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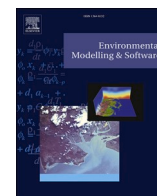
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Participatory modeling in the AI era

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A B S T R A C T

PM is a now established approach to improve the utility and actionability of modeling for decision making and management. With the advent of the AI era, there are multiple avenues for its use in the context of PM. We reviewed a number of recent papers that describe how various AI tools have been used to assist the PM process, both in improving the quality of modeling and the participation efficiency. We have identified AI applications that can help stakeholders in the process of knowledge acquisition and decision making during the steps of the PM process. We also looked at how AI has been put to several innovative uses in PM related areas, such as collective intelligence, deliberative democracy and participatory governance, and how these can be adopted and used in the PM process. These enhancements escalate in degree of AI intervention and autonomy. They start with augmenting approaches such as informing, modeling and data processing, and can lead to deeper AI engagement such as assisted facilitation and communication. The enhancements can include the use of AI agents as stakeholder assistants, but may also result in an increased delegation of human stakeholder tasks, and eventually possibly in the replacement of stakeholders in PM. We have identified the benefits of such AI penetration, and also found several risks and challenges that it presents in the PM process. The most threatening include risks associated with AGI and possible supplantation and surpassing of human abilities in decision making and management without meaningful controls and regulations put in place. We suggest that some coordination of efforts from all involved parties across the whole spectrum of countries and businesses is essential to ensure that humans can have a measure of control over their destiny. So far, neither the PM community, nor society at large are anywhere near implementation of the essential agreements, controls, and protective measures needed. We conclude that a critically considered, well organized, PM process could be used to engage all the interested parties and agents to account for the feedbacks and lessons learned and develop these much needed regulations, treaties, checks and balances.

1. Introduction

Participatory modeling (PM) has emerged as a way to make modeling more useful and more actionable for decision making and management (Voinov and Bousquet, 2010). As more models have been built and are subsequently better calibrated and validated, they have led scientists to a deeper understanding of socio-environmental systems and processes. However, it also has become increasingly obvious that there is a problem communicating model results to decision makers, and converting the knowledge acquired through analysis of these results into real changes in policies, regulations, management and planning (Sterling et al., 2019; Hedelin et al., 2021). There is an increasing demand for “actionable” science, for ways to make decisions and act based

on accumulated scientific knowledge (Palmer and Boyd, 2025).

One solution is to engage stakeholders in the modeling process to achieve the following:

- Knowledge sharing/dissemination and social learning.
- Leveling the playing field by ensuring that all stakeholders have: (1) access to the same information, (2) the same minimum basic understanding of the system and problem, and (3) an equal say in discussions and deliberations that evolve from this assimilated knowledge.
- Ensuring that the model delivers enhanced insight necessary for informed decision making. Having shared modeling goals and engaging in model development and analyses can enhance trust with

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stakeholders and improve PM-based physical, economic and social outcomes.

- Guiding the selection of the most appropriate modeling approach, ensuring that the model is ‘fit for purpose’, but not overly complex and contains the critical processes and elements.

Achieving the above goals has often led to improved modeling and decision making (Voinov and Bousquet, 2010; Ma et al., 2024). PM has developed as “a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality” (Jordan et al., 2018). Obtaining facts, information, and data can enhance decision making in PM or any kind of participatory engagement. Yet, a learning process is invariably subjective and also depends on questions of value – which affect the data, information or facts that are available, believed, or cherry-picked (Glynn et al., 2022a, 2022b; Voinov et al., 2014). PM constructions of reality are highly dependent on cognitive perceptions (or lack thereof), biases, beliefs, heuristics, values and social norms (i.e., what we term BBHV) (Glynn, 2017; Glynn et al., 2017).

This is because humans are adapted by biocultural evolution (Wilson et al., 2023; Richerson et al., 2010; Glynn et al., 2025). Wilson et al. (2023) views genes and culture in a dynamic feedback loop accelerated by symbolic thought and language while Richerson et al. (2010) maintains that genes and culture display inheritance systems - culture being faster and able to utilize more flexibility. Both paths foster the acquisition of knowledge (Walter, 2014; Mishra et al., 2015; Scrivner, 2024) using information and approaches from several sources (Cockerill et al., 2024), including:

1. Observations based on consciously explicit experimentation, detection of patterns, and logical deductive thinking;
2. Individuals providing information and feelings tacitly or through repeated experiential learning;
3. Social transmission adopted through acceptance or mimicry of statements or positions provided by trusted individuals (or non-acceptance from distrusted individuals);
4. Sharing and assimilation through mimicry of prevalent group beliefs, thinking, behaviors, norms and values, largely resulting from biocultural evolution and adaptations to the past.

Knowledge is produced by blending the information with feelings, preferences, values, which can reinforce each other or be in conflict. Hume (1739) stated that reason in humans can not be dissociated from emotions – unlike with machine calculations and deductions. One of the benefits of PM is that by co-learning, co-designing, co-planning, and co-managing, PM seeks to reconcile existing differences and uncertainties among participants, engage the participants in improved shared decision making, and foster social trust and actionability in the resulting decisions. Recently, new technologies grouped under the label of “Artificial Intelligence” (AI) have emerged which increasingly are penetrating the PM process. AI affects modeling and decision making in multiple areas of societal interest.

For the purposes of this paper, we define AI as extended cognition or performance capabilities provided by means of digital processing of information. This is in contrast to the human brain where analogue information processing takes place. AI systems are designed to perform tasks that typically require human intelligence, such as recognizing speech, making decisions, understanding language, and visual perception. Intelligence, in general, can be defined as the ability to learn, understand, reason, solve problems, adapt to new situations, and apply knowledge to navigate and interact effectively with the world. It involves not just the capacity to acquire knowledge, but also to use that knowledge in flexible and creative ways across different contexts. Intelligence can include skills like critical thinking, emotional understanding, decision-making, and even the ability to predict outcomes based on past experiences.

The AI industry often refers to three different categories of AI (IBM Data and AI Team, 2023; Johnson, 2024):

- Artificial Narrow Intelligence (ANI) or “weak AI” is a type of AI designed to perform a specific task or a limited set of tasks. This is what is already available from ChatGPT and numerous other AI models that are becoming more prevalent and effective at performing specialized functions within a defined scope.
- Artificial General Intelligence (AGI) or “strong AI” is a machine that possesses the ability to understand, learn, and apply knowledge across a wide range of tasks, much like a human; it is not limited to specific tasks like current narrow AI systems, but can adapt, reason, and solve problems in diverse domains. The level that we are likely to reach in the next 3–5 years, or to some extent even in 2025 according to Geoffrey Hinton (The Times of India, 2024).
- Artificial Super Intelligence (ASI) (IBM Data and AI Team, 2023; Johnson, 2024) is a theoretical form of AI that surpasses human intelligence in all aspects, including problem-solving, creativity, and emotional understanding. It is hard to predict when it will come, though it is likely to arrive earlier than we expect.

While we do not have any scientific evidence that ASI is imminently realized, current trends suggest that it is possible. This is because there is an exponential growth of computer power and AI functionality, coupled with evidence of humans slowing down or even regressing in their cognitive abilities and intellect (Bratsberg and Rogeberg, 2018). Moreover, it appears that this human ‘dumbification’ is accelerated by widespread use of AI tools (Kosmyrna et al., 2025).

The AI knowledge acquisition process differs considerably from human approaches in that AI is likely to discount the importance of emotions, sociality, and the unconscious. For AI these factors are simple data points that have to be processed. While PM has always been seen as a way to reintroduce science and technology back to emotional human deliberations and discussions, AI provides an alternative approach, raising questions about the efficiency of human knowledge acquisition process and optimality of the existing decision making processes.

The goal of this paper is to provide an assessment of how PM is being affected by the use of AI, and what benefits and problems may arise from future AI use in PM. To do so, this paper examines anticipated major challenges, the promises and potential peril of AI application in PM, focusing on the management of natural resources and environmental issues while drawing upon knowledge from many other fields of study and potential new areas of application. There are very few papers already published on this topic: e.g. Du et al. (2024), which focuses on participatory planning in the urban context. In contrast, our paper also looks at PM related areas, such as collective intelligence, deliberative democracy and participatory governance, on how AI has been put to innovative uses in those areas, and how these can be adopted and used in the PM process.

In the context of PM, AI is currently being utilized in two ways that are significant for future development and application:

1. On the ‘modeling’ side we see a proliferation of AI/ML generated models, which changes the modeling process. This includes an advanced capability to obtain and process vast amounts of data, increasingly available due to proliferation of new data collection methods with sensors, remote sensing, citizen science, image recognition, natural language processing, with results posted on the internet.
2. On the ‘participation’ side we see that AI is increasingly affecting and engaging in human interaction, communication, exchange of ideas, and manipulation of thinking and decision making.

What role can AI play in PM? How can human society benefit from it? AI can collect and statistically analyze data or information across the internet, to make inferences and detect patterns in the data through

machine learning. AI can also be used to influence the stakeholders engaged and play an active role in the PM process. Can AI tools go beyond their common current capabilities; can they help PM to lead to more meaningful decisions that address the goals and purpose of any given PM engagement? Is AI a threat or an ally or circumstantially both? What are the lessons already learned and what are the precautions that should be taken?

We start with an overview of how AI can impact the process of information acquisition and processing. Next we focus on the participation side, where knowledge is generated and where AI is involved in stakeholder interaction, co-sharing, co-learning and co-management, which is structured by the process of model building and analyses. We then present the results of our review of existing work in these and other relevant areas, and provide a discussion of possible pros and cons of AI engagement in PM.

2. AI and modeling

There is a proliferation of AI/ML generated models in environmental science. Here we may make a distinction between.

- Data acquisition, processing and analyses, and
- Model building and analyses.

Assuming the most general definition of a model as a simplification of reality, we can certainly think of data as models. However, in most cases data and data constructs are treated as information that potentially resides outside of a pre-existing knowledge domain (or set of beliefs). Models that we refer to in this paper are products of understanding, processing, and analyzing observed data. In this process information becomes knowledge. Knowledge is the intersection of beliefs (including justified true belief or scientific knowledge) and information (Glynn et al., 2022a, 2022b), which can also be acquired through tacit learning and/or social processes (Cockerill et al., 2024).

