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Leading the crowd in open collaboration for discovery: The informational role of emotions under radical uncertainty

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ABSTRACT

Open collaboration is increasingly used to advance scientific discovery, yet sustaining participation remains difficult when leadership is informal and problems are open-ended. We study projects from Polymath—a large-scale open collaborative initiative in which mathematicians jointly work on unsolved mathematical problems under conditions of extreme epistemic and social uncertainty. Drawing on public online discussion data from four Polymath projects and using computerized text analysis, we examine how leaders' emotional expressions facilitate continued participation. We find that leaders' emotional expressions are associated with higher crowd participation. This effect does not happen through emotional contagion but through cognitive inference. Participants interpret leaders' emotions as informational cues that help them contribute despite radical uncertainty. The relationship weakens when leaders' emotions are framed as questions rather than affirmative statements, suggesting that clarity in emotional signaling matters for sustaining participation. These findings show how emergent epistemic leadership operates as leaders shape collective inquiry not through formal coordination but by signaling meaning and direction through emotions.

1. Introduction

Leading open collaboration for scientific discovery refers to guiding communities of professional and non-professional scientists who jointly tackle complex problems through the shared use of resources, data, and insights (Beck et al., 2022; Cooper et al., 2010; Redding et al., 2019). Open collaboration for discovery has been applied to various domains, including identifying new galaxies or studying HIV transmission (Franzoni and Sauermann, 2014; Levine and Prietula, 2014; Nielsen, 2020). The leadership of these communities often operates online and under conditions of radical uncertainty, that is under both epistemic uncertainty (such as unknown solution paths and unclear progress criteria) and social uncertainty (such as spontaneous and unreliable participation) (King and Kay, 2020; Knight, 1921; Loch et al., 2011; Packard and Clark, 2020). In Polymath, an open online community of mathematicians, leaders face radical uncertainty in their endeavor. Polymath leaders attempt to resolve mathematical conjectures that have never been proven before (epistemic uncertainty) while relying on contributors who are involved on a voluntary and sporadic basis (social uncertainty). In such radically uncertain contexts, leaders often have difficulties in sustaining contributors' engagement over time (Crowston et al., 2019; Franzoni and Sauermann, 2014; Sauermann and Franzoni, 2015).

To solve complex scientific problems through online communities, prior research highlights task-oriented and relationship-oriented leadership. Task-oriented leaders actively contribute through their experience and expertise, they set project guidelines, coordinate projects, and integrate contributions (Faraj et al., 2015; Fleming and Waguespack, 2007; Johnson et al., 2015; Safadi et al., 2021). By contrast, relationship-oriented leaders play a key role in socializing newcomers, fostering a positive and collaborative climate (Faraj et al., 2015; Giuri et al., 2008). While both task- and relationship-oriented leadership behaviors are important in online collaboration, they are limited when participants do not know exactly what to do to solve the problem and when the collective itself is unstable. Under such conditions, leaders cannot solely rely on their expertise since the tasks are unclear and ill-defined (epistemic uncertainty), they also cannot rely on their socialization skills given that the participation is fluid and transient (social uncertainty). In radical uncertainty, online leaders must help participants make sense of what is happening and how to move the project

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forward despite unclear roles and goals.

One way leaders could facilitate participation in radical uncertainty is through their emotional expressions. People often feel emotions when they face situations that are uncertain, consequential, and difficult to control (Frijda, 1986; Lazarus, 1991; Ortony et al., 1988). This is precisely the type of situations that online leaders face under radical uncertainty (Van Kleef, 2016). In this context, followers lack clear interpretive frames, which increases their reliance on leaders' emotional cues to make sense of unfolding events. Therefore, leaders' emotional expressions matter not merely as personal reactions, but as signals that orient participants' attention and effort.

Existing studies on emotions in online communities often adopt an intrapersonal perspective, by examining how contributors are influenced by their own emotions (Bateman et al., 2011). In contrast, much less is known about the interpersonal perspective of emotion, that is, how leaders' emotional expressions shape others' behaviors. Prior research has devoted limited attention to theorizing the mechanisms through which leaders' emotional expressions could drive crowd participation and through which linguistic form. Scholars have predominantly focused on the beneficial role of leaders' positive emotions. In doing so, they have often overlooked the potential influence of negative emotions, reflecting an implicit bias toward viewing positive emotional displays as the appropriate leadership stance (Becker et al., 2022; Coussement et al., 2017; Johnson et al., 2015).

This research proposes that in radical uncertainty settings, online leaders' emotional expressions go beyond merely reflecting their internal emotional states or cultivating a positive emotional climate but function as cognitively meaningful signals that shape how others interpret the situation, which facilitate crowd participation. In line with the attention-based view of the firm, we argue that radical uncertainty amplifies these effects by increasing followers' dependence on leaders' emotional expressions as cues that capture, direct, and prioritize attention toward what leaders define as salient, urgent, or worthy of collective effort (Ocasio, 1997). Emotional expressions thus function as sensegiving and attention-shaping mechanisms through which leaders orient collective attention and enable collective action despite indeterminacy (Maitlis and Christianson, 2014). We also propose that the form of emotional expression—and more specifically, whether emotions are conveyed as questions or statements— influence how these signals are interpreted and acted upon.

To test our hypothesis, we analyze archival data from *Polymath,* an open online community of mathematicians collaborating on unresolved conjectures (Ball, 2014; Gowers and Nielsen, 2009; Polymath, 2012a). The dataset includes four completed Polymath projects conducted between 2009 and 2015. Polymath is an ideal context to study online leadership under radical uncertainty: there is no formal hierarchy or assigned roles, leaders do not know whether solutions exist, how to reach them, or who will contribute to the project. This research examines *how* (i.e., through what mechanisms) and *when* (i.e., under what conditions) leaders' emotional expressions affect crowd participation.

Theoretically, we draw on the interpersonal theory of emotions-as-social-information (EASI) (Van Kleef, 2009), which suggests two pathways through which emotional expressions shape others' behaviors: emotional contagion (i.e., others mirror the expresser's emotional state) and cognitive inference (i.e., others interpret emotions as cues for action). We extend this theory to the context of radical uncertainty (i.e., epistemic and social uncertainty) and online collaboration. Our findings indicate that, contrary to expectations, emotional contagion does not operate under radical uncertainty—leaders' emotions are not transmitted to other participants. Instead, we show that leaders' emotional expressions increase crowd participation by triggering cognitive inferences. Participants interpret leaders' emotions as informational cues about how to move the project forward. The effect depends on how leaders express their emotions: the positive effect of cognitive inference on crowd participation weakens when leaders' emotions are framed in messages with high equivocality, i.e. with multiple possible interpretations, suggesting that emotional expressions conveyed as clear and affirmative statements are more effective at guiding participants' inferences.

Our findings contribute to three literatures. First, we contribute to research on online leadership by identifying a cognitive mechanism through which emotional expressions influence participation. In radically uncertain contexts, leaders' emotional expressions become an indirect yet effective form of epistemic guidance. We also show that leaders' negative emotions, when clearly expressed, can have a positive impact on crowd participation. Second, we contribute to research on open science by showing that emotional cues facilitate collective discovery processes. Research shows that interpretive cues help scientists coordinate around emerging directions, and that shifts in framing influence whether promising lines of inquiry are pursued or abandoned (Ben-Menahem et al., 2016; Chai, 2017). We extend these findings by showing that interpretive signals can also take an emotional form to support collective discovery. Finally, we extend EASI theory by demonstrating the role of cognitive inferences in demanding and distributed collaborations. We identify a linguistic boundary condition showing that emotional expressions in messages with high equivocality are less effective at guiding cognitive inference.

