Collective Intelligence for Democracy: Empowering Minorities and Everyone in Participatory Budgeting

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Abstract

Currently, there are increasing attempts to better involve citizens in the political decision processes. A successful approach in that regard has been participatory budgeting (PB), which allows citizens to propose projects and then to decide how to distribute a given budget over them. In the meanwhile, literature on collective intelligence (CI) has shown that groups of people can solve complex problems and even outperform experts. Thus by combining CI and PB it should be possible for citizens to identify problems and create their own solutions.

In this article, we first explore how a system combining CI and PB produces solutions that strongly penalize minorities, as solution's quality depends on group's size. Then, we introduce an approach that can overcome the issue. Indeed, by using a common knowledge base for the storage of partial solutions, the quality of solutions of minorities can benefit from the work of the majority, thereby promoting fairness. Interestingly, this approach also benefits majorities, as the quality of their solutions is further improved by the work of the minorities, thus, reaching better solutions for everyone. This stresses the potential and importance of an open innovation approach, which is committed to information sharing.

1. Participatory Budgeting and Collective Intelligence

Participatory Budgeting (PB) is an innovation in democratic governance, which offers a platform for inclusive decision-making processes within communities [1, 2]. Originating in Porto Alegre, Brazil, in 1989, PB has since gained traction globally as a means to foster citizen engagement, transparency, and accountability in allocating public funds [3].

At its core, PB embodies democratic principles by inviting residents to actively participate in determining how public budgets are allocated. While many different formats exist, most PB initiatives can be divided into two phases. In the first phase, citizens collaborate with local governments to identify community needs as well as possible projects and initiatives. In the second phase, the

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population is called to vote on the proposed projects, some of which are then selected in accordance with the available budget [4].

While participatory budgeting allows to achieve legitimate decisions or to strengthen social cohesion [5, 6], it is not without its challenges and limitations. Indeed, despite its democratic ideals, PB initiatives may still face challenges to be inclusive, particularly with respect to marginalized communities who may lack access to information or face systemic barriers to participation [7].

One of the issues that can affect PB initiatives (as well as many other democratic decision-making processes) is the so-called tyranny of the majority [8, 9]. This concept usually refers to the idea that the majority can dominate [10] and, within the context of PB, this refers to the fact that, by using common voting systems, the majority could secure a disproportionate part of budget for their own project (excluding mobilization effects, which are not discussed here). Indeed, the most common voting approach, "majority voting", selects the project(s) getting the largest number of votes, until the available budget is used up. In an extreme case, it may happen that one selected project has a cost equal to the entire budget, leaving no budget for any other projects. To avoid this issue, one may instead decide to select the project(s) not only based on the share number of votes, but on the ratio between votes and requested budget, as done in the "Method of Equal Shares" (MES) [11].

So far, PB still relied a lot on experts and representatives in many steps of project generation [4], thus strongly limiting how much citizens can affect the final outcome. This seems to be unavoidable, as most projects require some level of expertise. However, citizens could be supported by collective intelligence [12]. Indeed, collective intelligence (CI) refers to the capacity of groups to make decisions, generate ideas, and solve problems more effectively than single individuals [13, 14, 15]. CI has garnered increasing attention in recent years, fuelled by empirical studies [12] as well as advancements in computational modelling [16, 17, 18], social network analysis [15, 19], and artificial intelligence [20, 21, 22], showing that groups of non-experts may even outperform experts [23].

Thus, CI could be used to support participatory methods that go beyond voting or beyond consulting citizens for problem identification: Citizens could also craft solutions to problems. However, as the literature on CI has shown, the quality of results strongly depends on the type of interaction between the people. Indeed, a smartly designed system may be structured such that individual efforts align constructively, producing high-quality results ("wisdom of the crowds") [24, 25]. In contrast, poorly designed systems may easily produce chaotic processes and low-quality results (sometimes framed as "madness of crowds") [26, 27, 28].

In this article, we explore the possibility of citizens to directly solve their own problems, with a special focus on the implications for minorities.

The remaining parts of this paper are structured as follows: in Section 2 we discuss how naively merging PB and CI would result in inequality, producing results which are much more favourable for big groups. In Section 3 we introduce some models merging CI and PB and explore them mathematically in Section 4. Section 5 will deepen this exploration by analyzing these models as agent-based simulations and Section 6 will study some additional variants to verify the stability of the model. Finally, in section 7 we discuss the results and their implications for future studies.