On the data acquisition and processing side the AI functionality is vast, if not overwhelming. Most of the case studies of AI usage in PM that are examined in this paper focus primarily on the data gathering function. This includes collecting data from sentiment analysis of stakeholder opinions (e.g. Calheiros et al., 2017; Karimzian et al., 2025), analyzing image information for object detection (e.g. Prandi et al., 2022; Wang et al., 2025; Wan et al., 2025), using agents or chatbots to parse narratives (Brugnone et al., 2024), and generating information summaries (Goldberg et al., 2024; Landemore, 2024; Tessler et al., 2024). A few go further and build models from their analyses (e.g. Anjum et al., 2021; Giabbanelli and MacEwan, 2024; Li et al., 2025). Table 1 and Fig. 1 include exemplary studies, classifying them based on the stage(s) of PM at which they use AI, and the kinds of issues they encountered.

AI algorithms excel at processing and analyzing vast and complex datasets from diverse sources, such as sensor networks, social media feeds, and existing textual data, which can be useful for the PM process (Santos and Carvalho, 2025). This capability allows for a more comprehensive and nuanced understanding of the system being modeled. For instance, in environmental management, machine learning can identify subtle, long-term ecological patterns or the impacts of climate change from extensive environmental data, insights that might elude human analysts or traditional statistical methods (Santos and Carvalho, 2025). Machine Learning can help process information from surveys (Taghikhah et al., 2021b), and help generate simulation models based on data (Taghikhah et al., 2021a).

An important feature to note is that most of the AI/ML models built are empirical (i.e., data-based) black box models. This is in contrast to the so-called process-based models, which, in addition to data, use theory, laws of physics, such as the law of mass conservation, or other principles, such as demand/supply relationships in economics, or theory of planned behavior in social sciences. While AI may be also used to

derive theoretical principles from data (e.g., Schmidt and Lipson, 2009), this practice is not yet commonly found in building process-based models in environmental modeling. Importantly, empirical models typically are built using data from the one particular system of interest, while theoretical models are typically constructed through the examination and testing of multiple systems, or from previously-derived principles.

Empirical models are trained on existing or past data. AI models today largely represent an evolution of statistical models that bring in much bigger datasets analyzed through far more powerful computers than previously available. However, just like with other empirical models, they are best suited to describing systems that existed in the past. They may fail when used to predict future states that were not previously observed (Alexandrov, 2025).

Empirical models are not new in the field of PM, and have enjoyed widespread use in the field of socio-environmental modeling. However, their role in PM has been constrained because black box models have limitations in explaining causality and communicating the likely result of environmental decision-making and stakeholder actions. Such models are typically not the best tools to teach or explain how a system of interest might evolve, in light of stakeholder actions or what drivers or stresses might better inform stakeholder decision making (Maeda et al., 2021). The ‘learning’ aspect of modeling has always been an integral element of PM. If process based models are phased out of PM-informed decision making, will the PM goals of sharing and learning continue?

In PM, most human learning occurs through the process of building system models. Running the model(s) and analyzing scenarios is also important and informative, especially to improve decision making. It is always the process of model building that allows the engaged stakeholders to understand how the systems work, to share their perspectives, and to learn from each other and from the model itself. Conceptual models are built initially to describe the interplay between various system elements and identify the feedbacks in the system. This allows stakeholders to weigh the relative importance of different elements or processes, and also to introduce their own lived and emotive experiences (i.e., BBHVs).

Process-based, theoretical models are not better or worse than those that are data-based. Models are built for a purpose and in many cases it is difficult to determine which modeling approach is better (Taghikhah et al., 2021a). It is also problematic that there is no one and unequivocal idea of what “better” means here. Better for what? In PM, the modeling process is regarded as most important for knowledge sharing, learning, stakeholder engagement, building trust and sense of ownership of the constructed model(s). While dissecting and exploring the system at stake, PM participants have the opportunity to arrive at a consensus on certain joint conceptualizations. Such an opportunity is rare or non-existent when AI generated black box models are used in place of deterministic process-based models. Running and analyzing all sorts of models offers insight into the workings of the focal socioeconomic system and these insights can manifest better management strategies. However, by themselves, these models provide only a crude emulation of the dynamics of the system being simulated. The models as such do not explain the system feedbacks, interactions among system elements and exchange with other systems, the role of control functions, etc. While there is increasing interest in the use of ‘explainable AI’ (xAI) for model building, so far, xAI is still mainly data driven and the resultant explanations of causality are imperfect.

Delivering models ‘on the fly’, quickly, and using vast data resources does have promise for more productive model implementation and use by the targeted stakeholder community. However, eventual use of these models may require a redesign of the PM process. Previously, PM focused on the model building process with no clear prior requirements for what the model had to consider or include, and the limits of model efficacy. In some cases, just agreeing on a conceptual model was sufficient to improve decision making and satisfy the stakeholders involved (Voinov et al., 2018).

Table 1

Selected list of examples of how AI has been already used in PM (refer to [Table S1](#) in Supporting Information for more details on these examples and for more examples). Acronyms used in the Table: NLP - Natural Language Processing, FCM - Fuzzy Cognitive Mapping, LLM - Large Language Model, GenAI - Generative AI, CSI - Conversational Swarm Intelligence, CI - Collective Intelligence).

Sl. No.	Author, Title	Description	AI Technologies	Informing	Facilitating	Agenting	Delegating
1	Anjum et al. (2021) : Discussoo: Towards an intelligent tool for multi-scale participatory modeling	An online PM platform for facilitating discussions among a large number of stakeholders spread across different locations. Group mental models extracted from these discussions in real time are visualized as cognitive maps, which are moderated by human moderators to provide feedback to stakeholders.	i) AI for topic modeling, ii) NLP for extracting mental models, iii) Network graph algorithms for visualizing conceptual maps	Dynamically extracts key topics, sentiment values, mental models, etc. from ongoing discussions. Helps in their visualization.	Human moderators use extracted models and maps to provide feedback to stakeholders and to guide discussions.	The online nature of discussions and their automated analysis allows participation by external agents.	Extracted models and maps make it possible for AI agents to take over moderation.
2	Berijanian et al. (2024) : Soft Measures for Extracting Causal Collective Intelligence	Uses LLMs to automatically extract fuzzy cognitive maps (FCMs) from text. Evaluates using a dataset of 318 short passages from research articles.	i) LLMs, ii) FCMs	FCMs can be used as tools to visualize text. E.g. stakeholder discussions.	FCM extraction when done in real time can be used to moderate discussions.	FCMs can help in grouping stakeholders based on their contribution to the discussions.	FCMs can facilitate automated reporting/ summarization of stakeholder discussions.
3	Boussiou et al. (2024) : The Crowdless Future? Generative AI and Creative Problem-Solving	Describes a crowdsourcing challenge for identifying solutions to circular economy problems. GenAI was seen to produce less innovative solutions but of higher value and feasibility.	i) Human-driven GenAI, ii) Prompt Engineering	Participants can generate novel ideas using GenAI with appropriate prompt engineering.	AI-created perspectives and personas can help in PM facilitation	AI persona- based prompt engineering can be used to generate novel ideas from different perspectives.	Prompt engineering can be automated using human-developed prompt guidelines.
4	Brugnone et al. (2024) : Is it from ought ? A comparison of unsupervised methods for structuring values-based wisdom-of-crowds estimates	Demonstrates an AI-based process for identifying expert subgroups within a population. Uses a case study of maternal and child health service utilization in three areas in Nigeria. Compares different clustering methods: each is found to be well-suited to a different use case.	i) NLP, ii) Factor Analysis, iii) Three Clustering methods: k-Means; HDBSCAN; Diffusion Maps	Identifies values from narratives of experts. Then applies clustering methods to categorise and group experts.	NA	NA	NA
5	Goldberg et al. (2024) : AI and the Future of Digital Public Squares (part 2 of 4: bridging systems)	Discusses use of LLMs to identify common grounds between people with different views. This is the second recommendation (out of 4) from 70+ civil society experts and technologists.	i) LLMs	Provides information on participant characteristics through social network analysis.	Helps in recruiting participants with different perspectives.	AI-led categorization and representation of both participants and perspectives.	AI systems may provide control and guidance to obtain meaningful discussions.
6	Gupta et al. (2024) : Using Digital Nudges to Enhance Collective Intelligence in Online Collaboration: Insights from Unexpected Outcomes	Tests the usefulness of providing digital nudges using bots to subgroups that meet online and do collective intelligence (CI) tasks. Uses “no nudge” control groups for comparison. While the nudges were found to often improve CI, they were found to decrease it under some conditions.	Bots to facilitate teamwork: i) Identify member skills, ii) Identify tasks, iii) Divide work, iv) Display individual status	Informs about outputs from each of the four nudges. The last nudge also came with a visual display.	Each of the four nudges help in facilitating some aspect of task management	NA	Using digital nudges may eventually lead to using AI agents that do the tasks themselves, either partially or completely.
7	Landmore (2024) : Can Artificial Intelligence Bring Deliberation to the Masses?	Describes two AI-assisted approaches for bringing quality deliberation to the	AI tools for: i) participant selection, ii) moderation, iii) translation, iv) fact	Participant selection and distribution; Translation; Fact-	Facilitation tools, biases, and solutions, are examined in depth	i) Clustering contributions of large number of people, ii)	Discusses AI delegation for deliberative democracy (DD),

(continued on next page)

Table 1 (continued)