The remainder of the article is organized as follows. Section 2 discusses how online leadership is challenged under radical uncertainty, and why leaders' emotional expressions offer epistemic guidance. Section 3 presents our hypotheses regarding *how* and *when* leaders' emotional expressions influence crowd participation. In Section 4, we describe the study context and data used. Section 5 reports our findings and robustness checks. Section 6 discusses implications for theory and practice.

2. Leadership trough emotion under radical uncertainty

2.1. The challenge of traditional leadership models under radical uncertainty

Prior research highlights the critical role of online leadership in fostering crowd participation (Bonaccorsi and Rossi, 2003; Huffaker, 2010; O'mahony and Ferraro, 2007). This literature identifies a range of leadership styles relevant for online and collaborative work, especially in open-source software communities. Task-oriented leadership, often associated with transactional models, focuses on assigning responsibilities, coordinating tasks, and leveraging technical expertise to solve problems (Faraj et al., 2015; Johnson et al., 2015). For instance, Dahlander and O'Mahony (2011) show that participants who make significant technical contributions and coordinate several tasks progress toward more central positions within the community. Similarly, Li et al. (2012) found that leaders' contributions increase other participants' intrinsic motivations to participate.

Other studies highlight the role of relationship-oriented leadership behaviors such as transformational leadership. Relationship-oriented leadership increases crowd participation by fostering trust, cohesion, and engagement among participants (Giuri et al., 2008; Huffaker, 2010)**.** Online leaders' communication skills are key in building social cohesion and maintaining relationships (Huffaker, 2010; Kayworth and Leidner, 2002; Luther and Bruckman, 2011). Given their central role in the community, their messages shape participants' motivations and actions (Faraj et al., 2015; Sparrowe and Liden, 2005). For instance, Li et al. (2012) found that leaders often post customized messages to respond to participants' specific concerns and needs.

These leadership styles are particularly relevant in collaborative settings where roles are flexible and expertise is dispersed. Task-oriented leadership tends to be more effective when tasks and deliverables are clearly defined. Transactional leadership is often more suitable when roles and expectations are stable because leaders can incentivize participation through clear reward structures. Relationship-oriented leadership thrives when social cohesion is high and when participants interact regularly. Transformational leadership can also be helpful to increase commitment and build shared vision. However, these leadership behaviors are often not sufficient in online collaborations operating under radical uncertainty. Indeed, most of these leadership models require task definition, goal clarity, and relational stability, which is not the case under radical uncertainty.

Under radical uncertainty, leaders face a dual challenge: they must cope with epistemic uncertainty (e.g., the solution paths are unknown and the criteria for progress are unclear) and social uncertainty (e.g., they face voluntary, and sporadic participation). In such conditions, traditional coordination mechanisms break down: there are no predefined roles, no clear milestones, and few stable relationships to build on. Instead, what is needed is a form of leadership capable of guiding participants through the project despite inherent uncertainties.

2.2. Emotional expression as a form of epistemic guidance

When formal plans are absent and roles are undefined, emotional expressions may become one of the few resources leaders can draw on to influence crowd participation. Few studies have explored emotions included in online leaders' messages. Prior research suggests that online leaders who express their positive emotions often increase participants' motivation and engagement within the community (Becker et al., 2022; Johnson et al., 2015; Rubin et al., 2005). The interpersonal perspective of emotions has been investigated in three main studies. Huffaker (2010) found that online leaders express more emotional content than other participants and that the emotional tones of leaders' messages trigger new conversation topics. Coussement et al. (2017) find that online leaders' positive emotions increase crowd participation in terms of quantity but not quality. Becker et al. (2022) argue that charismatic leaders often use positive emotions in their language. In contrast to Coussement et al. (2017), the authors find that positive emotions have a significant and positive effect on participation quality but not on quantity.

These studies provide valuable insights into the role of leaders' emotions in collaborative online settings. However, they focus primarily on positive emotions and do not investigate the mechanisms through which their emotions exert influence. Moreover, these studies do not examine how emotions function under radical uncertainty. In radical uncertainty, participants do not face only motivational challenges, but also cognitive uncertainty about what is happening and how to contribute. This connects with broader research on sensemaking and coordination under ambiguity, which emphasizes that when goals and roles are unclear, people rely on interpretive signals (e.g., frames, analogies, or affective expressions) to orient action (Weick et al., 2005). We extend this view by proposing that leaders' emotional expressions function as epistemic cues: they help participants identify next steps, and adjust their contributions accordingly.

3. Hypotheses development

We develop our hypotheses by mobilizing EASI theory (Van Kleef, 2009), which explains how emotional expressions affect observers' behaviors in social interactions via two pathways: emotional contagion and cognitive inference (see Fig. 1).

3.1. Emotional contagion

Emotional contagion is an unconscious process through which individuals "catch" and internalize emotions expressed by others (Hatfield et al., 1994). When leaders express emotions, followers tend to mirror these emotions without deliberate reasoning. In uncertain collaborative settings with a lack of stable reference points, group emotional dynamics rely on socio-emotional cues (Van Kleef, 2016). For instance, when leaders express positive emotions, they will increase group positive affective turn, fostering trust, openness, and collaboration (Chi et al., 2011; Clarkson et al., 2020; Sy et al., 2005). Similarly, leaders expressing negative emotions such as frustration or concern, increase a group's negative feelings. This is found to be particularly true in uncertain and cognitively demanding settings (Van Knippenberg and Van Kleef, 2016).

Once emotional contagion has occurred, group emotions will then influence participants' willingness to contribute. Positive shared emotions enhance engagement, foster openness, and facilitate collective momentum (Fredrickson and Branigan, 2005), potentially enhancing creative engagement (Baas et al., 2008; Visser et al., 2013). Interestingly, negative shared emotions can also support performance in problem-solving contexts by fostering sustained effort and deeper concentration (Sy et al., 2005). This is particularly valuable in contexts of radical uncertainty, where solving complex problems requires intense focus and sustained cognitive effort. Experiencing negative emotions narrows individuals' attentional scope, leading them to concentrate more deeply on the task (Fredrickson and Branigan, 2005), which in turn can promote analytical thinking and cognitive perseverance (De Dreu et al., 2008; Nijstad et al., 2010).

Moreover, emotional contagion also fosters social belonging and norm alignment, these factors are particularly relevant when participants are unsure of their role or uncertain about which contributions are expected. According to EASI theory, mirroring others' emotional expressions maintains harmony and reinforces a sense of identity (Van Kleef, 2016). In online settings, where social cues are limited, such mirroring may function as a subtle signal of engagement and commitment (Parkinson et al., 2005). Participants who mirror emotionally expressive leaders are more likely to feel included and aligned with the group's goals. This process helps sustain a sense of shared purpose and community, even in decentralized or asynchronous collaborations.

Finally, mimicked emotions function as a surface-level affective response to situational ambiguity. This process does not require deliberate interpretation, it is a rapid emotional alignment that helps individuals regulate their feelings in response to uncertainty. In the

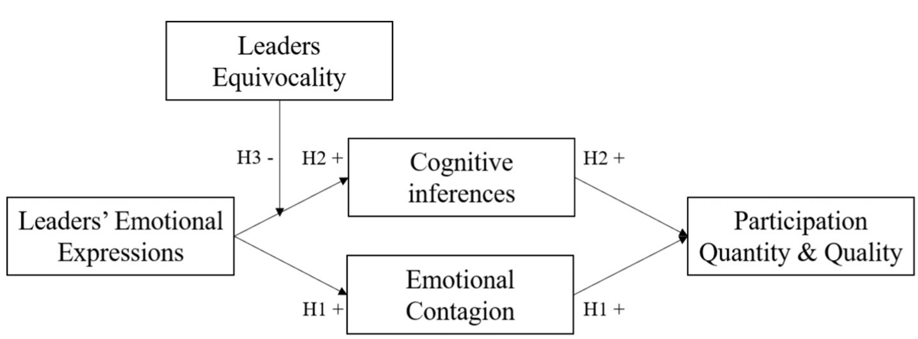

Fig. 1. Conceptual model.

absence of clear guidance, unconsciously mimicking the emotional tone of a leader represents a fast and intuitive way to make sense of the environment (Van Kleef, 2016). Participants adopting leaders' emotions facilitate an appropriate answer in a cognitive and uncertain context. Together, these mechanisms suggest that the spread of leaders' emotional expressions (be it positive or negative) can increase crowd participation by shaping collective motivation and engagement.