2. A New Approach to Participatory Budgeting

2.1. The Problem of Group Size

While the method of equal shares allows for a fair sharing of the budget, it still does not guarantee fairness in terms of the quality of solutions. To better understand this issue, we can consider the following hypothetical example, in which 90% of people would like to create a new park and 10% would prefer to build a new theatre. Let us call the two groups of people A and B, respectively. With classical voting methods, it is possible that more than 90% of the budget would be attributed to the park, leaving little or even no budget for the theatre. A proportional method, such as the method of equal shares instead would aim to reserve 90% of the budget for the first project and the remaining 10% for the second one, thus reaching budgetary fairness.

However, in a case where people craft their own solutions, the number of people working on the design of the park would be 9 times bigger than the number of people working for the theatre project. This means that people in group A would probably work out their project in much more detail. Indeed, a big group may afford to include several architects, engineers, and other experts, who could help to improve the project. In contrast, group B could only count on a much smaller "workforce", and therefore, their design of the theatre would be probably less elaborated, i.e. of lower quality.

To understand this problem more clearly, in the following we will analyse it mathematically. Let us define $u_g(X)$ as the average utility that people of group g attribute to solution X. Furthermore, let C_X be the cost of project X, and N_g be the number of people in group g. Then, we can define the "effectiveness" E_X of solution X by the ratio between the total utility and its cost (i.e., the utility per unit cost).

$$E_X = \frac{u_a(X)N_a}{C_x}. \tag{1}$$

By using a fair method for budget distribution, the cost of a project can be fixed to be proportional to the group size; thus, $C_x = \alpha N_a$. By plugging this into equation (2.1), we obtain:

$$u_a(X) = \alpha E_x. \tag{2}$$

Second, we assume that the more work W is dedicated to improve the solution X, the bigger its effectiveness will become. With "work" we mean the total time spent across the population (i.e., if one person spends 1 hour and another one 10 hours, the total time will be 11 hours). If we suppose that each person, on average, will work β hours, overall we have approximately $W = \beta N_g$ hours of work. Thus, we can see how the effectiveness will increase as the group size increases.

For the sake of simplicity, we assume here linear relationships between E, W, and N_a, so that we can write $E = \gamma N_g$.However, generalizations or more complex models are easily possible, one of which will be tested in Section 6. The resulting formula

$$u_g(X) = \alpha\gamma N_g. \tag{3}$$

shows that fairness of budget (re)distribution is needed, but it is not sufficient to guarantee the fairness of the result. Indeed, it may not be considered to be fair that some people obtain better results (i.e. larger utility values) just because they belong to a bigger group. This can be better seen by defining an inequality coefficient I. Since, in the following, we will mostly analyse two groups, A representing the majority and B representing a minority, we can define the following inequality measure:

$$I = \frac{u_a(X_a) - u_b(X_b)}{u_a(X_a) + u_b(X_b)}. \tag{4}$$

Herein, X_a and X_b represent the best solutions for each group. When the effectiveness of solutions depends on the group size, we can use the formula (3), obtaining:

$$I_0 = \frac{N_a - N_b}{N_a + N_b}. \tag{5}$$

Notice that we used the symbol I_0 to distinguish between formula (4), which is the general way to calculate inequality, and formula (5), which represents the case where the utility is proportional to the number of people in a group. As one may expect from this condition, when both groups would have equal size, we would have $I_0 = 0$, while the value of I_0 would be approximately 1, if $N_a \gg N_b$. Because of that, in the future sections we will study different models in situations where $N_a \gg N_b$.

2.2. Towards Making Solutions Fair

Many possibilities exist for restoring the fairness of solutions and thus bringing I close to 0. However, most of them end up introducing new imbalances to the process. For instance, one may limit the budget of bigger groups, but this would be quite restrictive and unfair in terms of budget allocation. Furthermore, it may eventually result in strategies where big groups divide themselves into smaller groups to obtain more budget. Others may think of forcing big groups to spend some of their time contributing to projects of smaller (interest) groups. However, this approach would again substantially interfere with big groups as it would take away some of their time. Furthermore, it would likely undermine participation altogether, as activities such as PB are heavily based on voluntary work. Forcing people to perform tasks they are not interested in would most likely be counterproductive.

In this article, we rather aim to develop a win-win strategy, thus a system that can help minorities, but not at the cost of bigger groups. Indeed, as we will observe in later sections of this manuscript, even majority groups will be advantaged by the presence of minorities. To achieve this, we make use of the fact that many solutions share common elements. For instance, the design of a pedestrian pathway may be common to many different city-level projects. Similarly, many buildings share common features such as doors and staircases, and legal requirements may also apply to many different projects. This means that part of a project could be reused in other projects, if an open innovation approach is pursued.

