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Non-hierarchic leadership collaboration: Exploring the adoption of AI-driven social networking for addressing social challenges in an extra-organizational environment

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ABSTRACT

The literature has explained how technology adoption and usage is affected by many socio-technical issues and how the emergence and evolution of networks is key for innovation. However, empirical analysis of interactions between leadership networks and new artificial intelligence-driven technologies is scarce. To shed new light on leadership communities around the adoption of an existing and a new technology related to leadership networks, we analyze the level of socio-digital engagement of a non-hierarchical network of individuals associated with a prestigious Spanish Foundation in the context of pressing social challenges. We apply a methodology that combines quantitative and qualitative methods, sentiment analysis, and insider research to analyze the strategy applied by the Foundation. Our main results show that the existence of strong, trust-based relationships and the introduction of a well-designed AI-based tool may only have a limited effect on the adoption of technology and the evolution of a network. Specifically, in the case studied, the network of leaders around the Foundation comprised peer leadership networks but not collective leadership networks focused on action on social challenges.

1. Introduction

In a world facing urgent challenges, increasing the collective intelligence of social and innovation leaders seems especially relevant [1] to solve complex problems and make informed decisions.

In this sense, fast technological advances in various topics such as advanced robotics, blockchain, artificial intelligence (AI),[1] and big data have become the focus of many public policies around the world [2,3] and are revolutionizing the way firms and individuals interact and address urgent social challenges, as recently evidenced by the Covid pandemic [4–6].

In particular, social networking is an activity that has been completely transformed in the digital age with the appearance of social media and social networking platforms that are pervasive and play a dominant role in fostering connections and communication between individuals and groups [7–9]. At the same time, we expect the evolution of social networks to be further revolutionized when combined with AI [10] which can enhance interaction experiences and yield important benefits [1]. However, it is foreseeable that the potential drawbacks of intertwining social networks and AI in terms of privacy [11], security, biases, and psychological and/or sociological changes in behavior will need to be addressed [12].

In this fast changing environment, the development of collective intelligence and action [13] and the nurturing and catalyzation of non-hierarchic leadership networks [14] are becoming important issues, as these provide resources and support to business, academic, and political leaders acting in different social spheres and increase their potential impact in terms of both scope and scale [15]. Despite this, empirical research analyzing these types of networks and their evolution in the digital and AI era is still scarce.

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[1] Systems or machines with cognitive capabilities based on algorithms that learn, reason, and adapt according to the data they collect [45,47].

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In light of the above, this study analyzes the level of socio-digital engagement among members of the non-hierarchical leadership networks associated with a prestigious Spanish Foundation (hereafter, the Foundation) dedicated to the training of leaders and the creation of a leadership community. We highlight that the Foundation has equipped these members with a self-developed AI-based social networking tool for collective action and to address urgent social challenges.

For this purpose, we apply a methodology that combines quantitative and qualitative methods to analyze the interactions between leaders in the networks, including sentiment analysis and research from within the Foundation.

The remainder of the paper proceeds as follows. Section 2 provides a literature review on the key issues related to the research. Section 3 describes the methodology, providing information about the case study and the specific methods applied to analyze social interactions, while section 4 presents the results of the analysis. Section 5 focuses on the discussion of results and section 6 on the conclusions.

2. Literature review

2.1. Technology adoption

Technological adoption has been widely studied from different perspectives within scientific literature, with a prevalence over the last decades for evolutionary theories and perspectives explaining how agents adapt and evolve in response to changing environments. On the one hand, we find extent seminal literature analyzing technological change, trajectories and patterns of innovation [16,17], macro processes of technology adoption and diffusion [18] and other technology adoption patterns affecting sectors [19,20], countries, and regions [21]. Recent literature has also made important contributions, analyzing the cumulative effects of technological complexity [2,3], the governance and regulatory challenges of new technology adoption [3], and the adoption patterns of specific technologies [22], including adoption in sectors specially affected by ethical concerns, such as medicine [23].

On the other hand, at the micro level and specifically from a managerial perspective, some authors have emphasized that the patterns of adoption of these technologies are complex and subject to a wide range of socio-technical factors, including interpretations [24], emotional aspects [25], and perceptions of existing barriers and incentives [26]. For example, potential users of a technology may experience ambiguity about the value that using such technologies brings to their work and lives [27] or may experience other feelings related to trust dynamics, such as apprehension or mistrust [28–30].

This second group of studies have explored the processes and factors affecting technology acceptance by users and organizations [31–34], giving rise to the emergence of diverse valuable models and theories [35]. According to the technology acceptance model (TAM), system design features, perceived usefulness, and perceived ease of use appear as primary drivers of technology use [36]. Subsequently, Venkatesh et al. [35] formulated a unified theory of acceptance and use of technology (UTAUT) that includes performance expectancy, effort expectancy, social influence, and facilitating conditions as direct determinants.

More recently, with the introduction of new technologies such as AI, blockchain, robotics, and platform technologies [37], research has focused on understanding the unique challenges that affect their adoption [38], including those related to the appearance of network effects and learning curves [39], to the influence of organizational size and digital capabilities [40], and to the impact of their adoption on net job creation or destruction [41].

