Technovation 132 (2024) 102969

Contents lists available at ScienceDirect

Technovation

journal homepage: www.elsevier.com/locate/technovation

Crowd mining as a strategic resource for innovation seekers

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ARTICLE INFO

Keywords:
Crowdsourcing
Crowd-driven innovation
Bounded rationality
Idea filtering
Topic modeling
Transactivity
Intermediation
Intermediary

ABSTRACT

This article explores how to help people who organize crowdsourcing events (called "seekers") choose the best ideas from those submitted by participants (called "solvers'). To this end, we created a method using techniques like topic modeling and text analysis to sort and group ideas. Then, we tested this method on data from crowdsourcing contests in Italy in 2021. In particular, considering the literature on intermediaries, we focus on intermediation in crowdsourcing to improve the decision-making processes in those initiatives where searching activities are intermediated by digital platforms, besides other human intermediaries. This method makes it easier for seekers to handle multiple ideas, and it also helps them find better-quality ideas. Moreover, from a theoretical point of view, our method could lead to better results in crowdsourcing challenges because it groups ideas based on their content without being influenced by the organizers' pre-existing knowledge or biases. This means that seekers might discover new and unexpected topics or solutions they hadn't thought of before. From a practical standpoint, for managers organizing crowdsourcing events, this method is valuable because it not only saves time and effort but also potentially uncovers innovative and diverse ideas. Additionally, the method includes a feature that shows how much participants interact and share knowledge, thus implementing the concept of "transactivity", which, to the best of our knowledge, hasn't been used in crowdsourcing studies before. This can help crowdsourcing organizers better understand which contests are more effective at encouraging collaboration and knowledge sharing among participants.

1. Introduction

Crowdsourcing concerns the search for new sources of innovation or solutions for challenges faced by an organization (Afuah and Tucci, 2012). This article questions crowdsourcing as a strategic resource to create and capture value from ideas. As to this issue, we consider the organizers' perspective of crowdsourcing initiatives (the *seekers* in what follows). While most previous research has considered the idea provider as the main subject of analysis, we focus instead on the bounded rationality of the solution seekers while searching for ideas that are "distant" or outside the established boundaries of an organization (Afuah and Tucci, 2012). In these cases, the seekers often estimate that the main cost of an idea challenge comes from the reward itself. Yet, making mistakes in the selection process for "building a crowd" (Dahlander and Piezunka, 2020) and picking the wrong idea might result in the seeker wasting time and money.

Nevertheless, the focus on designing solutions to these issues is still limited, and most of the studies follow the trend observed for academic research on technological innovation, where a theory-driven approach is the most frequently adopted (Romme and Holmström, 2023). In this paper, we address this gap in the literature. We aim to contribute to the corpus of study that proposes artifacts to support the seekers sorting and selection of ideas, especially looking at the use of artificial intelligence in innovation management initiatives (Füller et al., 2022) like the crowdsourcing of ideas and solutions for solving complex and ill-defined problems (Wahl et al., 2022). However, our focus is on one specific type of crowdsourcing where the external actors are asked to collaborate on ideas suitable to provide, e.g., corporate or industry foresight (Fergnani, 2020; Kapoor and Wilde, 2022), not necessarily having specialist competencies on the subject matter, but eventually being

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https://doi.org/10.1016/j.technovation.2024.102969
Received 4 September 2022; Received in revised form 15 December 2023; Accepted 30 January 2024
Available online 16 February 2024

informed on it. This specific type of crowd is close to the one labeled "collective production' by Majchrzak and Malhotra (2020, p. 29), which focuses on broad and ill-defined problems and generates solutions or ideas. Here, the scarcity of resources for engaging a vast number of external experts or judges and the effectiveness of a limited number of judges has been questioned in the literature interested in crowdsourcing for judgmental and super forecasting (Katsagounos et al., 2021) as well as in corporate and industry foresight (Fergnani, 2020; Kapoor and Wilde, 2022).

Considering these issues, mining the crowd engaged in innovation challenges enhances their status as strategic resources for the seekers. In particular, we pay specific attention to their effort and bounded rationality that may hinder the selection of ideas through innovation intermediaries, including digital platforms and human agents. Moreover, this intermediation impacts the assessment of the crowd quality in terms of received solutions. Accordingly, in this paper, we outline the design of the artifact aiming to provide a "satisficing" solution to these issues (Simon, 1947, 1956), guided by the following research questions (RQ).

- *RQ1: How can solution seekers filter satisficing ideas, considering their limited capability to process information?*
- *RQ2: How can solution seekers filter satisficing ideas, considering the knowledge that informs the problem representation at the basis of their selection process?*

Furthermore, the artifact is a method for idea filtering and pooling, implemented with topic modeling and text analysis on data from crowdsourcing challenges for corporate foresight held in Italy in 2021.

The rest of the paper proceeds as follows. Section 2 reviews the existing literature related to our research questions. Section 3 illustrates our chosen methodology, whereas Section 4 outlines the implementation and evaluation of the artifact. Section 5 discusses the research results, especially considering their boundary conditions, while Section 6 concludes the paper by discussing its contribution and limitations and suggesting further investigation directions.

2. Theoretical background

In the last two decades, private and public organizations have increasingly considered open innovation (Chesbrough and Bogers, 2014) as a way to obtain a competitive advantage or public value (see, e.g., Cordella et al., 2018). In particular, the value of open innovation has been connected to the exploitation of the opportunities and capabilities offered by the digitalization (Kohli and Melville, 2019) as well as a means of exploring alternative solutions for research and development. Among the phenomena related to open innovation, crowdsourcing raised interest among practitioners and scholars, especially for the opportunities in economies of scale and scope derived from the tokenization of work and the adoption of collective contests for ideas searching and problem-solving (Afuah and Tucci, 2012). In this paper, we are considering crowdsourcing from the specific lens of *crowd-driven innovation* (Viscusi and Tucci, 2018) as the search for new sources of innovation or solutions for the challenges eventually faced by an organization (Afuah and Tucci, 2012; Katila and Ahuja, 2002; Li et al., 2012). This search can either be "local," relying on the internal resources of an organization, or "distant" when also looking outside its established boundaries (Afuah and Tucci, 2012; Fayard et al., 2016; Jeppesen and Lakhani, 2010), with a consequent often implicit distinction between "internal" and "external" crowdsourcing (Zuchowski et al., 2016). Furthermore, the interest raised by the need for digital transformation into discovery-driven approaches (McGrath and McManus, 2020) poses questions about the role of crowdsourcing in supporting organizations in the early identification of the "inflection point" (McGrath, 2019), where changes in the business environment may radically change activities and business models.

The arguments of this article point out the potential theoretical and practical value of the strategic implications of crowdsourcing for innovation, especially considering the bounded rationality of the actors involved. In this article, we assume a bounded rationality that may differ among the seekers due to their actual knowledge of the problems they ask to solve with the crowdsourcing (Afuah and Tucci, 2012; Conner and Prahalad, 1996). Thus, the focus here is on i) how the knowledge is applied to solving problems for current business activities, ii) how it is searched and acquired for new ventures and developments, and iii) how that knowledge is organized either at the firm level or through the opening to external actors and markets (Afuah and Tucci, 2012; Conner and Prahalad, 1996). This perspective has been explored in management information systems for identifying the firm intentions to crowdsource (Ye et al., 2015). Also, considering now the literature on innovation, Cappa et al. (2019) have investigated how crowdsourcing may impact a firm's future profits, identifying two contingency factors: brand value and investment opportunities. Accordingly, in this paper, we argue that crowdsourcing can be a strategic resource for the *seekers* (i.e., individuals or organizations) that can identify, filter, and select innovative solutions to the problems they address.

The state-of-the-art literature in crowdsourcing recognizes that the agents involved in the search and problem-solving activities may have either the role of the *seeker*, an individual or organization asking for a solution, or the one of the *solver*, providing a solution to that problem (Jain and Deodhar, 2022; Natalicchio et al., 2017). From an organizational learning perspective grounded in bounded rationality and interested in how innovation can be assimilated from outside a given organization's boundaries, those roles can be considered a "system of prescribed decision premises" (Simon, 1991, p. 126). As shown in Table 1, the bounded rationality of the solvers has been emphasized by the state-of-the-art literature for the cognitive, information processing, and education limits that constrain their search space and their solutions (Koh and Cheung, 2022; Natalicchio et al., 2017; Shao et al., 2019; J. Yan et al., 2018). Although they have been considered as the factors that can orient the decision of the seekers to opt for crowdsourcing (Afuah and Tucci, 2012, p. 362), a lower degree of attention has been devoted to the same limits for the *seekers* sorting and selection of ideas (Gurca et al., 2023; Piezunka and Dahlander, 2015), as also shown in Table 1. Among the contributions of design solutions, the method proposed by Banken et al. (2019) is worth mentioning for addressing the cognitive loads and biases in supporting ideas allocation for improving the performance of the evaluation process in crowdsourcing. In this paper, we complement and extend their approach, which focuses on reducing the number of raters. Indeed, we study the intermediation of digital tools and platforms as the main intermediaries, and we focus on how ideas evolve and influence each other along the various stages of an idea challenge.

In general, the state-the-art literature has looked at the antecedents and the possible costs (e.g., codification of the problem, tasks, and evaluation costs) that can orient the use of crowdsourcing by seekers, (Gurca et al., 2023; Jain and Deodhar, 2022; Ye et al., 2017) or the incentives needed, e.g., for improving the quality of the solutions received with crowdsourcing (Moghaddam et al., 2023). Also, the state-of-the-art literature has outlined the limits set by the bounded rationality of seekers in terms of time (e.g., under high-urgency conditions) and attention in evaluating a large number of solutions to complex problems (Gurca et al., 2023, p. 3). Then, some studies have focused on the potential opportunities arising from the combined application of artificial intelligence and crowdsourcing for addressing the bounded rationality of the seekers, like the process model proposed by Wahl et al. (2022) for improving the problem understanding to gather better solutions from the crowd.

