Informal Learning in Social Networks During the COVID-19 Pandemic: An Empirical Analysis

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Abstract. The use of the Internet and social networks have increased dramatically during the COVID quarantine mainly because several activities were moved online. In education, numerous stakeholders stayed at home and their academic plans were modified and adapted to an entire virtual environment. This was the case of a live event (Science Café) whose purpose was to disseminate knowledge through Facebook and YouTube. Thus, this study aimed at verifying if there was knowledge construction in social networks through user interactions by using 1,083 comments posted by the audience. Comments were coded according to validated frameworks for language taxonomy and collaborative knowledge construction. Results show that the predominant interaction is that in which viewers pose questions to speakers. Our analyses also revealed that attendees hardly reached the highest levels of knowledge construction through unguided interaction. Often, user interactions went beyond emotional expressions towards evaluation and therefore, could reach a higher level of knowledge construction. This study shows that social networks may offer informal spaces for deliberation and collaborative interaction with the potential to support learning if guided properly. This research aims to contribute empirical evidence to the growing body of literature that online interactions in informal environments may provide productive learning.

Keywords: Informal learning · Knowledge construction · Social network analysis · Sociograms · SNA · COVID-19

1 Introduction

Access to the internet and social networks have increased in people’s lives. The proliferation of profiles on social network such as Instagram, Facebook or YouTube contributes to social, emotional and intellectual growth through a bidirectional structure in communication [1]. These environments can be perceived as a space where an empathic and reciprocal interaction is generated based on experiences, arguments or ideas. This enables users to find groups, communities, pages or specific content of personal or collective interest [2, 3].

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However, the use of social networks in educational contexts and processes of knowledge co-construction require special attention, since it is traditionally expected that the teacher should be the one who coordinates the online activity. That is, there must have a clear presence of a teacher to create an environment where students feel motivated to share knowledge. Despite that social networks may produce anxiety and risks, students seem to include these platforms in their learning more frequently [4]. On the contrary, some authors e.g. [5] and [6] argue that the use of social networks is primarily for leisure activities (e.g. watching movies) and communication but there are other investigations such as those of [7, 8] and [9] who confirm that the use of social networks has changed its functionality and now can be applied on academic tasks for learning and research.

Within the literature search, there is little empirical evidence that online interactions generate productive learning of conceptual domains, as well as research that adequately describe the way in which people learn informally online in daily life [10–12]. A direct interaction, debate and argumentation among users through networks allow them to confront their beliefs, ideas and thoughts [13]. Communication between peers, students and teachers favours the discovery of alternate conceptions, interpretation and fostering of understanding [14–19]. Consequently, the introduction of social networks may create new spaces for informal learning [20]. Networked learning has generated greater interest just as any other technology-mediated environment with large populations where users usually gather in smaller subgroups of learners [15]. Thus, by analysing conceptual dimensions, the current study aims to identify if user interactions have the potential to build social knowledge during a virtual educational event in real time through social networks.

1.1 Social Networks and Informal Learning

With the rise of web 2.0, social networks emerge to support interactions among users, because of their ubiquity which connects millions of people simultaneously [21–23]. It is necessary to mention that the rapid advances of the information society and its growing production of different kinds of content, according to Haseenf [24] has promoted the creation of learning spaces, generating new training experiences that are external to formal education. In other words, this is an independent learning field that occurs in settings that do not award academic credits [3, 20].

1.2 Social Networks and Their Relation with Informal Learning

Informal learning is spontaneous as it does not require organization or prior planning; it may arise from work or personal experiences [20]. Its structure is open through decentralized ecosystems of interaction where actors play a relevant role as content creators where they not only consume content but generate and share it for educational purposes. Through these processes each individual has the opportunity to argue on a topic of their interest [25], which occurs in a group or in virtual communities of common interests [3, 26]. These characteristics suggest that social networks can be considered as an educational medium [27–29].

For example in [20], researchers examined 1,530 asynchronous comments generated in six science videos on YouTube, to see if knowledge construction occurs as informal
learning. Their analyses showed that most comments were at the level of phase 1 (sharing) and phase 2 (meaning of negotiation) - 382 (37.5%) and 447 (44%) comments respectively. Only 122 comments (12%) reached stage 3 (elaboration), 26 comments (2.5%) reached phase 4 (synthesis), and less than 1% reached the highest level of knowledge construction, (Phase 5). It was also concluded that YouTube can provide an informal space for collaborative interactions with the potential to support lifelong learning.

