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Wisdom of stakeholder crowds in complex social–ecological systems

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Sustainable management of natural resources requires adequate scientific knowledge about complex relationships between human and natural systems. Such understanding is difficult to achieve in many contexts due to data scarcity and knowledge limitations. We explore the potential of harnessing the collective intelligence of resource stakeholders to overcome this challenge. Using a fisheries example, we show that by aggregating the system knowledge held by stakeholders through graphical mental models, a crowd of diverse resource users produces a system model of social–ecological relationships that is comparable to the best scientific understanding. We show that the averaged model from a crowd of diverse resource users outperforms those of more homogeneous groups. Importantly, however, we find that the averaged model from a larger sample of individuals can perform worse than one constructed from a smaller sample. However, when averaging mental models within stakeholder-specific subgroups and subsequently aggregating across subgroup models, the effect is reversed. Our work identifies an inexpensive, yet robust way to develop scientific understanding of complex social–ecological systems by leveraging the collective wisdom of non-scientist stakeholders.

Many environmental problems that influence human wellbeing, such as climate change, biodiversity loss and overexploitation of natural resources, are caused by a combination of social and ecological factors that occur in coupled systems across scales[1]. Managing resources under such complexity requires adequate system representation (models)[2], so that the system's response to management decisions can be anticipated before action is taken. However, the sheer number of intimately linked social–ecological systems that require management, limited knowledge and resources, and the difficulty of enumerating many system elements cause scientific model creation to lag behind decision-making needs in most natural resource contexts[3,4]. This limits the effectiveness of natural resource management and contributes to the collapse of many exploited systems, such as fisheries[5].

To address knowledge limitations and data gaps, resource managers frequently receive input and decision-making support from resource stakeholders[6,7]. Resource users sample the natural environment through their routine interactions with social–ecological systems (for example, while fishing or hunting)[4] and thus accumulate and refine knowledge and observations over years and, frequently, in different locations (for example, anglers moving among lakes)[8]. Therefore, monitoring and assessment of natural resource dynamics may be improved by leaning on the knowledge of diverse resource stakeholders (for example, fishers)[7] in ways that harness their collective intelligence[9]—the ability of a group to solve problems effectively. For example, natural resource management increasingly uses citizen scientists[10] to collect and aggregate observational data (for example, by observing bird distribution and abundance)[11].

Importantly, the collective intelligence held by a group can also be harnessed by pooling judgements, rather than observations, from large, loosely organized collectives or 'crowds'. The so-called wisdom-of-crowds (WOC) phenomenon was discovered more than a hundred years ago, when the average judgement of the crowd of observers accurately estimated the weight of a dead ox[12]. This phenomenon frequently leads to surprisingly accurate point estimates by averaging the judgements of a large collective[13]. In addition to simple estimation tasks, a WOC effect has also been researched in cases of higher solution complexity, such as combinatorial problems[14,15]. Understanding the complex social–ecological interactions in natural resource ecosystems, however, constitutes a considerably more difficult problem than counting the number of birds[10], guessing the weight of an animal[12] or solving a Euclidean travelling salesperson problem[15]. Natural resource managers frequently have to predict future system states (for example, in response to a planned management intervention), which requires more complex knowledge about the structure, connection and dynamic behaviour of natural resource systems, often associated with high uncertainty and with no clear 'correct or optimum' solution. It is currently unclear if the WOC approach can harness collective intelligence for such complex problem-solving conditions.

In this work, we explore if the WOC can be leveraged to provide accurate system knowledge about natural resources. Specifically, using a case from fisheries, we ask: can crowds of non-scientist resource users provide representations of the ecological and social cause-and-effect relationships that drive resource stock dynamics and mirror the best scientific understanding of the same social–ecological context? Given the urgent need to effectively manage globally declining fish stocks[16,17], this is a question of utmost relevance: if stakeholder crowds can provide accurate representations of complex social–ecological relationships, then by using the collective intelligence

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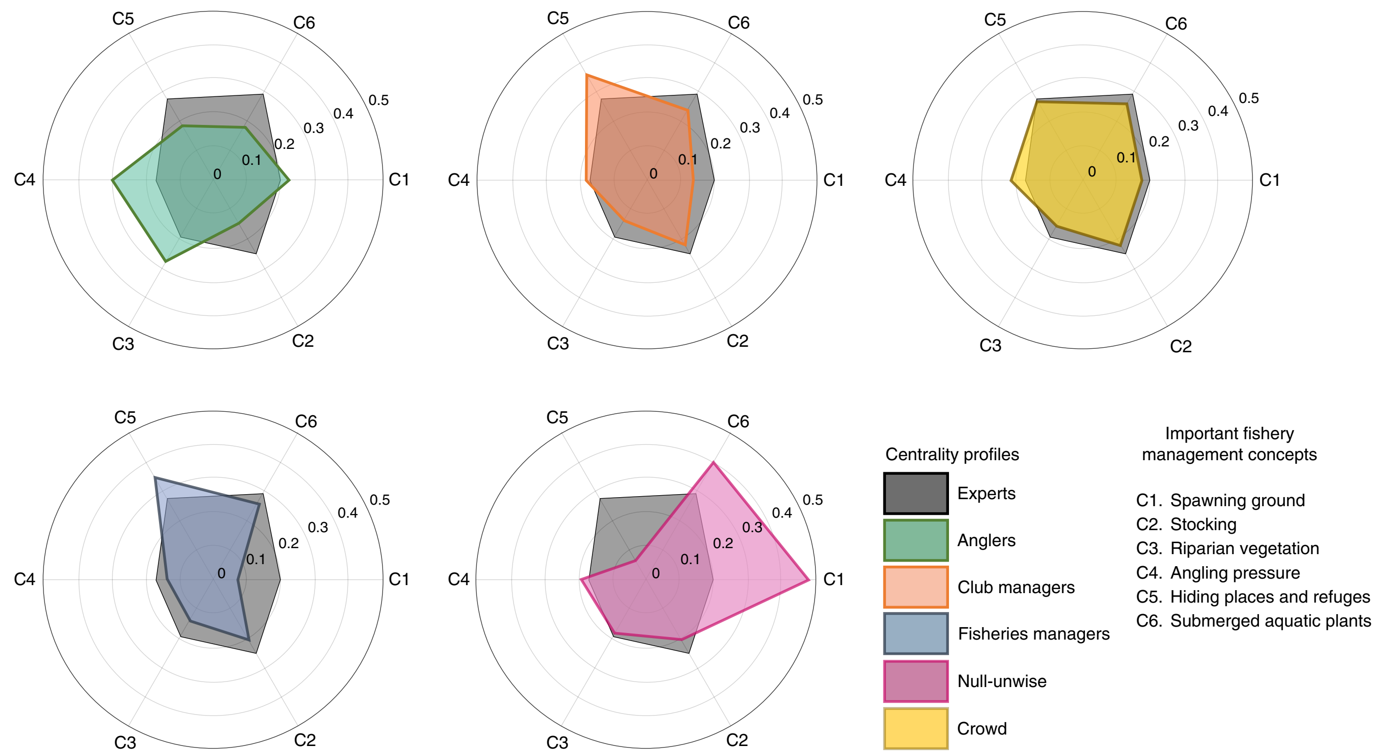