Sl. No.	Author, Title	Description	AI Technologies	Informing	Facilitating	Agenting	Delegating
		masses: "mass online deliberation" (MOD) and "rotating mini-publics" (RMP). Examines how these approaches could have improved the French 2019 Great National Debate.	checking, v) clustering, vi) summarization	checking; Data clustering and aggregation; Summarization		Deliberation output summarization	mainly from perspectives of ethics and legitimacy.
8	Lock and Pettit (2020): Social media as passive geo-participation in transportation planning – how effective are topic modeling & sentiment analysis in comparison with citizen surveys?	Analyses social media data on system performance, in conjunction with longitudinal big data on transport delay information broadcasts. Evaluates public transport performance and citizen satisfaction in Sydney, Australia. Compares with customer satisfaction surveys.	i) Topic, Tone & Sentiment Analysis for Social Media Analytics, ii) Machine Learning for Big Data Analytics	Gather topic, tone, sentiment information from customer reactions via social media tweets to identify specific issues.	NA	NA	NA
9	Rosenberg et al. (2024): Conversational Swarms of Humans and AI Agents enable Hybrid Collaborative Decision-making	Small subgroups of stakeholders participate in a fantasy baseball contest. They choose players within a budget constraint and try to maximize the score. While the AI agents demonstrated better performance relative to traditional methods, the infobots did not significantly improve CSI group performance. However, InfoBots helped level and balance the knowledge base within the subgroups.	Conversational Swarm Intelligence: Subgroups supported by: i) InfoBots for facts, ii) AI agents to pass discussion insights between subgroups	Subgroup-wise infoBots for individual members to get (or check) facts	CSI greatly extends human cognition and performance.	Subgroup-wise AI agents that capture the insights of subgroup discussions and pass them to other subgroups	CSI provides AI delegation support through the use of surrogate agents and their group reporting function.
10	Tessler et al. (2024): AI can help humans find common ground in democratic deliberation	Describes an LLM assistant trained to summarize subgroup-based discussions. This facilitates Habermas-style "communicative action" used to ensure that voices of all stakeholders are heard. It was compared with human-only alternatives and the group opinion statements generated by the LLM assistant were consistently preferred by group members over those written by human mediators. They received higher ratings from external judges for quality, clarity, informativeness, and perceived fairness.	LLM assistant to generate group statements that were then further critiqued by personal opinions, and again refined and selected for consensus.	Gathers individual opinions and creates group opinion statements. No fact checking is employed.	Mediation is one of the primary functions of the LLM assistant, a Habermas Machine. Hence, facilitation is a key PM process served by it.	Categorizes and represents participant points of view.	It does not take over human decision making but supports it.

Depending on the context, PM applications may need to consider using more than one AI -informed model, particularly where these tools are to be used by stakeholders for their exploration and near-immediate use in decision making. Instead of dissecting the subject system into elements and focusing on the interactions between these elements, PM may now focus on how the system performs as a whole, allowing more rigorous comparison of model behavior under a variety of environmental conditions and external forcings such as climate. Nonetheless, an in-depth understanding of underlying causalities may still be elusive and

yield an unsatisfactory delayed response while providing a useful assessment of different approaches. It is yet to be seen which PM approach will be more fruitful.

In instances where there is easy and inexpensive access to powerful computers, AI-informed PM can facilitate the use of highly technical optimization problem solution techniques and produce reliable and timely answers to problems stakeholders can formulate, analyze and discuss. In addition, such computational resources can minimize the time needed for model calibration and validation - processes that can be

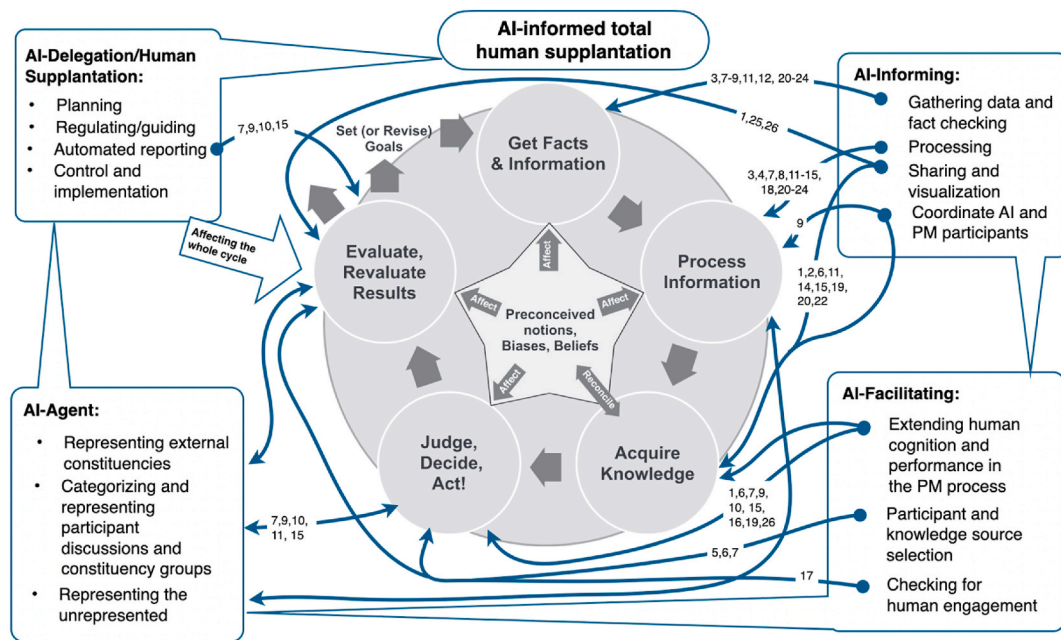


Fig. 1. The impact of AI on the cycle of scientific research and decision making in the context of PM. The inner loop starts with setting goals and ends with evaluation of results, which usually loops back into the cycle, as presented in Voinov et al. (2016). The outer loop shows the influence of AI as it evolved over the past years and into the future. Numbers refer to the references in Table 1 (and Table S1 in Supporting Information) which present examples of such influences. Note some links for AI agents have arrows on both ends to stress that agents not only affect the process, but also learn from the process themselves.

streamlined and automated.

With AI tools now available, the main focus of PM may potentially shift to a *multi-model approach*, for which various system simulations can be easily generated and compared. Rather than discussing the most important model elements and their connections (as in the past), stakeholders may now have to argue about which model of the system, generated by which AI package, looks better and presents outputs that they like best.

Zellner et al. (2025) provide a pertinent example in the field of Green Infrastructure planning that complements past work in this area by Abdeen and Sepasgozar (2022) and Adade and de Vries (2023). The hybrid approach advocated in the design of their *Fora. ai* platform creates realistic system representations using a suite of datasets and simulation models combined with techniques to apply community knowledge and values. These techniques help to define and test solutions to various well-defined problems. The *Fora. ai* platform has been customized to help with facilitation of stakeholder workshops. In these applications the protocol begins by identifying goals and important problems, followed by specifying the geographic scope, potential outcomes of interest that lead to the task of soliciting consensus on a number of acceptable simulation tools. The architecture of the platform includes a user interface coded in HTML, CSS, and Javascript with ReactJS. The platform uses a backend database and links to a suite of user-selected modeling tools.

Hybrid modeling approaches may have value because they combine the logic inherent in traditional simulation approaches with the capabilities of AI to assimilate past experience outside the immediate environmental planning domain. This potentially combines the conceptual model development task that has been shown to be important for PM acceptance with the wider scope offered by AI tools.

Here also, a major challenge is that a database enhanced with AI-based search results reflects past knowledge; it is incapable of the advanced analysis needed to suggest novel and innovative solutions that have not found their way into the published literature. This harkens back to the earlier definition of the various categories of AI software into “narrow”, “general” and “super” AI tools and the acknowledgment that super AI tools are still in their early stage of development. Du et al.

(2024) state that “new deep learning models can boost prediction and simulation performance. However, most of them cannot explain the causal relationships among variables, making some prediction models difficult to be applied in practice” (p. 192). If we eliminate the learning function associated with PM through these empirical black boxes, we lose the ability to deeply understand the complexity and function of a system and a place.

3. AI and participation

The participatory aspect of AI is diverse and constantly changing. We see an increasing number of possibilities where AI can be involved. As noted in Fig. 1, AI has already been used to augment multiple aspects of the PM process, including scoping and abstraction; data, facts, logic cross-checking; model formulation; model application to decision making; evaluation of outputs and outcomes; and facilitation of transparency. The various types of AI engagement in the stakeholder process can be categorized into four main types.

1. AI-informing: gathering, processing, and preparing information for effective use by stakeholders;
2. AI-facilitating: moderating and mediating PM processes.
3. AI-agenting: enriching the PM process with AI agents that can pursue given goals and tasks, have a level of autonomy to make decisions, learn, and adapt. Such agents can be used as stakeholder assistants, or, eventually, fully replace certain stakeholders, especially those that are important but unavailable to participate.
4. AI-delegating: performing entirely or partially the whole PM process, which was previously human-controlled.

As AI has been developing, it has moved from simply assisting in handling information, to active involvement in the facilitation techniques and helping manage groups of people, to actually participating in the process as a stakeholder, an agent on its own, performing various relevant tasks. Next we can anticipate it potentially handling the whole process, with a declining need for human engagement, while entire management and decision making tasks are delegated to AI. This can

include not only advanced (a) information-processing and reporting, (b) facilitating (internal or external to PM), and (c) agenting and representation. This can lead to planning, guiding, and controlling, as well as ensuring follow-up of PM recommendations or outcomes and/or implementation into actual decisions and actions.

3.1. AI-informing

The information pool that AI can access is vast and growing. Conversations and public discourse already frequently involve drawing information from the web, and/or using search algorithms to extract what is most relevant and useful. Natural language processing and interactive graphics-based software can extract information from social media posts and produce rich datasets that can be used in model calibration and validation (He et al.,; Karimiziarani et al., 2025). Web-based platforms can engage directly with stakeholders eliciting photos, articles and write-ups of relevant experiences that can be useful for calibration and validation of water quality models especially where little available data exist. Interactive games and informal surveys can give watershed planners insight on key stakeholder concerns and allow development of mind-maps reflecting their concerns and causality assignments. All these tools lead to welcome erosions of barriers to participation in PM. This may be seen as a positive trend, informing and enriching discussions with much greater quantities of available knowledge.

It is important at the onset to distinguish between various classes of AI/ML tools and suggest those that have the most potential for enhancing PM effectiveness.

Generative Adversarial Networks (GANs) are another AI/ML application which can also have utility in public participation modeling. GAN algorithms can generate synthetic data that resemble real-world scenarios to simulate public preferences or behaviors when data is scarce. By helping to communicate complex data and a wider array of potential outcomes to the public, GANs can ensure that minority voices are considered in the modeling process. GANs have been valuable for incorporating Diversity, Equity, Inclusion and Justice principles in PM (Erichson, 2024).