Thus, in the following, we will explore the introduction of a shared knowledge base, in which solutions are stored for re-use in other projects. In later sections, we will explore different versions of such a shared knowledge base and how it could be designed to promote high-quality solutions and fairness at the same time.

3. Model

In this section, we propose an agent-based model of how collective intelligence (CI) could be integrated into participatory budgeting (PB). The flexibility of agent based models allows us to explore different conditions, both mathematically and by means of simulations. Notice, however, that due to the complexity of the subject, the model may appear stylized [29], as it simplifies many aspects of human behaviour. This approach is usually chosen in these kinds of models to keep them tractable [30].

Our model represents the behaviour of two groups, “A” and “B”, across multiple participatory budgeting initiatives. Every initiative is uniquely identified by the time variable t, so that the first initiative will take place at $t = 1$, the second at $t = 2$, etc. Furthermore, every initiative consists of an idea creation phase and a voting phase. In the idea creation phase, each group g tries to develop a project $p_{g,t}$ with a solution $X_{g,t}$ that maximizes the group’s average utility $u_{g,t}(X_{g,t})$. Practically, this means that the project each group is working on changes in each time step (i.e. at each initiative), and thus also their utility function and best possible solution.

To keep the model simple and the results easy to interpret, for now we also assume that every person within the same group shares the same individual utility function, which accordingly agrees with their average utility function. Thus, in the voting phase, all agents belonging to the same group g will vote for the same best solution $X_{g,t}$. Let us also assume that the budget allocated to each project is proportional to the number of people supporting it (as in the Method of Equal Shares). For now, these assumptions allow us to focus on the dynamics of the idea generation phase, while Section 6 will generalize the model by adding diversity.

We define every solution X_g to be a point in a D-dimensional space, so that $X_g = (x_1, x_2, \ldots, x_D) \in N^D$. Every dimension here represents the domain of a sub-solution. For instance, if the problem concerns building a park, one of the dimensions may represent different pathway designs, another dimension the design of an artificial lake, etc.

D represents the set of all dimensions for all possible projects, while not all projects depend on all dimensions. For example, a theatre will usually not need an artificial lake. For simplicity, we further assume that every project depends on $\delta < D$ dimensions and write the overall utility as:

$$u_{g,t}(x_1, x_2, \ldots, x_D) = \sum_{d=1}^{D} w_{g,t,d} \cdot f_{g,t,d}(x_d) \tag{6}$$

Herein, $w_{g,t,d}$ is 0 if the project does not depend on dimension d, and $1/\delta$ otherwise. Instead, $f_{g,t,d}$ is a function linking the utility to the sub-solution x_d. This class of functions should be such that each function is independent of each other. Even if each x is modelled as a natural number, this value only represents a unique identifier, representing which solution was produced first. Furthermore, since the value of x does not represent similarity, two solutions x_1 and x_2 may be very close numerically, while still producing quite different values of $f_{g,t,d}(x)$. The final requirement on the f functions is that the average utility of the best solutions should linearly increase with the size of the explored space. In formula:

$$E[\max f_{g,t,d}(x)] = \lambda x_{_M}, \tag{7}$$

where x_M is the maximum value of x (assuming that the exploration started at $x = 1$). To respect all these conditions, we specify each $f_{g,t,d}(x)$ as according to

$$f_{g,t,d}(x) = \min\left(\frac{1}{v}, x_{_M}\right). \tag{8}$$

Here, v is a uniformly distributed random variable in the interval (0,1]. In Figure 1, we show why we included the minimum in Equation (8) instead of simply modelling f as $1/v$. Indeed, as shown in Figure 1a, already $1/v$ satisfies Formula (7). However, such a distribution has a large variance, where the standard deviation is more than 25 times as big as the mean value. This happens, as this distribution may produce massive numbers such as 10^6. Computationally, this is a problem as it introduces a massive variability in the results. Moreover, this is also highly unrealistic, as it implies the possibility of finding outstanding solutions in just a few steps. To overcome such problems, we introduced the minimum function in Eq. (8) above. As one can observe in Figure 1b, this still implies a linear increase (thus satisfying equation7), while still having a reasonable level of variability. In this case, the standard deviation is only 0.27 times the mean value.