Holland [7] reviewed 22 articles to detect if e-learning was built in online self-directed courses for an adult audience. The author identified two principles: (a) the opportunities of interaction which supported the construction of knowledge and student empowerment; and (b) segmented learning objects, labelled to facilitate personalised learning. The content shared in social networks can be used to facilitate and enhance individualised learning and discourse support for the construction of knowledge. Similarly, social networks can help evaluate the effectiveness of an educational activity. In [30], of the 128 students enrolled in a course, 100 (78%) joined a Facebook group. Those subject-specific posts obtained the highest number of interactions among students. The uniqueness of the learning environment was largely valued by students. The authors concluded that Facebook provided an informal environment of learning to discuss contemporary issues and the thoughts of invited experts.

In [27], it was addressed the impact of social media on the process of learning about creation and distribution of content related to education. An association analysis was implemented to identify the most common patterns of platform use. The results showed that 93% of students used Facebook to communicate with their peers but 40% used a Learning Management System (LMS) to communicate with teachers. To search contents, the LMS was used simultaneously by 31% of those surveyed, in the same way as in the search for articles and e-books + wikis (31%), scientific databases + wikis (28%) and e-books + scientific databases (27%).

1.3 Sociograms in Social Network Analysis

The study of social networks is based on concepts and methods of network theory, also called Social Networks Analysis (SNA). Therefore, the relationship of users is initially determined, then it is contextualized according to language and the set of actors are delimited according to the patterns that configure the structure of the network [31]. To represent the actors and patterns of social interactions, sociograms are used to visualize the effect of relationships in order to analyze the configurations of positions and flows of communication in which they emerge [32].

Social networks allow us to visualize a set of nodes that are connected by lines which represent relationships among people. In this way it is possible to analyze the flow of interactions that agglutinate social ties concatenated into structures that are linked at a macrosocial level [31]. Additionally, sociograms allow for exploring the behaviour of nodes and test which relationships are influencing on a behaviour [33]. Something to highlight is that networks have a limit to receive a number of social closures that can be identified visually [24]. To understand a sociogram, it is necessary to recognize the four basic elements that comprise it:

**Nodes** are the users on the network. They give naturalness and structure. **Relationships** are those didactic connections between nodes representing both directionality and
density. In this study, relationships can be identified by colors in the sociograms. Limit denoted as a social closure. Nodes that are out of the sociogram can be identified. Network analysis level, depending on where attention is focused, it can be egocentric, node subgroups or total structure.

2 Materials y Methods

This study uses a descriptive social network design with a naturalistic approach [34] i.e. researchers observed subject interaction without controlling for any variables. Data were gathered from posts of participants in an event called Science Cafe: Impact of teleworking in the efficiency of teachers and students (original name in Spanish, Café Científico: Impacto del teletrabajo en la eficiencia de los profesores y estudiantes). The event was hosted by Universidad de las Fuerzas Armadas ESPE and streamed in real time via Facebook Live and YouTube in its official social networks.

The study is approached from two coding perspectives; the first to determine the level of written interactions (within a built-in chat) generated during the two-hour broadcast, classifying those interactions according to the language-based taxonomy of Li and Kim [27]. It is intended to identify the network with its nodes, links and social relationships, which in this case were around the five speakers and the audience. Finally the interactions that were generated among them (represented in a structure [20]), with four types of functionalities and their respective definition based on language usefulness [31].

The second perspective is to examine the educational value of the virtual event in real time. Thus, we used a coding framework [28] to track the process of collaborative knowledge construction. We chose this framework because it has already been theoretically and empirically validated in previous studies. For Social Network Analysis (SNA), the relationship among users is firstly determined and then contextualized based on the language used. Later, a set of actors is defined and the patterns to configure the structure of the network are expressed [31, 32].

To represent the actors and patterns of social interactions, sociograms were used. It was possible to visualize the effect of relationships in order to analyze the configurations of positions and communication flows in which they emerged. For an accurate analysis of interactions, they were classified based on the categories for the language functions by Li and Kim [27]. In this sense, the comments found in the live chats of Facebook and YouTube were classified. Then, we matched comments according to the definition of each function. For this, we used the categories presented in Table 1. In addition, a code was generated for each category in order to facilitate the analysis (Figs. 1 and 2).