Variation encoders (VAEs) are a class of AI/ML tools that can enhance the modeling and analysis of public participation processes and have features distinct from Large Language Models (LLM's) and GANs. They can provide insights in support of more inclusive and informed decision-making by making complex public opinion data easier to analyze and visualize (Erichson, 2024). AI-powered tools can create dynamic and interactive model visualizations, making them more accessible to participants. AI can facilitate more sophisticated simulations, allowing for the exploration of a wider range of potential outcomes. This AI/ML variant is especially useful for uncovering underlying patterns and relationships in data to explore how changes in specific parameters might impact public sentiment.

Diffusion models have merit for public participation applications where images and interpretation of visual data are important. Useful features of diffusion models include an ability to analyze how information, opinions, or behaviors are spread within a population, that can have value for assessing public engagement and how attitudes often evolve over time.

On the downside, AI is commonly based on the information found on the web. This information does not necessarily have to be true, verified or even verifiable. Moreover, the information is not provided in a neutral, unbiased way. Search engines and other AI functionality are driven by various algorithms, which have their own embedded objectives that may have nothing to do with 'truth', 'importance', 'reliability', etc. In most cases, it is the performance and profitability of the search engines and chatbots themselves that are maximized. As a result, the information is provided in a way that may be counterproductive for PM. For example, there are at least two kinds of data sampling biases that emerge with AI's web-based data gathering: 1) biases toward a particular group, which can be amplified when processed by machine learning

methods skewing any modeling process or system outcome, and 2) data omission bias, e.g., to "exclude candidates from marginalized groups" (Ferrara, 2024; Du et al., 2024), impacting our analysis of demographics, education, etc.

Ultimately, what matters is not just whether or not the information found and processed is truthful or accurate, but rather how (mis/dis) information is perceived, processed, and reacted upon by human actors and constituencies, communities, and/or society as a whole (Glynn et al., 2022a, 2022b; Helgeson et al., 2022; Lim et al., 2023). This is now being realized in multiple ways and it has major implications for PM, especially in regards to what is needed to convert PM recommendations and knowledge into improved policy and decision making. The Narrative Policy Framework was created as a field of research that uses the knowledge and science of narratives to understand, influence, and improve public policy making and communications (Kuenzler et al., 2024; Shanahan et al., 2011). Additionally, sentiment analysis and natural language processing (NLP) are emerging as increasingly useful tools to analyze public emotive reactions and perceptions (e.g., Lin and Chen, 2024; Jin and Mihalcea, 2023). Sentiment analysis is often limited to recognition of positive or negative emotional valence in texts, often using dictionaries of valence-laden words (e.g., LIWC, 2022; Boyd et al., 2022).

However, emotion AI and affective computing are advancing well beyond textual valence-based recognition of sentiments. Machine learning and pattern recognition is now increasingly multi-modal (TheAIGRID, 2025) offering analyses of images, sounds, and a variety of expressions in addition to text. Analyses are starting to be done on facial micro-expressions, on tone, on physiological changes and brain waves – all with the aim of assisting professionals in interacting and understanding their subjects (e.g., Udahemuka et al., 2024). This is the case in the fields of medicine (Wankhade et al., 2022; Guo et al., 2024), education (Llurba and Palau, 2024; Marín-Vega et al., 2024), and beyond. Increasingly, the often subconscious or unconscious reactions of individuals – highly private and personal information that they may not be in control of – is being mined as a valuable information source for a wide diversity of potential applications, some of which may not be beneficial to the individuals being monitored. To what extent emotion AI and affective computing will eventually find their ways into PM processes is an open question, one that may have promise under certain circumstances, but also offers opportunities for great peril.

Much has to be improved in the field of PM and participatory processes before Emotion AI and affective computing can be effectively and ethically used, especially at the level of individuals. Most important in our view, is advancing the identification and recognition within PM processes of already well-known and widely shared BBHV, the norms and emotionally-resonant influences that broadly affect the beliefs and value prioritizations of different constituencies and communities, as well as the common behaviors, narratives, and mental models of individuals (often derived from biocultural evolution, Glynn et al., 2025; Cockerill et al., 2024). The question is how AI methods can be used to capitalize on the positive aspects of BBHVs, while mitigating their negative effects. So far, this has not yet been done.

For example, confirmation bias, a key BBHV, is one of several biases and heuristics that have been studied in the fields of psychology and behavioral economics to understand how people process and treat new information (Tversky and Kahneman, 1974; Kahneman, 2011; Gigerenzer, 2013; Marewski et al., 2010; Kruglanski and Gigerenzer, 2011). Confirmation bias can be clearly observed as electroencephalography signals in certain parts of the brain that fire up when we like what we hear, and others that become active when we are in disagreement (Singh et al., 2025). These reactions can be used to encourage individuals to make specific decisions, regardless of their level of conscious understanding of the rationales for or against the decisions. An AI agent or machine can efficiently master the usage of confirmation bias, adapt for cultural or individual peculiarities, and deliver messages to individuals in such a way that they will be more likely to choose what AI wants them

to choose. In fact, we already see confirmation bias used in how, for example YouTube algorithms generate the suggestions for next clips to be viewed. It is easy to notice that most of the suggestions that are offered are in some agreement with the message of the clip that is currently displayed. Viewers are more likely to click on the next episode if it seems to be confirming their already existing worldview - exactly what YouTube needs to increase the number of clips viewed.

AI based algorithms are already used to manipulate human behavior (Harari, 2024; Cadwalladr, 2019). And no matter how much the underlying data are distorted, the algorithms assume that the data are real, see them as historical and mechanically process them, hence, the terminology from Bender et al. (2021) of “stochastic parrots”. They do not yet have the capacity to anticipate new variables or inputs, much like the limitations associated with any kind of scenario modeling (e.g., not realizing the potential of the brown ocean effect in the intensity of Hurricane Helene in September 2024 in the Carolinas (World Economic Magazine, 2024; Zhong, 2024)). The combination of bias and historical data reliance leads to a loss of human ability to learn and grow through the PM process (Vallor, 2024). This issue can be particularly troubling for participatory planning and modeling given that we are often seeking potentially untried solutions and looking for untapped synergies in generating more equitable and responsive solutions to problems often faced by underserved communities. Here the bias is that little attention and hence a sparse literature exists to inform the participatory modeling and experiential database.

3.2. AI-facilitating

Since active stakeholder engagement and interactions have always been critical in PM, facilitation processes have always been important. Facilitation is relevant to all forms of participation, including traditional in-person stakeholder workshops and meetings, online virtual workshops or online discussions (Anjum et al., 2021). There are many ways AI can help with PM facilitation: AI-enabled meeting transcription and translation are basic facilitation services, but there are many more complex AI capabilities that can mimic, guide, or even supplant human facilitation. These include choosing PM participants, which either promotes more equitable inclusion, or effectively actualizes implicit and other biases generally present in all AI-available information (Du et al., 2024).

Most of the AI tools used here are based on LLMs such as ChatGPT, Gemini and Claude, typically used to interpret or generate text. Their “transformer architecture” measures the relative distance of words from each other in typical sentences and within paragraphs and draws inferences on these associations. Contemporary, cutting edge models are estimated to cost \$100 million or more and costs keep rising (The Economist, 2024). LLMs are effective at distilling knowledge from past studies and publicly available information but, as of yet, may lack the full cognitive and collective intelligence capabilities needed for PM. They are also being legally challenged for utilizing copyrighted materials in their generation (i.e., infringing on copyright by scraping copyrighted materials for training and data sourcing without permission) (Panettieri, 2025).

AI technologies (e.g., surrogate modeling, explainable ML, interactive visual analytics) may enhance human-computer interaction (HCI) within decision-support environments such as PM. By making model runs more accessible and numerous, allowing analyses of multiple scenarios and combinations of parameters, stakeholders can better appreciate the uncertainties involved in the systems of interest. This can lead to improving deliberation over trade-offs and making uncertainty more tractable for diverse users. AI has the potential to facilitate in the fields of collective intelligence and deliberative democracy, as well as through both new and old technical tools in social science research.

Collective intelligence. There are numerous examples of the use of AI in the fields of “Collective Intelligence” (CI) (Woolley et al., 2010) and of “Deliberative Democracy” (DD), especially when large groups are

involved (Rosenberg et al., 2024). These two domains of research are relevant to the PM context. First, CI ought to be the goal of any participatory effort, including PM. Woolley et al. (2010) define CI as “the general ability of the group to perform a wide variety of tasks”. There are several factors needed for CI, extending beyond the intelligence of individual participants in a group. For example, in addition to the average and maximum intelligence of participants, Woolley et al. (2015) determine that the average “social perceptiveness” of group members, i.e., the ability to work with others and with other perspectives, is an even stronger factor determining collective intelligence. Interestingly, diversity, especially cognitive diversity (i.e., in thinking styles/modes), is critically important in groups that need to be creative or to innovate. Cognitive diversity, however, can be a hindrance if the tasks to be accomplished by a group require efficiency rather than innovation. CI could be stimulated in a PM or small-group participatory process through the use of LLMs to increase accessibility and inclusion of a diversity of perspectives, experiences, cultural norms or ways, or of other forms of knowledge – while also retaining the meaningful engagement, trust, and sense-of-agency benefits of smaller group discussions (Burton et al., 2024; Landemore, 2024).

The use of AI-enabled “digital nudges” has been examined as a tool for increasing online collaborations, and found to usually benefit CI, but not always (Gupta et al., 2024). The digital nudges include (a) listing tasks to be done, (b) providing feedback (to the group or its facilitators) on participant activities or engagement levels, (c) suggesting or making participant-skill-informed assignments, and/or (d) devising strategies to divide complex problems to be addressed into simpler tasks that can then be optimally assigned to participants.

Deliberative democracy. AI tools can bring together a vast amount of information, and they can also help connect different perspectives, cultures, and experiences. PM occurs most often in the form of small group engagements of maybe 20 people at most, but does it have to? DD seeks to answer that question when it examines how to maintain principles of inclusion in democratic political systems while also enabling meaningful and representative deliberations and reflective thinking (Fishkin, 2019; Luskin et al., 2022; Sandefur et al., 2022). Just like DD, to be truly effective and impactful, PM processes probably need to expand their reach, possibly in the collection of important knowledge and perspectives, and also perhaps through greater diffusion of their findings and reasonings. AI can help in this process, by using systems of LLMs to synthesize and represent given perspectives (Goldberg et al., 2024; Landemore, 2024; Tessler et al., 2024).