Fig. 1 | Centrality profiles of different groups (in colour) and the expert reference model (in black/grey). Axes in the radar charts show the centrality of system elements that are important for fishery management decisions. Katz index[58] is used to measure the centrality (see Methods).

of stakeholders we could create a more complete coverage of localized social–ecological processes than any team of scientists can ever achieve when traditional scientifically driven assessments are limited and cannot cover the universe of local environmental and social interactions.

One way to elicit system representations from stakeholders is through cognitive maps. These are graphical models of system elements (concepts) and their causal connections (represented as signed arrows). They represent an individual's internal perception of external reality, referred to as mental models[18]. Mental models of complex systems can be represented in special semi-quantitative forms of cognitive maps called fuzzy cognitive maps (FCM)[19,20]. Importantly, individual mental models elicited by FCMs can be aggregated mathematically to create a model that represents the insights of all subjects[19,20]. However, there is a lack of empirical evidence to explicitly demonstrate a WOC effect in averaging a crowd's mental models about complex social–ecological relationships, such as human interactions with natural fish populations[21].

In this study, we explore using WOC principles to establish a presumably accurate understanding of natural resource dynamics by proposing and testing an approach for aggregating individual mental models collected from non-scientist stakeholders. We use an example of a recreational fishery ecosystem and independently generated mental models, represented by FCMs, from diverse resource users, composed of individuals who interact with fishery resources in different ways, either through exploiting fish populations (anglers), managing resources (fisheries managers) or governing communities of resource users (angling club managers).

In general, and especially for complex problems with many interrelated components, incorporating diverse knowledge and expertise into collective problem-solving improves the group's performance[22–24]. Similarly, diversity of perspectives has been identified as a critical driver of WOC[13]. Building on earlier theoretical reasoning[22–24], we hypothesize (H_1) that, a system model generated by aggregating the mental models of a crowd of diverse resource users outperforms the models of more homogeneous groups.

Yet, it is realistic to assume that users of the same social–ecological system are most likely to be socially influenced by their peers in real life, especially by those from the same stakeholder category (for example, anglers, club managers and fisheries managers) due to similarities in the ways they use and interact with the natural resources. Such interactions can be direct through face-to-face communications or indirect through sharing knowledge, information and assumptions over media and through being exposed to a similar set of information sources (for example, educational material codified in books). Socially influenced subgroups of individuals, however, tend to accumulate and represent correlated knowledge. Despite potentials for social learning and improving the accuracy of the collective judgements, prior WOC studies[25–27] have shown that under such conditions, averaging data points from a larger crowd of individuals increases the risk of amplifying biased knowledge that derives from direct or indirect exposure to social influences, thereby potentially diminishing the WOC effect[25–27]. Therefore, we hypothesize (H_2) that, when arithmetically averaging mental models of stakeholders with plausible real-life social influence, larger samples of mental models may amplify the negative effect social influence can have on WOC, thereby deteriorating collective performance as crowd size increases.

To deal with the latter issue, past theoretical and empirical WOC studies[26,28] have suggested that, once there are multiple 'modules' within a large crowd (smaller subgroups of individuals whose opinions are more likely to be directly or indirectly influenced by their subgroup peers), the WOC can be enhanced by averaging responses across modules[26,28]. Assuming that the crowd is suffering from the possible negative effect social influence can have on WOC[27] and building on prior theoretical work[26], we hypothesize (H_3) that a multi-level aggregation method that averages mental models within modules (subgroups of stakeholders from the same