For the coding of comments, gender, user number and social network were taken into account, that is, A_M_001_FB. Continuing with the coding process, the same procedure was carried out to identify the times in which interaction was registered. In order to organize the data collected according to the structure of the virtual event, we considered: general audience presentation, speaker 1, speaker 2, speaker 3, speaker 4, speaker 5, general audience round of questions and general audience dismissed, as can be seen in Fig. 1.

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1 https://www.facebook.com/100685501680368/videos/720278938736190.
2 https://www.youtube.com/watch?v=m8W0L8HV6T8.
### Table 1. Taxonomy: Functions of language. Adapted from Li and Kim [27]

| Codes | Language functions | Definitions |
|-------|--------------------|-------------|
| AG    | Agreements         | To express agreements with other points of view |
| LS    | Level of satisfaction | To evaluate the members of the groups |
| QU    | Questions          | To ask questions |
| AN    | Answers            | To react to others’ ideas |

**Fig. 1.** Coding system - Taxonomy: Functions of language

The second perspective - with which the analysis of the interactions recorded during the virtual event was carried out - refers to the coding scheme of Lucas, Gunawardena and Moreira [28], for the process of collaborative knowledge construction. This coding scheme evaluates the knowledge construction process through successive phases of collaborative interaction [29]. Table 2 presents the coding scheme with the respective definition for a better understanding of the categories and subcategories that comprise it, which were assigned a code for the analysis of interactions, as well as the audience and the five speakers of the event (Fig. 1).

### 2.1 Participants

The participants (n = 512) were mostly students and teachers from Ecuador. According to demographic data we collected, the highest percentage of participants was female (81%) and from the local province. We gathered 1,083 interactions as part of the dialogues generated in the live chats of the official social networks. We subsequently analysed those interactions to obtain the results for this research.

### 3 Results

The results obtained after the SNA from the two study perspectives applied in this research are presented below.
Table 2. Collaborative knowledge construction coding scheme

| Categories       | Subcategories         | Definition                                                                 | Code |
|------------------|-----------------------|-----------------------------------------------------------------------------|------|
| Evaluation       | Disagree              | Attack or literally disagree with the previous comment                      | E_Dis|
|                  | Counter claim         | Different opinion from previous speaker                                      | E_Con|
|                  | Agree                 | Agree with the previous comment                                             | E_Acu|
|                  | Question              | A comment that asks for clarification, elaboration or more facts             | E_Pre|
|                  | Claim                 | Does not agree or disagree with previous, neutral                           | E_Rec|
| New/Repetition   | Explanation           | Clarification of causes, context, or consequences of ideas that were presented| NR_Exp|
| Emotional        | Personal experience   | Justification based on personal experience                                   | EX_pEx|
| expressions      | Positive emotional    | Empathy, positive feedback, encouragements                                   | EX_Pos|
|                  | expressions           |                                                                             |      |

3.1 Perspective from the Taxonomy of the Language Function Adapted from Li and Kim (2016) Applied to Sociograms

Table 3 shows the results obtained after coding the comments generated in the live chats. The percentages of interactions obtained in the different categories analyzed, belonging to the language function taxonomy, are summarized and indicated.

Table 3. Coding of comments based on the language function taxonomy

| Categories | P1 | P2 | P3 | P4 | P5 | AG1 | AG2 | DCHS | Total | Percentage |
|------------|----|----|----|----|----|-----|-----|------|-------|------------|
| AG         | 12 | 25 | 17 | 5  | 11 | 20  | 60  | 0    | 150   | 13.85      |
| LS         | 15 | 12 | 5  | 5  | 2  | 100 | 0   | 1    | 139   | 12.83      |
| QU         | 37 | 86 | 33 | 21 | 62 | 5   | 0   | 0    | 244   | 22.53      |
| AN         | 5  | 450| 2  | 2  | 88 | 1   | 0   | 2    | 550   | 50.78      |
| Total      |    |    |    |    |    |     |     |      | 1083  | 100        |

The structure of the table consists of a column belonging to the category codes; agreements (AG), level of satisfaction (LS), question (QU) and answer (AN), the definition of each one is described in Table 1. The following columns refer to the categorization system described in Fig. 1. Additionally, it shows the total number of comments posted by category and their percentage. Thus, the study shows that within the AG language function, 13.85% of interactions were obtained; this is the least representative value. While in the LS category, 12.83% of comments were evidenced. On the other hand, and
increasing, 22.53% of interactions referring to QU were observed. Finally, with the most representative percentage of interactions is the AN function with 50.78%. The information described allowed to give way to the elaboration of the sociograms as explained in Fig. 2.