Moreover, increasing the complexity of adoption patterns at the micro level, the usages of many of these new technologies are often intertwined. For instance, AI, which is dedicated to the analysis of various data to improve decision-making in both the public and the private sector [42], is often complementary with blockchain, a decentralized digital ledger technology that stores data securely, immutably, transparently, and without intermediaries [43,44], allowing AI to be more secure and reliable and data to be used privately [45]. In turn, advanced robotics is made possible using AI, as it enables robots to perform versatile, complex, and adaptive activities [46], and hence be used in highly advanced and delicate tasks, such as those carried in hospitals to monitor and develop new surgical methods [47]. Another example of the practical combination of these technologies and their impact on social challenges is their use for improving agricultural methods and encouraging the sustainability of such methods [48].

Similarly, and as already stated, the increasing introduction of social media and networking platforms in combination with AI-based technologies has raised new specific concerns [49,50] affecting the adoption and acceptance of such platforms [51] and justifying the need for further research in this area of knowledge.

2.2. Social and collective leadership networks

Collaboration and knowledge sharing have been widely accepted as key activities for innovation [52]. In this sense, over the last decades, multinational companies have spent substantial amounts of money on the creation of information systems for collaboration and the creation of physical and virtual spaces for formal and informal networking and knowledge sharing [26,29,53,54]. Research acknowledging the key importance of tacit and sticky knowledge has emphasized the importance of the dialogue and sense-making that occurs through active networking [55], in which explicit and tacit knowledge held by individuals, teams, and organizations is exchanged [56,57]. As people who make up a network often belong to organizations with different knowledge domains, values, interests, and norms [58–60], this dialogue can lead to strengthening of the network and of innovation, but also create various barriers to collaboration.

A prolific thread of the literature has devoted attention to the analysis of networks and of the characteristics that affect knowledge sharing, including silos, culture clashes, or competing priorities [61,62]. In this regard, literature states that it is easier to transfer all kinds of knowledge through strong ties (i.e., personal ties with a strong emotional attachment or frequent communication that helps develop trust) and that these types of strong ties are more difficult to develop than weaker ties, as they require greater investments of time and hence involve higher costs [63].

Complementarily, trust building is one of the most crucial elements for the mobilization of knowledge resources within networks, as it has a significant direct effect on the strength of interpersonal ties [60,64,65]. Hansen and Løvås [66] state that, when seeking help, "teams may contact someone they know rather than someone who knows" (p.806), as knowledge exchanges are influenced by friendship ties and social networks. In contrast, interorganizational and interpersonal competition are negatively associated with knowledge exchange and collaboration [65].

Another group of authors has focused on the analysis of interpersonal networks from a systemic perspective, changing the focus from the individual to cliques and communities, and reconceptualizing a system from the idea of interrelated actors to an idea of interrelated roles [67]. From this perspective, although interpersonal ties are important for knowledge circulation, it is key to analyze the cumulative effects of individual and group learning [68].

Communities increase the potential for creativity and innovation (including social) and, through mutual engagement and joint endeavor, they can increase the ethical commitments of individuals and their willingness to contribute and share knowledge rising above self-interest, even in those cases when personal incentives are negligible and there is no expectation of future rewards [69]. In fact, within communities, interactions between agents participating in a network create unanticipated behaviors and emergent patterns at the collective level (collective behavior).

Coherent with this systemic understanding of networks, some authors identify leadership as a collective rather than an individual behavior [70], and hence consider that leadership cannot be studied independently from the system or from the collective behavior [71]. In this sense, collective leadership networks (CLN) are especially important, being defined as "self-organized system[s] of social ties among people attracted to a common cause or focused on a shared goal … often rooted in a sense of community and purpose" [15] (p.601).

These networks provide leaders with resources and support to increase their potential impact in terms of both reach and scale. They can be developed from scratch or as an evolution of a peer leadership network (PLN), defined as "a system of social ties among leaders who are connected through shared interests and commitments, shared work, or shared experiences", in which leaders share information, provide advice and support, learn from one another and, only occasionally, collaborate with each other for a common objective [15] (p.601).

A concept related to leadership networks is collective intelligence, understood as the overall ability of a group to perform a variety of tasks [72], considering that the group of people should be more efficient than the same people working in isolation and that diversity is beneficial to the group's performance [73]. From a perspective more associated with the digital age, a collective intelligence system allows the knowledge, experience, and resources of thousands of people to be gathered in an interactive process to solve complex problems and address challenging issues [74].

Combining the need to understand the patterns of adoption of the mentioned new technologies and their effects on collaboration with collective intelligence and decision-making, a more recent field of research has focused on understanding the characteristics that increase the collective intelligence of a group or network (e.g., diversity, independence, decentralization), and on how new technology, and specifically AI, enhances these cognitive capabilities, collective decision-making [75], collective action [13] and the potential to address important social challenges [76].