The field of DD has also investigated how to engage greater and/or different audiences and the ethical ramifications of the use of AI (Buhmann and Fieseler, 2023; Landemore, 2024). For example, Tessler et al. (2024) created the “Habermas machine”, a system of LLMs (based on DeepMind’s “Chinchilla” LLM) that combines (1) a pretrained generative LLM created with supervised fine-tuning to propose high-quality “group statements” and (2) separate (also pretrained) LLMs that uses a personalized reward model and scoring to predict and align with the preferences of individual group members. Resulting iterations of the Habermas machine both optimize the expressions of individuals, using LLM language that will appeal to the larger group, while also allowing minority positions/opinions to flourish. Consensus statements that include meaningful minority positions are efficiently created that have been judged to be of higher quality and greater fairness than what could be produced, much-less efficiently, by human facilitators or summarizers (Tessler et al., 2024). Importantly, the Habermas machine approach is scalable, in that it can be used and can compile issue-focused discussions occurring across many different small groups, or what the DD literature calls “mini-publics”. Addressing the issues of scalability and efficiency, while also maintaining inclusivity and representativeness, Landemore (2024) suggested and analyzed different strategies (“mass online deliberation” vs. “many rotating mini-publics”) showing how AI tools and LLMs might have been used (without the benefit of AI) for the massive-scale two-month-long government-sponsored French

Great National Debate of 2019 that addressed four broad themes (taxation, government service and organization, ecological transition, democracy and citizenship).

Despite the ubiquity of AI applications in the social sciences and records of success, application of these technologies are not without risks – one of the most important of which is the occurrence of hallucinations where the corpus of the data or questions asked of the data produce spurious results that can be misleading or even harmful. Advancing trustworthy AI is now a priority area of research and is enshrined in the United States' National AI strategic plan ([Select Committee on Artificial Intelligence and National Science and Technology Council, 2023](#)).

3.3. AI-agenting

As AI capabilities improve, AI agents may start engaging with human stakeholders during PM processes. LLMs can already generate text and images that are difficult for humans to distinguish as being AI generated. For example, [Boussieux et al. \(2024\)](#) experimented with “AI in the loop” processes inserted into human-centered solution search processes to drive innovation. Generative AI (GenAI) aided by prompt engineering was used to generate human-AI hybrid solutions that were found superior in terms of feasibility and value, financially and environmentally. [Hidalgo \(2018\)](#) suggested that politicians could potentially be replaced with personalized AI representatives that could participate directly in democratic decisions. Similarly, stakeholders might potentially be assisted by AI agents participating in PM that would bring the stakeholders' perspectives, ideas, information, and knowledge.

LLM-based applications of AI in the stakeholder engagement process could involve the use of AI surrogate expressions – AI created expressions that aim to represent those of a particular human constituency – to help emulate how stakeholders might react to other situations based on the models trained on survey data compiled from observations.

When the number of stakeholders is large, AI agents can help by dividing them into small subgroups for better deliberations, and support them by sharing insights from each subgroup with others and create a more democratic collective thinking ([Rosenberg et al., 2024](#)); the AI agent can also be used to provide facts to stakeholders when queried, helping make their thinking more fact-based.

While this paper was being written, a new powerful AI tool was announced: Manus (<https://manus.im/?index=1>). It became available as a general AI agent that can perform all sorts of tasks, many of which are directly relevant to what a stakeholder could be doing during a PM workshop. For example, one of the recorded experiments is when Manus is asked to “Compile a detailed list of key AI influencers globally, capturing perspectives from leading AI company executives, investors, government officials, and researchers regarding Deepseek R1” (<https://manus.im/share/TVKlor12JoYsJQuqflgrYT?replay=1>). It starts with developing a clear Task Plan, and then reports on all stages of the process, eventually preparing a user-friendly visualization in the form of a web page or a presentation. This seems exactly what we would expect from an actively participating stakeholder, if not more.

In the future, as AI agents become more and more self-sufficient and capable (relative to human counterparts), there may be a gradual displacement and exclusion of humans from the PM process. According to [O’Gieblyn \(2022\)](#), developers (and possibly users) of AI may be seeking meaning through a God-like figure manifested by algorithms, or, as she states “we... Have [built] sophisticated and largely opaque instruments to restore our broken relationship with the absolute.” ([O’Gieblyn, 2022](#), p. 195). AI algorithms offer an alternative approach to problem-solving, giving a certainty that humans seek, viewing the same information from an inherently un-human viewpoint ([O’Gieblyn, 2022](#)), while also representing the less attractive side(s) of humanity. This is already manifesting in interpersonal communications, when people choose to make friends with ChatGPT to the extent that they start experiencing attraction to and love for the AI bots that they create

([Bernardone, 2025](#)).

The ultimate question is whether, and to what extent, PM organizers and participants may be willing to accept AI-agent supplantation of humans in PM – originally designed to increase human community engagement and explicit, reflective, consideration of complex systems and issues. The use of AI agents may create efficiencies in PM, but may also end up decreasing human engagement and thought development. Alternatively, there is the possibility that AI and AI-agents could be used (a) to improve, rather than to replace, human cognition; (b) to increase human acceptance of uncertainty and of human cognitive limits; (c) to increase realization of the needs for human autonomy and creativity, and (d) to improve recognition of the role of BBHV, mental schema, biocultural propensities, and narratives ([Cockerill et al., 2024](#); [Glynn et al., 2025](#)) in human thought and decision-making.

Newly-introduced approaches in participatory planning, which are available as data inputs in participatory modeling, may not be replicable through AI. [Sweet and Ortiz Escalante \(2015\)](#) introduce visceral methodological approaches that conceptualize a person’s own body as the locus of experience and the ultimate “nexus of public-private space” (p. 1827). To garner this information, they use “body-map storytelling and shared sensory spatial experiences” ([Sweet and Ortiz Escalante, 2015](#), p. 1828). Even with the introduction of personal neuro-technology ([Farahany, 2023](#)) these would be hard for AI to replicate. [O’Gieblyn \(2022\)](#) characterizes humans themselves as “black boxes”. [Cockerill et al. \(2024\)](#) posit multiple forms of knowledge acquisition, including from: self, observation, social engagement with other humans, and culturally-shared knowledge (pp. 7–10). All of these sources overlap, forming the “black box” of human decision-making, which has a self-awareness or consciousness that is absent in lower kinds of AI. Albeit imperfect, it is the combination of these forms of knowledge that coalesce in human brains in ways that AI has yet to be able to replicate, even though, as [O’Gieblyn \(2022\)](#) states, “all the eternal questions [about humanity] have become engineering problems.” (p. 7).

With all this in mind, we should also still remember that AI, especially AGI and ASI, are not about replicating humans, their brains, their ways of thinking, reasoning and deciding. We cannot rule out a future where we may be dealing with agents that do all this differently and in a superb, more efficient, and more productive way. Humans may not like it, but will they be asked? This seems especially problematic bearing in mind that there is still quite a bit of controversy about defining and understanding what we actually mean by consciousness, and what AI consciousness may mean ([Butlin et al., 2023](#)). Instead of aiming at reproducing human consciousness with AI it may indeed be more productive to focus on new additional functionality and services that AI can offer ([Bengio and Elmoznino, 2025](#)). Apparently, this is also what has been adopted as an official approach in China, where they choose a “pragmatic” approach to AI, prioritising real-world industrial applications over speculative superintelligence ([Chin and Huang, 2025](#)).

3.4. AI-delegating

Human delegation to AI systems is increasing at a rapid rate. Of course, AI used to inform or facilitate PM or to represent or act as various entities in PM represent forms of AI delegation, tasks that in the past had to be done solely by humans. But what we consider in this section goes beyond what has been discussed so far. In our definition for this paper, AI-delegation represents a near or full delegation to an AI system of orchestrated, automated, feedback-sensitive, decisions and actions.

AI-delegation is already prevalent in many societal applications. Chatbots and AI agents are now answering customer queries and phone calls, replacing human agents ([Hemmer et al., 2023](#); [Fügner et al., 2022](#)). AI has transformed precision agriculture, enabling AI orchestration and automated control and feedback based on monitoring systems (e.g., soil moisture, temperature) and modeling of future conditions ([Gangwani, 2024](#)). AI-delegated project management is also coming into vogue, automating progress assessments and evaluations,

providing feedback as needed, and creating necessary reports, summaries, and communications (Diao, 2024). Similarly, AI-delegation of a wide diversity of administrative, project management, and diagnostic tasks has also major impacts on the delivery of health sector services (Waheed and Liu, 2024), even though concerns remain (Traylor et al., 2025).

The authors of this paper however have so far seen little evidence of AI-delegation in PM. This is apparent in the case studies presented (Table 1 below) and in supplementary material (Table S1). Nonetheless, the authors believe like many others (e.g. Miller (2025)) that AI delegation will become more prevalent in PM processes in the future. Major questions remain however regarding the amount of delegated control and orchestration that humans should explicitly give to, or that might (implicitly or explicitly) be taken by, AI-systems.

The real problem with delegation in PM is that, as O’Gieblyn (2022, p. 254) states, the AI systems “aren’t burdened with any of these rational or moral concerns—they don’t have to think about what is socially acceptable or take into account downstream consequences. They have one goal-winning—and this rigorous single-minded interest is consistently updated through positive feedback.” And this is where the goals—if controlled by humans—could allow us to optimize PM with AI delegation. This issue of goals and control, and questions of ethics, values, trust and legitimacy that it raises will be discussed in the next section.

The main uncertainty at this point is about the rate of development of AI and its capabilities. As mentioned above, most of the AI applications discussed in the papers reviewed are from the ANI category. When we started writing this paper the forecasts were talking about a 10–20 years window until any real AGI will be available (Milmo, 2024). Today the projections are expecting full scale AGI (or even ASI) in 2–5 years. We cannot even imagine what will be the situation by the time this paper is reviewed and published.

Reasoning and creativity are rapidly advancing in AI models. Novikov et al. (2025) report an algorithm that can improve itself to solve various problems. They describe an evolutionary coding agent that enhances capabilities of LLMs on various tasks such as tackling open scientific problems or optimizing critical pieces of computational infrastructure. AlphaEvolve improves an algorithm by making direct changes to the code, using an evolutionary approach, and embracing feedback from one or more evaluators. In a way that is already a participatory setting, which, as a result, can improve itself.