The first category of the language function taxonomy corresponds to Agreements (AG). This refers to the comments that express agreements with other points of view, either with the contributions and topics presented by the speakers, or with the comments issued by the audience in general (Table 1). Thus, Fig. 3 presents the results obtained in this category.

In this context, the analysis of the sociogram shows that within the five presentations, based on Table 3, interpreted in the sociogram (Fig. 3) indicates the most representative nodes in receiving high percentages of comments from the category agreements (AG) are the following: AG_R (General Audience_Round of Questions) with 29.50% characterized by being the node that is heavily involved in the relationship system, followed by P2 (Speaker 2) that receives 24%, P3 (Speaker 3) 16%, P4 (Speaker 4) 15.38%.
The directionality of the network relationships is direct, that is, there is an active node, in this case it is the AG_R (General Audience_Round of Questions) and the passive node is the AG_PRE (General Audience_Presentation) node, which is why the latter is not highlighted in the sociogram.

Its limit or social closure has been delimited in an empirical way, so it can be observed that certain nodes come out of the structure and are located in the upper and lower corners of the graph, specifically those that exceed the limits of the circumference. This turns the study towards a level of analysis focused on a total structure, since there are interactions with strong and weak ties. The second category analysed is that of assessing the members of a group, coded as LS (Level of Satisfaction). This considers the interactions where the audiences assess the presentation, the topic, the virtual cafe and even the audience of the event (Table 1). Thus, Fig. 4 presents the results obtained in this language function.

The analysis of the sociogram, in Table 3, shows that there are two representative nodes in relation to the comments categorized as Rating (CA); AG_D (General Audience_Dismissed) with a percentage of 33.53% and AG_R (General Audience_Round of questions) with 31.70%, which structure the network to a large extent within the graph.

Fig. 4. Sociogram: taxonomy for the language function – level of satisfaction (LS)

The directionality of the relationships is direct, since the active mode is AG_D and the passive mode is AG_PRE (General Audience_Presentation), which is not distinguished in the network. When delimiting the social closure, it can be seen that a single node is outside the structure, indicating that it has placed a comment of this type of category. The level of analysis is focused on a total structure, since there are interactions with strong and weak ties. The penultimate language function analyzed corresponds to Question, coded as QU. As can be seen in Table 1, this category refers to the questions or concerns that the audience asks the speakers during the presentations. In this sense, Fig. 5 shows the results obtained.

When observing Table 3, this sociogram shows that of the five presentations made during the event, the nodes that show the greatest interaction based on the comments with category Question (QU) are P2 (Speaker 2) with 35.17% and P5 (Speaker 5) with 24.11%, which is why they are highlighted in Fig. 6. Directionality is characterized by being direct, being the P2 active node (Speaker 2) being the one on whom the interactions or questions are focused.
The passive nodes are AG_D (General Audience_Discharged) and AG_PRE (General Audience_Presentation) since this type of category is directed towards the presentations, as well as the round of questions that takes place during the event. In the social closure, no nodes are distinguished outside the network, that is, the level of analysis of this sociogram is focused on a total structure, since there are interactions with strong and weak ties.

Finally, the language function Answer, coded as AN, according to its definition (Table 1), classifies all comments or interactions that react to the ideas of others or answering the questions asked. In the case of the present study, the answers given to the questions formulated by the audience towards the speakers during the respective interventions are considered within this category. Next, in Fig. 6, the results of this function are presented.