In this sense, literature has revealed the potential of AI to drive economic growth, reduce poverty, fight climate change, improve healthcare and address public health issues, and address urban planning, public safety, and education challenges [77] and has proposed guidelines for successful collaboration in addressing the challenges of implementing socially beneficial AI projects [78]. However, there is still little research that addresses this issue from an empirical perspective, linking the concepts of technology adoption, AI-driven collaboration, collective intelligence, and the evolution of leadership networks to address urgent social challenges [79].

3. Methods and context

In line with some authors who suggest that case studies of leadership networks can help us understand how networks evolve [15,80], our overall objective is to analyze the level of socio-digital engagement of the non-hierarchical network of individuals associated with a prestigious Spanish Foundation in the context of urgent social challenges, considering the participation and emotions conveyed by them via WhatsApp and the subsequent introduction of an AI-based platform.

3.1. The case study unit and its context

The selected Spanish Foundation is relevant for analyzing the influence of the quality of relationships and interactions on technology adoption and the development of leadership networks for different reasons. Firstly, it is a recognized non-profit institution that creates leadership in Spain and, since 2015, has implemented a strategy to develop leadership networks and communities of leaders focused on the common good, as particularly shown in this study. Secondly, it has co-developed and launched a new AI-based tool for social networking and collective intelligence for this purpose (see Appendix 1). Thirdly, the availability of internal data about the strategy and the outcome of the implemented action allows a deep understanding of the case, and the unique character of the group of leaders accessed makes this a singular case for understanding leadership networks and their evolution. Fourthly, the networks and communities analyzed have been built around the idea of leadership for good, and the Foundation remains independent, having no contractual relationship with the leaders invited to participate in its programs and no governmental, political, or ideological affiliation.

Because of its unique character, leaders gathered around the Foundation have a strong sense of independence and feel supported by the organization to share their personal views on often conflictive topics. Hence, the created leadership networks and communities are not an asset of the institution, as it has no mechanisms of control over them or their members, and its strategic actions are directed toward creating value so that Spanish leaders can feel a personal benefit from engaging with the Foundation and its communities. Consequently, this case sheds new light on how leadership networks develop in a non-hierarchical environment.

In particular, the analysis has focused on a specific community of leaders gathered around the innovation and entrepreneurship program (IEP) organized by the Foundation. Since 2016, this program has brought together every year, for five days, between 30 and 50 Spanish participants (Table 1) carefully selected through suggestions from former program participants, who attend a top-level training course at the prestigious MIT Sloan (Cambridge, MA, US). Since its creation, around 240 leaders—including public innovation procurers, Chief Innovation Officers of large corporations, entrepreneurs, scientists, academics, and other relevant practitioners in the field of innovation and entrepreneurship—have attended the program.

Each annual IEP has allowed the creation of a pre-existing network of leaders that share interests and experiences, exchange information and support, and occasionally collaborate for a common objective.

The continuity of the network after the program is facilitated by the WhatsApp group created for each cohort at the beginning of the program (Table 1).

After the third program (in 2018), and with the objective of consolidating the IEP community and making it evolve toward a CLN, the Foundation decided to develop and introduce an AI-based social networking tool, which was carefully designed in order to comply with diverse socio-technical criteria that could predictably affect leaders' acceptance of the technology. The tool was launched in September 2021, inviting the 240 leaders of the IEP community (the six cohorts together) to join the AI-based platform for collective intelligence (Table 1).

Analysis of this initiative is especially interesting as the design and development of the tool was actually facilitated by some leaders of the IEP community, answering the concerns of the Foundation and its wish to contribute to the common good.

3.2. Methodological steps

In order to reach the overall objective, we set two specific objectives.

The first objective is to know whether the quality of the relationships of each cohort making up the pre-existing non-hierarchical leadership

Table 1
IEP community.

IEP	Number of participants	Date of formalization of the network in a WhatsApp group
2016	36	24.07.2016
2017	35	01.06.2017
2018	46	25.06.2018
2019	40	19.06.2019
2020	44	28.05.2020
2021	39	01.06.2021
IEPCOMMUNITY	240	–

Source: Authors' elaboration

network associated with the Foundation achieves the status of a peer leadership network.

To achieve this specific objective, we first measured the intensity of the interactions between the leaders belonging to each network. We emphasize that higher intensity of interactions is associated with stronger trust and tends to facilitate the transfer of all types of knowledge [65,81].

In this case, the intensity of the interactions within the networks was measured by counting the number of interactions (comments made by the participating leaders) in each of the six WhatsApp groups corresponding to each IEP cohort. For this purpose, 10,760 interactions from the chats of each group, dated from the date of their creation (Table 1) until January 13, 2022, were analyzed.

An index of the intensity of interactions was created for each IEP cohort ($Interaction_{\mathrm{IEPcohort}}$) in order to consider the different years since creation of the groups, from the most recent (one year) to the oldest (six years), and the different number of participants in each group.

$$Interaction_{\mathrm{IEPcohort}} = \frac{number\ of\ total\ interactions}{number\ of\ participants * years\ since\ creation} \quad \text{(Eq. 1)}$$

If the result of the $Interaction_{\mathrm{IEPcohort}}$ index is at least equal to 1, it means that the number of interactions annually is at least equal to the number of participants. A result of less than 1 indicates that the number of interactions per year is lower than the number of participants.