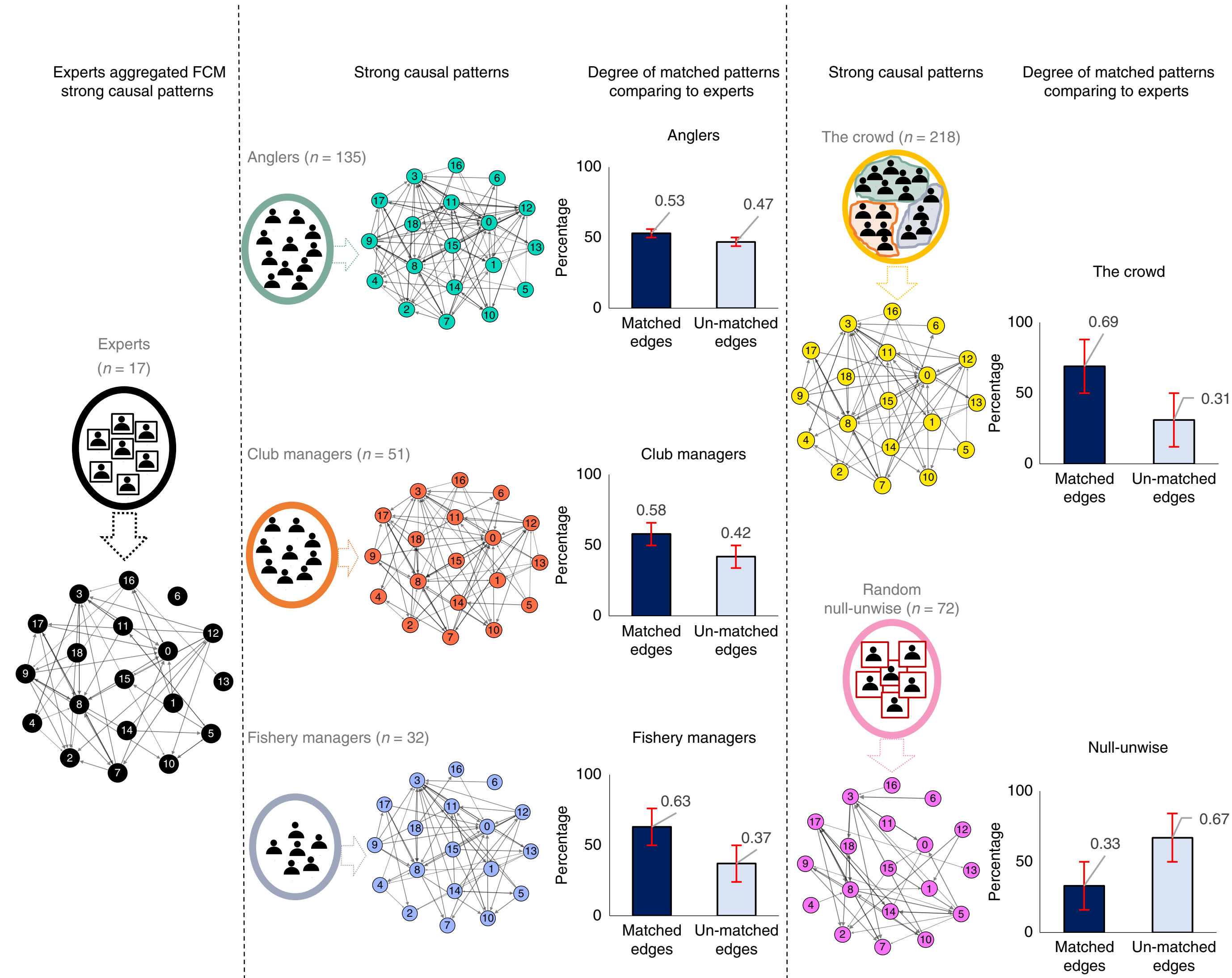

Fig. 2 | Agreement on strong causal patterns in the FCM of stakeholder-specific groups, the crowd and the experts. The crowd map has the highest degree of matched patterns (~70% matched) with experts; the stakeholder-specific groups perform substantially better (among 53% to 63% of correct matches) than the null-unwise model (only ~30% correct matches). Weak relationships with an edge weight less than 0.33 (the first tertile in zero to one continuum, corresponding to the weak interval) were removed from the maps to get the strong causal patterns (see Supplementary Fig. 2). Error bars display standard errors.

user type category), followed by a subsequent aggregation across modules, can dampen the negative effect of social influence. This multi-level aggregation approach may compensate for the possibly harmful biases as a result of social influence, thereby allowing larger crowds to demonstrate an improved WOC effect.

Our work tests the above-mentioned three hypotheses (H_1, H_2 and H_3) and thereby establishes that WOC can be leveraged to crowd-source system knowledge of social–ecological and other complex systems, while also offering methodological guidance for aggregating the input of crowds of resource users to generate high-quality system models similar to those developed by trained scientists. Our findings provide the basis for managing and planning interventions in complex social–ecological systems that are data-poor or even data-deficient but that have an abundance of local knowledge from resource users.

Experimental design. We collected graphical mental models of 218 stakeholders characterized as recreational anglers, angling club managers and fisheries managers through a FCM task in a series of workshops in angling clubs recruited from north-western Germany. The FCMs represented participant understanding of the fish ecology and fishery management of northern pike (*Esox lucius*) fishery (see ref. [21] for details). The individually collected mental models graphically displayed the perceived cause-and-effect relationships of ecological and social concepts affecting each other (see Supplementary Fig. 1). Additionally, we ran two FCM workshops with 17 fishery scientists, each of whom had formal training and scientific knowledge in fishery resource dynamics and pike ecology, to create a scientific reference mental model representing the best scientific understanding about the same ecosystem.

We experimented on various ways to draw and aggregate mental models from a population of stakeholders to explore the impact of diversity, possible biases raised because of real-life social influences and aggregation methods on the WOC. The effects were quantified by comparing the aggregated mental models against the scientific reference mental model (experts' group mental model).

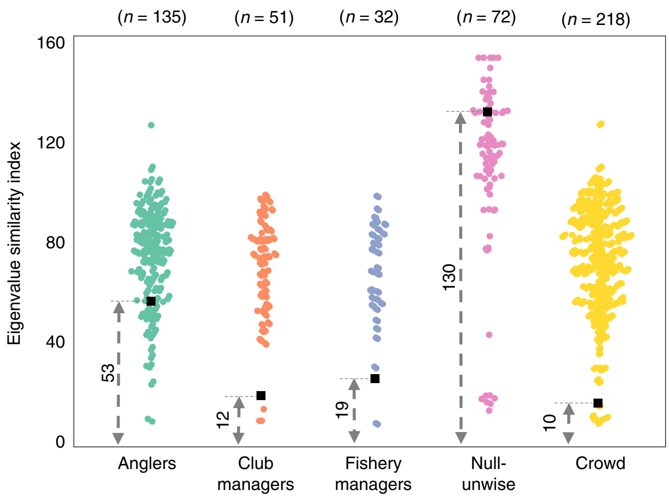

Fig. 3 | Eigenvalue similarity index. Within each group (*x* axis), each point represents one individual and is placed according to the eigenvalue similarity index (*y* axis). The similarity index represents the structural mismatch with the experts mental model. The swarm plots reflect the density of points around any distance value, while black squares represent the aggregated mental models for each group. The crowd model has the smallest distance from (highest similarity with) the experts model. Interestingly, for all stakeholder groups, aggregated model is located below the densest area of the plot, illustrating the WOC effect (the average model outperforms most individuals). Yet, this effect is notably higher in the crowd.

We used two aggregation methods: (1) single-level that is accomplished by arithmetically averaging the weights of all individually contributed links in FCMs of group members (see refs. [19,20] for details) and (2) multi-level that first divides the stakeholders into separate modules (smaller subgroups) and arithmetically averages the edge weights of all contributing maps within each module, and then, in the second level, uses the median to aggregate the maps across the modules (see Methods). We proposed to use median in the second level of aggregation because the median has been shown to outperform the arithmetic mean in likely skewed distributions[12,29,30].

We used the single-level aggregation method to form the averaged mental models of stakeholder-specific groups with members only from one stakeholder category (homogeneous groups of anglers, club managers and fisheries managers). We also aggregated all 218 individual mental models using the multi-level aggregation method to construct a crowd mental model composed of diverse stakeholders. To create the scientific reference model we aggregated the mental models generated by 17 scientists (experts) using the single-level aggregation method. We compared stakeholder-derived models against the experts' group mental model (reference model) in terms of their (1) centrality of concepts representing pike ecology and management, (2) strong cause-and-effect relationships, (3) network geometric structures and (4) dynamic behaviour (see Methods).

In addition, we built a 'null-unwise' model by aggregating a set of artificial mental models made by a random graph generator using the probability distribution of edge weights drawn from the population of all participants' mental models. We used this null-unwise model to test that any observed WOC is not simply an artefact of averaging mental models and is attributed to stakeholders' real-world relevant knowledge.

