

# Generative AI Voting: Fair Collective Choice is Resilient to LLM Biases and Inconsistencies

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## Abstract

Scaling up deliberative and voting participation is a longstanding endeavor – a cornerstone for direct democracy and legitimate collective choice. Recent breakthroughs in generative artificial intelligence (AI) and large language models (LLMs) unravel new capabilities for AI personal assistants to overcome cognitive bandwidth limitations of humans, providing decision support or even direct representation of human voters at large scale. However, the quality of this representation and what underlying biases manifest when delegating collective decision making to LLMs is an alarming and timely challenge to tackle. By rigorously emulating with high realism more than >50K LLM voting personas in 81 real-world voting elections, we disentangle the nature of different biases in LLMS (GPT 3, GPT 3.5, and Llama2). Complex preferential ballot formats exhibit significant inconsistencies compared to simpler majoritarian elections that show higher consistency. Strikingly though, by demonstrating for the first time in real-world a proportional representation of voters in direct democracy, we are also able to show that fair ballot aggregation methods, such as equal shares, prove to be a win-win: fairer voting outcomes for humans with fairer AI representation. This novel underlying relationship proves paramount for democratic resilience in progressives scenarios with low voters turnout and voter fatigue supported by AI representatives: abstained voters are mitigated by recovering highly representative voting outcomes that are fairer. These interdisciplinary insights provide remarkable foundations for science, policymakers and citizens to develop safeguards and resilience for AI risks in democratic innovations.

## 1 Introduction

Recent advances in artificial intelligence (AI) provide new unprecedented opportunities for citizens to scale up participation in digital democracy [1, 2, 3]. Generative AI in particular, such as large language models (LLMs), have a potential to overcome human cognitive bandwidth limitations and digitally assist citizens to deliberate and decide about public matters at scale [4, 5, 6, 7, 8]. This is by articulating, summarizing and even providing syntheses of complex opinions [9, 10, 7, 8], with a potential to mitigate for the voter fatigue and reduced voters turnout [11, 10], while fostering common ground for compromises, consensus and lower polarization [11, 12, 10, 13, 4]. However, understanding the implications and risks of using large language models for decision support/recommendations or even direct representation of human voters is a pressing

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challenge [14, 15, 16, 17]. In this article we study the inconsistencies of large language models to approximate both *individual* and *collective choices* as well as the inconsistencies of large language models across different preference elicitation methods. We explore causal links of these inconsistencies to potential cognitive biases triggered by the input to large language models based on which choices are made.

**Generative AI voting: a converging advance with inevitable challenges.** Large language models have been used to predict election winners using sensitive demographic data about the political profile of individuals [18]. They have also been used to predict pairwise comparisons of proposals for constitutional changes [6] and summarized opinions expressed with free-form text [19]. However, little is known whether this AI predictive capability can expand to more complex collective decision-making processes that involve more options to choose from, with more complex preference elicitation methods [5].

Participatory budgeting [20] is one such process put under scrutiny in this article. Here city authorities distribute a public budget by letting citizens propose their own project ideas, which they vote for and often implement themselves [21]. Projects may be pertinent to different impact areas (e.g. environment, culture, welfare), beneficiaries (e.g. elderly, children) and can have different costs. Voters can approve, rank or distribute points over their preferred projects, while winners are elected based on the popularity of the projects (*utilitarian greedy*) or based on a proportional representation of the voters' preferences (*equal shares*) [22, 23]. Recently though, a reinforcement learning approach has been used to elect winners by assisting voters to reach a consensus [24]. So far, the scope and citizens' engagement in participatory budgeting campaigns remains to a large extent a one-shot and highly local [25, 11]. What if there was a way to geographically spread such decision-making processes and run them on a regular basis? With such complexity and degree of design freedom, scaling up participatory budgeting turns into the ultimate democratic blueprint to assess capabilities and risks of generative AI voting.

Inconsistencies among different preference elicitation methods, known also as intransitivity of preferences [26], have not been studied so far for large language models. However, there is evidence that such inconsistencies do manifest even in human voters [22, 23, 27], especially under polarized contexts [28] that are usually subject of biases [29, 30]. Whether potential biases that explain the inconsistencies between human and AI choices are of different nature than the ones between different input voting methods is an open question studied in this article.

**How resilient representative voting outcomes are with generative AI.** We hypothesize that generative AI representatives of human voters build up resilience for representative voting outcomes in voting processes of low turnout if these human voters would otherwise abstain or would not have capacity to actively participate (see Figure 1d). In other words, we explore whether the inconsistencies of voting outcomes because of low voting turnout are higher than inconsistencies originated from generative AI representatives of abstained voters.