Secondly, the typology of predominant emotions and moods shared within each network was measured by analyzing the emotions conveyed by the emojis used in the WhatsApp conversations according to their association with specific emotions. Literature has shown that emojis portray emotions in an unambiguous manner, independent of the domain and the topic of the conversation [82]. Moreover, the meaning of emojis has been found to remain relatively stable across different languages and media [83]. Hence, a sentiment analysis allows us to observe the vibes of communications occurring in reality within the networks without the biases expected from direct surveys about perceptions.

For this purpose, we reviewed the archival records of each WhatsApp group and counted the total number of times that a specific emoji (x) appears, considering all interactions since the creation of the group.

In order to characterize each network in terms of the predominant emotions, we created an index of intensity of emotions for each IEP cohort ($Emotion_{\mathrm{IEPcohort}}$) by relating the total number of appearances of an emotion-intense emoji in relation to the number of participants and years since creation.

$$Emotions_{\mathrm{IEPcohort}} = \frac{number\ of\ time\ an\ emoji\ appears\ (x)}{number\ of\ participants * years\ since\ creation} \quad \text{(Eq. 2)}$$

We emphasize that if the result of the $Emotions_{\mathrm{IEPcohort}}$ index is at least equal to 1, it means at least one emotion-intense emoji for each participant each year. A result of less than 1 indicates that the number of emotion-intense emojis used is lower than the number of participants.

Following Mohta et al. [82], we codified the emojis into six basic emotions—happy (joy), sad, angry, fearful, excited, and bored[2]—and classified them in the two dimensions or scales suggested by Russell [84] in his circumplex model of affect: valence (degree of pleasure/displeasure) and arousal (level of activation/deactivation). Additional emotions (i.e., disgust, surprise, and trust), used by Awal et al. [85], were added to the codification in order to enrich the sentiment analysis and to adapt it to the emojis used by leaders in the analyzed context (Appendix 2).

For codification, we distinguished three categories of emojis by unifying them in the quadrants of Russell's [84] circumplex model of affect: 1) high valence (pleasure) and high arousal (activation); 2) low valence (displeasure) and high arousal (activation); and 3) low valence (displeasure) and low arousal (deactivation). The final list of the emojis used for the codification of interactions by leaders and their categorization into Russell's [84] quadrants is shown in Table 2: the remaining emotion-intense emojis did not appear in the analyzed conversations.

Insights gained into the strength of interactions with the analysis of emojis were reinforced with qualitative insights gained through direct participant observation during the training programs and the different initiatives organized by the Foundation (e.g., annual gatherings), and with an additional codification of the WhatsApp messages containing textual feedback and expressions of gratitude (i.e., the word "Gracias"), portraying more stable sentiments than emotions [86]. Complementarily, we qualitatively observed the typologies of issues shared by leaders through WhatsApp.

The second specific objective is to explore whether the leadership network, supported by the Foundation (which works together only occasionally), can become a more impactful and action-oriented CLN, primarily considering the introduction of a new AI-based tool.

For this purpose, we first confirmed that the AI-based tool that was subsequently launched is well-designed in terms of its system design features, after analyzing internal documents related to the technology development project, considering a document describing the technical and architectural features of the tool; a document containing reflections and notes on the project taken by the director of the Foundation, including discussions held with the technology developers (copy-pasted from the WhatsApp group created with them); and the promotional video created for the IEP network, which portrayed the purpose of the tool and the creation of the mission-oriented community.

Secondly, we obtained records of downloads of the app (or the AI-based platform) by the 240 leaders of the different cohorts of the IEP who were invited to use it, as well as actual use of the platform, considering the period from the launch of the app in September 2021 to March 2022, when the app records were downloaded. The analysis of these data was based on identification of the platform users by their IEP cohort of origin, which allowed us to establish a link between the characterization of each pre-existing network and the adoption of the platform by leaders of each network.

Thirdly, we analyzed the kick-off activities promoted by the Foundation to seed the network and to generate initial critical content and engagement around specific challenges. To do this, we specifically analyzed participation in the different thematic tables created by the Foundation around specific challenges of interest suggested by the Foundation itself and by the leaders. We analyzed the app records regarding leaders' explicit willingness to contribute to the different challenges: they could state whether they were willing to contribute with their time, financial resources, connections, or other personal resources to collectively find solutions.

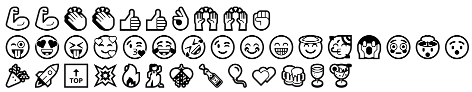
Finally, we also considered the assessment made by the leaders of the Foundation regarding the use of the new app and the behavior of the participants in relation to the social challenges posed in the thematic groups.