Nevertheless, the focus on designing solutions to these issues is still limited (as shown in Table 1), and most of the studies follow the trend observed for academic research on technological innovation where a theory-driven approach is the more frequently adopted by the state-of-the-art works (Romme and Holmström, 2023). In this paper, we address this gap in the literature, and we aim to contribute to the corpus

Table 1
Relevant studies on decision-making in choosing and sorting ideas.

Reference	Role considered	Key issues	Type of research
Koh and Cheung (2022); Natalicchio et al. (2017); Shao et al. (2019); Yan et al. (2018); Ye et al., 2015	Solvers	Cognitive, information processing, and education limits that constrain their search space and their solutions.	Theory-driven
Gurca et al. (2023); Jain and Deodhar (2022); Ye et al. (2017)	Seekers	Antecedents and the possible costs (e.g., codification of the problem, tasks, and evaluation costs) that can orient the use of crowdsourcing by seekers.	Theory-driven
Moghaddam et al. (2023)	Solvers	Incentives needed, e.g., for improving the quality of the solutions received with crowdsourcing.	Theory-driven
Gurca et al. (2023)	Seekers	Limits set by the bounded rationality of seekers in terms of time (e.g., under high-urgency conditions) and attention in the evaluation of a large number of solutions to complex problems.	Theory-driven
Wahl et al. (2022)	Seekers	Potential opportunities arising from the combined application of artificial intelligence and crowdsourcing for addressing the bounded rationality of the seekers.	Instrumental approach
Girotra et al. (2010)	Solvers	Theory that relates organizational phenomena to the quality of the best ideas identified on the basis of (1) the average quality of ideas generated, (2) the number of ideas generated, (3) the variance in the quality of ideas generated, and (4) the ability of the group to discern the quality of the ideas.	Theory-driven
Piezunka and Dahlander (2015)	Seekers	Seeker organizations narrow their attention by focusing on the solvers that share their same knowledge with them. Accordingly, crowdsourcing needs adequate filtering to address those issues.	Theory-driven
Schlagwein and Bjorn-Andersen (2014)	Seekers	Crowdsourcing as a way for the organization to learn from non-members that broaden its "base of minds."	Theory-driven
Hong and Page (2001), 2004	Solvers	Diversity of solvers can have benefits, but also challenges for collective problem solving.	Theory-driven
Banken et al. (2019)	Seekers	An idea allocation method to support seekers to allocate ideas to raters, reducing their cognitive load, by using cognitive biases and distribution of the workload.	Instrumental approach

of study that proposes artifacts to support the seekers sorting and selection of ideas (Banken et al., 2019). According to Girotra et al. (2010, p. 592), idea generation and selection are characterized by four factors impacting the outputs of each team or group involved in the process: (1) the *number of ideas generated*, (2) the *average quality of ideas*, (3) the *variance in the quality of the best ideas*, and (4) the *ability to accurately discern idea quality*. In this paper, we focus on the seekers' effort to address their cognitive burden associated with sorting, filtering, and selecting a large number of ideas and the possible biases in the idea evaluation, considering the crowd's quality through the quality of the ideas proposed.

2.1. Intermediaries

Innovation intermediaries are "organizations or groups within organizations that work to enable innovation" (Dalziel, 2010, p. 1) and "generate value to other actors within a system of innovation" (De Silva et al., 2018, p. 71). However, with the advance of information technology and the preeminence of platforms and ecosystems in the digital transformation of society and organization, the concept of innovation intermediaries has become more difficult to subsume under a unique definition among the ones available in the corpus of studies on the phenomenon (Caloffi et al., 2023). As to this issue, the state-of-the-art literature on innovation has proposed various typologies and taxonomies of intermediaries (Caloffi et al., 2023; Lopez and Vanhaverbeke, 2010; Santos et al., 2023). Among them, Caloffi et al. (2023), through a computational analysis of the different studies available on the topic, have clustered intermediaries according to their *type*, *performed functions*, and specific types of *other organizations involved*. Of particular interest for the research presented in the following pages is their cluster of "open innovation intermediaries", including intermediaries that "can be formal or informal organizations, operating in different fields, whose goal is to facilitate open innovation processes among firms or other organizations (e.g., universities) or individuals (e.g., seekers and solvers; communities of practice)" (Caloffi et al., 2023, p. 6). Also, the role of platforms as intermediaries has been considered (Daniel et al., 2018) besides or in support of innovation project managers or teams in search of ideas outside their organizations (Aquilani et al., 2017; Garcia Martinez et al., 2014; Hossain and Islam, 2015; Lopez and Vanhaverbeke, 2010). Thus, in these latter cases, the human and organizational intermediaries are connected to technical or digital tools that intermediate their search and collaborative goals along the innovation value chain (Katzy et al., 2013). As to these issues, our contribution focuses on the decision-making process (Gavetti et al., 2012) of a seeker organization that searches (Afuah and Tucci, 2012; Katila, 2002) and selects ideas, which eventually innovates their strategy, business models, products or services. In particular, considering the literature on intermediaries, we are interested in improving the decision-making processes where searching activities like crowdsourcing are intermediated by digital platforms, besides other human intermediaries.

2.2. Seekers effort

The study of crowdsourcing from an organizational learning perspective has been carried out in case studies such as the one of LEGO developed by Schlagwein and Bjorn-Andersen (2014, p. 771). The authors identify crowdsourcing as a way for the organization to learn from non-members that broaden its "base of minds." Consequently, crowdsourcing is found to enact one of the two ways outlined by Simon (1956, p. 125) for learning, i.e., "by ingesting new members who have knowledge the organization didn't previously have." Moreover, the organizational learning associated with crowdsourcing is further enhanced when used, for example, for foresight activities (Fergnani, 2020, pp. 832–833), like the crowdsourcing initiatives presented in this paper. However, although the diversity of solvers can have benefits for the collective problem-solving (Hong and Page, 2001, 2004; Page, 2007), the extended base of minds proposing a very large number of ideas may impact the seekers' attention and their cognitive burden, thus increasing the seekers' effort. Narrowing seekers' attention can reduce or invalidate the effort of having a crowd of solvers with diverse and unrelated perspectives (Park et al., 2023), which the state-of-the-art literature sees as critical for increasing the crowd's creativity and ideation performance (Boons and Stam, 2019). Those elements are relevant when considering the effect of the received solutions on their role in improving the performance of their selection process and their learning (Schlagwein and Bjorn-Andersen, 2014).

Furthermore, the challenges of screening ideas, i.e., sorting and filtering, have been emphasized, especially concerning the attention and, eventually, the information processing capacity of managers in charge of selecting the ideas or solutions to complex problems from a vast corpus of proposals (Gurca et al., 2023, p. 3). Accordingly, in this paper, we propose an artifact addressing the reduction of effort of the seekers by tackling the challenge of filtering a large number of ideas, making up a manageable corpus of solutions.

2.3. *Crowd's quality as the quality of the solutions*

Considering their bounded rationality, one of the critical issues for the seekers is to have an appropriate problem representation (Puranam et al., 2015; Simon, 1991, p. 132) to deal with the solvers' solutions or acquire a new problem representation from them. For example, having an appropriate problem representation may lead to using exemplars to guide the solvers in developing their ideas and support the seekers in gathering appropriate solutions. Koh and Cheung (2022) have shown that the use of exemplars by the seekers may result in fewer and lower quality ideas submitted by the solvers. The quality of the solutions coming from crowdsourcing is a crucial concern of existing platforms as intermediaries (Daniel et al., 2018, p. 27) and has received attention from state-of-the-art literature. However, in both cases, the focus is primarily on identifying the quality parameters, like the accuracy of the outputs (Daniel et al., 2018, p. 27), or the mechanisms that can act on the solvers' side, questioning, for example, the number and types of incentives to provide to the participants to crowdsourcing initiatives (Moghaddam et al., 2023). In the design of the artifact advanced in this paper, we consider from the seeker's side what could influence the overall *crowd's quality*, determined by the quality of the crowd system that produces the ideas (*crowd's system quality*) as strictly linked to the *quality of the solutions* proposed for a given crowdsourcing challenge. While information processing capacity is an essential factor influencing the seeker effort, in line with other state-of-the-art studies (Wahl et al., 2022), we argue here that the representation of the problem is relevant for its possible influence on the evaluation of ideas, thus adding a bias in the assessment of the quality of the solutions received and the overall crowd's quality. As to these issues, Piezunka and Dahlander (2015, p. 876) have shown, on the one hand, that seeker organizations eventually narrow their attention by focusing on the solvers who share the same knowledge with them. Regarding the bounded rationality of the seekers, this implies an alignment with their original representation of the problem and the ones of the selected solutions.

On the other hand, the attention effort of the seekers can be wasted in discerning good ideas from bad and misled by how ideas are expressed, believing that the loudest ones are the best. Accordingly, Piezunka and Dahlander (2015, p. 876) argue that crowdsourcing needs adequate filtering to address those issues, which is one of the motivations for our research. Moreover, the focus on filtering aims to provide support to seekers aiming at capturing the outcomes of the learning activity derived from the assessment of the ideas that are possibly distant from their knowledge and how they represented the problem (Afuah and Tucci, 2012). The assessment is often subsidized to intermediaries as expert evaluators involved in the idea's selection who possibly have different background knowledge and representation of the problem submitted to the crowd; thus, they either extend or maintain the bias toward the quality of the solutions proposed by the crowd. As to the role of experts, Sukhov et al. (2021) shows that they use and combine intuition, analysis, and sensemaking in an interpretation effort to select high-quality ideas; the consequent learning from the interpretation effort may lead to developing ideas further (Sukhov et al., 2021, p. 248).

2.4. *Transactivity*

Taking the above issues into account, we argue that the information processing capacity and problem representations, influencing the seekers' effort and the assessment of the crowd's quality, respectively, can be considered elements of an emergent transactive memory system - TMS (Brandon and Hollingshead, 2004), which frames the overall crowdsourcing learning process. At the state-of-the-art, TMS is often considered at group-level as a way to "share responsibility for encoding, storing, and retrieving of information from different knowledge areas, and have a shared awareness about each member's knowledge responsibilities." (B. Yan et al., 2021, p. 4). However, authors like Gupta and Woolley (2021) have proposed frameworks suitable to extend the concept of TMP to collective intelligence. Also, a connected stream of research has focused the attention on another group-level learning factor like the transactivity (Zoethout et al., 2017), which is "a quality of conversational behavior where students explicitly build on ideas and integrate reasoning previously presented during the conversation on learning" (Fiacco et al., 2021, p. 75). Furthermore, efforts have been made to understand the impact of transactivity on different domains and collective phenomena, such as, e.g., discussion fora in the education (Fiacco et al., 2021).

