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A Typology for AI-enhanced Online Ideation: Application to Digital Participation Platforms

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Abstract

Digital Participation Platforms (DPP) can enable a massive online participation of citizens in policy-making. However, this digital channel brings new challenges for citizens in the form of information overload and asynchronous dialogues. Various disciplines of online ideation provide different AI-based approaches to tackle these challenges, but the literature remains fragmented. In consequence, this paper develops a typology for online ideation consisting of six types of AI-enhanced solutions. The application of this typology to DPP shows a prominence of automated tasks, with few AI-human loop approaches, and a current lack of applications at the collective level. This general typology also allows us to compare current DPP solutions to other fields, such as open innovation or recommender systems, and to use these fields as inspiration for future solutions. Overall, this paper suggests a theoretical foundation to analyze AI-enhanced online ideation under the form of a typology. Its application to DPP enables identifying future research opportunities and serves as a basis to develop complex architectures for the use of AI in DPP.

Keywords: Digital participation platforms, E-participation, Idea generation, Artificial intelligence, Collective intelligence.

1. Introduction

The use of Digital Participation Platforms (DPP) has increased the number of citizens participating in policy-making activities, and thus fostered digital mass participation at different policy levels (Naranjo Zolotov et al., 2018). This has multiplied the amount of data generated, leading to new challenges such as information overload for participants (Arana-Catania et al., 2021) and difficulty to establish connections and discussions (Aitamurto and Saldivar, 2017).

Information overload describes the problem of comprehending and utilizing vast amounts of data due to the limited cognitive capacity of humans (Chun and Cho, 2012). This phenomenon is specially troublesome in digital participation activities based on the generation of ideas, such as crowd-sourced deliberation, participatory budgeting or idea contests. In these activities, citizens submit their ideas, vote and comment them with the possibility of combining and expanding other ideas. In that context, a limited capacity to interact with the information being generated affects the outcome of the ideation process (Fu et al., 2017) and the motivation of participants.

Digital participation platforms introduce new forms of online discussions and interactions but also complexify them (Aitamurto and Saldivar, 2017). Each participant can access the platform at a different time with no guarantee of actual real-time discussions. This makes participants replicate most of the traditional dialogue features by "finding" themselves related ideas from the pool of contributions, and reacting to their similarity or contrariness (Arana-Catania et al., 2021). These actions become more complex and less appealing as the number of contributions increases, reducing the feedback to ideas submitted by other citizens and thus the quality of the collective intelligence outcome.

The capacity of Artificial Intelligence (AI), and more specifically Natural Language Processing (NLP) techniques, to process large amounts of data makes it an ideal candidate to solve these two challenges. To tackle the impediments of information overload, we can encounter in DPP successful examples of the classification of proposals (Romberg and Escher,

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2022), summary of proposals (Segura-Tinoco et al., 2022) or the identification of citizens with similar ideas (Arana-Catania et al., 2021). To reduce the effects of the asynchronicity and lack of interactions, the open innovation field suggests features such as the tracking of ideation dynamics (Liu, 2017) and AI-generated individual feedback (Kenworthy et al., 2023; Zhou et al., 2020), but there are not present in DPP yet.

In fact, AI-driven solutions to ideation processes are scattered across various fields: open innovation (Aggarwal et al., 2019), citizen science (Zhou et al., 2020), recommender systems (Quijano-Sánchez et al., 2020) or e-participation (Segura-Tinoco et al., 2022). This diversity provides a rich variety of solutions that could be transferred and exploited by DPP. However, the scattered literature between fields makes it hard to evaluate the current state-of-the-art, the level of compatibility between these approaches, and their relevance for DPP.

In this paper, we tackle this issue by analyzing the literature at a more abstract level. We define a typology common to all the AI-enhanced solutions related to ideation processes, which allows us to comprehend and to evaluate the current challenges and opportunities in the DPP case. Then, we use this typology as a methodological tool to evaluate future avenues and challenges in the use of AI in digital participation platforms.

2. Methodology

To evaluate current and future AI-enhanced solutions for DPP, we develop a typology to be used as a methodological tool to facilitate the comparison between DPP and instances from different fields. This tool allows us to understand the current state of the art and to theorize about future applications in the context of e-participation.