We emphasize that it is an advantage that data generation for this study was facilitated by the authors' unique access to internal sources of the Foundation,[3] both as participants and as observers of the analyzed initiatives, which are only accessible to trusted insiders of the analyzed communities and which provide deep and rich understanding of the case.

[2] Since our analysis is only interested in emotion-intense interactions, we do not consider emotion-neutral emojis included by Mohta et al. (2020) nor anticipation by Awal et al. [85].

[3] Most of the authors were in executive leading positions at the Foundation and involved in the design and implementation of the analyzed strategy and initiatives.

Table 2
Emojis used for codification of intensity of emotion.

Emoji	Emotion	Russell's (1980) quadrant
	Disgust/sadness	Low valence - low arousal
	Excitation/surprise /joy/trust	High valence - high arousal
	Fear/anger	Low valence - high arousal

Source: Authors' elaboration

4. Results

Regarding results related to the first specific objective, analysis of the intensity of interactions in the WhatsApp groups of each IEP (Table 3) shows that approximately half of the interactions take place in the year in which the IEP is implemented and that all participants in each program use the WhatsApp groups created by the Foundation. In turn, the intensity of interactions index has an average result of 14.27, which is clearly above the critical number of the indicator (1) and is even higher for the networks of years 2018, 2019, and 2020.

The sentiment analysis within the WhatsApp groups corresponding to each network (Table 4) shows that the index of intensity of emotions for all cohorts but 2016 was higher than its critical number (1). However, the highest intensity of emotions occurred in the 2018 and 2019 programs. In turn, analysis of the categories of emotions (Table 4) shows a predominance of the category composed by high valence and high arousal, which is also much higher for the IEP cohorts of the years 2017, 2018, and 2019.[4]

In addition, observation of the interactions occurring among participants in each IEP over the years, both through their WhatsApp groups and during other encounters at the Foundation, confirms that participants share various resources, support each other, engage in bonding and networking activities, have common interests (also considering that this was a pre-requisite in their selection process and participation in the IEP), and discuss and reflect on various topics, but only occasionally collaborate with a higher level of engagement.

Regarding results related to the second specific objective, first of all, the analysis reveals that the team in charge of the design of the system took into account many critical socio-technical issues which were considered to be important for users. Table 5 describes the most important socio-technical system design features included in the AI tool.

Socio-technical issues relevant for acceptance and adoption of the technology were not only considered by the Foundation in the design and development phase of the tool, but also in the ways it communicated the vision that it pursued with its launch. In this sense, other aspects related to social influence were also taken into consideration, specifically through the promotional video shown in the encounter organized for the IEP community. In particular, questions related to image, mutual engagement, and the building of a common identity were considered by the Foundation, as the following paragraph evidences.

This is an extract from the inspirational video shown to the IEP community before the launch of the tool that aimed at motivating its adoption by creating an inspiring vision for the common good:

> *Massive impact happens when communities self-organize around a shared purpose to understand the challenges we are facing (…). In the past, networking was a matter of time and luck (travel, events, meetings, bumping into each other), but now networking will be a matter of data. Welcome to (the AI-based platform), a tool to leverage our collective intelligence (…); (it) offers relevant connections (symmetric, mutually desired, endorsed by people you trust, complementary, with strong purpose alignment, protecting your privacy). Only a few minutes* per *week to receive unprecedented and personalized insights.*

After the event, the Director of the Foundation received a lot of personal messages and feedback (including face-to-face statements, personal WhatsApps, and emails) from leaders expressing their intention to join the app and collaborate with the rest of the community to solve social challenges.

Subsequently, a pilot was launched in December 2021, inviting the 240 leaders forming the IEP community (all six cohorts of the editions of the program) to join the AI-based platform. Moreover—and in order to accelerate the learning curve and overcome adoption barriers—some initial activities were organized, such as 'fast dates' for leaders to know each other by means of the tool, or the creation of 'kick off' events and specific 'tables' around various topics in order to seed the network, create a clearer proposition, and generate content and incentives for participation. In addition, individualized user support was provided in order to make the leaders feel they were being taken care of by the Foundation.

Considering all the analyzed system design features and the actions taken by the Foundation, we believe that the developed technology is sufficiently well-designed.

However, results of the analysis of registers provided by the app about the adoption of the technology show a rather low level of acceptance of the new AI-based social networking and collective intelligence tool (Table 6). Records provided by the app reveal that, among the 240 invited leaders, only 93 downloaded the app (38.8 percent of the network), in contrast to the 99.2 percent of leaders that were still part of the diverse WhatsApp groups by August 2024. Moreover, among these 92 leaders, only 56 were real users of the tool in practice (23.3 %), meaning that they not only downloaded the app but also interact with the technology—for example, by joining some of the tables around specific topics.

Analyzing adoption of the app by IEP cohorts, the results show that although acceptance of the tool and adoption of the technology can be found in all networks, there are important differences among them in the degree of participation. In particular, the cohorts of the 2018 and 2019 editions of the program showed a higher percentage of actual users (7 percentage points above the mean adoption rate), while only 8.3 percent of leaders in the oldest network participated.