Finally, to test the impact of accumulated biases of socially influenced individuals on the WOC effect and the success of different aggregation methods in filtering out these biases, we formed numerous samples of individuals randomly drawn from the entire population of 218 stakeholders with different sample sizes. For each random sample of individuals we aggregated their mental models using two aggregation methods: single-level and multi-level. We then computed an overall performance error by comparing the aggregated mental model against the expert's mental model (see Methods for details).

Results

We find that the structural properties of the crowd mental model match scientific understanding about the social–ecological relationships driving pike fisheries. This was evidenced by evaluating agreement between the crowd model and the scientific model using three metrics: (1) centrality index (which represents the relative importance of a concept in the mental model), (2) strong causal patterns (which represents the arrangement of strong cause-and-effect relationships) and (3) graph eigenvalues (which represent hidden fundamental patterns of geometric structure that has implications for the networked functionality of a mental model). The centrality measures (see Methods) indicated that the three stakeholder-specific groups were biased toward specific management strategies (for example, anglers were biased toward angling pressure being particularly impactful for pike and fisheries and club managers were biased toward enhancement of habitat quality promoting pike) (Fig. 1). However, in support of our first hypothesis (H_1), when the mental models of all diverse stakeholders were aggregated, the crowd model demonstrated remarkable similarity to the experts (the reference model) regarding the centrality of six important concepts for possible impacts of fishery management decisions on pike population (Fig. 1). The crowd also showed the highest agreement with the reference model regarding the strongest cause-and-effect relationships in pike ecology and management (Fig. 2). Additionally, the eigenvalue similarity index (see Methods) also indicated that the structure of the crowd mental model had the most similar fundamental characteristics to the experts, suggesting yet again notable structural agreement (Fig. 3). We, therefore, conclude that the structure of the mental model of the crowd is similar to the one produced by experts and thus, a WOC effect is demonstrated.

Structure does not necessarily provide insights into how the fishery might react under changing social–ecological conditions. We, therefore, assessed the dynamic (functional) behaviour of the FCMs by simulating how changes in one or more system elements of the mental models affected the state of all system elements (see Methods). We find again in support of H_1 that the functional properties of the crowd mental model accurately match scientific understanding about pike ecology (Fig. 4). We revealed this agreement using a measure of dynamic distance, which represents the mismatch between two models in terms of the outcomes they produce as a result of changes in the state of one or more concepts. The functional properties of the mental models generated by the crowd and experts aligned, where the mean of the dynamic distance between experts and the crowd was the lowest compared to all stakeholder-specific groups (Fig. 4).

We also find that the impact of biases deriving from real-life social influences showed two distinct behaviours across different aggregation methods affecting WOC performance (Fig. 5). For the models built by single-level aggregation, larger samples of stakeholders amplify the accumulation of biases and thus group performance error increases at larger sizes in agreement with H_2 (Fig. 5a). By contrast, confirming H_3, for the models built by multi-level aggregation larger samples of stakeholders cancel out the biases and therefore group performance error decreases monotonically as more data points are drawn from the population of mental models (Fig. 5b). Consistent with prior theoretical and empirical works[26,28], we collectively show that the WOC effect is indeed observed for

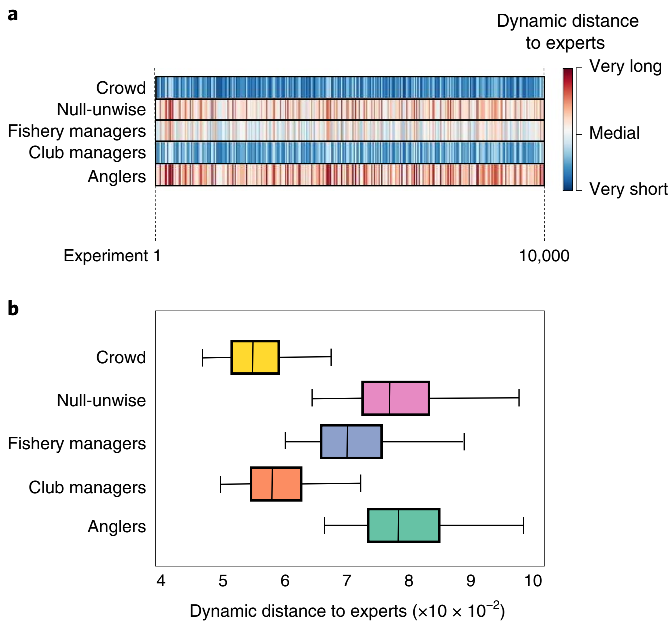

Fig. 4 | The dynamic distance between the experts model and the stakeholder-derived models based on 10,000 randomly generated scenarios (experiments). Each experiment randomly selects a set of concepts (nodes in the FCMs) and changes their values to produce outputs (see Methods). **a**, Each cell in the colour-bar graph represents a random scenario with colours denoting the dynamic distance. **b**, Boxplots illustrate the distribution of these dynamic distances for each group in 10,000 experiments. The mean of dynamic distances from the reference model is the smallest in the crowd.

the large crowds, which consist of multiple socially influenced subgroups of stakeholders (modules) but only if multi-level aggregation, as opposed to single-level aggregation, is used (Fig. 5). This result supports previous experimental studies[15,27], implying that social influences and their resulting biases, if not appropriately harnessed[31], will undermine the WOC effect in large crowds when averaging individually collected mental models about natural resource dynamics, at least under the conditions of our study.

Discussion

This study advances the science of collective intelligence by examining how the WOC can be leveraged to crowd-source mental models of social–ecological systems. We demonstrate that a large-enough group of diverse and informed stakeholders, who pool their mental models, can provide system descriptions that mirror the representations of system knowledge by scientific experts (Figs. 1–3). This is an important finding because there is a widespread lack of monitoring data and scientific models in many freshwater and small-scale coastal fisheries and other exploited ecosystems with which resource users regularly interact[5]. Our work supports an earlier hypothesis[4] that the knowledge of these local resource stakeholders can provide the insights necessary for sustainably managing exploited ecosystems and preventing their collapse.

Consistent with Page's diversity theorem[22], we found that the system model generated by a crowd of diverse individuals could potentially outperform the models of stakeholder-specific groups. However, assuming that the crowd is suffering from the negative effect social influence can have on WOC, and consistent with recent theoretical work[25,26], we also demonstrate that larger crowds do not necessarily perform better. Instead, aggregating more data points (individual mental models) in larger crowds may decrease performance under certain conditions (Fig. 5a). Our work thus extends prior theoretical work[25,26] by providing empirical evidence that shows the importance of knowledge distribution and aggregation methods in WOC tasks where correlated information could decrease performance with increasing group size.