Typologies are primarily conceptual top-down approaches which are deductively built based on first order constructs or dimensions (Bailey, 1994). These dimensions are combined into ideal types that represent a unique combination of values within the describing dimensions. The development of a typology allows us to define ideal types of AI solutions for online citizen ideation. In a still emerging topic, we consider that the definition of these ideal types can help researchers to understand the different characteristics of these solutions and to build more complex approaches.

While being a conceptual approach, an empirical study of the phenomenon under review may help to derive a typology (Stapley et al., 2022). Thus, as a first step, we reviewed the literature on current AI solutions from which we could derive the essential dimensions. First, we conducted a Scopus search based on title, abstract and keywords using the search terms (AI OR “Artificial intelligence”) AND (“Idea generation” OR “E-participation” OR “Participatory budgeting” OR “Open innovation” OR “Citizen science” OR “Digital participation platforms”) for articles after 2009. A coverage check was performed on Google Scholar with the same keywords, verifying that no new papers emerged in the ten first pages of the search. Relying on this coverage check verification, and given the multidisciplinary approach of the typology, other databases like DGRL[1] were not used. Overall, the searched provided 483 articles that were then filtered to 46 based on the evaluation of the abstracts. Subsequently, we used the snowball method where the key articles found through the Scopus search were used as a starting point to find other relevant papers. In total 64 papers were used to develop the typology and identify existing solutions in the literature.

We initially coded all papers based on their methodology, AI contribution and field of application. To build the typology we took inspiration in the four steps’ typology building approach of Kluge (2000): definition of analyzing dimensions, grouping cases, analyzing empirical regularities and finally constructing the types. In this work, the main question assessed by the typology refers to how AI is involved in the online ideation process. Thus, as part of the first step, the papers were mapped into a list of all encountered AI techniques and their role in the ideation. This allowed us to group the different works and analyze their relationships. Based on this classification, and grouping, two main dimensions were extracted. The first dimension regards the level of automation and the role of AI (Sætra, 2021). The second dimension is based on the scope, from individual to collective, at which the AI can help in collaborative processes (Chiang et al., 2023). These two dimensions, and the different spectrum values retrieved from the literature, were used to build the proposed typology and to derive six ideal types.

In addition, while iteratively developing the typology we were guided by four criteria (Scott and Davis, 2015):

- The typology is *intuitively sensible*. It captures the intuitive variables associated to the interaction with AI in a collaborative process. This criteria was used in the evaluation of the literature and the deduction of common variables.
- The typology is *collectively exhaustive and*

[1] https://faculty.washington.edu/jscholl/dgrl/

mutually exclusive. Our typology accounts for all types of AI-enhanced ideation activities, not only the ones related to DPP. At the same time, it provides mutually exclusive archetypes which are not necessarily independent. High level approaches, such as overarching AI architectures, would be considered a modular combination of some of these types.

- The typology has a *construct validity*. It defines specific spectrum values associated to each ideal type and it differentiates from other AI typologies (Hoekstra et al., 2021; Sætra, 2021). This criteria resulted in the addition of a second axes to represent the level at which the AI assistance is carried out during the ideation process, while the spectrum values were based on existing definitions associated to these dimensions.
- The typology should be *conceptually elegant*. In this case, it provides six ideal types based on two intuitive dimensions that rely on clear concepts.

The advantage of typological theories is that the ideal-type constructs allow to represent synergies and to move forward beyond the limitation of current applications (Doty and Glick, 1994). Accordingly, we used the typology to spot current gaps in the DPP literature and, based on the high level constructs, compare applications from other fields, deducing the properties potentially transferable to the citizen participation context.

3. Typology for AI-enhanced solutions in collective ideation processes

We propose a typology which is built along two main dimensions. The first dimension considers the role of AI while performing a given task, going from fully automated to human-based activities, see Fig. 1. We characterize the role of AI under the definition of the task. Based on the scope of the task, the AI-human interaction will have a role or another. The ideal types of the typology are associated to two specific values within this spectrum, established by the following definitions:

Automation: Machines taking over humans (Johnson et al., 2022). The outcome of the AI-assistance is directly the outcome of the planned task. The task is automated with no human intervention.