Regarding participants' willingness to contribute to specific challenges aiming at collective action, records provided by the app evidenced modest engagement by participants. In this sense, the most successful thematic table in the app, registering the highest number of leaders, was the one called "Work of the Future", which attracted 40 leaders (71 percent of app users), followed by the topics "Digital Inclusion" (37 %), "Hospital of the Future" (30 %), and "The Future of Education" (25 %).

The AI-based tool also allowed participants to express the type of contribution they were willing to make to the group: this represented different levels of engagement and hence depth of collaboration with the

[4] Adding to these results, 12.7 percent of total interactions included expressions of gratitude toward the network.

Table 3
Intensity of interactions within the WhatsApp groups.

IEP networks	Date of creation of the WhatsApp group	Number of participants using this tool	Interactions during the first year of the network (number and %)		Number of total interactions*	Index of intensity of interactions
2016	July 24, 2016	36	196	33 %	590	2.7
2017	June 01, 2017	35	572	45 %	1276	7.3
2018	June 25, 2018	46	1765	49 %	3629	19.7
2019	June 19, 2019	40	1926	55 %	3477	29.0
2020	May 28, 2020	44	346	26 %	1343	15.3
2021	June 01, 2021	39	454	100 %	454	11.6
$IEP_{COMMUNITY}$		240	5259	49 %	10,769	14.27**

Notes: *Total interactions since group creation to January 13, 2022. **Mean intensity index.
Source: Authors' elaboration

Table 4
Predominant emotions within the WhatsApp groups.

IEP networks	Number of interactions* by emoji and predominant category of emotion (highlighted)			Number of participants	Index of intensity of emotions
	Low valence - low arousal	High valence - high arousal	Low valence - high arousal		
2016	7	86	1	36	0.40
2017	3	299	1	35	1.71
2018	9	1375	20	46	7.47
2019	9	626	2	40	5.22
2020	1	168	2	44	1.91
2021	2	58	1	39	1.49
$IEP_{COMMUNITY}$	31	2612	27	240	3.0**

Notes: *Total interactions since group creation to January 13, 2022. **Mean emotions index.
Source: Authors' elaboration

network and the selected social challenge. Taking as an illustrative example the case of the most successful topic (the table on the work of the future), we observed that the most sought-after typologies of contributions were those that required a lower level of engagement or compromise, namely the contribution of ideas (55 percent of participants) and experience (40 %). In contrast, those options requiring higher personal cost or involvement were less attractive to participants, namely sharing contacts (22.5 %), time/work (20 %), or investment and assets (10 %).

Finally, a self-analysis of the development of the initiative and the lessons learned by the Foundation's own leaders suggests that the new network of leaders was not able to organize itself and, hence, the Foundation should have provided additional support to boost participation of leaders. According to the Foundation, this situation also evidences the difficulties leaders found in devoting time to activities alongside their key responsibilities at their origin organizations, and hence the complexities of promoting the creation of non-hierarchic collective leadership networks.

Table 5
Socio-technical system design features considered.

Socio-technical feature	Conceived characteristic	Mechanism through which characteristic was included in the design of the AI tool
Heightening value proposition for users	Reducing serendipity of social valuable encounters	• Creation of enriched profiles with knowledge of users and their interests (particularly social challenges). • Endorsement and recommendation mechanisms. • AI-enabled new connection suggestions based on reciprocal matching (similar to Tinder). • Feature to fine-tune the AI engine for finding new social connections.
	Facilitating collaboration around social challenges	• Feature for users to create specific 'meeting tables' around specific topics of interest and challenges, which leaders from different networks (not necessarily connected to the creator of the table) could join. • Feature for specifying the kind of resources (e.g., experience, contacts, ideas, time/work) that each user is willing to offer to help solve the specific challenge. • Different channels and chats to share contents and facilitate collaboration among members of the meeting tables.
Lowering socio-technical barriers for users	Security, privacy, and trust-building	• Creation of a panic button that allowed users to erase for good all data related to their profile.
	Effort and ease of use	• Enabled by AI, the tool was designed to lower the cost/effort of building social connections. • Tutorials to accelerate the app learning curve.

Source: Authors' elaboration

5. Discussion

The emergence of strong and pro-active leadership that aims at solving urgent social challenges through innovation and collective action seems crucial in our fast-changing world. However, understanding how to promote the evolution of such networks, from a less action-oriented leadership network toward a more action-oriented community, in a non-hierarchic and extra-organizational context is not straightforward. Moreover, it is not yet clear how AI-based tools for social networking can assist in the evolution of such networks and how these tools will be adopted by leaders. Through the case study of the strategy and actions implemented by a Spanish Foundation, we aimed at shedding new light on these issues.

We consider that the selected methodology has been useful to characterize the strength of leaders' networks within a context, and to determine whether or not such networks enable action on urgent social challenges under certain management and circumstances.

We believe that our study enriches the criteria for defining PLNs and CLNs, as we found evidence that the strategy pursued was successful in aligning the interests of various leaders around specific social challenges and actions, even allowing them to express their willingness to

Table 6
Level of adoption of the new AI-based tool.