2.5. *Gaps analysis and contribution*

Regarding the previous issues, discussion fora are often used in crowdsourcing platforms for ideas debate and evaluation, both in what Gurca et al. (2023) identify as "fishing" and "collective production" types of crowdsourcing. However, a gap exists in the current literature concerning understanding transactivity in crowdsourcing and among the agents involved (i.e., solvers and seekers). Consequently, we address this gap by considering transactivity as an essential factor to observe for understanding the effects of the seekers' effort on the crowd's output quality assessment as well as on the solvers' learning and creativity in developing new ideas. Also, we consider the quality of those ideas by assessing individual ideas as a catalyzer for the crowd (Boons and Stam, 2019). Furthermore, the joint analysis of transactivity and the fitness of ideas with the request of the seekers along the different stages of a crowdsourcing contest can tell us how the seekers' *problem representation* bounds the choice of the solvers to satisfy it, as well as the degree of conservativeness rather than the novelty of the ideas developed with regard to the *knowledge of the seekers* in their final choice (by exhibiting a positive learning outcome in case of distant and novel ideas or a negative one in the other case).

In summary, adhering to and going beyond the initial request may require a different degree of transactivity along the various stages of a crowdsourcing contest. Consequently, the proposed artifact aims to act on the seeker bounded rationality, as effort and bias in assessing the crowd's quality, to improve the transactivity and the quality of the proposed solutions. Thus, also in this case, we see a specific role of the seekers not only on the final outcome of a crowdsourcing contest but also in the performance of the solvers and their eventual learning dynamics.

3. Methodology

This Section illustrates the methodology chosen to answer our research questions. We position our study in the field of design science research (DSR) (Hevner et al., 2004; Romme and Holmström, 2023), and we present an artifact for idea filtering and pooling.

Our artifact brings knowledge of operational principles and architecture but is not a well-developed design theory about the phenomena under study. Instead, the proposed artifact addresses a well-known problem where existing theory has shortcomings (high cognitive burden for idea seekers using crowdsourcing platforms) and finds a place in the "*improvement*" quadrant of DSR contributions proposed by Gregor and Hevner (2013). Accordingly, we define our design theory as a nascent theory.

Considering these issues, Table 2 summarizes the steps of the research methodology followed to design and develop the artifact presented in this paper. In particular, we adhere to the steps proposed by Peffers et al. (2007) among the different implementations of DSR proposed in the literature. In the following Sections, we discuss them in detail.

3.1. Identify the problem and motivate

The purpose and scope of our paper have been described in Section 1 and further grounded in the state-of-the-art literature discussed in Section 2. In summary, in this paper, we focus on the bounded rationality of seekers to question the conditions under which they can efficiently exploit crowdsourcing for ideas generation. The chosen problem is relevant because solution seekers should be able to improve how they filter ideas, which is challenging due to bounded rationality. The two effects we want to mitigate are a) a high cognitive burden for the idea seeker and b) biases in the idea evaluation step.

Table 2
The DSR methodology adapted from Peffers et al. (2007).

DSR Steps	Comments
1.Identify the problem and motivate	a) Reduce high cognitive burden b) Reduce biases in idea evaluation
2.Define the objectives of the solution	a) Reduce seeker effort (Solution for RQ1) b) Increase the crowd's quality (Solution for RQ2)
3.Design and development	a) Design principle 01 – *Idea Filtering*: Use structural topic modeling to filter a set of small text messages. b) Design principle 02 – *Idea Pooling:* Use visualization of the clusters to identify catalyzing ideas that were not selected by reviewers.
4.Demonstration	We collected ideas from an online platform with six idea challenges, including 42 items from Stage 1 and asking: *how many should go to Stage 2?* a) Testable proposition 01: *Idea filtering* should reduce the number of ideas while retaining a recall above 80%. b) Testable proposition 02: *Idea Pooling* should underlie the potential collaboration among ideas submitted at Stage 1.
5.Evaluation	a) Result 01: Our prototype reduces seeker effort. The seeker needs to assess only 15 ideas over 42 in total. b) Result 02: Our prototype increases crowd quality. The seeker can find catalyzing ideas that influenced the final result but were not selected.
6.Communication	The prototype has been presented at academic conferences and in a technical report for practitioners. Current limitations of the mutability of the artifact are: i) *Low/High numbers of ideas.* ii) *Low/high amount of text to describe an idea.* iii) *Low/High number of participants.*

3.2. Define the objectives of the solution

To solve our problem, we rely on the DSR approach and propose an artifact, which, in our case, is a method based on topic modeling. Hence, our paper evaluates a methodological approach in a particular context. Considering the theoretical background of our artifact described in Section 2, we assign two constructs to describe our problem: "seeker's *effort*" and "crowd's *quality*." To operationalize each construct, we refer to the variables that, according to Girotra et al. (2010, p. 592), *"affects the quality of the best ideas produced by a team or a hybrid group"* and are: *"(1) the average quality of ideas generated, (2) the number of ideas generated, (3) the variance in the quality of ideas generated, and (4) the ability of the group to discern the quality of the ideas."* (*Ibid.*, p. 592). Hence, the four measures are divided into two categories operationalizing our two target constructs.

A) *The seeker's effort* can be measured by
  - *The number of ideas generated.* Ideas of high quality are more likely to appear in a more extensive idea pool.
  - *Ability to discern idea quality.* The process to assess raw ideas and predict the eventual innovation and market performance of the products and innovations that they grew into.

B) *The crowd's quality* can be measured by
  - *The average quality of ideas.* To accurately determine the raw quality of an idea, it is preferred to use the idea description in the form it was proposed.
  - *The quality of the best ideas.* Idea quality is typically assessed by several experts in agreement on several well-known and accepted criteria, being the novelty, feasibility, relevance, and specificity of the idea.

3.3. Design and development

The proposed artifact is a method made up of two key functions, "Idea filtering" and "Idea pooling". These are described in this Section according to the theoretical framework that grounds them, discussed in previous Sections and shown in Fig. 1. It is worth noting that the study presented in this article is framed under the current stream of contributions that adopt big data, data science, and analytic models for data-driven research, either at the theoretical or empirical level (Berente et al., 2019; Hannah et al., 2021). In particular, in the research presented in this paper, we adopt a semantic network analysis (Sowa, 2006) with the joint use of clustering techniques and text mining.

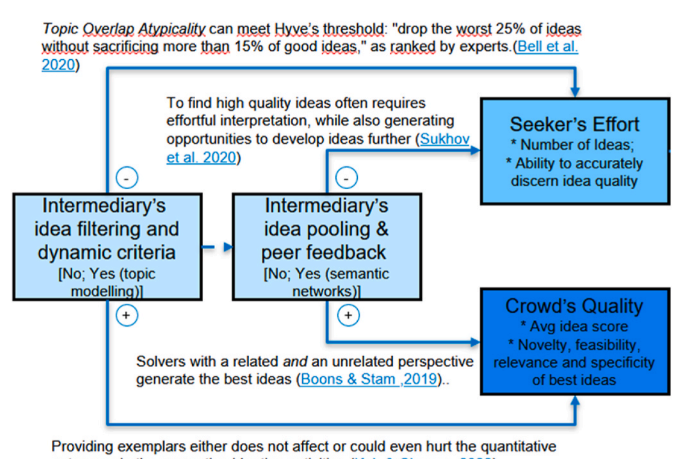

Fig. 1. The theory that informs the design of our artifact: two features (light blue) influencing two performance indicators (dark blue).

Considering now Fig. 1, it shows the four primary constructs suitable to describe our artifact. As said, the two key functions (light blue boxes in Fig. 1) of the artifact are grounded in the existing literature considered in Section 2, while the two other constructs (shades of dark blue boxes in Fig. 1) describe our objectives: a) to lower the *seeker's effort* and b) to increase the *crowd's quality*. Accordingly, we split these factors into two subsets associated to the key functions.

Idea filtering or "automated idea screening" can be used to reduce the set of ideas evaluated by experts. This decreases experts' cognitive load and helps them make better decisions. We follow Bell et al. (2020) and use the threshold defined by Hyve, a European innovation company: "*The standard provided by Hyve's manager of the contests for a potential use of the algorithms is that it would already be helpful to screen out the 25% worst ideas without sacrificing more than 15% of 'good' ideas, where 'good' is equivalent to making the shortlist, which is the set of ideas selected by company experts for further consideration*" (Bell et al., 2020, p. 6, p. 6). Hence, our first design principle about idea filtering is.

DP01: *Use structural topic modeling to filter a set of small text messages.*

For what concerns the second function, *Idea pooling* can be defined following Malhotra and Majchrzak (2014, p. 106) as "a knowledge integration approach to innovation challenges," which explicitly encourages "participants to create solutions that combine either ideas or other relevant knowledge that other participants have previously shared." This function requires a different approach than idea filtering. Malhotra and Majchrzak (2014) state that a simple creation of teams does not follow the knowledge integration process since knowledge is not automatically shared, highlighted, and combined among all participants in the innovation challenge. Hence, to measure the performance of this function, we assess the *transactivity* of the ideas, and our second design principle about idea pooling is.

DP02: *Use visualization of the clusters to identify catalyzing ideas that reviewers did not select.*

3.4. Demonstration

As outlined in Table 2, we collected ideas from an online platform with six idea challenges. Forty-five big-size companies operating in Italy in different sectors responded positively to the participation call launched by the University of Milan-Bicocca in May 2021. As an academic-practitioner research collaboration, a custom-designed crowdsourcing contest was implemented with the name *YourVision 2021*. People working within their organizations were invited to join the contest. Three hundred eighty-six professionals from various levels, tenures, and locations across marketing, finance, supply chain, market research, human resources, sustainability, and research and development were invited to a website hosting the crowdsourcing contest. A market solution, Crowdicity (https://www.medallia.com/crowdicity/), was chosen as the technology platform for this contest. Multiple participants indicate their ideas about future outcomes (e.g., innovative organizational design and process management, innovative skills development methods, digital solutions, multi-sector cooperation scenarios, etc.) in six different challenging areas (see below), keeping in mind the space-time framework "Italy" in the next three/five years. These are the six challenging areas proposed.