A somewhat similar evolutionary self-improving approach has been reported by Zhang et al. (2025). They developed a novel self-improving system that iteratively modifies its own code (thereby also improving its ability to modify its own codebase) and empirically validates each change using coding benchmarks. Again we see some advances that already go beyond the reasoning power of humans. There are also attempts to optimize and contain the teaching process that helps AI algorithms to evolve (Cetin et al., 2025). Now we can expect that the algorithms are not only improving themselves, evolving, but also improving the way they evolve. The scope of potential improvements and advances seems really limitless.

4. Discussion

In Table 1 we have collected some ten examples of how AI has been already used in PM. Their detailed description, along with several more examples (total: 26) are listed in Table S1 in the Supplementary Material. By no means does this cover all of the applications, but it is an attempt to both identify and classify the examples according to some of the considerations listed above.

The earliest example we looked at, Anjum et al. (2021), tries to overcome the problem of getting stakeholders together at the same time under the same roof, by creating an online PM platform that facilitates asynchronous discussions among a large number of stakeholders spread across different locations. AI methods and NLP techniques are used to automatically extract group mental models that are emerging from these

discussions, and these are visualized as cognitive maps using network graph algorithms. These models and maps are then used by human moderators to provide feedback to the stakeholders and guide their discussions.

Note that in the last several years, AI technology has developed so rapidly that some of the functionality assumed by Anjum et al. (2021) can now be delivered in new ways that we could not even imagine previously. For example, today we can ask an AI agent, say, [manus.ai](#) to build a conceptual model of a system you may have in mind and in minutes you will get a result that would be definitely as good as some of the results from stakeholder deliberations during several workshops. As an illustration, consider the results of our experiment with [manus.ai](#) in Appendix IV of the Supplemental Material, when asked the following: “I am part of a small community of some 50 urban dwellings. Some of us have solar panels on the roof. We would like to explore some options for building a renewable community energy system, so we can share the electricity that we produce. Could you build a conceptual model of the system that we are dealing with?”

Several examples during the last year started using LLMs/GenAI for various PM purposes. Berijanian et al. (2024) uses LLMs to extract directed graphs called fuzzy cognitive maps (FCMs) from stakeholder discussions to help stakeholders visualize and understand these discussions better. Another example uses GenAI-in-the-loop to help stakeholders in generating ideas for solving various problems (Boussieux et al., 2024). Brugnone et al. (2024) demonstrates an AI based process for identifying subgroups within stakeholders based on values that individual stakeholders express in their narratives; aggregated knowledge of each subgroup is then used as the wisdom of the crowd as it is more accurate than estimates by individuals. Goldberg et al. (2024) discusses four such novel applications of LLMs; it is an exploration of AI-technology enhancements to existing needs in deliberative democracy and digital squares, and is in the early stages of development. For example, one of the applications they discuss in detail is the use of LLMs to identify common grounds between people with different views. Landemore (2024) describes two AI-assisted approaches for bringing quality deliberation to the masses.

There are also several other examples where LLM based tools are used in the PM process. As mentioned earlier, Rosenberg et al. (2024) describes the usefulness of: i) fact-providing infobots that help in leveling the knowledge base of various subgroups, and ii) AI agents in connecting these subgroups together. Lock and Pettit (2020) describes how readily available social media data from stakeholders can be used, together with other big data using sentiment analysis and other NLP tools, for evaluating performance of any system; they illustrate it using the case study of public transport systems in Sydney, Australia.

However, overall, AI usage in PM, particularly in the area of environmental modeling, seems to lag significantly behind its usage in other areas, such as in business and marketing applications, for example. And conceptual model building from stakeholder opinions is quite primitive, compared to the strides that are already being made by LLMs in their analyses and summarizations of documents (e.g. <https://www.youtube.com/watch?v=jJCJV6iYvMk>).

4.1. Questions of control, value, trust, and legitimacy for AI in PM

If human participants in PM (or in other processes) become increasingly inferior to AI represented stakeholders, PM orchestration, agenting, and decision-making may end up delegated to an AI system; and human active participation may become redundant and perceived as an obstacle. It is also possible that in that case PM, as an engagement practice, could become irrelevant because AI-systems (assisted or not by humans) might find more productive ways to co-learn, co-design and co-manage. By who and how will goals be defined and controlled? By who and how will decisions be made? How will context come into play, and how will trust and legitimacy for AI in PM be affected?

As artist Sougwen Chung states, “if we think about machines as

human extension in a lot of ways, or manifestations of human intent or extensions of ourselves, there are some dark aspects of humanity that can be extended through machine apparatuses. I think that drives a lot of how we construct this idea of the AI. But at the same time, there could be just as well machines of care and machines of stewardship and machines that steward nature that we don't see as much because we haven't built them yet." (<https://www.ttbook.org/show/does-ai-dream>).

AI may eventually control us humans, at which point humans will become, at best, a tool or just a background for AI agents. In the meantime, before that stage is reached, AI offers increasingly powerful tools and technology capable of extending human cognition and performance. Humans operate with often differing and competing notions of "what is good and right to do". What is good for specific individuals often differs from what is "good" for specific groups or communities, or from what is good for the current planetary human population, or from what is good for the next human generation, or from what is good for other species (MacIntyre, 2016). Consequently, there is often no single "good" or "right" thing to do, and questions of value and trade-offs always come into play in any meaningful decision making. In terms of LLMs or any AI-enabled assessments of "value to humans", with the frequent opacity of AI-training-data and the importance of contextual understanding, many problems are likely to arise if AI-derived value assessments or trade-offs are blindly accepted. Furthermore, AI assessments and LLMs are driven by preponderance of accessible information, not by quality judgements about social or other contexts, especially ones that are not frequently or readily available. In this, AI may reflect typical human judgements (esp. group judgments) which are often driven by social proofing rather than by reason or high quality evidence.

People generally do not use impersonal "information", facts, or data, to decide on what is good or right to do. Instead, they use their feelings, unconscious reactions, community/group norms or values, and personal experiences to shape their decisions (Setiya, 2025; Barnes, 2025). Those feelings, reactions, norms, and experiences are generally derived from the sometimes rather distant past of cultural and genetic evolution. Therefore they may be completely inadequate to meeting the challenges, or even less the conflicts, of modernity.

What the above means for PM is simple. AI tools and technology are, currently, mainly cognitive and performative extensions whose use commonly reflects human problems in dealing with matters of fact and questions of value. Like most tools derived initially by humans they tend to increase already existing human desires and propensities in their use (Glynn et al., 2025). The typical problems that already exist in decision making and often also in stakeholder and community engagements include:

- lack of inclusivity or representation of needed constituencies;
- lack of transparency in constituency/participant motivations;
- lack of trust between represented constituencies;
- lack of trust or belief in facts, data, information or models brought forward;
- lack of understanding or acknowledgment of differing value prioritizations or beliefs held by different constituencies or participants;
- lack of communication or understanding of the different types of knowledge brought forward for discussion
- power and information asymmetries or other types of unfair or unequal possibilities for representation.

To the above, we also need to add an especially strong and prevalent problem: social proofing and group think that basically deletes the potential for the collective intelligence of multiple independent minds to exert itself and meaningfully appear, at least initially (cf. Glynn et al., 2022a, 2022b; Woolley et al., 2015; Landemore, 2024).

PM seeks to address the above problems through structured stakeholder engagement, however, many of these problems remain in the PM process. Lim et al. (2023; <https://sesmo.org/article/view/18509/18038>) mention some of the above issues as well as the tyrannies of

participatory processes brought forward by Cooke and Kothari (2001): the tyranny of control, an overriding of legitimate concerns sometimes enabled by facilitators, the tyranny of the group that sometimes results from group dynamics reinforcement of the already powerful; the tyranny of method that may offer a less useful or worthwhile result than if a PM process had not been used or participation engaged. AI tools often seek these same objectives. Therefore, this suggests that AI-enabled PM may easily magnify problems and tyrannies of PM and decision-making. It is yet to be seen whether AI can, instead, help mitigate the problems, including social proofing and group think. Researchers in CI and DD suggest that AI tools used judiciously can do so (e.g., Goldberg et al., 2024; Landemore, 2024; Tessler et al., 2024).

Even if CI and meaningful DD can be made integral to PM processes, another major problem may occur. For PM to be effective and result in implemented decisions and actions, PM needs to bring together and bridge initially separate identities, beliefs, motivations and wants (human or AI-derived) into strongly shared, eloquently visioned and stated recommendations or requests for decisions and actions. Obtaining such shared PM communicative action is not a trivial process; however, it is a problem that existed well before the recent rise of AI technology. Given the research and experiences of the CI and DD fields, the authors of the present paper believe that if properly used, AI tools and technologies have the potential to increase human capabilities for critical reflective conscious thinking during PM processes. Generally, developing useful AI/human collaboration in PM will require setting appropriate safeguards and controls.

O'Gieblyn (2022) makes the point that even in instances where AI systems are not designed with any purposeful emotional attributes, humans are still capable of emotional transference, often unintended, thereby creating false emotional connections. In the context of PM, this could distort the intended value of AI systems by imbuing them with some of the same characteristics as the human participants. The greatest fear is the supplantation of humanity and the beguiling effect (Vallor, 2024), in which AI assumes not just the agent role, but the actual thought processes for the PM participants. AI may exceed its currently enumerated roles in Fig. 1 through the introduction of personal neuro-technology. The consequence, according to Farahany (2023), is that our thoughts may no longer be our own, with a monumental loss of mental privacy. Perhaps this is already happening with the increasing role that social media internet channels are playing. We see a rapidly developing encapsulation of the society into bubbles of like-minded people, who do not understand and do not want to understand anybody with opposing views.