In the Answer (AN) function, a large number of interactions are evidenced regarding answering the questions that the audience asked. As can be seen, answers to the audience were mostly provided by the following nodes: AG_PRE (General Audience_Presentation) with 33.16% and node P1 (Speaker 1) is the one who stands out in the network compared to the other presentations with the 21.84%.
The sociogram has a direct directionality, like the first two previous sociograms; as active node is AG_PRE (General Audience_Presentation) and passive P3 (Speaker 3), which does not stand out in the network. No nodes outside the network are distinguished in the social closure, that is, the level of analysis of this sociogram is egocentric since it focuses on the active node. However, it should be noted that in this category, node P3 (Speaker 3) is the one that predominates in relation to the other presenters, because he responded to the concerns of the viewers.

3.2 Perspective from the Coding Scheme of Lucas, Gunawardena and Moreira (2014) for the Process of Collaborative Knowledge Construction

From the perspective of the coding scheme, the knowledge construction process is evaluated through successive phases of collaborative interaction [20]. To do this, the process is evaluated taking into account three categories; evaluation, new/repeated and emotional expressions. Each category has subcategories as can be seen in Table 2.

Next, the results of the interactions obtained during the presentation of the speakers are described, with the knowledge construction coding scheme - Fig. 7. These results were reflected in a timeline, where the interactions were located in the corresponding categories in chronological order of presentations.

![Collaborative knowledge construction coding scheme](image)

**Fig. 7.** Collaborative knowledge construction coding scheme

The collaborative knowledge construction analysis carried out on the data collected from the virtual event broadcast in real time in Facebook and YouTube allowed us to detail the most representative percentages together with their categories. In the emotional expressions’ category, specifically in the positive emotional subcategory, the interactions showed that P1 (Speaker 1) is the one who receives 17.85% of empathic and positive comments from the audience, in relation to the other speakers.

Regarding the new/repetition category with its explanation subcategory (where causes and contexts or consequences of ideas are clarified), it is evident that P2 (Speaker
2) receives 10.46% of the comments, being the one that stands out the most in the timeline (Fig. 7). The evaluation category and the question subcategory indicate that speaker 2 receives 11.94% of clarification-type comments - which in relation to the rest of the speakers is the one that predominates. In this category, the audience had the opportunity to place concerns in regard to the topic presented.

Regarding the evaluation category, specifically in the agreement subcategory, speakers 2 and 3 represent 1.23% in agreement-type comments. In the same way, it is possible to show the less representative percentages together with their categories. Whereas in emotional expressions within the personal experience subcategory, no interaction was recorded during the presentations. While in the category new / repetition with the subcategory evidence, only during the participation of speaker 2 is 0.12% evidenced where a repeated idea that is supported or disapproved is expressed. In the evaluation category with the complaint subcategory, it is reflected during the presentation of speaker 1 that reaches 0.12% and speaker 4 registers 0.36%, where the disagreement of the audience is indicated against comments, the latter is the one who is accentuated in the timeline (see Fig. 7).

Finally, in the evaluation category with the subcategory against claim, only in presentation 4 is 0.12% obtained by the audience in which they indicate a different opinion, it can be said that this category allowed us to detect that their viewpoint was argued by the audience in relation to the other presentations. Furthermore, in the evaluation category with the disagree subcategory, during presentation 2, 0.37% was recorded. As for speaker 3 and 5, they registered 0.24%, with speaker 4 remaining in last place with 0.12% in disagreement from the audience. Since two of the five presentations had high significance (Fig. 7) in this type of category, viewers were dissatisfied with their approach.

4 Discussion

The goal of this research is to verify if it is possible to build knowledge based on the audience interactions in a live chat during an educational event broadcast via Facebook and YouTube. Comments made during the event were coded based on the taxonomy on the language adapted from Li and Kim [27]. We also seek to examine the educational value of the virtual event in real time, classifying the existing interactions according to the coding scheme of Lucas, Gunawardena and Moreira [29] for the process of collaborative knowledge construction. In doing so, it is possible to detect if there is informal learning on social media platforms such as Facebook or YouTube.