I. *Open Innovation and Collaboration between Big-size Companies, Small and medium-sized enterprises (SMEs), Start-ups, and Universities.*
II. *Territories and Businesses in the Digital Age, between Proximity and Distance.*
III. *Public-Private Partnership.*
IV. *Mindset and Digital Vision.*
V. *Sustainable HR and Social Innovation: Environment, Diversity, Inclusion.*
VI. *People and Relationships, between the Physical and Digital Workplace.*

Participants could post ideas for as many of the six challenging areas as they desired. They could return any number of times to update their ideas or add foresight up to the close of the contest. In order to maximize, common background information about the six challenging areas was made available when participants logged into the technology platform such as descriptive text and data provided by the scientific committee (composed of scholars of management, organization studies, and innovation of University Milan-Bicocca, Department of Business, and the Imperial College Business School, London, United Kingdom). Participants were encouraged to share ideas for future solutions about the given domains (future challenges). The ideas were posted publicly after a pertinence check from the editorial board (composed of academic researchers). Once posted, ideas could be commented on and voted on. The contest was structured in different stages.

3.4.1. Stage 1

1. *Pre-start* - the editorial board uploads some introductory content onto the crowdsourcing platform.
2. *Idea Posting* - the participants propose ideas – individually or as a team - and put them on display with the scope of identifying novel strategic opportunities. At the end of this stage, only the ideas evaluated as significant by the crowdsourcing community and by the editorial committee - through the voting system where participants rate ideas on a scale between 1 and 5 – will have access to the following stage.

3.4.2. Stage 2

3. *Ideas Refining* - In this stage, ideas have to be further developed by the proposers with the help of other participants. To facilitate the idea development, multi-organizational teams are formed, and indicators are provided for the following evaluation:
   a. *"Wow" effect!* Does the proposed solution give you a positive feeling/do you like/excite you/seem interesting to you?
   b. *Degree of innovation.* How innovative/original is the proposed solution?
   c. *Potential value for the organization.* Would the proposed solution bring value to organizations (competitive advantage, performance improvement, product or service innovation, etc.)?
   d. *Potential value for the community.* Would the proposed solution bring value to people and the community (response to people's needs, development of the local economy, positive impacts in terms of environmental sustainability, social innovation - participation, inclusion, increase in learning opportunities, etc.)?
   e. *Knowledge produced or transferred.* Does the proposed solution bring the acquisition of new knowledge to organizations/people/companies or facilitate collaboration with research centers and/or universities?
   f. *Internal or external collaboration.* Does the proposed solution produce opportunities for collaboration between the various functions of the organizations, other organizations, customers, or other actors in the area?
   g. *Planning.* Does the proposed solution suggest what could be an implementation plan?
   h. *Degree of feasibility.* Is the proposed solution feasible from a technical/financial/material or human resource/knowledge or skills point of view?
   h. *Implementation costs.* Is the proposed solution feasible from the point of view of conceivable costs?

i. *Time of realization.* Could the proposed solution be developed and implemented relatively quickly (3–6 months)?
j. *Degree of sustainability.* Would the proposed solution, if implemented, be sustainable over time in terms of financial/material or human resources and environmental impacts?

Only those solutions which are further developed will have access to the following steps of Stage 2.

4. *Ideas Evaluation* - During this step, the community had time to explore and evaluate all the posted ideas to elucidate public preferences for various alternatives. Each indicator provided (see above) is rated from 0 to 10 for each idea, by the community and the scientific committee. Only the most voted ideas will be given access to the following step.
5. *Feedback Review* - During this step, proposers will have time for subsequent developments of their ideas based on the feedback received during the previous voting step.
6. *Challenge Closed* - No more ideas or comments can be uploaded or modified; the editorial committee edits the content of ideas and discussions to draft the *Manifesto for The Future of Work and Enterprises.*

The technology platform provided participants with a way to interface with the crowdsourcing application, and other participants also shared their personal profile page (name, company, role, interests) in a provided section of the platform. The incentives built into the contest motivated participating, proposing innovative ideas, and performing well. In this contest, participants could earn a reputation by first participating and contributing positively to the crowdsourcing community. Reputation points could be gained by proposing ideas, commenting, and voting on others' ideas. No prizes were awarded for the winning ideas, but these would have the chance to be included in the final project report/book *Manifesto for the Future of Work and Enterprises.* The crowdsourcing contest ran for five months to maximize the opportunity for participation and to give the participants sufficient time to perform their own research and ideation.

Taking the study context into account, the evaluation is guided by the following testable propositions based on the statement that the functionalities of the artifact positively influence our constructs. As shown in Fig. 1., our testable propositions verify if the two functionalities of the artifact positively influence our two constructs, "seeker's *effort*" and "crowd's *quality*". More in detail.

- **Testable Proposition 1 (P1)**: *Idea filtering* reduces the seeker's effort measured by the number of ideas while retaining a good ability to discern idea quality, as measured by the recall of the classification algorithm (P1. b). Accordingly, *idea filtering* should reduce the number of ideas while retaining a recall above 80%.
- **Testable Proposition 2 (P2)**: *Idea Pooling* increases crowd quality as measured by the capacity to assess transactivity as the quality of the raw idea (P2. a) and contributes to improving the quality of best ideas in Stage 2 b y underlying potential collaboration among ideas submitted at Stage 1 (P2. b). Accordingly, *idea Pooling* should underlie the potential collaboration among ideas submitted at Stage 1.

Furthermore, the justificatory knowledge for our testable proposition is based on the theoretical background described in Section 2.

- *Theoretical background for the first proposition (Th1)*: Bounded rationality states that idea seekers should focus on good ideas. However, the artifact extends human skills but does not replace the human (Sukhov et al., 2021). In this sense, topic modeling has already allowed passing the Hyve threshold by filtering 25% of ideas without sacrificing more than 15% of good ideas (Bell et al., 2020). Moreover, dynamic criteria better predict quality than static criteria (Koh and Cheung, 2022).
- *Theoretical background for the second proposition (Th2)*: Knowledge combination is known to increase the quality of the best ideas (Malhotra and Majchrzak, 2014), and peer feedback increases transactivity since individual ideas can act as a catalyzer for the crowd (Boons and Stam, 2019).

3.5. Testing the implementation of the design principles: our explanatory instantiation

To test the prototype, we use data from a real idea competition, the *YourVision2021* contest discussed in the previous Section. The goal is to show how we can perform idea filtering and support transactivity across ideas between Stages 1 and 2. In Stage 1, each idea received scores from other participants, and the organizers selected the best ones. In Stage 2, selected ideas were improved by the idea owner with the help of participants whose ideas were not selected. Improved ideas received a score from other participants as well.

Then, Hyve's threshold introduced in Section 3.3 can be converted into a classification problem to test the prototype. The dependent variable we are trying to predict is 0 (="Bad") if the idea is not selected. In our case, since more than 50% of ideas did not pass to Stage 2 of *YourVision 2021* (the Stage where the ideas selected in Stage 1 can be further developed), we got more than 50% of ideas defined as "Bad." Accordingly, we define "Good ideas" (=1) as those in the top 25%, which is the top 50% of the top 50% of ideas that have been selected. Hence, we use the score of Stage 2 to choose the best ideas: we give 1 to those with a score of Stage 2 in the top 50% and 0.5 otherwise. Here there is an example with four ideas.

- Idea 01 got 3/5 in the first stage but did not get selected. This idea would earn 0 points.
- Idea 02 got 4/5 in the first stage but did not get selected. This idea would earn 0 points.
- Idea 03 got 4.5/5 in the first stage and 3/5 in the second stage. This idea would get 0.5 points because its score for Stage 2 is outside the top 50% of the selected ideas.
- Idea 04 got 4.5/5 in the first stage and 4.5/5 in the second stage. This idea would get 1 point because it got a top score and deserves to be in the top 25%.

In the end, we obtain a table like Table 3, which identifies: the *True Positive (TP)* that will be filtered correctly; the *False Negative (FN)*, which will not be filtered but should have been; the *True Negatives (TN)*, which are good ideas that will not be filtered and the *False Positive (FP)*, which are "Good ideas" that have been filtered. To measure performance, we can use the definition of "*recall*" in classification and measure with the following results.

- Recall to filter *Worst ideas* = TP/(TP + FN) = 50%. All ideas in the worst 50% are screened (false negative = 25%).
- Recall to not filter *Good ideas* = FP/(TN + FP) ≥ 85%. Only 15% of good ideas are screened (false positive = 15%).

Table 3
Example of classification of ideas: predictions and true results.

	Worst idea (Q1 – ideas that were not selected)	Best idea (Q4 – Selected ideas with top scores)	Q2-Q3 (Selected ideas with low scores)
Filter idea	True Positive TP = 50	False Positive FP = 15	–
Don't filter idea	False Negative FN = 50	True Negative TN = 85	–

- The Recall of the selected ideas with low scores does not matter in this paper.

3.6. Communication

As shown in Table 2, our approach has been presented at academic conferences and in a technical report for practitioners. Moreover, the details of the papers published after each iteration of our design cycles are described in Appendix 2. The discussion of shortcomings and possibilities for future research is in Section 6. However, our prototype can adapt to different scenarios according to three dimensions.