IEP cohort	Number of leaders in the network	Number of downloads of the app	Percentage of acceptance (intention of use)	Number of real users	Percentage of actual users
2016	36	10	27.8	3	8.3
2017	35	9	25.7	6	17.1
2018	46	21	45.7	14	30.4
2019	40	17	42.5	12	30.0
2020	44	18	40.9	12	27.3
2021	39	17	43.6	9	23.1
$IEP_{COMMUNITY}$	240	93	38.8*	56	23.3*

Note: *Mean.
Source: Authors' elaboration

contribute to the cause with different resources (not only experience, but also time and effort). However, the level of self-organization of the network was limited and did not comply with CLN criteria [15]. Among the explanations we can find, the most relevant follow the so-called Occam's razor because of its simplicity. Specifically, we believe firstly that the Foundation should have taken a stronger leadership role and carried out activities that allowed the participants in the different cohorts to get to know each other and strengthen their relationships face-to-face, as a community, in order to achieve greater interaction in the new app, greater collective intelligence, and greater self-organization in the search for concrete solutions to urgent social challenges. Secondly, we believe that the initiative did not comply with a key recommendation for successful adoption of AI for social good and collaboration—namely, that the goals and use cases should be clear and well-defined [78].

Using as a metaphor the tetrahedron of fire, essentially known by firefighters, in order to maintain the fire of an ignited community and release its collective intelligence, we believe it is necessary to have at the same time four elements that cannot be removed: the fuel (the collective need for and interest in solving societal challenges); the oxygen (the network of leaders willing to contribute with resources); and the heat or a spark with sufficient energy to ignite the fire (a specific action or initiative, such as the creation of a clear and well-structured problem to solve) and maintain a chain of reactions (i.e., a self-sustained collective action). In this metaphor, technology is just one of the possible locations in which collective action is ignited. We believe that in this case the spark that the pilot ignited was not sufficiently powerful.

The following are some lessons learned from this case study that might be useful for policymakers or organizations similar to the Foundation to consider when seeking to establish a CLN to address social challenges.

a. The leadership behind the desire to create a collective leadership network must be very strong at the beginning and oriented toward union and synergy to create a spark strong enough to identify and excite members according to the established purposes.
b. The creation of an app must be a tool that is perceived as truly practical by the leaders who will use it to streamline solutions to social challenges.

Finally, in terms of managerial implications, we believe that leaders have an individual incentive to join a leadership network in order to increase their social contacts and influence. In turn, the incentive to participate actively and proactively in these types of networks is probably fundamentally linked to the possibility of improving their professional results directly or indirectly (not necessarily in the short term). In this context, even though these individual leaders have an incentive to leverage and strengthen their relationships with leaders from different organizations and spheres of action (e.g., academics or high-level public officials) and are willing to contribute their time and resources to the social good, they probably need clearer information and instructions to be able to better fine-tune their personal cost vs. personal and social benefit equation.

6. Conclusions

This study is based on non-hierarchical leadership networks made up of leaders from different sectors in Spain who have participated year after year in the Innovation and Entrepreneurship Program of an important Spanish Foundation.

In the first phase, the networks were separated by WhatsApp groups linked to their cohorts in the IEP, but later, the new AI-based app created by the Foundation and other actions of the same organization allowed the different leaders to interact according to their topics of interest related to grand social challenges.

In this context, we can conclude that the level of socio-digital engagement related to the urgent social challenges of the leadership networks was practically nil, since they only achieved the formation of peer leadership networks and not collective leadership networks focused on action, as desired by the Foundation.

The analysis shows that the networks complied with the requisites of the peer leadership network category because all IEP participants interacted in the WhatsApp group corresponding to their cohort; the index of intensity of interactions and the index of intensity of emotions were above their critical levels in almost all cohorts; high valence and arousal emoticons predominated; and program participants managed to carry out activities to create and strengthen their bonds.

However, despite the Foundation's efforts, this study found that the network of leaders (considering all the cohorts as a single group, as a community) did not become a collective leadership network because they failed to self-organize [15]. This was evidenced by the fact that the app created by the Foundation did not reach a minimum critical mass to be actively used.

Consequently, these results show that the Foundation should seek other strategies to achieve collective leadership networks with great collective intelligence in the face of urgent social challenges, and that these actions do not necessarily need to be organized by means of an app for collective intelligence.

Finally, we acknowledge the limitations of this case study in providing generalizable insights into the issues analyzed, especially how to ensure the successful adoption of AI-based tools for collective intelligence and how to facilitate the emergence of proactive and self-organizing collective leadership networks to address societal challenges. However, we believe that the insights provided allow us to learn some interesting lessons from the unsuccessful adoption of the AI tool introduced in the analyzed case.