The multi-level aggregation method that we present offers a solution: it first creates subgroup-level models for user groups assumed to be under group-specific social influences, based on the arithmetic mean (filtering out system aspects the subgroups did not agree on, thus reducing variance). It subsequently aggregates those initially formed subgroup models, using the median of the mean values (reintroducing variance). This approach benefits from both modularity that creates a situation of optimum knowledge variation[26] and compensates for a skewed distribution of opinions through using the median rather than mean, thereby enabling improved performance in larger crowds (Fig. 5b). This is a very important finding for guiding the application of the methods we present in a natural resource context. Even though simple aggregation can provide accurate models with an optimal (small) sample size (Fig. 5a), in our case, this optimal sample size that minimizes the group performance error[25] is not theoretically quantifiable due to the unknown correlation between individual beliefs. Our multi-level aggregation method addresses this issue by triggering a WOC effect that monotonically improves with relatively larger sample sizes. This is of practical relevance for sustainable natural resources management, where often no robust criterion exists for exclusion of some stakeholders, and contrarily, an unbounded inclusion of all stakeholders' perspectives is highly encouraged for democratic reasons[32] (see Supplementary discussion and Supplementary Fig. 3).

A few limitations are worth outlining. First, we used a particular format, namely FCM[33], to capture, represent and aggregate mental models, as well as to explore the structure and dynamic behaviour of the system these models represent. Other system formats may lead to different results. Also, while great care went into the selection of experts, knowledge elicitation, modelling and model testing, we cannot claim that the reference model is the best possible representation of the participating scientists' knowledge of pike ecology, nor does it necessarily represent the best known science. However, because any existing limitation of the reference model equally applies to the other models in this study, our conclusions regarding the WOC for obtaining system knowledge from stakeholders remain robust. A further limitation is that our findings were generated from a specific natural resource management context with a unique governance system: in Germany, local level angling clubs are self-managing their privately owned fishery resources[34] and both managers and anglers have to pass training that exposes them to concepts of aquatic ecology, fisheries management and conservation and fisheries legislation[35,36]. This, in addition to the workshop settings for data collection, which probably attracted more avid and experienced anglers, means that our sample probably included ecologically interested and rather educated anglers. It is therefore uncertain whether our results translate one-to-one to other natural resource systems, where resource users are less heavily engaged in the local management of resource systems. Also, in our experiments, all participants were provided with a standardized list of system components (see Methods) in favour of model comparability[37]. Therefore, the extent to which our findings would apply to situations where there are considerable debates concerning the constituents of a system is unknown. Finally, while our findings demonstrate that WOC can be leveraged to provide accurate system representations, it is unknown whether the crowd has the ability to quantify the status of natural resources, assess human pressures on them and derive sustainable harvest rates—all of which are critical components of sustainable management[4,5]. These are important directions for future research.

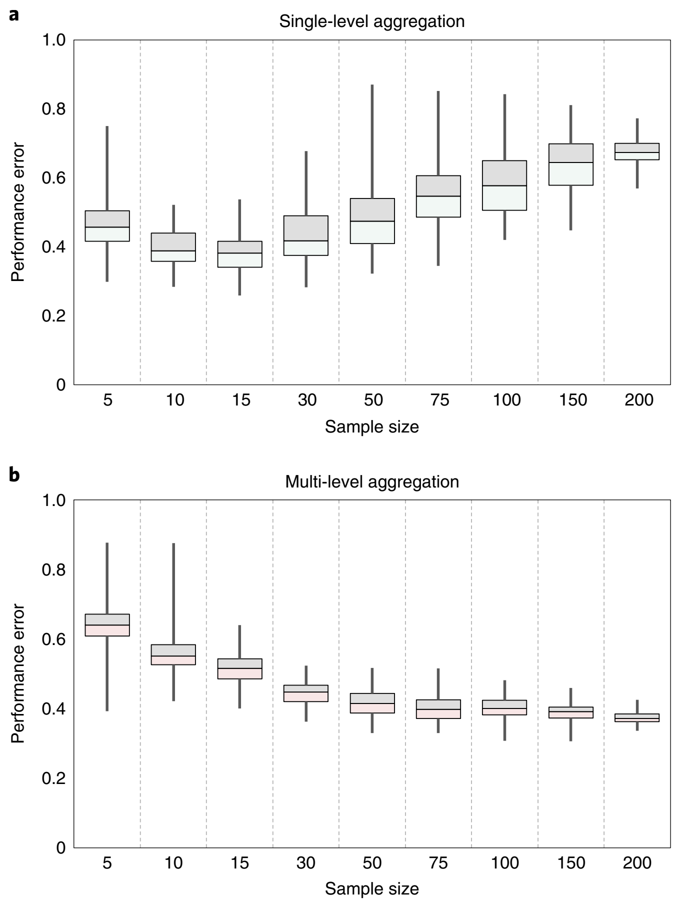

Fig. 5 | The sampling and averaging effect on performance error in crowds built by drawing and aggregating mental models using two aggregation methods. a, Single-level aggregation. **b**, Multi-level aggregation. Samples were formed by randomly drawing individuals from all 218 participants. Data are shown for 100 repeats per sample size. Tests of >100 random crowd assignment show no significant difference.

When looking at possible applications of our findings, importantly, the crowd's model not only approximated the structure but also the dynamic behaviour of the scientist-provided model in response to changes (Fig. 4). This is relevant for designing inclusive processes and adaptive co-management practices that require stakeholders, managers and scientists first model probable outcome scenarios and then jointly agree on possible management actions for uncertain ecosystems[6,38]. While frequently proposed to manage uncertainty in social–ecological systems, such adaptive management approaches often suffer from a lack of readily available simulation models[6,39]. On the basis of our work, we instead recommend proactively involving local stakeholders in system simulation by aggregating individual mental models resulting from online or other survey means.

To conclude, we found that robust scientific information of complex ecosystem dynamics can be generated from a group of informed stakeholders. In fact, when done at the right scale and for the appropriate problem, leveraging the collective intelligence of stakeholders through a crowd-sourcing approach can be a stepping-stone for fostering institutional fit[40] and accommodating nested governance in environmental decision-making[41,42]. For example, certain natural resource problems are local in orientation (for example, overfishing of a coastal fishery for non-migratory fish, such as coastal pike) but are still data-deficient and in need of urgent conservation action that is agreed upon by local communities of resource users. Here, harnessing local stakeholder knowledge through a systematic approach, as proposed in our study, can provide much-needed information for sustainability. When this information is paired with also granting local users sovereignty for making local conservation decisions, we can anticipate increased legitimacy of the resulting management actions[17]. Management authorities at larger scales (for example, regional, national or international) can, in turn, focus on environmental problems operating at those scales, yet their decisions might also be influenced by harnessing the collective intelligence of regionally operating stakeholders. Ultimately, collecting system understanding may operate in a nested fashion by first organizing understanding at lower levels through user group-specific mental models, with ultimate decisions being coordinated at higher levels through across-group models (see Supplementary discussion).