Hypothesis 1. – Emotional contagion mediates the positive relationship between online leaders' emotional expressions and crowd participation.

3.2. Cognitive inference

Cognitive inference is another central mechanism through which online leaders' emotional expressions may influence others. Unlike emotional contagion, which involves automatic emotional mirroring, cognitive inference is a deliberate and effortful process in which observers interpret the meaning of emotional displays (Van Kleef, 2009). In radically uncertain environments, individuals often lack reliable information to assess the situation and decide which actions to pursue. Under such conditions, emotional expressions from leaders become an important informational signal. As Van Kleef (2016) notes, when observers are uncertain, they are especially motivated to interpret emotional cues to make sense of their environment. In this perspective, participants interpret leaders' expressions of anger, concern, or joy as leaders' appraisals of the current situation, providing insight into whether the project is on the right path or not.

Once followers infer interpretations from leaders' emotional expressions, these inferences guide their decisions regarding how and where to direct their effort. Radical uncertainty contexts heighten the salience of emotional expressions, especially when they are expressed by high-status individuals. In the absence of clear behavioral norms or performance benchmarks, participants are more likely to behave following the meaningful signals inferred from leaders' emotional expressions (Van Kleef, 2016; Van Knippenberg and Van Kleef, 2016). For example, participants could interpret a leader's positive emotion (e.g., expression of enthusiasm or joy) as a signal that the project is moving in the right direction, which encourages them to sustain their efforts. Conversely, participants can interpret leaders' negative emotions (e.g., expression of frustration) as signals that they must deepen their engagement to move the project in a more appropriate direction. These interpretive processes have been particularly demonstrated in negotiation and interpersonal feedback studies (Sinaceur and Tiedens, 2006; Thompson et al., 1995).

Cognitive inferences are more likely to occur in contexts of radical uncertainty. As Van Kleef (2010) stated: "The deeper the information processing, the stronger the relative predictive power of inferences; the shallower the information processing, the stronger the relative predictive power of affective reactions" (p. 336). Cognitively demanding contexts require participants to engage in complex reasoning, analyze technical information, and generate new solutions— these conditions promote interpretive engagement. In such contexts, leaders' emotional expressions serve as valuable feedback cues. These effects are well documented in negotiation and leadership research. For instance, inferring dissatisfaction or firmness from angry opponents lead individuals to make greater concessions (Sinaceur and Tiedens, 2006). In customer service, inferring high standards from others' displays of disappointment lead observers to increase trust and engagement—particularly when they are epistemically motivated (Wang et al., 2017). Inferences of affirming ongoing strategies from leaders' positive emotions or inferences of ineffective current approaches from leaders' negative emotions can guide decision-making, redirect effort, and ultimately increase participation (Van Kleef, 2009, 2010).

Hypothesis 2. – Cognitive inference mediates the positive relationship between online leaders' emotional expressions and crowd participation.

3.3. The moderating effect of equivocality

While emotional expressions can serve as cues for cognitive inference (H2), their effectiveness depends on how clearly these emotions are communicated. According to EASI, emotional inference is more likely when emotional signals are clear. In contrast, lack of clarity in the message format can blur the emotional signal, making it harder for participants to extract meaning (Johnson et al., 2015; Van Kleef, 2014).

We argue that the equivocality of the message, i.e. the number of possible interpretations influence how much participants interpret emotional cues. Specifically, we propose that whether the leader expresses emotions via an affirmation or a question changes the inference processes. When online leaders express their emotions through affirmative statements, these expressions act as strong informational signals that help participants infer leaders' evaluations of the situation and adjust their contributions accordingly. In contrast, when leaders express emotions through questions, the emotional signal becomes more equivocal. The lack of clarity stems not from the emotional tone itself, but also from the uncertainty about its meaning. Questions carry multiple signals, they can express doubt, criticism, invitation, or even sarcasm (Clark, 1996). As such, questions signal uncertainty or openness, which can undermine the confidence with which observers interpret the associated emotional content.

We thus hypothesize that equivocality weakens the inferential process, as it becomes less clear what the leader truly feels or intends. Emotional inference, according to EASI, is a conscious and effortful process. If the emotional signal is not easily interpretable, participants are less likely to engage in deep analysis or adjust their behavior in response. This is particularly problematic in the context of radical uncertainty such as Polymath where participants rely on cues to coordinate efforts. When emotional cues are fuzzy, individuals may default to their own interpretations or disengage from collective direction-setting. We therefore expect that leaders' emotions expressed in questions reduce cognitive inference and, in turn, on participation.

Hypothesis 3. – The mediating effect of cognitive inference on the relationship between leaders' emotional expressions and crowd participation is weakened when emotions are expressed through messages with high equivocality.

4. Method

4.1. Context of study

This study is an empirical analysis of *Polymath*, an open online collaborative community established in 2009, where professional and non-professional mathematicians collaborate to achieve mathematical discoveries (Ball, 2014). Polymath operates as an open and decentralized form of online collaboration. Polymath is structured around blog posts and discussion threads, where mathematicians exchange solutions, proofs, to prove mathematical conjectures that have never been proven before. Polymath follows a meritocratic and emergent governance model, leadership is not assigned but rather develops organically through contributions. There is no formal hierarchy or designated leadership roles, the project decisions emerge through consensus-building. Polymath projects are often moderated by the project initiators, such as Timothy Gowers (*Cambridge University*) or Terrence Tao (*University of California, Los Angeles*). Rather than having specific leaders, each project is overseen by its host and active contributors, ensuring a decentralized and flexible approach to managing discussions and progress.

The analysis focuses on four completed Polymath projects. These projects were chosen because they were the only ones completed by the time of data collection in June 2015. Our sample includes Polymath 1, Polymath 4, Polymath 5, and Polymath 8. These four projects represent a total of 393 individuals and 6868 posts. The projects lasted between 20 and 70 months, they included between 600 and 2600 online posts and involved between 44 and 110 participants. These four projects resulted in publications in top-ranked journals in mathematics (Castryck et al., 2014; Polymath, 2010, 2012a, 2012b, 2014; Tao, 2017). Polymath 1 aimed to find a new combinatorial proof of the density version of the Hales–Jewett theorem. Polymath 4 was related to deterministic methods for finding primes. Polymath 5 aimed at solving the Erdős discrepancy problem. Polymath 8 was about improving the bounds for small gaps between primes.

4.2. Identification of leaders

Given that there is generally no formal leadership in online collaborative communities, defining who the online leaders are is not trivial. Leaders can emerge during the project, leadership can be distributed among individuals, and the roles and responsibilities of leaders might shift over time (Johnson et al., 2015; O'mahony and Ferraro, 2007). To identify the leaders for each of the four Polymath projects, we drew on nine measures used in existing research on online leadership (Dahlander and Frederiksen, 2012; Dahlander and O'Mahony, 2011; Gargiulo et al., 2021; Huffaker, 2010; Johnson et al., 2015). These measures represent four main factors: (1) quality of participation, (2) quantity of participation, (3) duration of participation, and (4) social network analysis, the last factor capturing different measures of participants' positions within the network (degree centrality, closeness centrality, betweenness centrality, and coreness). These factors were given equal weight in the calculation of this leadership index to identify leaders in each Polymath project (for more details, see appendix A). Table 1 outlines the 10 participants with the highest leadership indices for each of the four Polymath projects. As shown in this table, in each Polymath project, two participants often stand out significantly compared to the others. As a consequence, the two top participants of each Polymath project were identified as the leaders.