CRediT authorship contribution statement

Oihana Basilio Ruiz de Apodaca: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vicente J Montes Gan:** Writing – review & editing, Validation, Resources, Conceptualization. **Fernando Moreno-Brieva:** Writing – review &

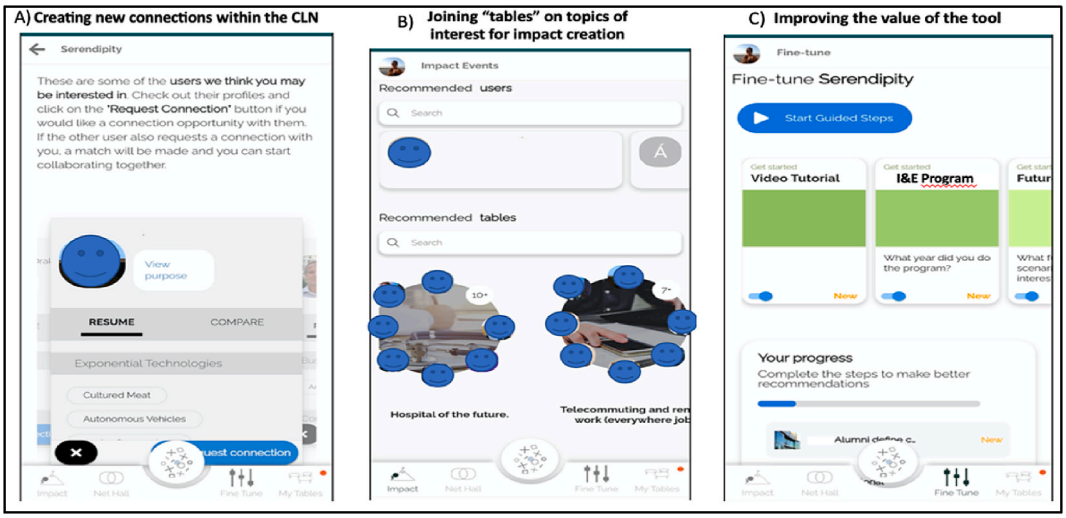
editing.

Declaration of interests

We declare that two of the three authors have held management positions in the foundation mentioned in the study.

Appendix 1. The first toe of the AI tool

In 2018, the Foundation brought together three IEP alumni (experts in new innovative technologies) and asked them to develop the tool, introducing relevant features in its design to facilitate new connections among participants of different networks and lower the barriers for accepting the technology. The following images illustrate some of these features.



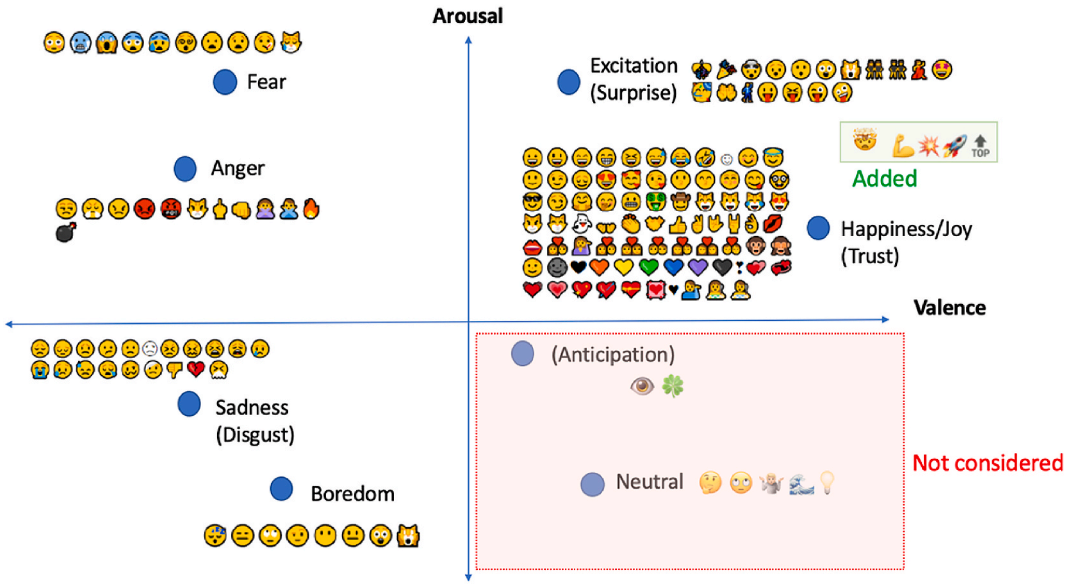
Appendix 2Classification of emojis by emotions

The following figure shows the classification of emojis according to the emotions of happiness, sadness, fear, anger, excitation, and boredom, along with neutrality, applied by Mohta et al. [82]. They were combined with the classification of emojis applied by Awal et al. [85] to account for additional emojis and emotions (in brackets). We also added emojis not considered by those authors (e.g.,

within excitation) and reclassified a few emojis according to their intended meaning in the analyzed context (e.g.,

for excitation and not for anger, or

for surprise and not for fear). The different emojis have been segmented according to the four quadrants proposed by Russell [84].



Source: Authors' elaboration based on Mohta et al. [82] and Awal et al. [85].

Data availability

The data that has been used is confidential.

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