Despite its promise, our work also clearly shows the importance of carefully designing WOC approaches in natural resource contexts. In particular, if the wrong aggregation method is chosen, increasing sample size can produce a solution worse than one produced by intermediate sample sizes. Because the size for optimum performance is not known, the crowd's response may become unreliable. Fortunately, perhaps, when using the right aggregation method, as we show, a large-enough crowd of diverse stakeholders can produce a science-like understanding of even complex social–ecological dynamics. While further research is needed to confirm the application of WOC to natural resource contexts, it has considerable potential for addressing pertinent problems of unsustainable natural resource use and biodiversity loss.

Methods

Description of study system and context. Many global fisheries are in trouble[5,43]. Harvest regulations and stocking practices have been promoted as a common management response in inland and marine fisheries[44]. While stocking is a common management practice for freshwater fisheries around the world, researchers have recently begun questioning the sustainability of these decisions, given their negative consequences and the highly uncertain context in which many of these decisions are made[45]. Alternative and complementary management options to stocking include social wellbeing-oriented measures (for example, decreasing angling pressure through input controls) and habitat rehabilitation policies (for example, increasing spawning habitat, increasing refuge and increasing riparian vegetation)[46]. The degree to which different fishery decision-makers understand the ecological and social tradeoffs of management decisions is currently not well understood[47] and there is abundant documentation that fisheries stakeholders and managers find themselves in disagreement about which policy to follow[48]. Moreover, it is notoriously difficult to understand social–ecological interactions and how various ecological factors affect the productive capacity of renewable natural resources striving in the natural ecosystem. The problem is elevated in inland fisheries given the multitude of ecosystems that exist in water-rich landscapes. The multifaceted origin of the fisheries system gives rise to a complex social–ecological problem with substantial data deficiencies, which lends itself for an investigation of WOC effect for complex system modelling: stakeholders who either use or manage the fisheries interact with the system in different ways and thus accumulate diverse system knowledge that results in different mental models of the structure and function of the system[21]. These different mental models could be used in WOC applications to harness their collective intelligence.

Germany offers a compelling case for application of WOC as many local recreational fisheries are managed by angler communities organized in angling clubs[34]. As opposed to open-access systems in the United States and other regions of the world, in Germany as in much of central Europe, angler communities own or lease fishing rights from water owners and in this position have sovereignty to engage in certain management actions (for example, stocking and increasing harvest regulations). Angling clubs number around 10,000 in Germany alone, meaning that there are 10,000 or more individual decision-makers in the natural resource user community. Roles in angling clubs differ, with some anglers becoming elected as club managers, mainly tasked with running the voluntary body. On the other hand, selected anglers take training courses in fisheries management and become fisheries managers or water bailiffs taking over the management tasks. A further group entails ordinary anglers who, in Germany, also have to pass a 30-h training course to acquire a fishing license and be allowed to join angling clubs. The angling course is mainly directed to legal and practical issues[35,36]. Participants' fisheries knowledge and education metrics was assessed using questionnaires after the mental model exercises (see Supplementary Table 3).

Mental models. Mental models about social–ecological systems and in fact any type of system, can be elicited and represented as FCM[33]. These can be analysed with regard to structure and dynamic behaviour of the system[49]. Moreover, FCMs from individuals can be aggregated into a larger FCM that represents the collective knowledge of all contributors[20] and thus provide a tool for WOC. In this study, we used the FCM format to collect data from a crowd of 218 stakeholders who manage their own lake and river section fisheries in Germany[34]: recreational anglers, who are organized in clubs, fishery club managers and fisheries managers, who are responsible for the entire ecosystem. In addition, we collected the system models from 17 fishery scientists and used their model for comparison.

Between 10 and 20 anglers, managers and club heads of Lower Saxony, Germany, were invited to one of our 17 workshops (for details see ref. [36]), where graphic mental model representations of the ecology and fishery management of the model species 'pike' were individually collected through FCM technique. We used pike as an example because it is a valuable species in the study region in high demand by anglers[21]. To standardize the collection of FCMs for this study, all participants received the same set of ecological concepts, representing key factors affecting pike population dynamics. These factors were derived from independent focus groups with anglers and mental model pretests with both anglers and experts to identify key concepts relevant to pike fishery. We also completed a thorough review of pike literature to identify key aspects of their life history and what determines population dynamics (for example, macrophyte abundance)[50]. We added human-centred concepts representing angling impacts (for example, fishing pressure) to outline a social–ecological, rather than merely an ecological, system. The task was to arrange the concepts and draw connections between them on the basis of their own understanding and knowledge ("please indicate the factors of importance to pike population biology and their relationships in terms of direction of influence and strength of influence"). The participants were given freedom to add additional concepts (they received blank cards to be able to outline concepts not mentioned so far) and instructed that not all concepts had to be used in their model (see Supplementary Table 1 for a complete list of concepts). The final drawings were photographed for further analyses (Supplementary Fig. 1). The mental models were obtained at the beginning of the workshops before any influence by the team of researchers and workshop organizers and before any other type of information was exchanged with the stakeholders.

The visualizations that result from FCM modeling (see Supplementary Fig. 1) are similar to so-called causal maps, which can be structurally explored in terms of network characteristics. Furthermore, FCM models are also quantitative simulation models that can be used to assess the dynamic behaviour of the system under study. FCM computation shows the changes in the state of system elements given a particular input or combination of inputs (input scenario)[51]: when one concept increases (or decreases) this triggers a cascade of changes in other system elements until the system converges to a so-called 'steady state'[52]. FCM can thus answer 'what if' questions, such as how an increase in one concept (for example, angling pressure) affects all other elements in the system[52].

In summary, FCMs are directed graphs and, therefore, using graph theory, they can be analysed structurally to represent system knowledge about the elements and connections of the system. Also, to represent how the system behaves in response to input changes, FCM can be analysed dynamically (functionally) using fuzzy causal algebra for simulating causal propagation[33] (see Methods: Dynamic analysis and inferences). Moreover, FCM from different participants can be mathematically aggregated if their matrices are brought to the same size and thus include information about every system element that is mentioned in any of the contributing maps.