4.3. Data extraction and sentiment text analysis

Leaders and participants do not post messages every day. Therefore, we focused our analysis on active days, i.e., days when at least one message was posted. Our unit of analysis then corresponds to a specific day within a given Polymath project. The total number of daily observations across the four projects is 839. We structured the data at a daily frequency so that we could study the relationship between leaders' emotional expressions during the previous active day (i.e., Day D-1)[1] and crowd participation during the next active day (i.e., Day D). Day was chosen as our unit of analysis because contributors post at irregular times and only briefly on a given day, making a smaller time window not adequate, and because a longer time window would exclude the meaningful short bursts of activity that matter for how leaders' emotional expressions are received. To investigate this relationship, we examine the links between the control variables, the leaders' emotional tones, and crowd participation. We investigate the emotional tone of the leaders' online messages with LIWC text analysis application (Pennebaker et al., 2001). LIWC consists of dictionaries containing over 2300 words categorized by independent judges into 68 psychological and cognitive dimensions. As the words in the dictionary are categorized, the score given as output by LIWC represents the percentage of words related to a specific LIWC dimension. Several innovation and management scholars have used LIWC (Beretta, 2019; Bharadwaj et al., 2017; Coussement et al., 2017; Harrison and Dossinger, 2017; Kim et al., 2019; Kruft et al., 2019; Piezunka and Dahlander, 2019). Validity and efficiency of LIWC has been largely demonstrated (Becker et al., 2022; Graf-Vlachy et al., 2020; Ludwig et al., 2014; Neuendorf, 2017; Tausczik and Pennebaker, 2010). To validate our theoretical variables, we conducted an in-depth analysis of several threads where leaders' positive and negative emotions were associated with significant changes in crowd participation (see more details in appendix B). Following Becker et al. (2022), we also confirmed the validity of our LIWC-based measures of positive emotions and negative emotions with appropriate inter-rater reliability measures (see appendix C).

Table 1
Identification of leaders by leadership indices scores.

Polymath 1	Polymath 4	Polymath 5	Polymath 8
Timothy Gowers 2.8	Ernie Croot 4.2	Timothy Gowers 6.9	Terrence Tao 6.9
Terrence Tao 2.7	Terrence Tao 4.0	Alec Edgington 3.0	Eytan Pal 6.4
Ryan O'Donnell 1.9	Gil Kalai 2.4	Gil Kalai 2.1	Aubrey De Grey 3.2
Kristal Cantwell 1.2	Timothy Gowers 2.3	Klas Markstram 1.6	Pace Nielsen 3.1
Jozsef 0.9	Mark Lewko 1.6	Sune Jakobsen 1.5	Andrew Sutherland 2.0
Jason Dyer 0.8	Kristal Cantwell 1.5	Obryant 1.0	Gergely Harcos 1.6
Michael Peake 0.6	Harald Helfgott 1.0	Jason Dyer 1.0	Emmanuel Kowalski 1.5
Randall 0.4	Emmanuel Kowalski 0.8	Moses Charikar 0.8	James Maynard 1.1
Gil Kalai 0.4	François Bruneault 0.6	Terrence Tao 0.8	Xfxie 0.8
Klas Markstram 0.4	Harrison0.4	Mark Bennet 0.7	Wouter Castryck 0.7

4.4. Variable definitions

4.4.1. Dependent variable: Crowd participation

Each participant was assigned a unique ID, and we aggregated the data to determine the number of crowd participants and the number of posts per active day. We used two variables to measure crowd participation: participation quantity and quality. Participation quality, a count variable, is measured by the number of participants on Day D (*Participation Quantity*) (M = 2.14; SD = 2.11). Following the approach of Becker et al. (2022), Cohn et al. (2004) and Ludwig et al. (2014), participation quality is measured by the number of cognitive words expressed by participants on Day D using LIWC software (*Participation Quality*) (M = 10.39; SD = 5.87). These studies argue that the average score of cognitive words (e.g., "cause", "know," or "ought") is a valid measure of the depth of cognitive engagement. According to Pennebaker et al. (2015), such words, recognized using LIWC, serve as makers of cognitive activity and processing.

4.4.2. Independent variable: Leaders' emotional tones

We use the following independent variables: *Leaders Emotions Day D-1*, the average daily scores assigned to leaders' emotional tone on Day D-1, aggregated from the "affect" LIWC score, including both positive and negative emotional tones. Leaders express positive words for various reasons, such as to inform participants about current progress. For instance, Terence Tao posted:

*"**This sounds like excellent news!** I'll try to confirm the polynomial decomposition at least. It looks like James has some independent code for this sort of thing, **so hopefully we'll get confirmation soon** ..."* (*Terence Tao, Polymath 8, January 29, 2014*).

4.4.3. Mediator: Cognitive inference and emotional contagion

The hypotheses H1 and H2 examine the mediators of the relationship between leaders' emotions and crowd participation. These hypotheses

[1] A day on which there was at least one message posted.

propose that cognitive inferences and emotional contagion will mediate this relationship.

In line with EASI theory, we suggest that participants interpret leaders' emotional expressions of emotions as information cues, inferring what leaders think about the project's current state and what actions should follow. To measure the information participants gain, we analyze their degree of future focus—the extent to which they express attention toward upcoming tasks. Acquiring information is associated with focusing on the project's next steps: the more information a person receives, the more they will direct their efforts toward the next task. Thus, we use the extent of future focus expressed by participants as a proxy of cognitive inference. Future focus is measured using the LIWC "future focus" category (e.g., "will," "shall," "going to") (DesJardine and Shi, 2021; Nadkarni and Chen, 2014; Pennebaker et al., 2015; Um et al., 2022). The degree of future focus is computed as the average future focus score among participants on Day D (*Participant Cognitive Inference Day D*) (M = 0.83; SD = 1.16).

According to the EASI theory, leaders' emotional expressions can influence participants' behavior through emotional contagion (Barsade, 2002; Van Kleef, 2009). Emotional contagion means that when leaders express emotions, others will tend to experience the same emotions. In our research, emotional contagion is operationalized as a convergence in the emotional tone expressed by leaders and participants over time. Specifically, we test whether leaders' emotional tone expressed on Day D-1 is associated with a corresponding change in participants' emotional tone on Day D (Goldenberg et al., 2020; Gruda et al., 2022; Hung et al., 2024; Zhou et al., 2023). We use *affect* LIWC scores aggregated at the day level for measuring the emotional tone expressed respectively by leaders on Day D-1 (*Leaders Emotions Day D-1*) (M = 2.54; SD = 2.46) and by participants on Day D (*Participant Emotional Contagion Day D)* (M = 3.05; SD = 2.93).

4.4.4. *Moderator: Leaders' equivocality day D-1*

Leaders' Equivocality Day D-1 variable is used to test hypothesis H3 and control for the possibility that the effect of leaders' emotional expressions on crowd participation may depend on the extent to which leaders express questions or not. The amount of questions expressed is computed by taking the average score of the "interrog" category of LIWC (e.g., "how", "when", "what") from leaders on Day D-1 (M = 0.74; SD = 0.90).