The technologies that humans have created, however, now have the unprecedented potential to completely alter the existence and roles of human (and non-human) beings in social-ecological systems (SES) (Glynn et al., 2025; Cockerill et al., 2024). Human exceptionalism therefore might need to give way to human humility and self-recognition if AI tools and technology are to be used wisely (i.e., in line with our designation as Homo "sapiens"). Humility means a willingness to critically examine ourselves and our inadequacies in confronting the challenges of modernity, rather than believing by default that human ingenuity will always be adequate to meeting these challenges. PM processes should foster critical reflective thinking about issues, and therefore need to become more aware of the traps laid out by social predispositions and human tendencies (e.g., BBHV). Tools and technologies like AI may be able to help, but only if we use them wisely and with a strong measure of self-recognition of default human behaviors. In contrast, human exceptionalism leads to believing that we humans are always and will always be in control of all of our tools (like AI) and that we can "invent ourselves or our technology" out of any new or future problems that arise. Therefore, exceptionalism leads to unreflective, uncritical thinking or examination of the issues that we face in the present or the tools (like AI) that we use (Glynn et al., 2025).

Summarizing some of our above mentioned concepts and concerns, Vallor (2024; pp. Vii - 2) presents the fundamental philosophical

question about the use of AI, asking:

What does it mean to be human? ... humans endlessly make ourselves anew: we are always more, always unfinished—and for this reason, always uncertain of ourselves and one another ... AI is the first technology that can make us forget how to answer our own question [of what it means to be human] ... another power of AI mirrors, one that is harder to notice but even more dangerous ... is their power to induce in us a type of self-forgetting—a selective amnesia that loosens our grip on our own human agency and clouds our self-knowledge.

4.2. Ethical considerations as constraints to AI proliferation

AI technologies are increasingly leveraged in participatory processes, inviting stakeholders to engage with data-driven models. These practices heighten ethical considerations surrounding participation, consent, privacy, and accountability, among others. Foremost in discussions of ethical AI in participatory settings is the principle of *informed consent*. Ensuring that participants understand how their data will be used, what AI systems will do, and the implications of their decisions is paramount (Law et al., 2024). The ethical design frameworks outlined in Lindgren et al. (2025) emphasize the importance of participatory design processes that incorporate values and address ethical dilemmas from the outset. This aligns with findings advocating for specific ethical guidelines sensitive to local contexts to enhance stakeholder participation and safeguard privacy (Mwogosi, 2025).

Data privacy and security is also a major concern. AI in PM often involves the collection and analysis of vast amounts of personal data, raising concerns over who has access to this information and how it is secured (Kieslich et al., 2022). An ethical AI framework must therefore prioritize robust data protection measures and transparency in data handling practices (Huang et al., 2023; Zhang and Zhang, 2023).

The issue of bias and algorithmic fairness is critical as AI systems can perpetuate existing biases if not designed thoughtfully, which can lead to unfair or discriminatory outcomes in participatory models (Petersson et al., 2023). AI may exacerbate an already skewed system, with the potential to exclude participants and promulgate human divisions. Supplanting humanity through reliance on unevenly distributed and historical data will further promote political polarization, emotional responses to one another, transactional relationships, and ultimately deepen inequality (Ferrara, 2024; Du et al., 2024). Until we have stronger AI that includes reasoning capability we are stuck with the limitation that the future will merely be an optimized version of the past and true innovation will be limited. Where the past has been impacted by past biases this may further erode the virtue of AI in participatory planning and may erode trust in PM deliberations. The research by Prikshat et al. (2022) underscores the necessity for multi-stakeholder ethical frameworks that actively consider bias in AI usage across different contexts. These frameworks encourage collaboration among diverse groups to address and mitigate these biases effectively, promoting fairness and equitable outcomes in participatory processes.

In PM, the importance of *inclusive* stakeholder engagement cannot be overstated. All relevant stakeholders—and especially marginalized voices—need to feel welcomed and included to ensure that the AI systems and PM processes serve the community's interests and respond to their needs (Rice et al., 2025). This participatory approach fosters trust and accountability; and ethical engagement with stakeholders should adhere to principles of transparency and inclusivity (Goirand et al., 2023). Such strategies can prevent miscommunication and misalignment between technological outcomes and community expectations, ultimately enhancing the ethical integrity of AI applications. Ethical AI deployment should also ensure that human stakeholders maintain control and responsibility over decisions and that AI systems complement rather than supplant human judgment (Farisco et al., 2022). Developing clear ethical norms in AI governance is crucial for harnessing its potential without undermining human agency (Fan, 2024).

The use of AI in PM raises questions about social accountability and various stakeholders' responsibilities. Morrison et al. (2025) highlight the growing need for ethically grounded policies that guide the integration of AI in ways that are socially responsible and sustainable, that are continuously reflected on, thereby reinforcing the societal commitment to responsible AI use.

When used by PM organizers, facilitators and participants, AI needs to uphold principles and implement processes ensuring informed consent, data privacy, bias mitigation, inclusive engagement, human autonomy, and social accountability. Enabling and integrating these principles will enhance the efficacy and integrity of AI in PM. Otherwise, we are playing with a technology that makes unsubstantiated claims which should be validated (Du et al., 2024), at the least, and more critically assessed in controlled experiments. This would entail creating a PM process without AI (solely human-driven) and others with different AI intervention points per Fig. 1 to meaningfully assess the differentiated processes' effects on both social and ecological outcomes.

The problem is that, as already mentioned in some of the early studies of PM, it is very difficult to design a baseline process for comparison. In PM we are dealing with human beings, who have a wide range of individual variability of thoughts and behaviors, and who are influenced by the processes that they engage in. It makes no sense to do the same exercise with a group of stakeholders with and without AI involved. After the first exercise it will already be a different group. Similarly it will be hard to compare how two different groups will perform with one group using AI, and the other - not. From the start the groups will be different. The only solution here is to simply accumulate performance data, analyze the results and try to derive some experience and understanding. In part, this is what we tried to deliver with this paper.

In practice, as noted above, ethics and emotions may be hard to account for, in particular in the context of AI in PM. On the one hand, ethics and moral principles are often not constant with time or universal across different locations. What is ethical today was a taboo 50 years ago, what is ethical in Africa may be considered abusive in Europe, and vice versa. Moreover, double standards often occur. "Quod licet Iovi, non licet bovi" is a Latin phrase that remains relevant in many situations in everyday life and politics. Literally it means "What is permissible for Jupiter is not permissible for a cow". And this lack of consistency in developing and applying ethical principles is why continuous, thoughtful, reflection on ethics is needed for AI in PM processes and follow-ups.

On the other hand, humans tend to see AI progress only through the lens of human needs and priorities. As mentioned above, with greater humility, the commonly shared perspectives and values of modern humans, including ourselves, may benefit from reflections and possible modifications considering what is ultimately needed for the sustainability of SES, of the human species, and of its communities. There is also no reason to expect that AI will always have to be bound by the norms and standards of our species. The ethics that autonomous AI-systems may choose to develop may be quite different from those found in today's human communities.

We acknowledge that historical information has value, but we should recognize that AI does not discriminate, unless we ask it to, between old information and recent information and could risk omitting the latest thinking and evolution of culture. This bias to build on past decisions and prior information can, in some instances, constrain thought and may hamper the human to human engagement that fosters creative thinking and outcomes which are one of the strengths of the PM process. This is a factor that needs to be considered. Moreover, in much of our discussions we assume that we will always be in control and that we will be deciding the appropriate role of AI, with its constraints and permissions. However, this also can change. Wilson (1998) described the central problem of humanity like this: "We have Paleolithic emotions, medieval institutions, and godlike technology." AI elevates our technology yet to the next level of divinity. We are hardly prepared for that.

4.3. An imaginary AI-for-PM platform: what might be needed, what would it do

Imagine an AI-for-PM platform that seeks to improve rather than supplant all aspects of a PM process. Our idealized platform is called ASH because it thoughtfully considers ethics and the human condition (like Hannah Arendt; e.g. [Arendt, 1981](#)), it raises questions rather than just providing answers (like Socrates; e.g. [Plato, 375BCE](#)), and it addresses the need for communicative action (like Jurgen Habermas; e.g. [Habermas, 1996](#)). ASH can provide efficiencies – including automated recognitions, interpretations, or representations. It encourages and enhances human thinking and agency in PM by asking questions to improve *human recognition of and address* PM problems. ASH keeps track of and facilitates – through human-created standards and guidelines – the resolution of ethical, trust, and legitimacy issues.

For any given task or problem the platform will start with carefully scoping the available data and information related to the topic. It will assemble the references and provide an overview of the relevant knowledge. It will generate some conceptual models of the system at several levels of detail, and will carefully identify the system boundaries, as well as the relevant spatial and temporal scales.

ASH will then help identify potential PM participants, i.e., not just their names but also their likely sources of knowledge, possible PM-contributions, and/or PM-engagement reasons. Engagement reasons would include needs for representation of important constituencies, such as cultural groups, or by proxy, non-human species or future human generations. ASH would suggest human actors suited to representing the unrepresented. If that was not possible, ASH would ask whether AI agents could represent the unrepresented.

During the facilitation phases of the PM process, ASH would aid the human agents working with it, and explicitly help to:

1. Recognize human inadequacies relative to the PM challenges at hand (e.g., inappropriate norms or narratives resulting from BBHV or biocultural evolutionary adaptations);
2. Point out possible constituency/participant motivations and conflicts of interest;
3. Discern value positions and ask questions of ethics;
4. Improve knowledge communication/translation (information and beliefs) between PM participants (and external entities);
5. Provide position summaries, and information on participant position aggregations or disaggregations
6. Ask, reflect, and provide feedback on feasibility of PM outcomes and recommendations. What chance do the PM recommendations have of being put into practice? What are longer-term larger-scale likely consequences if they are, beyond those considered during the PM process?
7. Assess and/or suggest process or n changes with the goal of improving the efficiency and utility of PM and the societal and political adoption of its results.

As part of the facilitation process ASH will start generating simulation models of various levels of complexity to inform the participants about the system dynamics and the outcomes of various possible scenarios that may be discussed in the meanwhile.

ASH will bring transparency and accountability by recording PM processes and steps, thereby helping create Records of Engagement and Decision-making (RoED; [Cockerill et al., 2019](#); [Glynn et al., 2018](#)).

Throughout the PM process, some form of control and/or of control-determining principles would need to be established to assess when, where, and how (1) the different AI capabilities of the ASH platform come into play, and (2) humans users (or human components) of ASH had responsibility to provide answers and/or make decisions.