Augmentation: Humans and AI work in close collaboration (Johnson et al., 2022). The outcome of the AI-assistance is a step, a component or related to the planned task. The task performance of the human is augmented thanks to the AI-assistance.

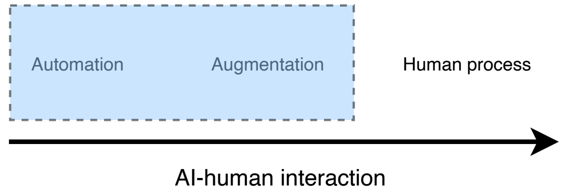

Figure 1. AI-human interaction spectrum and the selected range in this work.

An example of automated task in ideation processes can be found in the topic classification of proposals presented by Romberg and Escher (2022), as the task of classification is completely automated and carried out by an NLP algorithm. On the other hand, the AI-based argumentative feedback used by Borchers et al. (2023), which evaluates the contributions based on some criteria, *augments* the tasks of generating ideas in a collaborative group innovation.

The second dimension defines the scope of the AI solution, see Fig. 2. In collaborative processes, AI-assistance can be performed at the individual or group level (Chiang et al., 2023). This dimension ranges between these two extremes considering the cases of: individual level (enabling participation), peer-to-peer level (enabling interactions and communication) to the collective level (outcome of the process). These levels are formally defined as follows:

Individual level: It aims at enabling the individual factors affecting the participation, at a cognitive or informational level. The goal is to improve individual aspects or tasks.

Peer-to-peer level: It interacts and affects multiple individuals in one degree or another. The goal is to create communication and interactions between participants.

Collective level: The AI interacts with the ideation process at the global level. It focuses on the global outcome and the statistical aspect of the collaboration. The goal is to improve the overall outcome of the process.

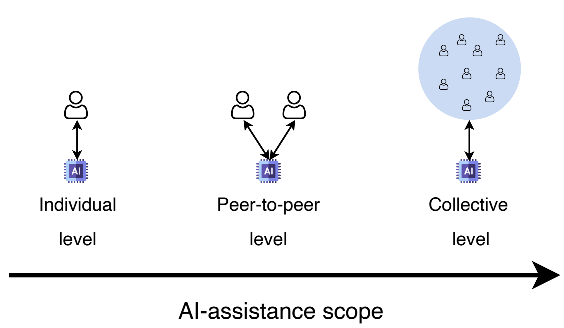

Figure 2. AI-assistance scope spectrum.

We can find examples in the literature belonging to the 3 specific levels considered in the spectrum. At the individual level, the feedback system from Borchers et al. (2023) uses individual information and provides an individual output. Peer-to-peer level applications can be represented by recommender systems (Egger and Yu, 2022) as they connect different users by comparing their individual information. Collective level AI can be observed in the use of network analysis to represent the ideation dynamics, as the information and outcomes of these analysis concern the overall process (Shin et al., 2022).

Note that a typology is a combination of constructs into ideal types (Negoita et al., 2018) defined by specific values of each dimension. As such, many applications could be identified as hybrids between two types.

The resulting typology provides six ideal types of AI solutions distributed along the two aforementioned dimensions. Each type is defined by the intersection of the different values associated to each dimension. The typology is summarized in Table 1. This table includes the description of each type accompanied by representative examples and implementations chosen from the literature to clarify the concepts presented. The following subsections develop each type and provide additional examples of their applications in several fields, with special attention to the cases found in digital participation platforms.

3.1. Processing tools

This type of AI-based solutions automates the processing of information at the individual level. The task is fully automated and the outcome is used at the individual level.

One of the main issues of online ideation is associated to information overload (Davies et al., 2021). The access to other participants' contributions can be complicated and discouraging. In this context, this kind of automated solutions can be very practical as the main goal of these tasks is to process high amounts of data.