4.4.5. *Control variables*

To rule out alternative factors that could explain a variation in crowd participation, we consider several control variables regarding (1) the participants, (2) the online leaders, and (3) the Polymath project. First, we included control variables related to the participants. For instance, the level of emotion expressed by participants on Day D-1 may significantly explain crowd participation on Day D. We thus include *Participant Positive Day D-1* and *Participant Negative Day D-1*, i.e., the average daily scores for the positive and negative emotional tone of participants' messages during Day D-1. In addition, we also controlled for the possibility that the number of participants' posts during the previous active day (i.e., Day D-1) (*Participant Number Posts Day D-1*) influence participation on the current active day (i.e., Day D) (Cranshaw and Kittur, 2011). Also, participants' anonymity may influence online participation. It may be possible that people respond less to anonymous participants. For each day, we thus counted the number of anonymous authors. *Number anonymous Day D-1* indicates the number of anonymous participants for the previous active day. In our dataset, 40.7% of the participants are anonymous.

Second, we included control variables related to leaders. We controlled for the number of posts from the leaders on the previous active day (*Leaders Number Posts Day D-1)*. Moreover, leaders may influence crowd participation through their communication and linguistic styles. In line with Huffaker (2010), we controlled for the degree of leaders' talkativeness, i.e., the number of words per post on the previous active day (*Leaders Talkativeness Day D-1)*. We also controlled for the sociability of leaders (*Leaders Sociability Day D-1)* to capture the extent to which leaders exhibited social behavior during the project (Faraj et al., 2015). *Leaders Sociability Day D-1* was measured using the LIWC category "social processes", which includes words related to social processes.

Finally, we controlled for the fact that participation may vary across the Polymath projects and their respective timeline. The four Polymath projects studied in this research may have different levels of complexity, which may influence crowd participation. We added the variable *Polymath#* to our multi-level analysis to account for each project's specificities. Participation may also be significantly lower on weekends than on weekdays. The dummy variable *Weekend* was included, equaling 1 when day D is a weekend day and 0 otherwise. Finally, the *Project Timing* variable is used.t. This variable indicates the number of active days elapsed since the start of the project (i.e., the first post of the project). As the four projects had varying durations (from 100 to 300 active days), we considered the timeline of each project in terms of the number of active days (i.e., the number of days in which participants were active) and standardized this variable for each project. *Project Timing* is measured in percentages, with 50% indicating the middle of the project and 100% denoting its end.

5. Results

5.1. *Descriptive statistics*

Table 2 provides an overview of the descriptive statistics. On average, *t*-tests reveal that leaders express fewer positive emotions ($t(843) = -3.21$; $p < .001$) and fewer negative emotions ($t(843) = -3.00$; $p < .01$) compared to crowd participants. The correlation matrix (Table 3) indicates that the correlation factors between the dependent variables and each independent variable are lower than 0.7. The variance inflation factor (VIF) for each model shows a maximum value of 1.40, which reduces the risk of multicollinearity.

Table 2
Descriptive statistics.

Variable	Mean	S.D.	Min	Max
Dependent Variable				
1. Participation Quantity	2.14	2.11	0.00	12.00
2. Participation Quality	10.39	5.87	0.00	33.34
3. Participant Number Posts	4.83	6.01	0.00	44.00
4. Analytical Thinking	69.73	29.61	0.00	99.00
Mediators				
5. Emotional Contagion Day D	3.05	2.93	0.00	35.42
6. Cognitive Inferences Day D	0.83	1.16	0.00	20.00
Moderator				
8.Leaders' Equivocality Day D-1	0.74	0.90	0.00	9.09
Independent Variable				
9.Leaders Emotions Day D-1	2.54	2.46	0.00	19.61
Control Variable				
11. Participant Emotions Day D-1	3.06	2.94	0.00	35.42
13. Participant Number Posts Day D-1	4.85	6.02	0.00	44.00
14. Number Anonymous Day D-1	0.36	0.63	0.00	3.00
15. Leaders Number Posts Day D-1	3.77	5.31	0.00	39.00
16. Leaders Talkativeness Day D-1	51.43	96.89	0.00	881.00
17. Leaders Sociability Day D-1	2.18	2.26	0.00	18.18
18. Project Timing	50.24	28.88	0.27	100.00
19. Weekend	0.28	0.45	0.00	1.00

N = 839 project-day observations.

Table 3
Correlation matrix.

Variable	1.	2.	3.	4.	5.	6.	7.	8.
1. Participation Quantity	1							
2. Participation Quality	0.31***	1						
3. Participant Number Posts	0.87***	0.23***	1					
4. Analytical Thinking	0.31***	0.53***	0.24***	1				
5. Emotional Contagion Day D	0.14***	0.35***	0.10**	0.29***	1			
6. Cognitive Inferences Day D	0.12***	0.26***	0.09**	0.17***	0.12***	1		
7. Leaders Equivocality Day D-1	0.23***	0.06	0.20***	−0.02	0.01	0.01	1	
8. Leaders Emotions Day D-1	0.12***	−0.05	0.11***	−0.03	0.01	0.08*	0.24***	1
9. Participant Emotions Day D-1	0.05	0.10**	0.02	0.09**	0.07*	0.08*	0.01	0.02
10. Participant Number Posts Day D-1	0.65***	0.15***	0.61***	0.16***	0.05	0.03	0.24***	0.14***
11. Number Anonymous Day D-1	0.31***	0.06	0.25***	0.07*	0.04	−0.02	0.09*	0.09**
12. Leaders Number Posts Day D-1	0.56***	0.09**	0.54***	0.09**	0.01	0.01	0.31***	0.25***
13. Leaders Talkativeness Day D-1	−0.09**	−0.10**	−0.09*	−0.11**	−0.08*	−0.00	0.23***	0.09*
14. Leaders Sociability Day D-1	0.18***	0.04	0.15***	−0.00	−0.03	0.06	0.57***	0.40***
15. Project Timing	−0.50***	−0.13***	−0.47***	−0.21***	−0.08*	−0.06	−0.11**	−0.12***
16. Weekend	-0.05	−0.04	−0.04	−0.02	−0.03	−0.03	0.01	0.04

	9.	10.	11.	12.	13.	14.	15.	16.
1. Participation Quantity								
2. Participation Quality								
3. Participant Number Posts								
4. Analytical Thinking								
5. Emotional Contagion Day D								
6. Cognitive Inferences Day D								
7. Leaders Equivocality Day D-1								
8. Leaders Emotions Day D-1								
9. Participant Emotions Day D-1	1							
10. Participant Number Posts Day D-1	0.10**	1						
11. Number Anonymous Day D-1	0.13***	0.45***	1					
12. Leaders Number Posts Day D-1	0.05	0.66***	0.27***	1				
13. Leaders Talkativeness Day D-1	−0.14***	−0.16***	−0.08*	−0.15***	1			
14. Leaders Sociability Day D-1	−0.00	0.19***	0.04	0.30***	0.19***	1		
15. Project Timing	−0.07*	−0.46***	−0.28***	−0.38***	−0.02	−0.10**	1	
16. Weekend	0.03	−0.03	−0.06	0.01	0.00	0.03	−0.03	1

N = 839 project-day observations.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

5.2. Data analysis procedure

Because the data had a nested nature, we used MLSEM in Mplus 8 (Muthén and Muthén, 2017) to estimate a system of equations related to multilevel data and account for the partial interdependence of text data belonging to the same Polymath project. As such, MLSEM allows researchers to analyze multi-level phenomena more accurately by considering variance components of the variables and their relationships at multiple levels (Lüdtke et al., 2008; Mehta and Neale, 2005; Muthén and Asparouhov, 2011). Concerning *participation quantity*, due to the limited nature of the dependent variable (it is a count variable) and the fact that we examined four Polymath projects, a non-linear estimator was employed in that case, i.e., multilevel count analysis. We then controlled for the level corresponding to each Polymath project, as participation can vary from one Polymath project to another. The Polymath project level explains 15% of the variance in the number of participants, 8% of the variance in the number of participants' posts, and 2% of the variance in the participation quality.