Mental model aggregation. Individual FCMs can be aggregated mathematically to create a model that represents the insights of all study participants and thus provide a tool for testing WOC. There are two aggregation methods used in this study to build the crowd model. (1) Single-level aggregation; aggregation is obtained in one step.

$$A_{ij}^{\mathrm{FCM_{crowd}}} = \sum_{p=1}^{N} A_{ij}^{\mathrm{FCM_p}} \Big/ \sum_{p=1}^{N} \left(1 | A_{ij}^{\mathrm{FCM_p}} \neq 0\right) \quad (1)$$

where $A^{\mathrm{FCM_p}}$ is the adjacency matrix used to represent the FCM of participant p, N is the total number of participants and $A_{ij}^{\mathrm{FCM_p}}$ indicates the element of this matrix with the value equal to the weight of the edge between node i and j. $\mathrm{FCM_{crowd}}$ represents the crowd's FCM with the corresponding adjacency matrix $A^{\mathrm{FCM_{crowd}}}$. (2) Multi-level aggregation; aggregation is obtained in two steps. Step (1) is computing the mean FCM of each subgroup:

$$A_{ij}^{\mathrm{FCM_G}} = \sum_{p \in G} A_{ij}^{\mathrm{FCM_p}} \Big/ \sum_{p \in G} \left(1 | A_{ij}^{\mathrm{FCM_p}} \neq 0\right) \quad (2)$$

where FCM_G represents the aggregated FCM of subgroup G and $A_{ij}^{\mathrm{FCM_p}}$ indicates the element of adjacency matrix with the value equal to the weight of the edge between node i and j. Step (2) is averaging subgroup means. We can use the arithmetic mean of subgroup means to average them; however, forming subgroups which consist of individuals with the same role in the fishery club carries the risk of amplifying stakeholder-specific biases in each subgroup and can be expected to increase the skewness of subgroup models distribution. Biases are likely to exist in our sample as prior work has shown that there is considerable bias in anglers' understanding of fishery management[53,54], which is the largest group in our dataset. Most importantly, to further remove the effect of biases, to form collective solutions, rather than using the arithmetic mean of subgroup means, we propose to aggregate subgroup means using the median. Earlier studies, in which the crowd is asked to provide single variable estimates and in which there are substantial biases in individual judgements, show that the median outperforms the arithmetic mean[12,29,30]. Thus we used the median to combine group means in the second level of the aggregation.

$$A_{ij}^{\mathrm{FCM_{crowd}}} = \mathrm{Median}\left(A_{ij}^{\mathrm{FCM_{G1}}}, A_{ij}^{\mathrm{FCM_{G2}}}, \ldots, A_{ij}^{\mathrm{FCM_{Gn}}}\right) \quad (3)$$

Additionally, to remove the effect of subgroup biases, we can also use weighted-mean and geometric-mean in the second level of aggregation based on prior theoretical and empirical studies[27,55–57]. We measured the performance of the crowd model built by different averaging methods in the second level of aggregation and our result showed that the median had the best performance amongst other aggregation methods (see Supplementary Table 2).

FCM analyses. FCM concepts (nodes) represent the qualitative characteristics of the system with an absolute value between 0 and 1, characterizing their so-called 'activation level' in the model[52]. Arrows (edges) are characterized by a number in the interval of $[-1, +1]$, corresponding to the strength, direction and sign of causal relationships between concepts. The steady state that an FCM reaches in response to an input change (a forced change in the activation of one or more of its concepts), depends on how the activated concept(s) is connected to other concepts in the system. How nodes and edges are arranged is thus of great importance and is frequently used to analyse FCM. A common measure to investigate this connectivity is centrality: a concept's centrality shows the contribution of this concept in a cognitive map which is determined by accumulating the strength of causal relationships linking this node to the other nodes[52]. One individual considers concepts with higher centrality more important since they are more strongly linked to the other system elements and consequently play more important roles in the dynamic of the system. Comparing the centrality of particular sets of concepts in different cognitive maps translates the differences in the system definition and its important components. In this study, we used Katz centrality index[58], since it is expected to provide the most appropriate centrality measurement for comparing aggregated maps with higher density and presumably higher abundance of feedbacks[59].

Structural analysis. In this study, we compared the structure of FCMs using three approaches. The first approach is to compare the centrality of six concepts of central relevance to fishery management decisions, namely 'stocking', 'spawning ground development', 'angling pressure management', 'enhancement of hiding places and refuges', 'enhancement of riparian vegetation' and 'enhancement of submerged aquatic plants' by making the centrality profiles. Each centrality profile displays the Katz centrality of these six concepts in a radar chart (Fig. 1). We calculate the Katz centrality of each node i with:

$$X_i = \alpha \sum_j A_{ij} X_j + \beta \quad (4)$$

where X_i is the Katz centrality of node i, A is the adjacency matrix of FCM, α is the attenuation factor and β is the extra weight attributed to the immediate neighbourhood. What Katz centrality measures is the relative influence of a node within the FCM by taking into account the weight of the immediate neighbours and also all other nodes in the FCM that connect to the node through these immediate neighbours. Extra weight would be given to the nodes located in the immediate neighbourhood through parameter β (in our case $\beta = 0.5$). Connections made with distant neighbours are penalized by the attenuation factor α (in our case $\alpha = 0.3$). The Katz centrality of each node is a function of the Katz centrality of other nodes. Thus, this centrality computation is an iterative process (in our case maximum number of iterations is 10×10^4 and the error tolerance used to check convergence is 10×10^{-6}).

The second approach to analysing and comparing the structure of FCMs is an investigation of agreement of strong causal patterns. These patterns emerge when we remove weak edges with absolute weights less than 0.33 from aggregated FCMs (Fig. 2). The remaining edges illustrate the strong causal patterns used for model description.

$$U_g = \left\{\mathrm{EDG}_g^{0.33}\right\} \cup \left\{\mathrm{EDG}_{\mathrm{Exp}}^{0.33}\right\} \quad (5)$$

$$M_g = \left\{\mathrm{EDG}_g^{0.33}\right\} \cap \left\{\mathrm{EDG}_{\mathrm{Exp}}^{0.33}\right\} \quad (6)$$

$$\mathrm{PM}_g = \frac{\mathrm{Size}(M_g)}{\mathrm{Size}(U_g)} \quad (7)$$

where $\left\{\mathrm{EDG}_g^{0.33}\right\}$ is the set of strong edges with weight ≥ 0.33 in the FCM of group, $\left\{\mathrm{EDG}_{\mathrm{Exp}}^{0.33}\right\}$ is the set of strong edges with weight ≥ 0.33 in the FCM of experts, M_g is the intersection of strong edges in FCMs of the group g and experts (set of matched edges), U_g is the union of strong edges in FCMs of the group g and experts and PM_g is the proportion of matched edges between group g and experts.