NLP is a technology that has demonstrated to be very efficient in processing and summarizing unstructured text contributions (Egger and Yu, 2022). Examples of its use to label and classify contributions can be found in open innovation (Kenworthy et al., 2023), citizen science (Amarasinghe et al., 2021) and digital participation (Lago et al., 2019). **Citizen participation** presents several examples of application. Romberg and Escher (2022) show the advantages of semi-supervised techniques in terms of performance and classification time when labelling citizen proposals, while Arana-Catania et al. (2021) summarize these contributions helping the presentation of information to participants and practitioners. These ideas have been further exploited in the participation context, so as to provide the main argument of each contribution (Segura-Tinoco et al., 2022), allowing to classify ideas depending on their view with respect to certain discussion topics.

3.2. Recommendation tools

Recommendation tools are a type of AI solutions that automatize a process concerning several participants. While they affect several users, their approach is still related to individuals tasks and how they are interlinked. This type usually considers the task of creating these links automatically and explicitly.

In online ideation, automated processes can be used to connect users and contributions (Arana-Catania et al., 2021) or to help participants to connect with similar participants (Romberg and Escher, 2022).

Classifying contributions into topics allows to create an information space with all ideas. This space can be built based on semantic connections but also on users connections (Weng et al., 2023). The field of recommender systems has heavily exploited these aspects (Fkih, 2022), providing different techniques to measure "distance" between ideas, and also approaches to select interesting contributions for the user. Quijano-Sánchez et al. (2020) detail the potential of recommender systems in smart cities and their applicability to **digital participation platforms**, helping to create connections between participants. In this context, Cantador et al. (2017) demonstrates how these algorithms can be directly applied to participation activities for personalized recommendations.

3.3. Analysis tools

The third type of AI solutions that belong to the dimension value of automation are denoted as analysis tools. In this case, the information used by the AI belongs to the overall process and the outcome is also related to the ideation as a collective activity. The main difference with the previous type is that the data collected and the actions carried out relate to the process as an aggregate.

Considering the ideation process as a network and applying network analysis techniques to evaluate the process are examples of this type (No et al., 2017). Depending on how these networks are formed: semantic contributions, user interactions or contributions topics; they can provide different kinds of indicators (Siew et al., 2019).

Amarasinghe et al. (2021) use network modelling

Table 1. Typology of AI-enhanced online ideation activities

	Individual level	**Peer-to-peer level**	**Collective level**
Automation	Processing tools *Description:* Processing information that facilitates the individual tasks of the participants during the ideation process. *Examples:* Topic analysis (Romberg and Escher, 2022) *Implementation:* Summarize a selected proposal	Recommendation tools *Description:* Generating potential links in terms of proposals or users. *Examples:* Recommender systems Egger and Yu, 2022) *Implementation:* Find similar proposals/ similar users	Analysis tools *Description:* Generating quantitative indicators related to the outcome of the ideation process. Examples: Network analysis (No et al., 2017) *Implementation:* Identify topics and key contributors
Augmentation	Individualized feedback *Description:* AI interaction to improve the performance, motivation or knowledge of individuals. *Examples*: Individual performance feedback (Borchers et al., 2023) *Implementation*: Feedback on the suitability of a submitted idea	Enriching feedback *Description*: AI interaction to trigger knowledge relations and enrich the individual and collective inputs. *Examples:* Boundary spanner recommendations (Wahl et al., 2022) *Implementation:* Provide relations with other potential topics	Ideation feedback *Description:* AI interaction based on processed collective data to optimize the overall creativity process. *Examples:* Feedback based on ideational dynamics (Kenworthy et al., 2023) *Implementation:* Feedback to develop more current ideas or move toward unexplored areas

to characterize the ideation process in citizen science, identifying main contributors and important ideas thanks to the network topology. In this context, Chen et al. (2019) show how building semantic networks can be later used by exploring algorithms afterwards to the creativity of successful ideas. In **digital participation platforms**, these indicators can also be used as a way to compare the evolution of different participatory budgeting processes (Shin et al., 2022) facilitating the evaluation of their outcomes.

3.4. Individualized feedback

When the AI-human interaction helps individuals to carry out a given task we denote these solutions as individualized feedback. In these cases, there is an individual interaction between AI and human that helps to improve the outcome of the human task.