Table 4 depicts the detailed results of the relationships of our model following the MLSEM analysis. Model 1 estimates the link between the control variables (including the moderator) and the dependent variables. Model 2 adds the independent variables and the mediators to the control variables. Finally, Model 3 is the full model with the interaction terms. Table 5 addresses hypotheses 1 and 2 by comparing the indirect effects through cognitive inferences and emotional contagion, i.e., participants' future focus and emotions. Finally, Table 6 addresses hypothesis 3 by examining how leaders' equivocality moderated the indirect effect of leaders' emotional expressions through cognitive inferences.

5.3. Main findings

Our findings indicate a positive correlation between leaders' emotional expressions and online participation, both in terms of quantity and quality, through cognitive inference. We also find that this indirect relationship through cognitive inferences is moderated by leaders' equivocality.

We find that the relationship between leaders' emotional expressions and crowd participation does not occur through emotional contagion. The relationships through emotional contagion between leaders' emotional expressions and both the number of participants ($\beta = 0.001$, n.s) and the participation quality ($\beta = 0.021$, n.s.) are insignificant. H1 is thus not supported. In contrast, the relationship through cognitive inferences is significant, showing that our results support H2. Leaders' emotional expressions are positively related to crowd participation through participants' cognitive inferences. Indeed, the coefficients of the indirect relation through participants' future focus between emotional expressions and number of participants ($\beta = 0.003$, $p \leq .01$) and participation quality ($\beta = 0.059$, $p \leq .01$) are both positive and significant. In addition, our results support H3, as leaders' equivocality moderates the relationship between leaders' emotional expressions and online participation (see Table 6). Leaders' equivocality moderates the indirect association through participants' cognitive inferences between leaders' emotional expressions and participation quantity ($\beta = -0.002$,

Table 4
Results of the relationship between leaders' emotions and online participation.

	Model		
	1.[a]	2.[b]	3.[c]
Leaders Emotions Day D-1 → Participation Quantity		−0.01	−0.01
Emotional Contagion Day D → Participation Quantity		0.18***	0.18***
Cognitive Inferences Day D → Participation Quantity		0.11***	0.11***
Leaders Emotions Day D-1 → Participation Quality		-0.11*	-0.11*
Emotional Contagion Day D → Participation Quality		0.31***	0.31***
Cognitive Inferences Day D → Participation Quality		0.22***	0.22***
Leaders Emotions Day D-1 → Emotional Contagion Day D		0.03	0.03
Leaders Emotions Day D-1 → Cognitive Inferences Day D		0.07	0.11***
Leaders' Equivocality x Leaders Emotions Day D-1 → Cognitive Inferences Day D			−0.09***
Participant Emotions Day D-1 → Participation Quantity	-0.00	-0.03	-0.03
Participant Number Posts Day D-1 → Participation Quantity	0.38***	0.35***	0.35***
Number Anonymous Day D-1 → Participation Quantity	0.00	0.01	0.01
Leaders Number Posts Day D-1 → Participation Quantity	0.14*	0.16*	0.16**
Leaders Talkativeness Day D-1 → Participation Quantity	-0.09	−0.08	−0.08
Leaders Sociability Day D-1 → Participation Quantity	0.02	0.01	0.01
Leaders' Equivocality Day D-1 → Participation Quantity	0.16**	0.17***	0.17
Weekend → Participation Quantity	-0.10**	-0.08**	-0.08**
Project Timing → Participation Quantity	-0.60***	-0.57***	-0.57***
Participant Emotions Day D-1 → Participation Quality	0.07*	0.04	0.04*
Participant Number Posts Day D-1 → Participation Quality	0.10*	0.08*	0.08*
Number Anonymous Day D-1 → Participation Quality	−0.02	0.00	0.00
Leaders Number Posts Day D-1 → Participation Quality	−0.04	0.01	0.01
Leaders Talkativeness Day D-1 → Participation Quality	-0.10**	-0.07*	-0.07*
Leaders Sociability Day D-1 → Participation Quality	0.02	0.05	0.05
Leaders' Equivocality Day D-1 → Participation Quality	0.05	0.04	0.04
Weekend → Participation Quality	−0.04	−0.02	−0.02
Project Timing → Participation Quality	−0.09	−0.06	−0.06

N = 839 project-day observations.
Two-tailed *p*-values
Control variables were included in each path of the model.
* $p \leq .05$.
** $p \leq .01$.
*** $p \leq .001$.
[a] Model 1: Controls only.
[b] Model 2: Main effects added.
[c] Model 3: Interactions added (hypothesized).

$p < .001$) and participation quality ($\beta = -0.032$, $p < .001$). This correlation weakens as leaders express more equivocality through questions. Fig. 2 illustrates how both the indirect relationship between leaders' emotional expressions and participation outcomes—via cognitive inferences—and the direct relationship with cognitive inferences vary across different levels of leaders' equivocality.

Regarding control variables related to crowd participation, our analysis shows that emotions expressed by participants on Day D-1 are positively associated with the participation quality ($\beta = 0.04$, $p < .05$). Additionally, the number of posts written by participants on Day D-1 is positively related to both participation quantity ($\beta = 0.35$, $p < .001$) and participation quality ($\beta = 0.08$, $p < .05$). The number of messages sent by leaders on Day D-1 shows a significant association with participation quantity ($\beta = 0.16$, $p < .01$). Finally, leaders' activity on Day D-1 is negatively related to participation quality ($\beta = -0.07$, $p < .05$).

To better understand the role of emotional tone, we ran additional analyses where we separated positive and negative emotional expressions from leaders and looked at their individual effects on different aspects of participation—such as quality, quantity, number of posts, and analytical thinking. These results support those found in main analysis, however, this pattern appears only for negative emotions: the effect of leaders' negative emotional expressions on participation happens through participants' cognitive inferences but not through emotional contagion, and it is influenced by whether leaders express more equivocality through questions. Positive emotions do not show any significant effect (see appendices D and E). Moreover, we conducted robustness checks to validate our results by introducing alternative measures and performing supplementary analyses (see Appendices F–J).

6. Discussion and contributions

The question of how online leaders motivate participants to solve complex problems in open collaborative online communities has gained growing interest in management and organizational research (Franzoni and Sauermann, 2014; Johnson et al., 2015; O'mahony and Ferraro, 2007; Poetz and Sauermann, 2024). While prior literature focuses on how leaders assign tasks, foster cohesion, or model expertise, less is known about how they support collective problem-solving when goals and roles are undefined. Our study investigates this question by examining how leaders influence participation in contexts of radical uncertainty, where both the path to solutions (epistemic uncertainty) and the participation (social uncertainty) are highly uncertain. Based on data from four Polymath projects, we find that leaders do not influence participation because they transmit their emotions to others. Rather, leaders' emotional expressions affect crowd participation through cognitive inferences. Participants interpret leaders' emotions as cues about project progress and direction. This interpretive effect depends whether emotions are expressed through questions or not. In the sections that follow, we clarify how this research contributes to literature on online leadership, open science, and EASI theory.