3.1. Structure of the Model

In order to better understand the properties of the co-creation system we are interested in, we will study and simulate different agent-based models. Despite

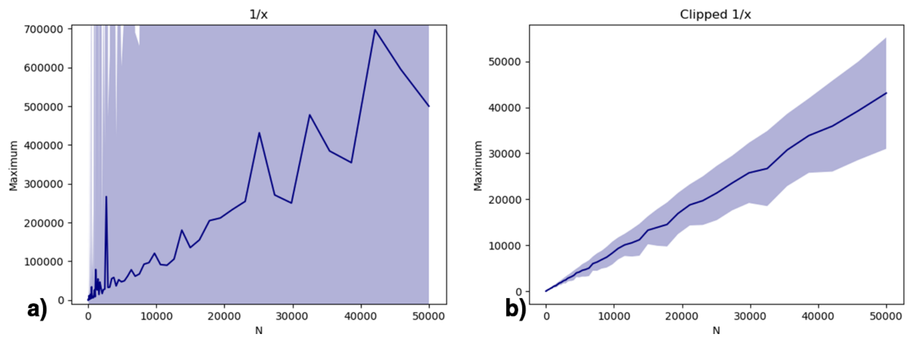

Figure 1: Expected maximum over N trials for (a) $1/v$ and (b) clipped $1/v$ as shown in Equation 8.

the differences between models, however, they still have similar structures such that we can define a base model M_0 and define the other models as its variants.

In model M_0, each group has a short-term knowledge base k_g. This is a repository where the sub-solutions x_d are stored, and it will be the only repository used by agents during the idea creation phase. This short-term knowledge base is complemented by a long-term one K_g. The main difference between the two is that k_g starts empty at the beginning of each initiative (thus erasing previous information), while K_g will indefinitely preserve everything that is stored in it.

Our model simulates a total of T initiatives. For each initiative, the following steps are followed:

1. **Project identification:** For each group, δ domains are selected out of the D possible ones. These will remain the same until the initiative is completed. These are selected independently from previous initiatives and from other groups.
2. **Knowledge base exploration:** Each short-term knowledge base k_g starts empty. On the contrary, the long-term knowledge base K_g may contain previous solutions from previous rounds. If this is the case, all solutions relevant to the current dimensions are copied into the project's knowledge base k_g, and the respective values of $f_{g,t,d}(x_{d,i})$ are calculated for all the solutions $x_{d,i}$.
3. **Idea generation:** Every agent generates n new solutions on average. This is done by repeating the following loops nN times (where $N = N_a + N_b$ is the total number of agents):
   (a) Select an agent with a probability proportional to their group's size N_g. (Accordingly, bigger groups will be selected more often.)
   (b) Let the agent choose a domain from the ones relevant to the project of their group.
   (c) Let the agent produce a solution $x_{d,i}$ for domain d.
   (d) Calculate the value of $f_{g,t,d}(x_d)$.

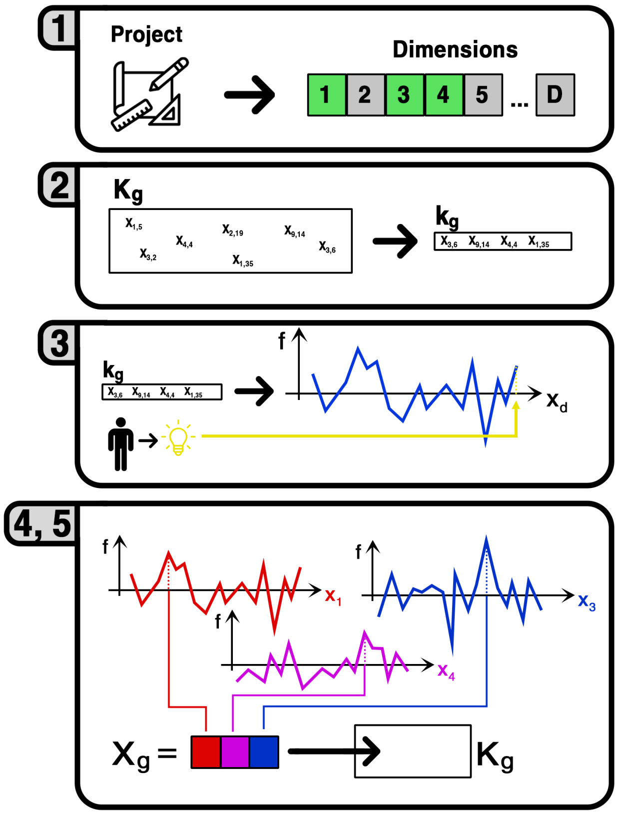

Figure 2: Schematic representation of the algorithm. (1) The dimensions of the project are identified. (2) The short term knowledge base is loaded from the long term one. (3) New solutions are added to the knowledge base and their values of f are calculated. (4) and (5) the best partial solutions are used to create the solution X_g, which is then loaded on the long term knowledge base.