1. *Low/High numbers of ideas.* We tested the system with as few as 30 ideas, and it kept working. In theory, high numbers of ideas would be easier to assess because the number of redundancies would increase, and the patterns would emerge more quickly.
2. *Low/high amount of text to describe an idea.* The chosen approach to model topics works best with a low amount of text, although it has been used to analyze large texts. We have noticed that long texts are usually harder to process because they often have a lower readability score. For a description of techniques used by our package to assess readability, we refer to Quanteda (2022). For larger texts, we intend to develop and test a prototype version that uses the same constructs but is based on a technique called Embedded Topic Modeling.
3. *Low/High number of participants.* The number of participants can influence the number of teams created in the step of idea pooling of an idea generation process. Indeed, the number of teams should be aligned with the number of topics. If the number of topics the system generates is low (for example, 3), each topic is very generic. If the number of topics is high (for example, 20), some topics are very specific, but others do not make much sense. As a rule of thumb, we suggest setting up some ten topics and having groups of 5 people working together.

4. Implementation and evaluation

In this part of the article, we explain how we put our method into action using the R statistical software (R. Core Team, 2000), specifically using two tools: Quanteda (Benoit et al., 2021) for text analysis and STM (Roberts et al., 2019) for Structural Topic Modeling. This technology is pretty standard and easy to use for anyone who knows how to use R. If we can make an existing process better with this standard method, then it's likely that the improvement is because of our method's design, not just the technology we used. We'll talk more about how to enhance our method with newer techniques in Section 5.

We applied our method to data from online crowdsourcing challenges found on the "All Our Ideas' website (www.allourideas.org) and the *YourVision2021* initiative. To analyze this data, we followed a well-established process known as the knowledge discovery in databases (KDD) process. This includes selecting the data, preparing it, transforming it, mining the data, and then interpreting and evaluating the results.

4.1. Data analysis and pre-processing

We obtained 74 ideas from the platform from six challenges.

1. Mindset and digital vision
2. Public-private partnerships
3. Sustainable HR and Social Innovation: environment, diversity, inclusion
4. Territories and businesses in the digital age, between proximity and distance
5. People and relationships between physical and digital workplace
6. Open Innovation and collaboration between large companies, SMEs, start-ups, and universities

Five idea challenges had scores for the two stages of the contests, while one idea challenge had only scores for one stage and had to be removed. That shifted the total amount of ideas to 57. At Stage 1, each idea has received a score, and the best ones have been selected. At Stage 2, only 25 ideas remained. For each idea, we use the name of the challenge, the description of each idea, the score at Stage 1, and the score at Stage 2 for the selected ideas. Fig. 2 shows the distribution of scores for the first stage (formalizing the structure of the challenges discussed in the introduction, each stage has been modeled as having three Stages: *ideation*, *refinement*, and *voting*). Each box plot is a challenge.

We used a tool called Quanteda in the R software to prepare our text for analysis (https://quanteda.io/reference/dfm_select.html). When we were processing the language in the texts, we chose not to remove words that are verbs. This let us look at groups of words together (called *N*-grams), but it also meant we kept some helper verbs that don't mean much on their own.

4.2. Data transformation

We turned the text from each idea into numbers. We collected these texts from two stages of our project, creating a group of texts called a corpus. Again, we used the software Quanteda in R to break down these texts into words or sentences and then analyze the most important words (keywords) in them. This process is called "keyness analysis.' For example, we found that popular ideas in the "Mindset and digital vision' challenge often used words like "management" and "digital' more frequently than less popular ideas. To understand how these keywords were used over time, we grouped them into themes using a technique called topic modeling. This is a type of machine learning where the software automatically sorts texts into groups, or "topics,' based on common keywords. We chose a specific approach called Structural Topic Modeling, which considers extra information like who wrote the text and when. This helps the model work better. For instance, in the "Mindset and digital vision' challenge, we identified five main topics with keywords like "Digital, generation,' "Skills, could be,' and "Robots, fear."

4.2.1. Idea filtering with topic modeling

The same keyword could appear in multiple topics. Consequently, every idea belongs to different topics; thus, we measure the fit with the topic with the variable gamma, which is between 0 and 1. The sum of the

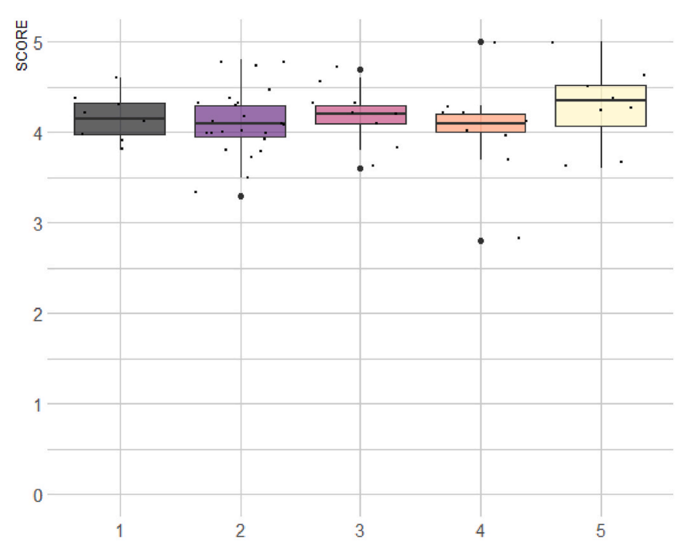

Fig. 2. Scores of ideas at Stage 3. Each challenge has a different color: challenge 1 is represented in dark grey, challenge 2 is violet, challenge 3 is pink, challenge 4 is orange, and challenge 5 is yellow.

gamma of the interaction of each idea with each topic should be 1: for example, one idea could belong to the first topic at 30% and to the second topic at 70%. For every topic modeling algorithm, the choice of the number of topics is key since it impacts the algorithm's performance, as measured by *semantic coherence*, *held-out likelihood, and residuals*.

After having explored different numbers of topics, we chose five topics since that number strikes a nice balance between the need for semantic coherence (the most probable words in a given topic frequently co-occur together) and for the exclusivity of words to topics (few words should appear in more than one topic).

Fig. 3 shows the distribution of scores across the topics of the same challenge. Topics belonging to the same challenge have the same color and a similar number: for example, topics 11 and 12 belong to challenge 1, listed in Section 4.1. One should notice that we do not use average ideas. Our algorithm is meant to identify unique ideas in each topic: similar ideas would be gathered together in one topic, and unique ideas would be put in a topic for themselves.

4.2.2. *Assessing transactivity with similarity among ideas*

Using the Quanteda package, we can also measure the similarity between two texts.[1] For example.

- Text 01 is "A dog enters the house"
- Text 02 is "A dog sleeps in the garden"
- Text 03 is "A woman travels by car"

The similarity between Text 01 and Text 02 depends on the word "Dog" since "A" and "the" will be removed from the analysis. Text 03 has low similarity with the other two texts. We can represent this result in a matrix with three rows and three columns. At the intersection of each column and row, we show the similarity degree, as we do in a correlation matrix. Once we have a matrix, we can use the package Circlize (Gu, 2022) to create a Chord diagram to display flows between entities.

Fig. 4 shows the cord diagram for an idea challenge. To obtain the image in Fig. 4, data needs to be prepared. Each idea has a code that

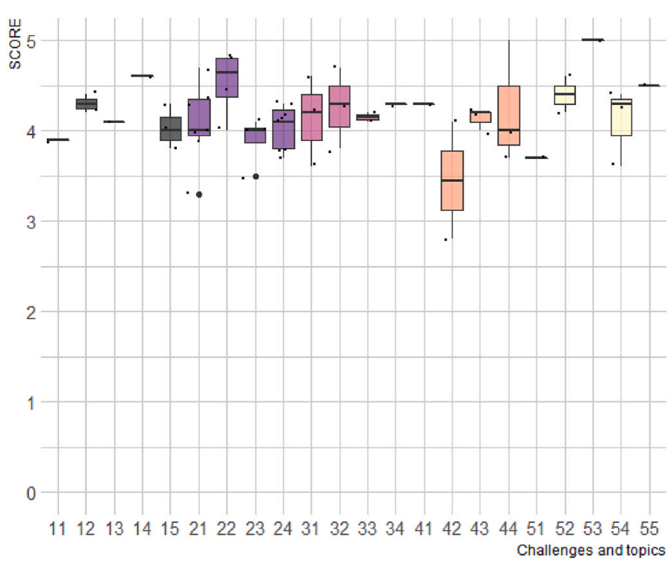

Fig. 3. Scores of ideas at Stage 3, with challenges and topics. Each challenge has a different color: challenge 1 is represented in dark grey, challenge 2 is violet, challenge 3 is pink, challenge 4 is orange, and challenge 5 is yellow.

[1] More information about how the Quanteda package calculates text similarity can be found here: https://quanteda.io/reference/textstat_simil.html (Accessed: 14 December 2023).

contains multiple pieces of information, which we explain in what follows.

- "N" = "New" indicates an idea from the second stage of the challenge. Hence, N!1 is an idea from Stage 2
- "!" indicates that the idea score from Stage 2 is in the top 50%. Hence, N!1 is an idea from Stage 2 with a top score.
- "?" indicates that the idea has been selected in Stage 2 but was not in the top 50%. Hence, "?1 × .1" is an idea selected for Stage 2 without a top score.
- "*" indicates that the filtering algorithm did not filter the idea, and it was marked as a candidate to pass to Stage 2. Hence, "?1 × .1" is an idea selected for Stage 2 without a top score, which was correctly classified by the idea filtering algorithm.
- The number used to identify each idea has two parts. The part before the dot tells us the number of clusters obtained by topic modeling. Hence, "?1 × .1" and "?1 × .1" are both ideas from cluster 1 that passed to Stage 2 without top scores. Nonetheless, "?1 × .1" was selected by the idea filtering algorithm, whereas "?1.1" was not.
- The color of each item tells us the performance of the idea filtering algorithm. Blue is a true positive, Green is a true negative, Grey is a false negative, and Red is a false positive. Hence, "?1 × .1" was selected by the idea filtering algorithm, as shown by the "*" sign, but it did not end up in the top 50% of Stage 2, as indicated by the "?" sign. Hence, it is colored grey (false negative). "?1.1" was filtered by the idea filtering algorithm, and it did not end up in the top 50% of Stage 2, as shown by the "?" sign. Hence, it is colored green (true positive).
  "!1 × .1" was selected by the idea filtering algorithm, as shown by the "*" sign, and it ended up in the top 50% of Stage 2, as indicated by the "!" sign. Hence, it is colored blue (true negative).
- The link between the items shows the degree of assessed similarity. "! 1 × .1" was the text in Stage 1, which evolved as "N!1" in Stage 2. There is a big cord between the two items to show that their text is very similar. Nonetheless, we can also see that "N!1" has also been influenced by "?1.1", which was in cluster 01, and "?4 × .1," which was in cluster 04. This supports the intuition that the best ideas combine elements from different backgrounds (topics in this case). It is also interesting to notice that green links occur within ideas in Stage 1, leading to the belief that ideas filtered by the algorithm were those that did not contribute to the best ideas in Step 2.