In online ideation, individualized feedback solutions have a great potential. They keep a human-centric approach while being able to overcome several handicaps of the online ideation. Precisely, in digital participation platforms, one of the main concerns in this kind of activities is the participation of citizens and their engagement during the process.

In ideation activities, individual feedback has been explored from different angles depending on the discipline. Jung et al. (2010) studied the importance of feedback in collective innovation activities, showing how performance feedback at the individual level also improved the collective outcome of the process. Zhou et al. (2020) studied in detail the effects of feedback and its different modalities in citizen science activities. They divided the feedback actions into 3 groups: motivational, reinforcement and informational, showing how they differently affect the individual behaviour.

Citizen participation has provided several chatbot solutions aiming at this augmentation of the individual experience (Androutsopoulou et al., 2019). More specific to ideation, Borchers et al. (2023) provide an example of NLP approach which helps to understand if the contribution fits into a given topic, *augmenting* the performance of the participants in urban participation, and resulting in a more elaborated argumentation during the discussion.

3.5. Enriching feedback

Enriching feedback is a type of AI solution that focuses on creating additional connections between participants and distant knowledge spaces. In this case, there are not explicit links to other ideas/users, but the AI provides the participants with the tools and knowledge to create the links themselves, implicitly or explicitly. This type of AI-assistance can help to enlarge the knowledge and scope of the contributions. These solutions concern several participants while acting on their individual outcomes.

Boundary spanners are participants that help to create connections of knowledge between different topics discussed (Shi et al., 2023). This kind of participants are of great importance to improve the outcome of these collaborative activities.

The use of AI could replicate the role of boundary spanners and increase the interaction between different knowledge fields. Wahl et al. (2022) use AI-generated stimuli from other perspectives to affect the idea outcome in innovation, providing early examples of these kinds of applications. While these solutions are not found yet in the literature of **digital participation platforms**, given the importance of their human counterpart, their development offers a high potential.

3.6. Ideation feedback

Ideation feedback represents the AI-based solutions that aim to augment the overall performance of the ideation process by focusing on the collective outcome. This means to influence the collective behaviour, e.g. promote certain topics, so to improve some global indicators associated to the online ideation activity.

The sharing of information and knowledge in online ideation platforms can be disrupted by the characteristics of digital discussion, which hinders the final outcome of these activities and the convergence of some ideas. These obstacles can be overcome by monitoring these outcomes and providing feedback to lead the contributions towards more effective areas.

Works on AI and machine learning have explored how the ideation dynamics evolve and which way AI feedback can help to improve this overall process (No et al., 2017). In the open innovation field, Kenworthy et al. (2023) study the development of a computer-assisted assessment of ideation dynamics which would help to improve the discussion's semantic space towards more successful ideas.

In **digital participation platforms**, personal interests of citizens are sometimes hard to convey into more general and aligned ideas (Aitamurto, 2016). While more advanced concepts of ideation feedback are not yet applied to citizen participation, promising results can be seen in AI-based agents facilitating crowd discussions (Ito et al., 2022).

4. Applying the Typology to Digital Participation Platforms

The presented typology provides an overall picture of the potential use of AI in online ideation activities. The definition of ideal types allows us to analyze the current solutions based on these references, their similarity with respect to other fields and to identify which are the main elements missing in the current literature on digital participation platforms.

4.1. Typology as a lens to identify research gaps

In this section, we specifically frame our typology to the field of citizen participation. In it, we briefly summarize and group examples of DPP applications that relate to the different ideal types. Figure 3 represents the current outlook of AI solutions with respect to the presented typology. The maturity and number of current applications is represented by the opaqueness of the colored area. The purpose of this figure is to provide a synoptic summary of the current state of AI solutions in DPP and the current gaps.

Current citizen ideation solutions are primarily represented by processing and recommendation tools. Topic analysis (Romberg and Escher, 2022), summary of contributions (Arana-Catania et al., 2021) and recommendation of contributions (Cantador et al., 2017) are examples of implementations that are equivalent to these ideal types. The last type associated to automated solutions, analysis tools, is less present, but we can still find the use of big data to compare the performance of different sessions of participatory budgeting (Shin et al., 2022). In general, while there are less examples of automated processes evaluating collective and complex indicators, AI solutions based on the automation of tasks are frequent and display promising results.