(e) Add the solution $x_{d,i}$ to the short-term knowledge base of the group.

4. **Project selection:** For each group, select the best solution $X_{g,t}$ from their own short-term knowledge base k_g.
5. **Knowledge base update:** Copy the δ sub-solutions $x_{d,i}$, which compose the final solution $X_{g,t}$ from the project's short-term knowledge base k_g to the long-term knowledge base K_g.

In the next sections, we analyze four variants of this model:

- **M1: Separate knowledge bases and no long-term knowledge base:** This model represents the case in which groups work independently and store no information for later rounds. So, the only difference to M_0 is that step (v) is removed such that the long-term knowledge base is always empty.

- **M2: Separate knowledge bases plus long-term knowledge base:** In this case, every group works with different knowledge bases, but they store all partial designs for future rounds. Thus, in this model, instead of copying only the final, best design, in step (v) they copy everything from the short term knowledge base k_g into the long term knowledge base K_g.
- **M3: Common knowledge base containing final designs:** This model differs from M_0 only in the aspect that groups do not maintain separate knowledge bases, but instead a shared one.
- **M4: Common knowledge base with all designs:** In this case, both groups share their long-term knowledge base and also store all partial designs.

We can notice that the M1 and M3 models are "optimality-oriented" in the sense that they are mainly focused on the optimal solution for the current initiative. On the contrary, M2 and M4 have a more "evolution-oriented" where many alternatives are still present. Indeed, this resembles biological systems, which are not dominated by a single specie, but they are based on the presence on multiple different species. In a similar way we can notice how M1 and M2 are more based on a private approach, while M3 and M4 are based on sharing knowledge. In the next sections we will study such models using both mathematical analysis and simulations.

4. Mathematical Exploration of the Model Variants

Combining Equations (7) and (6), the expected value of the best solution (hereafter indicated by $\hat{u}_{g,t}$) is proportional to the size of the explored solution space, hereafter represented by $L[k_g]$. This term can be further broken down into the designs that were imported from the long-term knowledge base K_g and the ones which, instead, are produced during the current initiative. Let us call them $L_{l,g}$ and $L_{s,g}$, respectively. Then, we have:

$$\hat{u}_{g,t} = E[\max[u_{g,t}(X_g)]] = \frac{\lambda}{\delta} L[k_g] = \frac{\lambda}{\delta}(L_{l,g} + L_{s,g}) \tag{9}$$

While a detailed discussion of the model results, based on agent-based simulations, is presented in the next sections, here we explore how the different models are expected to behave for large values of t.

Notice that model M1 does not require any approximation. Indeed, we have $L_{l,g} = 0$, and $L_{s,g}$ is always equal to nN_g. Thus, in model M1, the utility is proportional to the number of people in a group: $\hat{u}_{g,t} = \frac{\lambda}{\delta} nN_g$. Consequently, inequality (2.4) is equal to the benchmark value I_0.

In model M2, every initiative produces nN_g solutions over δ dimensions. The main complexity is introduced by the fact that some dimensions may be selected more often than others. However, in the approximation of large values of t, we can assume that, for every dimension, approximately $\frac{nN_g t}{D}$ solutions have been produced over the past initiatives. To obtain this number, we consider that $nN_g t$ solutions x are produced over t initiatives, and divide this value by the total number of dimensions D. As the long-term knowledge base contains δ dimensions that are relevant to the current project, and they have been produced until $t-1$, we can write $L_{l,g} = \delta \frac{n}{D} N_g(t-1)$. To this, we should add the nN_g new designs from initiative t, obtaining:

$$L[k_{g,t}] = \frac{\delta}{D} nN_g(t - 1 + \frac{D}{\delta}) \approx \frac{\delta n N_g t}{D} \tag{10}$$

Note that, in the last term, we have simply applied $t \gg -1 + \frac{D}{\delta}$.

One can see that the utility of each group increases from nN_g in model M1 to $\frac{\delta n N_g t}{D}$ in model M2. Furthermore, in M2 both groups A and B produce solutions which progressively become better and better as t increases. However, in both models, the utility is proportional to the group size N_g, thus resulting in an inequality level of size I_0.