4.3. *Data mining*

In this subsection, we explain how we analyzed the data.

4.3.1. *Rejecting the null hypothesis: is it possible to predict future scores?*

We need to verify if it is possible to predict scores at Stage 2. Hence, we perform logistic regression by using the scores of the ideas at Stage 1. To increase the quality of our model, we also use the name of the challenge as factors, allowing us to treat ideas from challenge 1 separately from the ideas from challenge 2 listed in Section 4.1. Hyve's threshold states that 25% of bad ideas should be filtered without losing 15% of good ideas. The dependent variable we are trying to predict is 0 ("Bad") if the idea is not selected. Since 34 out of 57 ideas did not pass Stage 2, we got more than 50% of ideas defined as "Bad." Accordingly, we define "Good ideas" as those in the top 25%, which is the top 50% of the ideas that have been selected. Hence, we use the score 02 to choose the best ideas: we give 1 to those with a score of 02 in the top 50% and 0.5 otherwise. Here there is an example with four ideas.

- Idea 01 got 3/5 in the first stage but did not get selected. This idea would get 0 points
- Idea 02 got 4/5 in the first stage but did not get selected. This idea would get 0 points

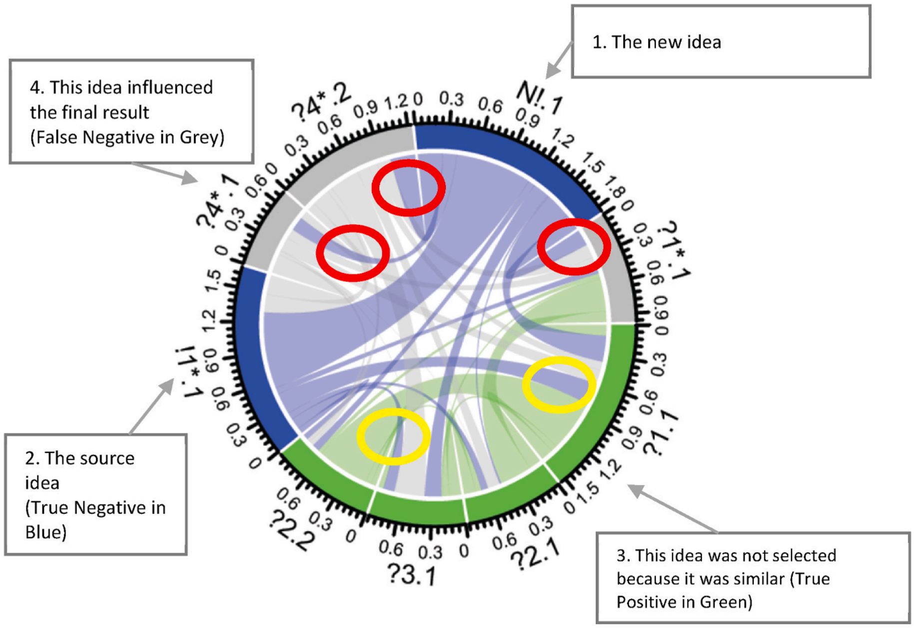

Fig. 4. Example of visualization to assess transactivity among ideas in Stage 2 (N!1) and ideas in Stage 1. False negatives are in grey, true negatives are in blue and true positive in green. Links among ideas show contributions between Stage 1 and Stage 2.

- Idea 03 got 4.5/5 in the first stage and 3/5 in the second stage. This idea would get 0.5 points because its score for Stage 2 is not in the top 50% of the selected ideas
- Idea 04 got 4.5/5 in the first stage and 4.5/5 in the second stage. This idea would get 1 point because it got a top score and deserves to be in the top 25%

In our case, we obtain 57-25 = 32 ideas with 0 points because they have not been selected for Stage 2. Hence, we obtain 25%*25–8 best ideas with 1 point, and 57-32-8 = 17 ideas with 0.5 points. We train our model with 70% of the available data: 57 × 70%–41 ideas. Then we create a confusion matrix to see how many of the remaining 16 ideas we can predict correctly. Thus, considering the data in Table 4 we have that.

- The Recall for the selection of Worst ideas is TP/(TP + FN) = 8/9–89%
- The Recall for the selection of Best ideas is 1/1 = 100%

Both results seem to respect Hyve's threshold, which states that 25% of bad ideas should be filtered without losing 15% of the good ideas. Here, we filter out the worst ideas and do not lose any good ones. Therefore, we can reject the null hypothesis that scores at Stage 2 cannot be predicted.

4.3.2. Assessing effort and idea quality after idea filtering

There are two limitations of the logistic regression model shown before. First, it can be built only at Stage 2 when ideas are already selected. On the one hand, this is not useful for the seekers since they need to know how to filter ideas at Stage 1. On the other hand, it could be helpful in a future idea competition if one assumes that the logistic regression parameters will not have to change. As a second limitation, the logistic regression model uses scores of the overall competition. Thus, it cannot find the best idea for each challenge, while it finds the idea with the best scores across challenges. Taking these issues into account, we are going to use instead our sub-groups obtained with topic modeling. Accordingly, to select the best ideas, we can use simple heuristics, such as.

- *Take the idea with the best score for Stage 1 in each topic.* This approach is reasonably straightforward, but it is risky. On the one hand, by taking the best score for each topic, the model will resemble the one used by the logistic regression, which will not be beneficial. On the other hand, by using the score of the idea, the seeker benchmarks all ideas over one single dimension and loses additional information.
- *Take the first and the last ideas for each topic.* This approach uses the date of submission, and it is not linked to the score. The underlying logic is the same as the one used, e.g., for patents: the first idea is rewarded, and the last idea is assumed to have been built on the previous ones. This approach might lower the chance of having the best ideas selected since we do not use the score, but it should increase the heterogeneity of ideas.

Since there is no training dataset, the idea filtering approach is tested over the whole set of 57 ideas. Thus, considering the data in Table 5 we

Table 4
Results of the classification with supervised learning (data from Stage 1 and Stage 2).

	Worst idea (Did not pass Stage 1)	Best idea (Top 50% of Score 02)	Extra (Ideas with low Score 02)
Predict: Filter idea *according to log. Regr.*	True Positive (TP) 8	False Positive (FP) 0	5
Predict: Don't filter idea	False Negative (FN) 1	True Negative (TN) 1	1

Table 5
Results of the classification with unsupervised learning (data from Stage 1).

	Worst idea (Did not pass Stage 1)	Best idea (Top 25% of Score 02)	Extra (Idea with low Score 02)
Predict: Filter idea *according to the topic model.*	True Positive (TP) 15	False Positive (FP) 2	5
Predict: Don't filter idea *according to the topic model.*	False Negative (FN) 17	True Negative (TN) 10	8

have that.

- The Recall for the selection of Worst ideas is TP/(TP + FN) = 15/(15 + 17) ~ 47%
- The Recall for the selection of the Best ideas is 10/12–83%

Therefore, we can claim that idea filtering can reduce the effort of the idea seekers while maintaining the overall quality of the ideas. Thus, we collected evidence to support the first testable proposition (P1), and we can claim that.

a) *Result 01: Our prototype reduces seeker effort. The seeker needs to assess only 15 ideas over 42 in total.*

4.3.3. Assessing effort and idea quality after idea pooling

Fig. 5 shows the assessment of transactivity across the five different challenges. For the sake of simplicity, we only offer the links with the top ideas in Stage 2 for the challenges listed in Section 4.1.

- By observing challenge 1, we can see that the algorithm did not correctly filter one idea: it is called "N!2", marked in red, and depends on the idea "!2.1". All the ideas in green are those that the seeker would not have to analyze. It seems that both ideas "N!1" and "N!2" did not profit from the combination of multiple ideas: they have only strong links with the main source "!1 × .1" and "!2.1," respectively.
- Challenge 2 and challenge 5 had only one top idea that combined multiple ideas from Stage 1. Challenge 3 had two ideas that heavily relied on two ideas from Stage 1.
- Challenge 4 had one top idea that was not correctly identified. Such an idea was based on multiple ideas from Stage 1.

Therefore, we can claim that idea pooling increases crowd quality as measured by the capacity to assess transactivity as the quality of the raw idea and the contribution to increasing the quality of best ideas in Stage 2 b y underlying potential collaboration among ideas submitted at Stage 1. This feature allows seekers to identify and valorize ideas that were filtered in the manual process and that acted as catalysts for Stage 2. Thus, we collected evidence to support the second testable proposition (P2) and we can claim that.

b) *Result 02: Our prototype increases crowd quality: Seeker can find catalyzing ideas that influenced the final result but were not selected.*

5. Discussion

In this section, we discuss our results by following the argumentative model of Toulmin (2003), which is composed of (i) a background that describes the problem and the research question, (ii) a set of claims backed by reasons, which are supported by pieces of evidence. Such claims are associated with a few qualifiers (boundary conditions when the claims hold), which deal with possible reservations (limitations or grounds for rebuttal of the claims).

***Background*.** As shown in Section 1, our research question concerns how to lower the effort for the idea seekers in an idea challenge while increasing the quality of the ideas. Our focus is on one specific type of crowdsourcing where the external actors are asked to collaborate on ideas suitable to provide, e.g., corporate or industry foresight (Fergnani, 2020; Kapoor and Wilde, 2022).