Furthermore, we can compare the network structure of FCMs with regards to the quantitative aspects of their graph geometric shapes. In this study, we evaluate combinatorial and geometric properties of FCM graphs using a graph similarity index, namely 'eigenvalue graph similarity'[60,61]. Given two graphs, this index evaluates how similar they are in terms of the important features of their structures. Therefore, it provides a comparison between each FCM and the expert FCM regarding their fundamenl structure. In fact, the eigenvalue similarity index measures the Euclidean distance between two graphs in a new coordinate system wherein coordinates represent eigenvalues. In this coordinate system, each graph is determined by a point and the distance between two points demonstrates the structural similarity between these two graphs. The shorter the distance, the more similar the graphs are in terms of the essential components of their structures (Fig. 3). To measure the eigenvalues similarity index, we first calculate the eigenvalues of Laplacian of adjacency matrices of both FCMs. For each FCM the Laplacian matrix is calculated by

$$L = D - A \tag{8}$$

where L is the Laplacian matrix, D is the diagonal matrix and A is the adjacency matrix.

Then, for each Laplacian matrix, we find the smallest k such that the sum of the k largest eigenvalues constitutes at least 90% of the sum of all of the eigenvalues[61]. If the values of k are different between the two graphs, we use the smaller one. Thus, the eigenvalues similarity index is the sum of the squared differences between the largest k eigenvalues of the group g and experts FCMs. This gives us a number in the range [0,∞], where values closer to zero are more similar:

$$\mathrm{sim}_g = \sum_{i=1}^{k} \left(\lambda i_{L_{\mathrm{Exp}}} - \lambda i_{L_g}\right)^2 \tag{9}$$

where sim_g is the eigenvalue graph similarity index, $\lambda i_{L_{\mathrm{Exp}}}$ is the ith eigenvalue of the Laplacian matrix of experts FCM and λi_{L_g} is the ith eigenvalue of the Laplacian matrix of group g FCM.

Dynamic analysis and inferences. In addition to network structure, we analyse the dynamic behaviour of FCMs. As prior studies suggested, the dynamic behaviour of FCMs can be assessed through analysing their responses to several 'what if' scenarios[49,62]. To do so, in each scenario, we change the value of one or more concepts (nodes) in a map and record the alterations of the system state from the 'steady state'[52]. The value of each concept in the steady state is calculated using:

$$c_i^{(k+1)} = f\left(c_i^{(k)} + \sum_j c_j^{(k)} A_{ji}\right) \tag{10}$$

where $c_i^{(k+1)}$ is the value of concept c_i at iteration step $k+1$, $c_i^{(k)}$ is the value of concept c_i at iteration step k, $c_j^{(k)}$ is the value of concept c_j at iteration step k and A_{ji} is the weight of the edge relationship between c_j and c_i. Function $f(x)$ is the 'threshold function' used to squash the values at each step[49]. Our threshold function is a sigmoidal function:

$$f(x) = \frac{1}{1 + \mathrm{e}^{-\lambda x}} \tag{11}$$

where λ is a real positive number (in our case $\lambda = 1$) which determines the steepness of the function f.

To run a 'what if' scenario, we force the system to take fixed activation value in one or multiple concepts and use equation (10) to compute the value of other concepts. The scenario results are the differences between the values of the system's concepts when the system is self-administered (steady state) and when it is bounded by fixed manipulations in the state of some concepts (scenario). For each concept c_i the change in its value as a result of running a scenario is:

$$d_i^{\mathrm{sc}} = c_i^{\mathrm{ss}} - c_i^{\mathrm{sc}} \tag{12}$$

where d_i^{sc} is the change in the value of concept c_i, c_i^{ss} is the value of concept c_i in the steady state and c_i^{sc} is the value of concept c_i after converging into a new steady state while scenario concepts are clamped on fixed values.

Comparing the scenario outcomes in different FCMs gives us a clear picture of how differently the system dynamic behaviour is perceived by different mental models. To compare dynamic behaviour of each group mental model with experts (reference model), we compute the Euclidean distance between their outputs of a scenario (Fig. 4). The mean of these distances in all of the scenarios (10,000 random scenarios in our case) represents the degree of agreement on simulation outcomes and therefore compare their dynamic behaviour:

$$\mathrm{DD}^g = \frac{1}{N}\sum_{j=1}^{N}\sqrt{\sum_i \left(d_i^{\mathrm{sc}_{j\mathrm{Exp}}} - d_i^{\mathrm{sc}_{jG}}\right)^2} \tag{13}$$

where DD^g is the dynamic distance between group G and experts, $d_i^{\mathrm{sc}_{j\mathrm{Exp}}}$ is the result of scenario j in concept c_i in experts map, $d_i^{\mathrm{sc}_{jG}}$ is the result of scenario j in concept c_i in the group map and N is the total number of scenarios.

Normalized error and performance. The normalized dynamic and structure errors are, respectively, the standardized dynamic and structure distances between the crowd and expert models:

$$\mathrm{ES}_{\mathrm{normal}} = \frac{\mathrm{sim}_{\mathrm{crowd}}}{\max\limits_g(\mathrm{sim}_g)} \tag{14}$$

$$\mathrm{ED}_{\mathrm{normal}} = \frac{\mathrm{DD}_{\mathrm{crowd}}}{\max\limits_g(\mathrm{DD}^g)} \tag{15}$$

where $\mathrm{ES}_{\mathrm{normal}}$ is the normalized structure error and $\mathrm{ED}_{\mathrm{normal}}$ is the normalized dynamic error.

The normalized total error is the mean of normalized dynamic and structure error:

$$\mathrm{ET}_{\mathrm{normal}} = \frac{1}{2}(\mathrm{ES}_{\mathrm{normal}} + \mathrm{ED}_{\mathrm{normal}}) \tag{16}$$

Finally, the normalized performance is calculated by subtracting the normalized total error from one:

$$P_{\mathrm{normal}} = 1 - \mathrm{ET}_{\mathrm{normal}} \tag{17}$$

Data availability

All data supporting the findings of this study including data for obtaining the FCM of individuals are available and can be downloaded as Excel spreadsheets (Supplementary Datasets 1,2,3). Raw data files are available from the corresponding author on reasonable request.

Code availability

Codes for mental model aggregation and FCM analyses are publically available and can be obtained on GitHub at https://github.com/payamaminpour/PyFCM/wiki.

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Author contributions

P.A., S.A.G., A.J.J. and J.E.I. conceived the study given data collected by R.A. All authors were involved in theoretical development. P.A., S.A.G. and A.J.J. analysed the data. All authors were involved in interpretation and writing.

Competing interests

The authors declare no competing interests.

Additional information

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