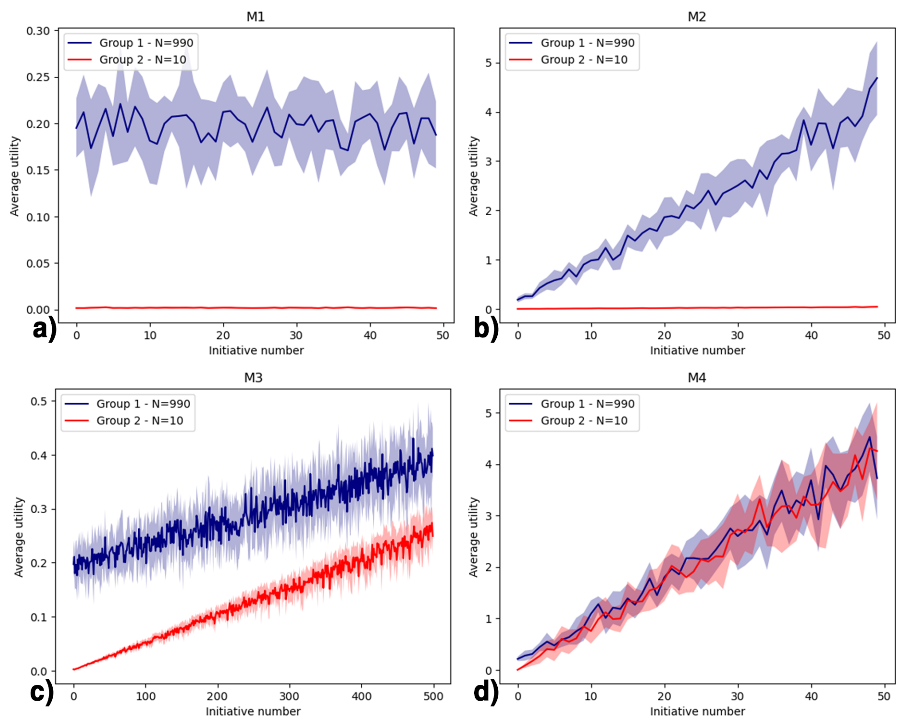

Figure 3: Simulated utility for majority (blue) and minority (red) in all four models, shown over time. Solid lines represent the mean, while the shaded area represents the standard deviation. The respectively simulated models are: a) M1, b) M2, c) M3, d) M4.

Models M3 and M4, in contrast, are based on the idea of a shared knowledge base. For model M3, the two groups add only their final solution to the knowledge base, so that $L_{l,g} = 2\frac{\delta t}{D}$ (as only δ solutions are added each time by each of the two groups). By applying the approximation of big t again, we find that the number of solutions in the long-term knowledge base is much bigger than the number of solutions produced in the last initiative (i.e., $L_{l_g} \gg L_{s_g}$). From such approximation, we find that the utility of the two groups is identical, bringing the inequality value down to 0. While this is a great advancement in terms of fairness, it also represents a step backward compared to M2, as the utility values are now much smaller, namely by a factor nN_g. Thus, the approach of model M3 achieves fairness by slowing down the entire problem solving process.

Finally, let us consider M4. In this case, for big t, the utility of the best design $\hat{u}_{g,t}$ depends uniquely on $L_{l,g}$. However, $L_{l,g}$ does not depend on the number of people in the group N_g, but on the total number of people in the entire population N. Indeed, $L_{l,g} = \frac{\delta n N t}{D}$. This result combines the favorable features of models M2 and M3, while outperforming each of them. Similar to M3, the inequality value is 0, and similarly to M2, the utility is proportional to the number of people. Since we designed the entire system to decrease inequality, it is expected that the utility of the minority group is much bigger than in the other models. Indeed, in this system, the minority benefits a lot from the work of the majority. Interestingly, however, the situation is also improved for the majority group, which benefits from the work conducted by all minorities, as the utility of each group is proportional to the size of the entire population.

Note that, even in case the majority represents as much as 90% of the population, moving from M2 to M4 produces a significant performance increase of 10% for the majority. In the more common case, where the biggest group represents less than 50% of the population, while the remaining people are distributed over many minority groups, moving from M2 to M4 allows the biggest group to more than double their utility.

Model	Expected utility of best solution $\hat{u}_{g,t}$	Inequality I
M1	$(\gamma/\delta)nN_g$	I_0
M2	$(\gamma/D)nN_g t$	I_0
M3	$(\delta/D)t$	0
M4	$(\gamma/\delta)nNt$	0

Table 1: Comparison between the different models and how their utility changes over time (for the approximation of big t). Notice how M4 is able to outperform all models in terms of $\hat{u}_{g,t}$, while also getting the inequality level down to 0, thereby maximizing fairness.