In the augmentation category the picture is different. Individualized feedback is found in AI-assistance so to improve the quality of the contributions (Borchers et al., 2023) or to improve the participation experience (Segura-Tinoco et al., 2022). However, while enriching feedback and ideation feedback are types of AI solutions that are found in other fields such as innovation and creativity groups, they are still rare in citizen participation. In general, as we move forward in any of the axes of Figure 3 (towards collective and augmentation levels) less applications in digital participation can be found.

Overall, most solutions in DPP belong to the individual level. Processing tools and individualized feedback have provided very interesting results with applications to city-scale platforms such as *Decide*

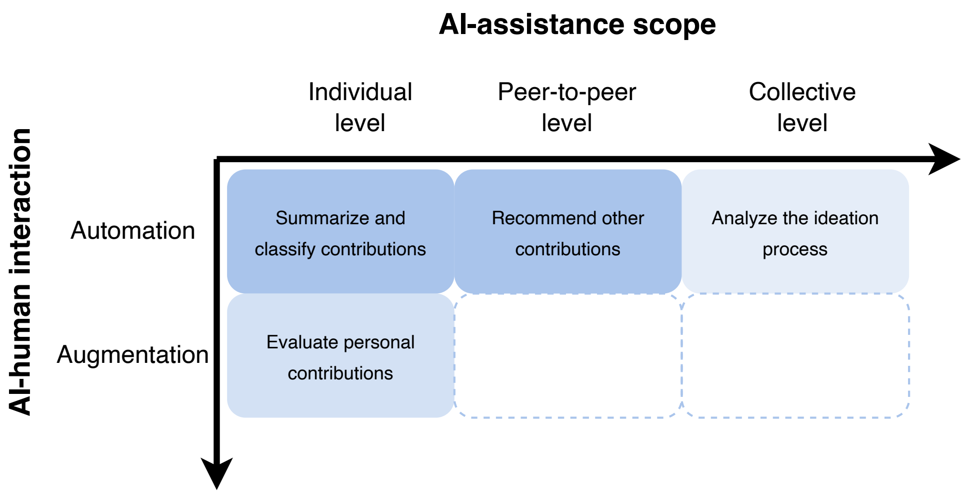

Figure 3. Current AI-enhanced solutions for ideation in digital participation platforms.

Madrid and *Decidim Barcelona* (Smith and Martín, 2021). At the peer-to-peer level or collective level, however, successful applications are still missing, primarily in the augmentation spectrum. From a research point of view, this situation can be seen as a potential niche to test ideas from innovation and citizen science so as to better lead citizen's input towards a more effective outcome for policy making or service development.

From the comparison with other disciplines, it can be spotted that fields like open innovation or recommender systems exploit more the similarity and knowledge connections between participants. This transfer of knowledge towards digital participation platforms has already been tested successfully (e.g., Cantador et al., 2017) as automation solutions have the advantage of being more easily transferable applications between fields. On the other hand, collective oriented applications such as analysis tools and ideation feedback, while tested in citizen science (Amarasinghe et al., 2021) or innovation (Kenworthy et al., 2023), are still very scarce in the citizen participation context.

4.2. Typology as the foundation of a global architecture

Another lecture to the current state of AI-based DPP applications, and the absence of more collective approaches, can be made based on the nature of these activities. Digital participation platforms have a dual nature, they are instruments of dialogue to improve the interaction and trust between government and citizens, and at the same time they are socio-technical systems that aim to optimize the number and quality of ideas generated. This duality makes the inclusion of AI in a global overarching approach a real challenge, contrary to other crowdsourcing idea generation activities, such as open innovation, where the collective goal (successful innovative ideas) is clear.

In this case, it is necessary to define collective and individual objectives together while understanding their complementarity. The typology, varying scope and level of automation, does not have to be seen as a guide for transitioning from automation towards augmentation or individual towards collective. The ideal types are different approaches which are useful in different contexts and that are not mutually exclusive. In fact, we argue that these different approaches should be combined according to the aforementioned goals. Notably, this combination in the context of DPP, taking into account citizen and governments goals, remains one of the main impediments for the implementation overall AI approaches.