The interactions of the spectators during the virtual event were analysed from a two-fold perspective. In the first one, the taxonomy of the language function was applied to sociograms. A high interaction was registered in the category Answers (AN) at the beginning of the event. On the other hand, the category questions (QU) presents a moderate level of interaction. In the category Level of Satisfaction (LS), there is a high flow of interactions in the round of questions (AG_R) and farewell (AG_E). The category that registers a slight interaction flow compared to the others is that of agreement (AG). These results were expected since it does not require prior organization and planning and originates from the work or personal experiences of people [20].
Secondly, by applying the coding framework for collaborative knowledge construction [31], it was possible to discover how the knowledge construction progressed during the event. Results revealed, in general, a high percentage (36.95%) of comments in the category of emotional expressions, positive emotional subcategory, which reflects empathy and positive comments. The findings revealed a high proportion of posts in Phase 1 that is similar to the results of previous studies on synchronous and asynchronous online discussions in formal settings.

Specifically, during the intervention of the speaker 1 (man) in was obtained 17.85% of data in this category, which means that the viewers agreed and were comfortable with the topic and the presentation of the speaker. However, in the subcategory pertaining to personal experiences, no interactions were recorded. In contrast to the findings, the new/repeated category, 27.04% is registered in the explanation subcategory, where speaker 2 with 10.47% resolved doubts and concerns of the spectators of the event. No significant data is recorded in the evidence subcategory, that is, there are no new or repeated ideas or information that approves or disapproves of an idea by viewers. Similar to findings from previous studies, online discussion reviews report a small percentage of publications that advanced to Phase 2. In the last category, called evaluation, significant data is recorded in the subcategory of questions (29.19%). That is, there are no relevant percentages or interactions in agreement, disagreement or opinions regarding a comment. Speaker 2 is the one who receives 11.69% of questions. Relating the results, speakers 1 and 2 are the ones who stand out from both perspectives in the analysed categories.

After the analysis of knowledge construction, a pattern is observed. The number of posts decreases with each successive phase of knowledge co-construction. It is consistent with the literature [29, 31]. However, it is evident that those who were more active reached, in low percentages, phase 3 of the highest level of co-construction, belonging to the evaluation category, disagreeing subcategory. In other words, the majority of viewers were not able to reach all the stages of the scheme and it should be noted that there are subcategories (e.g. agreements, disagreement and counterclaim) in which there is no interaction. Interactions in these categories refer to disagreements. This suggests that participations with opposite viewpoints are a necessary condition for collective reasoning in online discourse, which is consistent with formal and face-to-face online discussions [15]. It is important that a statement of disagreement incorporates evidence or explanation to encourage its author to engage in superior collaborative elaboration and which in turn encourages more constructive interactions [20].

Of the most active users, just a few of them reached the highest levels of knowledge co-construction (Phase 3). This suggests that motivated and engaged users are more likely to reflect and reach the conflict resolution stage [32]. Therefore, it is likely that the nature of the social networks can generate informal knowledge due to their characteristics of interaction and collaboration only if viewers remain motivated and interested in participating, generating opposing points of view. In the same way, it is recommended that challenges are presented as this can stimulate collective participation [29]. Yet, new questions are open in this research, such as whether the educational value and the high percentages of participation of the spectators, specifically in speakers 1 and 2, depend on the topic addressed or the chronological order of their presentations.
5 Conclusion

This empirical analysis allowed us to detect that interactions were not recorded sequentially in all the phases of the coding scheme for the construction of collaborative knowledge. In spite of that, findings reveal that user comments went beyond emotional expressions towards the level of evaluation, and thus attaining a higher level of knowledge construction in this informal environment. This study shows that social media has the potential to offer informal spaces for collaborative discussion and communication if guided by a moderator.

We can conclude that the audience needs to spontaneously get involved and generate a dialogue that allows cultivating productive knowledge among all participants. For this, the accompaniment of a professional who understands the topic addressed in the event is required. A moderator can foster the need and interest in collaboration which can initiate productive interactions where the three phases of the coding scheme can be developed.

Finally, it does not depend solely on the accompaniment of a professional, but also on the audience’s predisposition to get involved, supported by their interest and curiosity. These conditions have been reported as important factors for a collaborative behaviour, such as the active posting of comments in online discussions [18, 33]. Therefore, social networks, because of their content, which is based on the transmission and communication of users personally and collectively through social communities and pages of interest, have the potential to produce effective informal learning. The involvement of a professional who guides and accompanies pedagogically the event promoting interactions that lead to reaching all levels of the knowledge construction scheme deserves additional research. This has a paramount importance given the growing need for informal learning opportunities. Future studies might incorporate concepts of motivation and self-regulation in social networks during online events.

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