We recognize that the imaginary ASH platform that we envision could be used for many different types of participatory deliberations, beyond the field of PM, wherever we seek to maximize CI as well as

inclusivity of perspectives, fairness in opportunities offered or enabled, etc. Currently, AI development and use seems to have few controls offered by human agency except for the important drivers of technological and commercial or economic advancement. At its core, PM is concerned with improving societal well-being, including through judicious use of resources and more sustainable life environments, but also through improved societal engagement and agency. ASH would be an enabler of these goals and could serve as one model of what might be needed in an AI-for-PM platform.

When imagining and designing the ASH platform, we have been guided by traditional thinking that humans are in control of the systems that they create and that it will remain up to them to add or remove functionalities and performance characteristics as needed. With the advancement of AGI and ASI, this may not hold true. We are already seeing an increase in the use of self-improving, self-evolving algorithms. These algorithms constantly reprogram themselves and optimize their performance in ways that may be hard for us, humans, to appreciate, and, perhaps, even to track. We agree with [Rainey and Hochberg \(2025\)](#) that it would be best for the human species if AI remained a tool and part of human evolution – rather than a driver in the evolution of a new integrated AI-Human species. It seems safer for humans to remain in control of how AI systems interact with human lives, share responsibilities, and how the composite human–AI systems evolve.

5. Conclusions

In this paper we have looked at the developments in AI through a lens of PM, an approach which has been hailed over the past 50 years as a way to improve our decision making processes. We have summarized our observations in [Table 2](#).

The proliferation of AI technologies and their deployment in many aspects of modern life in the past decade has astonished even those technical experts who have pioneered many recent innovations. Many of these experts are aware and readily acknowledge the latent dangers associated with this development ([The Times of India, 2024](#)). However, largely because of these risks and the ultimate powers that are associated with AI, the nature of business and international competitiveness and the fear of being left behind or being disadvantaged by a rival in the marketplace has provided little in the way of constraint. Again and again we see that instead of experts that guide the field, it is now the entrepreneurs and investors who determine what and how AI is progressing. Commercial ventures such as OpenAI that were initially conceived as a non-profit firm with the goal of embracing responsible and ethically sound development of AI concepts have since applied to change their business model and instead transform into a for-profit entity with an associated lapse of ethical guiding principles. Although the current political climate in the US is unlikely to witness the entry of government to provide leadership in the role of regulator addressing ethical concerns and allaying public fears of an eventual takeover by AI technology or forces closely allied with these forces, most practitioners nonetheless see a long term need for this type of intervention. The US is unique among nations in giving legal recognition to corporations as persons ([Hartmann, 2010](#)) and some infer the potential for AI agents to similarly be granted rights under current law ([Harari, 2024](#)).

Despite the current clamor of AI proliferation in the commercial sphere and media coverage of the dangers of unregulated AI development, AI is recognized as having scope for the enhancement of current participatory modeling practices. Perhaps the greatest impediment to the widespread use of algorithmic AI models and other tools for decision making is the lack of transparency ([Cheong, 2024](#)). Requiring that all AI code development should be open source – the most obvious solution to issues of transparency and fair use – may turn out to be problematic in the case of AI, where we are dealing with potentially harmful and dangerous technology if used inappropriately. Open sourcing such applications may have quite devastating results in the wrong hands.

Prior discussion has suggested that without meaningful insight into

Table 2

A brief overview of AI applications in PM.

PM goals, needs and advantages	AI solutions	+ benefits	- risks
Modeling			
Data collection and processing	Social media analysis; Intelligent sensors with automated data logging & analysis; Factor analysis	Saves time and labour involved in surveys; Makes continuous data acquisition possible; Helps identify critical factors	Misinterpretation, biases
Model generation	Pattern recognition algorithms to identify patterns within large sets of data	Faster modeling; Multi-model approach	Lack of transparency and explainability
Simulation, model analyses (including sensitivity and uncertainty)	Parameter optimization; Synthetic data generation; Automated simulations	Improved understanding of model behavior; Faster model analyses; More scenarios analyzed; Increases stakeholder confidence in the models	Prone to manipulation by expert stakeholders; Unrealistic scenarios may creep in; Lack of transparency makes uncertainty more difficult to communicate
Visualization and interpretation	Prompt engineering; Interactive dashboards; Nudging	Easier interpretation of results; Persuasive and informative output	May require special training; Inequity with various levels of access and power
Participation			
Process transparency	AI tools for exposing biases, preparing detailed documentation, etc.	Better process understanding; Increased public awareness	Less control over what is transparent and what is not.
Stakeholder selection	Subpopulation identification using cluster & network analysis; AI agents as stakeholders	Ensures voices of stakeholders are heard by facilitating stratified stakeholder selection; Helps represent the unrepresented/external perspectives	May violate privacy of individuals and lead to segregation; AI agents may dominate the discourse because of their superior data access and analytical skills
Stakeholder discussions	Online discussion platforms; Fast generation of group mental models based on discussions; Cognitive maps for visualization; Digital nudges using bots; Summarize discussions	Inclusion of larger numbers of stakeholders for asynchronous (in time and space) engagement; Power control to avoid hijacking discussions; Empower moderators to provide fast feedback; Matching individual skills & group tasks	Humans may slowly lose control of the PM process; Overspecialisation; Detachment of some stakeholders

Table 2 (continued)

PM goals, needs and advantages	AI solutions	+ benefits	- risks
Scenario generation	GenAI and appropriate prompt engineering	Increases range of scenarios that are both valuable & feasible	Losing track of subjective/emotional needs
Scenario analysis	Automation tools for faster model runs and result analyses	Provides actionable insights with reduced human bias	Neglect of human judgment, ethical principles, and loss of context
Detection of emotions or human priorities	Emotion AI, sentiment analysis, affective computing	Quicker understanding of participatory perspectives	Manipulation of human emotions and perceptions; group think
Recognition of prevalent BBHV and norms; or of overly simplistic and inappropriate mental models and narratives	AI-enabled recognition and socratic questioning of common BBHV, narratives and mental models	Potential countering of mental models and narratives that are inappropriate	Countering prevailing mental models, values, or norms risks exploding PM or at a minimum not achieving consensus.
Creating strategic fuzziness and diplomatic tones in communications	AI (e.g. Habermas) changing communications so that they are toned in more diplomatic language, or include sufficient strategic fuzziness	More easily allowing common ground to develop.	Lack of efficiency in the short-term. May not work, or may be perceived as untruthful or illegitimate.
Proof of humanity or of identity or sourcing for digital contributions	AI identification of humanity, individual identities, and source verifications	Establishing origins for digital contributions	May fail and/or provide a false sense of security

the weighting factors and decision process, impacted communities cannot adequately engage in the planning process and may feel disempowered. Furthermore, bias and decision outcomes favoring dominant stakeholder interests are difficult to challenge without a clear accounting of the factors considered in the selected model algorithm(s). Further potential bias that is inherent in the use of LLMs in PM is the fact that some indigenous and less advantaged communities may rely on forms of communication that are non-verbal and not documented and therefore absent from the data being processed (Muller and Passoth, 2022). Inclusion of ethical participatory modeling factors can help to screen AI-aided PM tools from this oversight.

While the development of AI is still often seen as a race (Wold, 2025), there are growing concerns about its future and about this whole process becoming a race to human extinction. We cannot say when and how exactly this “race” will end, so in the meanwhile there are certainly many tools and functions that AI can provide to enhance and facilitate the PM process.

The main unknown remains the goal-setting issue of future development. So far, we could assume that the decision making process has been following the goal of improvement and refining of certain conditions for the sake of the *Homo sapiens* as a species as a whole, or for some groups or categories within this species. PM as such has been invented as an approach to help us reach these goals by improving the decision making process. For as long as humans can control AI and remain responsible for the choice of the goals that they define, AI will remain yet another ‘assistant’ working for the benefits of the humans. Here we have considered how this assistance can be used within the framework of the PM process.

So far we have no idea what goals an ASI might choose in the future. We can only imagine what kind of relationships our species will develop with ASI. If humans are lucky, they may become nice companions, which ASI will take care of, perhaps to satisfy certain emotional needs, if the ASI will have any. Just like humans have pets, the ASI may love, feed, and enjoy humans. In this case we may still have some realization of what is happening and how history is developing. Just like dogs or cats may understand what their owners are up to, and in some cases may even have a say in what will be happening.

Otherwise, we may end up with an arrangement similar to what we have with the billions of bacteria that inhabit our body. Bacteria live their lives, focused on their local sensing environments, reacting thereto, and performing functions, likely without great cognizance of human bodies as a whole, and without attention to human plans and goals.

Finally, we cannot exclude the scenario in which there will be simply no need and no place for humans to exist. The superb intelligence of the ASI will wipe us out as a species, and will continue developing towards some goals unknown to us. Just like many other species that existed in the past and served as stepping stones on the way of human evolution, we would have played our roles, did our job creating superb intelligence and would be simply erased by the evolutionary process as no longer useful. One way to save ourselves could be to build “maternal instincts” into AI models, so that they care about us even if they become more powerful than us (Wright, 2025).

In any of these cases there will be hardly any need for PM. In the meanwhile, we can certainly improve our decision making process by using PM and incorporating the AI functionality in the many stages that we have listed above. Perhaps that will also bring us closer to a broader discussion about our own goals and the role of AI that we wish to allow. It is also yet to be seen whether we decide to somehow interfere in the evolutionary process, whether we even can do it or not, to preserve the intellectual dominance of *Homo Sapiens* and prevent new forms of intelligence from eliminating us.

If humans want to assert some control over their evolution and survival as a species (Rainey and Hochberg, 2025), some agreements and regulations are urgently needed. It is becoming increasingly clear that AI development can easily go out of control and some decisions are clearly overdue. With our experience in the PM domain and being strong advocates of this approach for decision making, we can only suggest that a well organized PM effort could bring together all the important stakeholders needed to come to some concrete decisions about how we oversee the advancement of AI, or at least create standards and guidelines, if not even regulations for how it is developing. We can even already start using the AI tools that are available to make this process more productive.

CRediT authorship contribution statement

Nagesh Kolagani: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Pierre D. Glynn:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Alexey Voinov:** Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Conceptualization. **Nigel W.T. Quinn:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **Jennifer Helgeson:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Caitlin S. Dyckman:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envsoft.2025.106762>.

Data availability

We have shared a link to a Google Doc in the Supplementary Materials.

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