Based on these challenges, relying on a theoretical framework such as Collective Intelligence (Salminen, 2012) could provide a structure to build upon, as it examines how from local interactions between individuals a more efficient collective outcome is generated, the so-called *emergence*.

Collective Intelligence (CI) is a form of universal "distributed intelligence which arises from competition and collaboration of many individuals" (Salminen, 2012). This paradigm, also referred to as wisdom of crowds (Surowiecki, 2005), is aligned with digital participation platforms, where one of the premises is to improve the decision of individuals and group of experts by aggregating individual knowledge from large citizen groups (Arana-Catania et al., 2021).

From a technical point of view, the next question concerns the selection of the AI approach used to reach this paradigm. Casadei (2023) defines Behaviour oriented CI as an artificial CI developed based on the coordination and cooperation problem, and Knowledge oriented CI as the case where the AI is in charge of the processing of information. Framed into our typology, the first case develops an architecture where the collective outcome is improved thanks complex ideation and enriching feedback that generates the phenomenon of emergence. In the second case, the AI is focused on enabling connections at the individual level and then using analysis tools to process and merge the information generated.

In other words, in knowledge oriented CI the emergence is explicitly enhanced by AI, and it creates a system where ideation feedback is implemented (Kenworthy et al., 2023). In Behaviour oriented CI the emergence phenomenon is developed naturally, by providing the right online ecosystem (individual and enriching feedback (Ito et al., 2022)). In both cases, the collective configuration to solve complex social problems based on dynamic connections is still an open problem (Galesic et al., 2023).

From a societal point of view, the next question is whether digital participation platforms should aim at optimizing the collective outcome of the ideation process, as it could be done in managerial innovation, or if the main focus should be exclusively on the enabling factors for participation. Given the complexity, possible bias and difference in objectives, certain goals of applying AI to these activities should be re-evaluated from a societal perspective.

5. Discussion and Conclusion

This paper provides a typology of AI-based solutions for online ideation activities which is later framed into the context of digital participation platforms. The typology brings a general overview of the possibilities and the current state of AI-enhanced solutions. This general approach is necessary to understand relations with other fields to design more complex solutions.

The main theoretical contribution of this work concerns the conceptualization of AI-solutions for DPP. On the one hand, by developing the typology we provide a reference to determine “what is” in terms of AI-enhanced DPPs. This can be seen as an analysis theory (Gregor, 2006), which is one of the missing foundations in the literature of AI applied to citizen participation. At the same time, as pointed out by Doty and Glick (1994), typologies can be used to study “how to” develop new solutions. Thanks to the generation of ideal (not necessarily existing) types, our typology could help to generate explicit prescriptions to further develop a design theory on AI-enhanced ideation.

Similar typologies regarding AI solutions have been proposed in the field of politics (Sætra, 2021), public institutions (Hoekstra et al., 2021) or innovation (Paschen et al., 2020). The main difference with respect to our typology is that, given the different levels of granularity within the collaborative ideation process, we consider an additional dimension related to the level of abstraction at which the AI will perform its activities.

Concerning the limitations of this study, conceptual and methodological aspects could challenge the validity of the presented typology. From a conceptual point of view, the methodology used to develop the typology has a certain subjective component, which added to the will to obtain simple and usable types, might lead to some loss of granularity. Additionally, other aspects of the nature of AI, such as which type of techniques are used (e.g., ruled-based AI or probabilistic AI) are not explicitly tackled by the typology. We argue that this specificity would not provide additional descriptiveness in an exploratory work on a still emerging field. However, these additional features could be extended in future works or be investigated by other typologies more focused on these other dimensions.

From a methodological point of view, the literature-based approach used to build the typology could be biased by works not covered by our search or AI solutions not published in the scientific literature. In this sense, future works will focus on the development of guidelines to build more complex and general AI approaches (Section 4) for digital participation platforms. We aim to devise these guidelines relying on the Collective Intelligence framework and by performing interviews with practitioners and participants, so to formalize the objectives and requirements in the definition of the AI-enhanced tasks. These steps will help to evaluate and to refine the exhaustiveness of the typology.

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