Our first research question concerns filtering ideas while considering the seeker's goals and the learning dynamics. As shown in Section 2, the relevance of this question comes from a general underrepresentation of the role of the idea seeker in the literature about idea challenges. Our first *claim* is that our method to filter ideas based on topic modeling allows filtering bad ideas while keeping good ideas. The *theoretical ground* for our claim is described in Section 2. Bounded rationality constrain the focus of the idea seekers on good ideas, and the artifact extends human skills but does not replace humans (Sukhov et al., 2021). In this sense, topic modeling has already allowed passing the Hyve threshold (filtering 25% of ideas without sacrificing more than 15% of good ideas - Bell et al., 2020). Moreover, dynamic criteria better predict quality than static criteria (Koh and Cheung, 2022).

As to those issues, Section 4 has offered supporting *evidence* for our claim from the implementation and evaluation of the artifact: the classification results were done over 57 ideas from 5 idea challenges. Compared to traditional classification algorithms based on the scores of the ideas, which mimic an idea seeker trying to guess the ideas to retain, our approach is based on textual analysis, allowing to obtain satisfactory results (some 25% of bad ideas filtered while not filtering more than 85% of good ideas). From a theoretical point of view, we claim that our filtering system might increase the quality of the idea contest. By gathering ideas together by textual proximity with an unsupervised algorithm, the method can identify topics the idea seekers might not have thought about when they devised the idea challenge.

Nonetheless, a possible *reservation* regarding our approach concerns the choice of a technique that requires some data to work correctly (Structural topic modeling for unsupervised machine learning) and the choice regarding the selected parameters (for example, the number of topics).

Another reservation that could be made is that evaluating less than 100 solution ideas, which are neither highly technical nor complex, is not a context where the bounded rationality of seekers is a source of concern.

Therefore, our *boundary conditions* are set around using this system with idea challenges with at least 30 ideas with short descriptions. Other solutions, such as Embedded Topic modeling,[2] might perform better in the case of ideas with a long description. Moreover, we point out that our explanatory instantiation outlined in Section 3.5 serves the purpose of setting the foundations of the artifact, which needs to be further developed in more demanding and complex settings, such as tens of thousands of highly technical solutions from numerous knowledge sets, which require specialist knowledge to be correctly understood, evaluated, and integrated.

The second research question asked how to support filtering of satisficing ideas considering the knowledge informing the problem representation of the seekers. The solution proposed in Table 2 is to increase the crowd's quality. As shown in Section 2, the relevance of this question comes from a general underrepresentation of transactivity in the literature about idea challenges. Our second *claim* is that the idea pooling function can identify links among ideas and show which ideas are combined. The *theoretical ground* for this claim is described in Section 2: the notion of transactivity explains how idea providers work together to improve their initial ideas, but it needs to explain clearly how to implement this concept. Knowledge combination is known to increase the quality of the best ideas (Malhotra and Majchrzak, 2014), and peer feedback increases transactivity since individual ideas can act as a catalyst for the crowd (Boons and Stam, 2019). Moreover, in Section 4, we offered supporting *evidence* for our second claim. Using a chord diagram, we have shown the text similitudes across ideas in the same challenges and between Stage 1 and the best ideas of Stage 2. This approach allows idea seekers to rapidly assess which competitions increased the knowledge exchanges among participants and act accordingly.

Nonetheless, a possible *reservation* regarding our approach concerns the need for more empirical testing of our hypotheses. Moreover, the participants in our competition were willing to cooperate and share knowledge. In contrast, participants in other competitions might have concerns regarding the creation, sharing, and/or appropriation of

[2] See, for example, https://cran.r-project.org/web/packages/topicmodels.etm/index.html (Accessed: 14 December 2023).

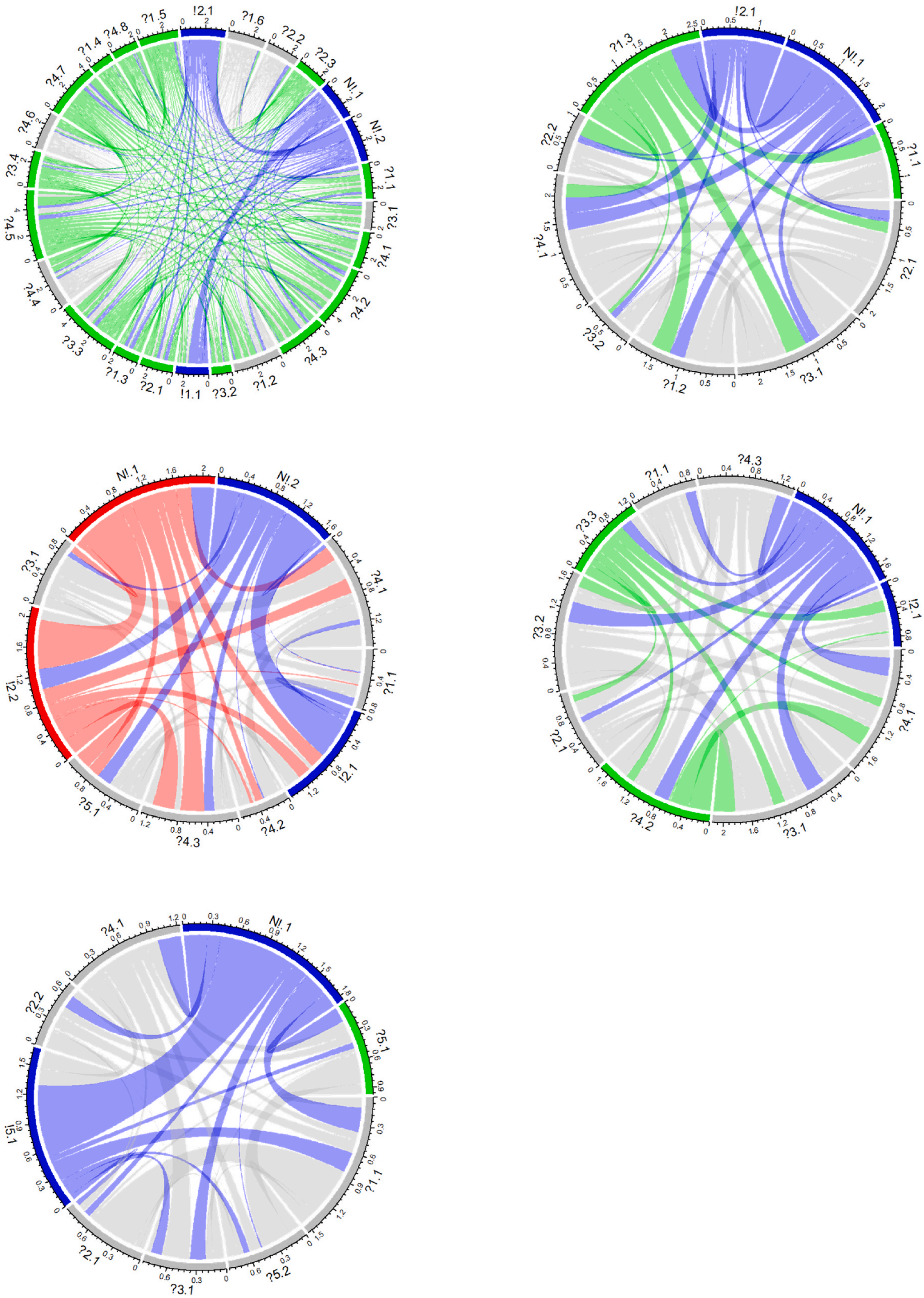

Fig. 5. Assessment of transactivity across five different challenges. False negatives are shown in grey, true negatives are in blue and true positive in green. False positives are in red. Links among ideas show contributions between Stage 1 and Stage 2.

intellectual property.

Therefore, our *boundary conditions* are set around this visualization for a dashboard while keeping the idea filtering algorithm as a support system. In the future, we intend to improve the performance of the filtering algorithms by adding decision rules based on the data collected by the idea pooling function. Additional work will be required when testing the idea pooling features in a context where participants cooperate and compete simultaneously. Finally, as mentioned above, our model is appropriate for just one type of crowdsourcing, where the crowd targeted is not a specialist crowd; thus, future work will address other types of crowdsourcing, namely the one seeking high skills in the crowd.

6. Conclusion

This article questions crowdsourcing as a way for organizations to create and capture value. In particular, the paper has considered ideas and organizing forms emergent from the challenges as sources of sustainable competitive advantage, eventually rare, imperfectly imitable, and not substitutable. In line with the current stream of contributions that adopt big data, data science, and analytic models for data-driven research either at the theoretical or empirical level, we have considered semantic networks with the joint use of clustering techniques and text mining for the analysis of the data from the challenges made available on the website “All Our Ideas” (www.allourideas.org) and from the *YourVision2021* inter-company and participatory project of the University of Milan-Bicocca, Italy. Here, it is worth mentioning that the semantic network analysis for the projects has shown how relevant ideas evolve during the challenge and how a seeker can eventually consider them for a potential portfolio of ideas that complement the one, resulting in the winning idea at the end of the project. Notwithstanding, the current work is at an exploratory stage.

Further analysis is ongoing for moving from descriptive insights to a theoretical contribution grounded on data and based on the application of analytic tools. The following summarizes the theoretical and managerial contribution of our artifact’s instantiation and evaluation. Then, we mention the limitations of research and future work.

6.1. Theoretical contributions

The article’s theoretical contribution presents an artifact that addresses the bounded rationality of the seekers in crowdsourcing, especially supporting them in sorting and selecting ideas. Thus, the contribution is not incremental or alternative to other theories but addresses the issues they have pointed out and designs instrumental tools to solve them. However, the proposed artifact could eventually contribute to “trigger efforts to develop new theory or adapt existing theory” (Romme and Holmström, 2023, p. 2). As to this issue, compared to other state-of-the-art articles, in this paper, we don’t look for the design of our artifact at the antecedents that can orient the adoption and use of crowdsourcing by seekers, (Gurca et al., 2023; Jain and Deodhar, 2022; Ye et al., 2017) or the incentives needed for improving the quality of the solutions received with crowdsourcing (Moghaddam et al., 2023). The proposed artifact targets instead the cognitive burden of the seekers when faced with sorting large numbers of ideas and identifies *filtering* as a critical point of the application (Piezunka and Dahlander, 2015) of techniques such as topic modeling. Then, the proposed artifact targets the potential biases connected to the problem representation that the seekers make up for asking solutions to the crowd; here, we have identified *pooling* as the critical point of application of clustering techniques to visualize ideas not eventually selected according to the problem representation of the seekers.

