.

RQ2, in turn, relates to how social influence, as captured by the proposed metrics, captures aspects of curiosity stimulation not covered by novelty, complexity, conflict and uncertainty, which are other collative variables associated with curiosity stimulation that have already been studied in several domains (though not in group communication). Towards answering this question, we first presented seven metrics that capture these collative variables for our target environment. The derivation of these metrics is greatly inspired by previous studies of the same variables in other setups, notably our own effort to model user curiosity in LastFM [28], which, in turn, are rooted, once again, on Berlyne's seminal work.

In particular, as done in prior work, we considered two different elements that may stimulate one's curiosity, namely: content, captured by the categories associated with the several portions of the message, and the user sharing the content itself. We then proposed metrics that capture the role of both elements on curiosity stimulation with respect to the four aforementioned collative variables.

Having defined these metrics, we answered RQ2 by evaluating how correlated the metrics of social influence are to the metrics related to the other variables. This analysis, as all others discussed below, were performed on a large dataset containing over 2 million messages shared by over 7.5 thousand users in 335 publicly accessible WhatsApp groups in Brazil. The dataset covers a one-year time interval, which includes a period of large use of WhatsApp for the political debate in the country.[22] As shown in Fig. 3, our key result is that the four metrics related to social influence are complementary to the other metrics in the vast majority of cases. Thus, social influence, as captured by our proposed metrics, does indeed represent a novel component of curiosity stimulation that is not covered by the other variables.

Having addressed RQ2, we then proceeded to tackle RQ3 by performing a broad characterization of social curiosity stimulation at three levels of aggregation, namely individual messages, individual members of a group (i.e., users) and all members of a group. Our key take-home messages from this characterization are:

1. Curiosity stimulation varies greatly in all three levels, i.e., across individual messages (Fig. 4a), and, taken in terms of average stimuli, across different users (Fig. 4b) and different groups (Fig. 11).
2. By employing clustering analysis, we were able to uncover profiles of social curiosity stimulation at both message and user levels.
3. At the message level, we uncovered three profiles (Table 5), which indicate that, although social influence does not always play a clear role as a component of curiosity stimulation (profile independent), in almost 30% of the cases, either direct or indirect social influence, as captured by our metrics, are indeed important components driving one's curiosity to share content (profiles dependent and indirect, respectively).
4. At the user level, we showed that the evolution of user curiosity over time with respect to the three message-level stimulation profiles present great heterogeneity, revealing five different user profiles (Fig. 8). While some users do exhibit a rather stable curiosity stimulation process, remaining at the same message-level profile over time (e.g., users in profile U_0), for many other users, the role of (direct/indirect) social influence as a component of curiosity stimulation changes greatly over time, probably in response to the dynamics of interactions within the group. This is the case of users in profile U_3, which are more sensitive to direct social influence, and users in profile U_4, for whom the indirect social influence plays a more important role in curiosity stimulation.
5. We also showed evidence that curiosity stimulation may change significantly depending on the group the user participates in (Fig. 10 and Table 7). This observation validates one of our key assumptions, offering also insights into the role that such (often small) groups have as drivers to user behavior (notably content sharing). In some sense, these results mimic what we see in real life when the same person may behave quite differently (more or less participative/chatty) depending on the group of people she is interacting with.
6. At the group level, we noted that the role of social curiosity is more clearly observed when group members are more engaged in the ongoing discussions, more often sharing content (thus interacting with others), as these actions suggest a greater susceptibility to social curiosity (Fig. 12).

[22] https://www.niemanlab.org/2018/10/what-to-know-about-whatsapp-in-brazil-ahead-of-sundays-election/.

To our knowledge, these findings are novel, with respect to prior efforts to characterize social curiosity as well as prior studies of user behavior in group communication platforms (notably WhatsApp). As such, they offer valuable insights into user behavior (i.e., content sharing) on a platform that has had paramount importance as major source of information (including misinformation) in several countries, with reported impacts on political and social aspects of these societies.[23] Understanding the factors driving users to share content in such platform, social curiosity being one of them, is thus valuable not only from the perspective of human behavior analysis but also because such understanding may motivate future developments to build more socially driven spaces for online communication.

6.2. Directions for future work

There are several possible directions for future investigations. One such direction consists of follow-up studies that build on our present effort, tackling the limitations raised in Section 5. In particular, investigating alternative (finer grained) categorizations of the messages, especially if message content is available, could offer deeper insights into how different types of content stimulate one's curiosity. In that case, exploring the role of content itself as a component of (social) curiosity is also worth pursuing. Similarly, expanding our metrics to capture inter-group effects and investigating other approaches to modeling the temporal dynamics of curiosity stimulation are also directions worth pursuing in the future.

Complementary, our metrics could be applied to analyze social curiosity in other platforms of group communication (e.g., Telegram), or adapted to other types of social media applications (e.g., Twitter, Facebook). Moreover, one could further analyze the relationship between user and group-level social curiosity stimulation. Our proposed social curiosity metrics could be employed, jointly with metrics related to other collative variables, to build more sophisticated curiosity models, which in turn could be explored to improve information dissemination in the target platforms (e.g., as a component of recommendation or search systems).

CRediT authorship contribution statement

Alexandre Magno Sousa: Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Jussara M. Almeida:** Conceptualization, Methodology, Writing – review & editing, Supervision, Resources. **Flavio Figueiredo:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[23] https://www.washingtonpost.com/news/theworldpost/wp/2018/11/01/whatsapp-2/; https://www.bbc.com/news/world-asia-india-44856910; https://www.bbc.com/news/education-55332321.

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