5. Model Exploration via Agent-Based Simulations

The use of agent-based computer simulations allows us to study the four different models in more detail without imposing approximations or constraints. However, to run the simulations, we have to choose certain parameter values, by which we lose some of the generality that an analytical mathematical analysis offers. We start by simulating 1000 agents, where 990 of them belong to group A, while the remaining 10 people constitute group B. This ratio has been chosen such that the benchmark inequality value I_0 is close to 1 (precisely I_0=0.98).

In the following, we assume $D = 10$ possible dimensions, while $\delta = 3$ of these dimensions matter for each solution. We set n (the average number of solutions per person) equal to 10. Since our simulations include random elements, we simulate every configuration 100 times and display the results for the utilities in Figure 3 and the inequality values in Figure 4a. As expected, M1 represents a case in which there is no growth (i.e. no learning) from one round to another, while the inequality value is very close to 1. As each group learns from their own previous successes, model M2 allows the majority to make quick progress, moving from utility values close to 0.2 (as produced by M1) to more than 4 over 50 rounds. However, the minority group progresses much slower, thereby keeping the inequality value close to 1.

As model M3 progresses very slowly compared to the other models, we display our results up to $T = 500$, while all other models are shown up to $T = 50$. Indeed, even after 500 rounds, the maximum utility is still 10 times smaller than for model M2 at $T = 50$. As observed before, model M3 could reduce inequality on the long run, but it progresses extremely slowly and penalizes the majority compared to model M2.

Finally, model M4 shows results for the utility that compare well with model M2, while also reducing inequality very quickly. Indeed, its values of inequality are around 0 from approximately the tenth initiative onwards. In Figure 4b we also explore how models M2 and M4 would perform in a case where the majority represents 60% and the minority 40% of the population. Since the two groups sizes are quite similar, then, in model M2 we do not observe big differences in group utilities anymore. However, M4 allows the two groups to benefit from each other, thereby largely outperforming the utility values achieved in model M2.

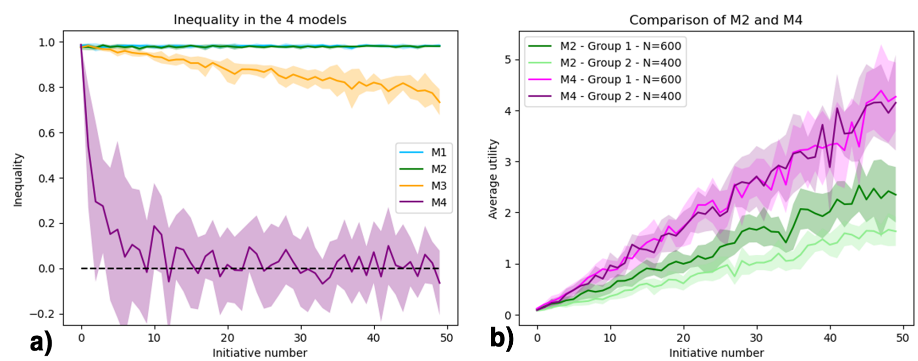

Figure 4: (a) Inequality in the 4 models. (b) Comparison of model M2 (represented in green) and model M4 (represented in purple) when the two groups represent 60% and 40% of the population. Solid lines represent the mean and the shaded are the standard deviation

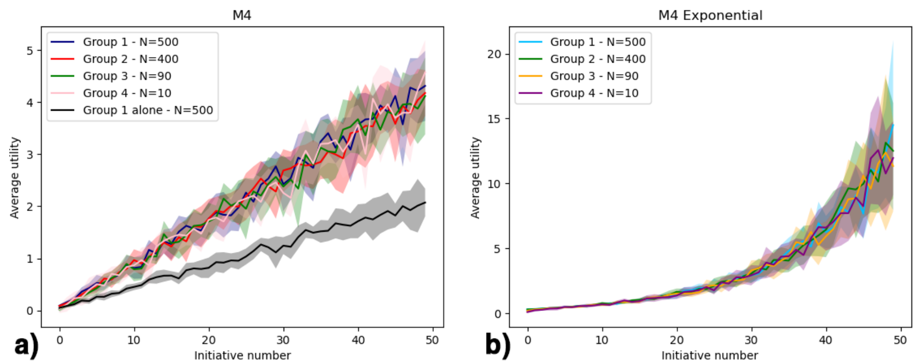

Figure 5: Simulations of model M4 adding personal variations of utility for a) 4 groups of different size (colors) in comparison with the biggest group working alone (black). (b) four groups in the case of exponential increase.