6.1. *Contribution to theory on online leadership under radical uncertainty*

This research deepens our understanding of how online leaders foster voluntary crowd participation under radical uncertainty. Prior research has documented a wide array of leadership behaviors in online environments, including task-oriented actions (Faraj et al., 2015; Fleming and Waguespack, 2007; Johnson et al., 2015; Safadi et al., 2021), and relationship-oriented behaviors (Becker et al., 2022; Coussement et al., 2017; Huffaker, 2010). While effective in stable collaborative settings, these approaches may be insufficient under radical uncertainty. Our findings reveal a different form of leadership influence, one that operates through emotional expression to structure collective inquiry. We show that leaders' emotional expressions increase crowd participation by prompting cognitive inferences. Even in a highly analytical environment like Polymath, where logic and rigor dominate, emotions serve a cognitive function, helping participants interpret progress and align their contributions accordingly.

In addition, our study challenges the assumption that only positive emotions are beneficial. While prior research has emphasized the motivational value of positive expressions such as encouragement and enthusiasm (Becker et al., 2022; Coussement et al., 2017), we show that

Table 5
Mediation analysis.

Independent variable	Mediator	Dependent variable	Indirect effect	CI	Mediation?
Leaders' emotional expressions	Emotional Contagion	Participation Quantity	0.001	[−0.003; 0.006]	N
	Cognitive Inferences		0.003**	[0.001; 0.006]	Y
Leaders' emotional expressions	Emotional Contagion	Participation Quality	0.021	[−0.053; 0.099]	N
	Cognitive Inferences		0.059**	[0.011; 0.126]	Y

Two-tailed *p*-values
CI, confidence interval, N, no, Y, yes.
* $p \leq .05$.
*** $p \leq .001$.
** $p \leq .01$.

Table 6
Moderated mediation – Leaders' equivocality day D-1.

Leaders Emotions Day D-1 → Cognitive Inferences Day D → Participation Quantity		
Index of moderation	Leaders Equivocality Day D-1	Indirect effect
−0.002***	−1 SD	0.003***
	Mean	0.002*
	+1SD	0.000

Leaders Emotions Day D-1 → Cognitive Inferences Day D → Participation Quality		
Index of moderation	Leaders Equivocality Day D-1	Indirect effect
−0.032***	−1 SD	0.059***
	Mean	0.035**
	+1SD	0.007

* $p < .05$.
** $p < .01$.
*** $p < .001$.

under radical uncertainty, negative emotions such as doubt, frustration, or confusion are the emotions that provide informational values. Negative emotions act as salient cues that signal obstacles and the need to intensify cognitive effort. Byron (2008) explains that in online settings, individuals tend to interpret negative emotional expressions as more negative than they actually are. We argue that a cognitively demanding context makes negative emotions more noticeable and more likely to be interpreted as cues for project direction. Under radical uncertainty, negative emotions seem to prompt deeper inference and engagement than positive emotions. Taken together, we introduce the concept of *emergent epistemic leadership* to describe this influence dynamic. It does not rely on formal authority, stable roles, or long-term relational engagement, but emerges from leaders' ability to signal meaning and direction through affect.

6.2. *Contribution to theory on open science*

Our findings contribute to the growing body of research on open science by highlighting how participation is sustained when contributors face problems that are complex and hard to decompose. Much of the literature on scientific crowdsourcing has emphasized the value of modular project design—breaking tasks into small, independent units that can be distributed to participants working in parallel (Franzoni and Sauermann, 2014; Poetz and Sauermann, 2024). This approach works

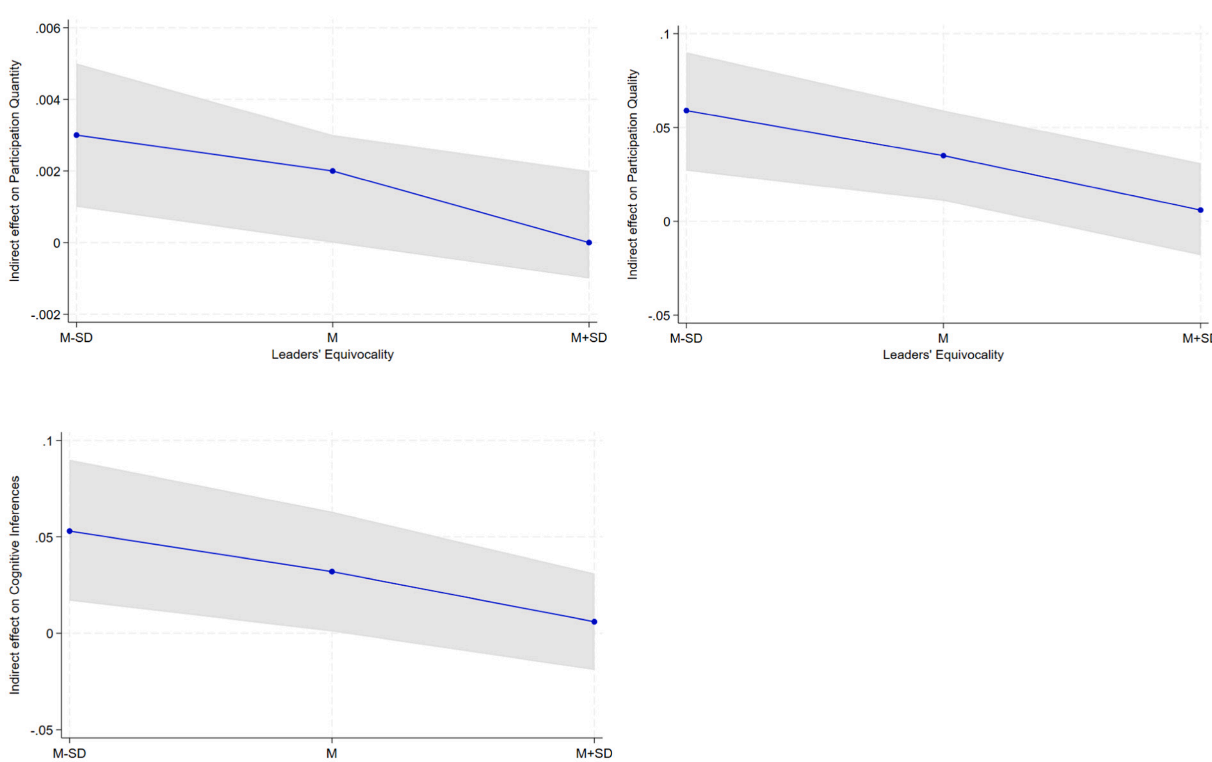

Fig. 2. Moderated indirect effect of leaders on emotional expressions.

well when problems are clearly structured, and when coordination can be achieved through artifact design or incentives (Beck et al., 2022).

However, not all scientific problems can be broken down into modules. In collective discovery projects like Polymath, problems are ill-structured, contributions are deeply interdependent, and the path to the solution is not known in advance. In these cases, leaders cannot rely on task definition alone. Instead, they must guide participants by helping them interpret what is happening, where the project stands, and what needs to happen next. Our results show that emotional expressions—especially when formulated as clear statements—help participants navigate this ambiguity. They act as cues that help others infer progress, recognize turning points, or reframe their approach.

This complements work on knowledge coordination in early-stage discovery, which shows that when the structure of the task is still being formed, scientists rely on interpretive cues to align around emerging directions (Ben-Menahem et al., 2016). It also echoes findings from Chai (2017) who shows that minor shifts in framing can influence whether a group pursues or abandons a promising line of thought. Our study extends these insights by showing that such interpretive signals can take an emotional form—and that they shape participation even in highly technical domains. In sum, our work expands the understanding of how collective discovery unfolds in non-decomposable problems. In settings where coordination cannot rely on predefined roles or stable categories, leaders' emotional expressions help contributors make sense of the evolving inquiry.