Also, we have connected the filtering of the seekers to transactivity among solvers, exhibiting them as fundamental mechanisms addressed by our artifact for making crowdsourcing a valuable resource for organizations. To the best of our knowledge, that connection has yet to receive attention from theory-driven research in crowdsourcing innovation management; thus, our artifact could be considered an early research effort on the topic, although at an instrumental level, eventually triggering further theory-driven research, likewise. Accordingly, the proposed artifact aims to act on the seeker’s bounded rationality in terms of effort and bias in assessing the crowd’s quality to improve the understanding of the relevance of transactivity and the quality of the proposed solutions. Thus, also, in this case, we see a specific role of the seekers on the performance of the solvers. In summary, the artifact connects at the instrumental level the transactivity of the solvers to the seekers’ effort and the assessment of the crowd’s quality, respectively, thus advancing that they could be considered elements of an emergent transactive memory system - TMS (Brandon and Hollingshead, 2004). This argument emerges from an instrumental tool and opens a potential research subject for theory-driven studies on crowdsourcing innovation management. This point is relevant for our paper, which presents a solution-oriented contribution to the literature on intermediaries. We especially look at the stream considering the cases where the human and organizational intermediaries are connected to technical or digital tools that intermediate their search and collaborative goals along the innovation value chain (Katzy et al., 2013). As to these issues, in this article, we have presented an artifact that can improve the decision-making processes where searching activities like crowdsourcing are intermediated by digital platforms, besides other human intermediaries.

Then, the presented research contributes to applying the computational techniques adopted by our artifact. As to this issue, we have collected empirical data to support using unsupervised classification algorithms based on text analysis for idea challenges with a small number of ideas. This raises questions at a theoretical level on the minimum number of ideas needed for satisficing solutions while preserving the diversity of the contributions, a goal that the pooling of ideas in our artifact addresses considering the challenges and gaps highlighted by other state-of-the-art contributions (Davis-Stober et al., 2015; Hong and Page, 2004; Piezunka and Dahlander, 2015). Moreover, we suggested that topic modeling might give insights to idea seekers and increase idea quality, thus addressing the issue of problem representation as an essential element of the bounded rationality of the seekers influencing their understanding of the problems to be solved by the crowd (Wahl et al., 2022). Finally, our paper contributes to increasing the corpus of design science research on using artificial intelligence in innovation management initiatives (Füller et al., 2022) with a specific focus on crowdsourcing.

6.2. Managerial contributions

As for the managerial contributions of the paper, we designed a method based on open-source and free software, which small and big firms can quickly implement. By lowering the cost for idea assessment in Step 1, the idea seeker can use the resources to improve the idea challenge and take advantage of the gain in time. Considering the application to our case study, the idea seeker would have to assess 35 ideas instead of 57. Assuming that three reviewers evaluate each idea and each reviewer needs 10 min to assess an idea, our approach will save 22 ideas $\times$ 10 min $\times$ 3 reviewers = 660 min (11 h).

Moreover, by increasing the quality of the ideas, the idea seeker can increase the return on investment. Finally, by considering filtering and transactivity as crucial mechanisms for making crowdsourcing a valuable, rare, inimitable, and non-substitutable resource for organizations, these latter must focus on appropriate organizing mechanisms and capabilities suitable to address the challenges associated with their bounded rationality like their problem representation and available knowledge.

Considering again the application to our case study, as shown in Table 5 and Fig. 6, we found 17 additional ideas that were not selected in Stage 2 but whose influence can be seen in the best ideas of Stage 2. Since they were not selected, we cannot give economic value to those

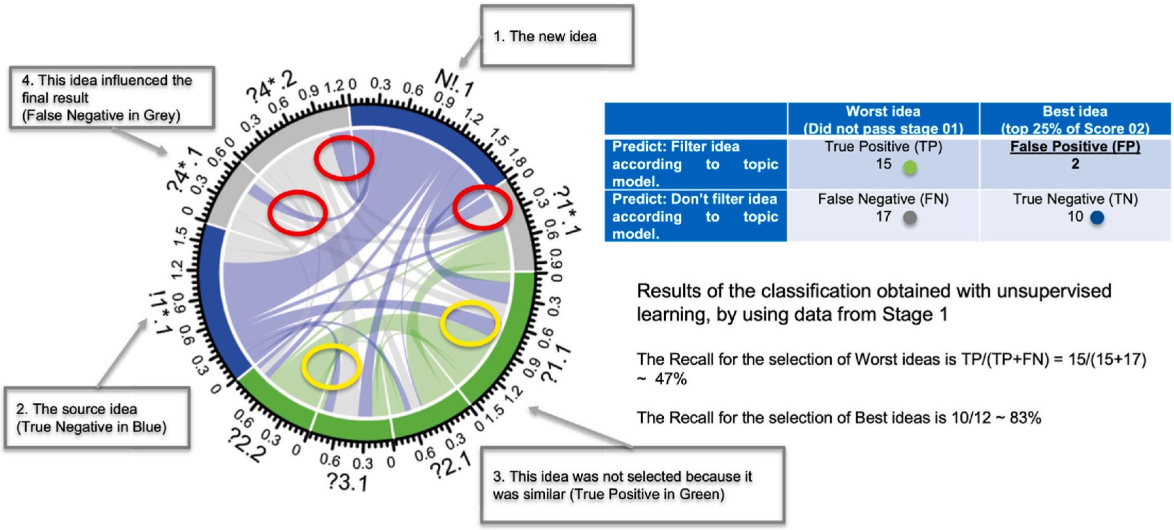

Fig. 6. Assessing crowd quality. A summary of Fig. 4 and Table 5.

ideas. Nonetheless, we can look again at the circle shown in Fig. 6, which describes challenge 2, *"Mindset and digital vision":* the grey ideas came from topics 1 and 4. Topic 01 concerned *digital mindset across generations*, whereas topic 04 concerned *fear of robots*. Thanks to the combination of those two topics, the selected idea went beyond the initial guidelines of the idea seeker. Hence, the idea seeker gets better ideas and questions to ask to gather more ideas in the future.

6.3. Limitations and further research

Future work will be focused on the quality and type of expertise emerging from further digitalization and automation of ideas challenges based on a larger dataset of ideas. Also, we are going to develop a qualitative study on seekers to understand how they make sense of the outcomes of the challenges as well as whether they enact learning dynamics during the analysis and selection process (Daft and Weick, 1984; Weick et al., 2005). Notwithstanding the current limitations, we believe that the study outlined in this paper would represent the first step toward an improved understanding of how to exploit the opportunities offered by analytical tools for fostering crowdsourcing as a strategic resource for organizations, thus bridging the gap between technical and managerial perspectives characterizing the two state-of-the-art stances with regard those topics.

CRediT authorship contribution statement

Riccardo Bonazzi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Gianluigi Viscusi:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing. **Adriano Solidoro:** Conceptualization, Resources, Writing – original draft, Writing – review & editing.

Data availability

The data that has been used is confidential.

Appendix 1. How to select the right number of topics?

The function search of the R package STM uses a data-driven approach to selecting the number of topics. The function will perform several automated tests to help choose the number of topics.

Fig. 7 shows the example for challenge 1: "People and relationships between physical and digital workplace."

The Held-out likelihood and *residual analysis* give a good understanding of the model fit: the held-out likelihood is highest between 11 and 21 topics, whereas the residuals are lowest between 13 and 30 topics.

Semantic coherence and *exclusivity* focus on the quality of the topics: between 10 and 14 topics, the most probable words in a given topic frequently co-occur together, and that delivers topics with a combination of words that seem reasonable to humans. The lower bound for exclusivity increases with the number of topics, and that makes sense since having more topics allows to have words that are exclusive to only one topic. In the end, the good number of topics for challenge 1 is between 13 and 14.

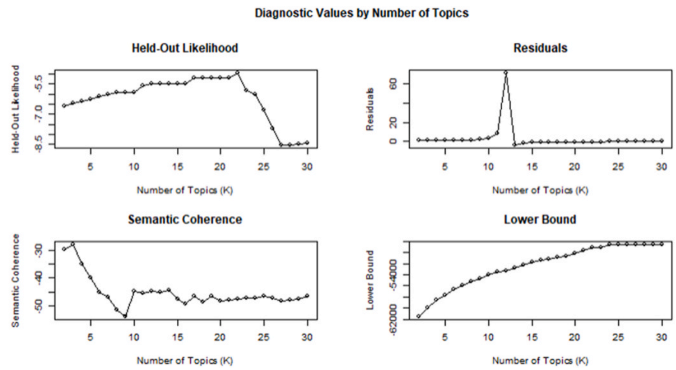

Fig. 7. Example of metrics to determine the right number of topics for challenge 1.

Appendix 2. Details about the three design science research cycles

	Cycle 01: Exploring the potential of topic modeling	Cycle 02: Focus on the idea seeker and cognitive effort	Cycle 03: Extension to the notion of transactivity
Period	2019–2020	2020–2021	2021–2022
Problem domain	Most work in an idea competition is done manually.	Idea seekers want to obtain many ideas from an idea competition but then spend a lot of time filtering ideas.	Idea seekers are afraid to filter good ideas and struggle with the second stage of idea competitions where ideas are merged
Design requirement	How can we find the perfect quote across multiple topics?	How can we automatically filter ideas from online competition?	How can we filter bad ideas and pool good ideas together?
Solution domain: cumulated knowledge as a list of design knowledge (DK)	DK 1.1: Topic modeling using Latent Dirichlet Allocation (LDA).	DK2.1: Structural topic modeling instead of LDA.	DK3.1: Natural language understanding to pre-process data before STM. DK3.2: Machine learning algorithm for idea classification
Prototype tests	Data collected from multiple sections of Wikiquote	Data collected from multiple challenges of Allour ideas.org	Data collected from online competition
Communication of results	ACM collective intelligence 2020	Academy of Management Meeting (AOM, 2021); World Open Innovation Conference (WOIC, 2021)	Strategic Management Society Meeting (SMS, 2022)

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