6. Alternative explorations and stability

In the previous sections we have focused on studying two homogeneous groups, in which each agent had exactly the same value of utility. In this section we repeat the previous analysis of model M4, but instead with four groups of sizes 500, 400, 90 and 10. Furthermore, we will now assume the values of the utility functions to be different for each agent. For this, we introduce a function f which depends on the agent i, thus being written as $f_{g,t,d,i}$. Since u_g is the average utility function, then from (6), we can consider $f_{g,t,d}$ as the average of $f_{g,t,d,i}$:

$$f_{g,t,d}(x_d) = \frac{1}{N_g} \sum_i f_{g,t,d,i}(x_d) \tag{11}$$

Accordingly, we modelled each $f_{g,t,d,i}(x_d)$ as a normally distributed function with a mean value of $f_{g,t,d}(x_d)$ and a standard deviation of 1.

Results are presented in Figure 5a, where we show the utility of the 4 different groups (in color) compared to the performance when the majority works entirely by itself (in black). Our results show that, when all groups are share their results, they are able to achieve similar levels of utility, thus bringing the inequality down to 0. In addition, every group benefits from the results produced by each other group, as we can see from the fact that they all exceed the performance of the biggest group when it works in isolation (black line).

Another approximation that we carried out through all the analysis is the proportionality between the number of solutions in the knowledge base and the quality of the best solution. However, in general, the relationship may be non-linear. Because of that we also tested M4 in the condition of exponential increase. We achieved this by changing the random distribution in (3.3) to a normal distribution with variance 2^x. As we can see fro figure 5b, all groups are still growing together, just in this situation they experience an exponential, instead of linear growth.

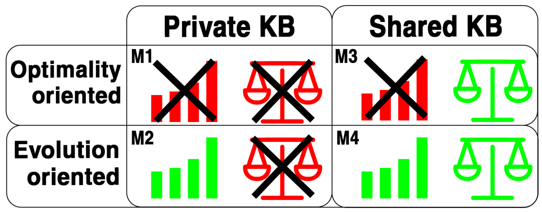

Figure 6: Summary of the results from the 4 models. Depending on the choices on the knowledge base (KB) and whether results are shared between groups or not, we find four different outcomes: M1)low quality results and inequality, M2) high quality results and inequality, M3) low quality results with fairness, and M4) high quality results and fairness.

7. Discussion

In this article, we have discussed the possibility of using collective intelligence in participatory budgeting. In particular, we have studied four different decentralized co-creation scenarios, for which we found:

- low efficiency and inequality (in model M1): this happens when groups do not share their solutions and do not save them for later use;
- high efficiency and inequality (in model M2): this happens when groups save their solutions for later (re-)use, but do not share them with other groups;
- low efficiency and equality (in model M3): this results when groups share information among each other, while saving only their final results;
- high efficiency and equality (in model M4): this results by preserving and sharing all partial solutions (design results).

A particularly favorable result of model M4 is that it does not only perform highly while allowing to quickly reduce inequality. It also produces a win-win situation, where every group, independent of its size benefits from the results obtained by every other group. This is in stark contrast with scenarios, where big groups are burdened by having to help minority groups. We would also like to point out that such a win-win setup may strongly promote social cohesion, thereby possibly overcoming polarization [31]. Furthermore, the so-called "Ikea effect" [32], according to which individuals value their own creations higher than other products, could play significantly promote the adoption and appreciation of solutions derived from the process underlying model M4. The expected reduction of inequality is also well aligned with the United Nations resolution on trustworthy AI, which aims at closing the digital divide [33].

Of course, we are aware that there are many additional research directions that future studies may explore. For instance, one might investigate the role of expertise. It may be important to distinguish between a design developed by an expert and one developed by a person with basic knowledge on a topic, but the availability of generative AI may increasingly help to close the knowledge gap. Similarly, the level of detail of a solution could be considered.

We expect that, in the future, various AI technologies will play an increasing role in connection with co-creation processes. For instance, AI could be used to assess the quality, completeness and feasibility of solutions. We would also like to propose testing various relevant settings in laboratory, online, or real-life experiments, considering ethical aspects. This will allow one to find the kinds of settings people like and that work particularly well in practice.

In conclusion, we believe that co-creation and participatory budgeting can strongly benefit from collective intelligence. This non-hierarchical approach allows people to be fully integrated in decision making processes, and to contribute own solutions to urban problems, as the Kreyon project also suggested [34].

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