6.3. Contribution to theory on EASI theory

This study extends EASI theory (Van Kleef, 2009) by identifying radical uncertainty as a contextual moderator that shifts the balance between its two core mechanisms (i.e., emotional contagion and cognitive inference). In cognitively demanding environments characterized by both epistemic and social uncertainty, leaders' emotional expressions do not prompt emotional contagion but through cognitive inference. This finding advances EASI theory by identifying radical uncertainty as a boundary condition that favors cognitive inference over emotional contagion. Several features of Polymath help explain the reasons why leaders' emotions are more likely to trigger cognitive inference than emotional contagion.

First, Polymath's participants are highly epistemically motivated: they voluntarily engage in solving complex mathematical problems that require sustained cognitive effort. Prior research suggests that individuals with strong epistemic motivations are more likely to process emotional cues through deliberate inference than affective mimicry (Van Kleef, 2009). Second, the epistemic complexity of the problems creates ambiguity about progress. In this setting, emotional expressions from leaders act as contextual signals. For instance, expressions of enthusiasm may be interpreted as signs that the project is advancing well, while frustration may suggest that the project has reached a dead end. These signals are interpreted, and help contributors decide how to move the project forward. Third, Polymath's asynchronous and text-based communication restricts the sensory channels (e.g., tone of voice, facial expression) that often facilitate emotional contagion. Contributors encounter emotional cues in written form, often with time delays, which strips them of nonverbal context and encourages interpretation over automatic response. As a result, emotional expressions become inputs for reflective analysis, reinforcing cognitive inference. Fourth, the interaction expectations of Polymath emphasize analytical rigor over emotional displays. Participants are expected to contribute through mathematical reasoning and logic, not through affective display or social bonding. In line with EASI theory (Van Kleef, 2009), such norms shape how emotional expressions are processed. Taken together, these conditions help explain why, in this context, emotions influence participation through interpretive processing rather than automatic contagion.

Finally, our study extends EASI theory by identifying a linguistic boundary condition that influences the inferential power of emotion. Specifically, we find that emotional expressions in messages with high equivocality, i.e. in interrogative statements, are less likely to affect participation than those in affirmative statements. While we do not measure equivocality directly, this pattern suggests that questions introduce a lack of clarity that may blur the emotional signal. Questions are inherently designed to elicit information rather than provide it (Clark, 1996) and can carry multiple pragmatic functions (e.g., doubt, critique, sarcasm). As such, they may reduce the confidence with which observers interpret the leader's emotion, weakening the likelihood of behavioral adjustment.

6.4. Implications for practice

Our study offers practical implications for online leaders seeking to foster scientific discovery in open online collaborative communities. Online leaders play a crucial role in guiding and sustaining participation, yet they often focus too narrowly on the task-related issues. Our findings show that even in very technical communities such as Polymath, crowd participation is influenced by online leaders' emotional expressions. Online leaders should recognize that their emotions serve as informational cues, shaping how participants interpret project progress and direction. Rather than focusing solely on technical contributions, leaders can express engagement by sharing their emotions as motivational signals. Importantly, leaders should express their positive emotions but also their negative emotions when they feel that projects are not moving in the right direction or when the results are unsatisfactory. When projects stall, or results are unsatisfactory, expressing frustration or concern can signal urgency and complexity, prompting deeper cognitive engagement. Overall, our results encourage cultivating epistemic leadership that focuses less on authority or social bonding and more on signaling meaning and guiding exploration through affective cues. This form of leadership is especially useful for crowdsourcing, open science, and innovation ecosystems where roles are fluid and goals emergent.

6.5. Limitations and future research

While our findings provide valuable insights, they also present limitations that open avenues for future research. The first limitation relates to the generalizability of our results. Our study focuses on Polymath, a unique crowd science community where participants engage in complex mathematical problem-solving (Franzoni and Sauermann, 2014). This setting requires high cognitive efforts and involves problems with unknown solutions. Our findings are applicable in open online collaboration contexts characterized by radical uncertainty. Future research could examine whether our results hold in collaborative communities that involve more modular tasks (e.g., Galaxy Zoo). Our sampling is based on the analysis of four completed Polymath projects as our goal was to observe how participation occurs when collective problem-solving is sustained through to closure. Future research could extend this analysis to unsuccessful projects to understand how emotional expressions operate in contexts where momentum is lost.

Second, the specificity of the Polymath setting needs to be acknowledged. Polymath is a unique scientific crowdsourcing initiative where contributors solve highly complex, non-decomposable mathematical problems in a text-based, asynchronous environment. This context is characterized by radical uncertainty and high epistemic motivation. As such, it may not generalize to other forms of crowdsourcing that involve simpler or intuitive tasks.

Third, we also acknowledge that our study does not test variation in leader effectiveness, nor do we compare different leaders' influence. The leadership variable is used only to identify messages by core contributors, not to evaluate differences in style or credibility. Future research could examine how individual characteristics (e.g., experience, prestige, communication clarity) moderate the emotional influence of leaders on the crowd. Additionally, while we distinguish between participation quantity and quality, our hypotheses do not differentiate between these outcomes, as EASI theory does not explicitly predict how emotions might affect them differently. EASI suggests that one person's emotions influence others' behaviors and actions but remains quite unspecific about the nature of those behaviors. Future research could investigate whether different emotional expressions impact participation quantity and quality in distinct ways, refining theoretical predictions about when and how emotions shape distinct forms of crowd engagement. Moreover, while crowd participation is crucial (Becker et al., 2022; Coussement et al., 2017), high participation does not guarantee the resolution of complex problems. Online leaders' ability to attract skilled participants can also play a pivotal role. Future research might explore participants' individual characteristics, for instance, to know whether or not all types of participants are sensitive to the same leaders' emotions, and also explore how the crowd's emotions affect the contribution of other participants.

Fourth, another limitation concerns our research methodology. Our reliance on archival research, encompassing 7200 posts from 2009 to 2015, offers the advantage of high statistical power over an extended period, potentially reducing Type I or II errors (Barnes et al., 2018). However, establishing causality remains challenging, even though we have ensured that reciprocal causality is not skewing our results by regressing the independent variable on a lagged dependent variable. Moreover, even if the LIWC tool is gaining traction in literature and has proven effective in analyzing word usage in archival datasets and accurately identifying emotionality in language use, it has its constraints. For instance, LIWC might not capture nuances like sarcasm or irony, leading to potential miscoding. Also, the measure of emotional contagion can capture emotional convergence, reflecting parallel emotional reactions to project dynamics rather than direct influence. Furthermore, we conceptualize cognitive inference as participants' interpretive reasoning about the project's direction. To our knowledge, no prior observational study has directly measured cognitive inference in text-based interactions. As such, our measure represents a behavioral linguistic correlate rather than a direct assessment of inference itself. Thus, we acknowledge that our operationalization through the use of LIWC future-oriented linguistic markers might not fully capture the complexity of this construct. Future work could strengthen this construct validity by incorporating complementary indicators of cognitive inference, such as evaluative, diagnostic or implications assessment elements of inferential reasoning. Despite these acknowledged limitations, our study develops a deeper understanding of how online leaders' emotional expressions relate to crowd participation.

7. Conclusion

Our study examines whether online leaders' emotional expressions influence crowd participation when engaged in open collaboration projects characterized by high epistemic and social uncertainties. Based on an empirical study of Polymath, we find that participants interpret leaders' expressions of emotions as cues about project progress and direction, which prompts them to contribute more and with greater relevance. This interpretive effect is stronger when emotions are expressed through clear, affirmative statements rather than questions. These findings offer valuable insights into how online leaders can guide participation and foster collective problem-solving in radical uncertainty.

CRediT authorship contribution statement

Alex Cayrol: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thomas Gillier:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Olga Kokshagina:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.respol.2026.105453.

Data availability

Data will be made available on request.

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