The inconsistencies of generative AI, along with the potential biases explaining these inconsistencies, are systematically studied here for the first time using a novel factorial design based on real-world empirical evidence. It consists of 5 dimensions (see Figure 1): (i) *Real-world voting scenarios* - datasets from the 2012, 2016 and 2020 US national elections [31] as well as the mock and actual participatory budgeting voting of the 'City Idea' campaign of 2023 in Aarau, Switzerland [32] are studied. They come with different number of ballot options and voters, see Figure 1a and Section 4.2. (ii) *Personal human traits* - for each voter, multiple incremental levels of additional information are given as input to large language models to generate ballots. This information includes socio-demographics, political preferences, preferences for project categories and preferences for qualities of voting outcomes (popular vs. fair election of winners, individual vs. collective benefit). These are derived from real-world evidence including survey data collected along the voting campaigns (see Section 4.1, and Table S3 and S4). (iii) *Voting input methods* - four methods with incremental level of complexity and expressiveness are compared [28, 33]. These include single choice for all voting scenarios, approvals, score (assigning a preference score to each option) and cumulative voting (distributing a number of points over the options) [34, 35, 36] for the participatory budgeting scenarios. (iv) *AI models* - Three large

language models are assessed along with a more mainstream predictive machine learning (ML) model used as a benchmark. GPT 3, GPT 3.5, and Llama2 are chosen covering a large spectrum of capabilities in open and closed generative AI [37], see Section 4.1 for more information. (v) *Voting aggregation methods* - majority is used for the scenario of US elections. The standard utilitarian greedy and the method of equal shares [38] are used for the participatory budgeting scenarios. The former method iterates to elect the next most popular project as long as the budget is not exhausted. It has been the standard method used in real-world. The latter method elects the projects that make the most people ‘happy’, meaning a combination of projects that maximizes a proportional representational of voters’ preferences. This is the method that was actually used in City Idea campaign to elect the winners [39], providing significance and realism for the findings of this study. See section 4.1 for more information.

The dimensions of the factorial design are illustrated in Table 1 and the studied combinations are marked with the colored boxes in Figure 1a. This broad spectrum of analysis based on real-world evidence allows us to generalize the findings of the study and make them highly relevant for a broad spectrum of research communities and policymakers.

**Assessing generative AI voting in action.** Voting personas are constructed using input prompts of large language models as depicted in Figure 1b. This designed process aims to emulate the three voting scenarios with the different settings of Figure 1a. Each input prompt consists of a standardized description of the voter’s profile (see Section S1 in SI) and an instruction to vote according to the ballot format. The individual and collective real-world choices of humans and AI personas are compared for the first time by measuring the overlap (Jaccard similarity) of their selected/winning options as an indicator of consistency [28]. These consistency values are then becoming the dependent variable to predict using the personal human traits as independent variables (features), which are fed in a neural network (see Section 4.5). Based on a systematic mapping of human personal traits to the cognitive biases as illustrated in Figure 1c (see Section 4 for more detail), this prediction model causally explains the human traits that contribute to inconsistencies and the potential underlying biases that explain these inconsistencies. This novel analysis is designed to provide a significant conceptual advance to understand how voting design reinforces or mitigates different AI biases in real-world practice.

## 2 Results

The following three key results are illustrated in this article:

1. Fair voting methods to elect winners are more resilient to human-AI inconsistencies, demonstrating a striking underlying win-win relationship: fairer voting outcomes for humans with fairer human representation by AI (Figure 2). These inconsistencies are particularly prominent in complex ballot formats with a large number of alternatives, while simple majoritarian voting tends to be highly consistent. GPT 3.5 shows transitivity of preferences among different ballot formats (Figure 3).
2. By representing half of the human voters who abstain with AI, a significant lost consistency is recovered in voting scenarios with low number of alternatives and fair voting aggregation methods to elect winners (Figure 4). For more than 50% of voters turnout, consistency is fully recovered by representing at least 25% of abstained voters with AI in single-choice majoritarian voting with two alternatives.
3. Conformity biases explain consistency of human-AI choice, while unconscious biases explain inconsistency (Figure 5). Political/ideological profile determines the human-AI consistency in single-choice majoritarian voting with two candidates. Time discounting factors explain transitivity of AI preferences between different ballot formats, while unconscious biases explain intransitivity.

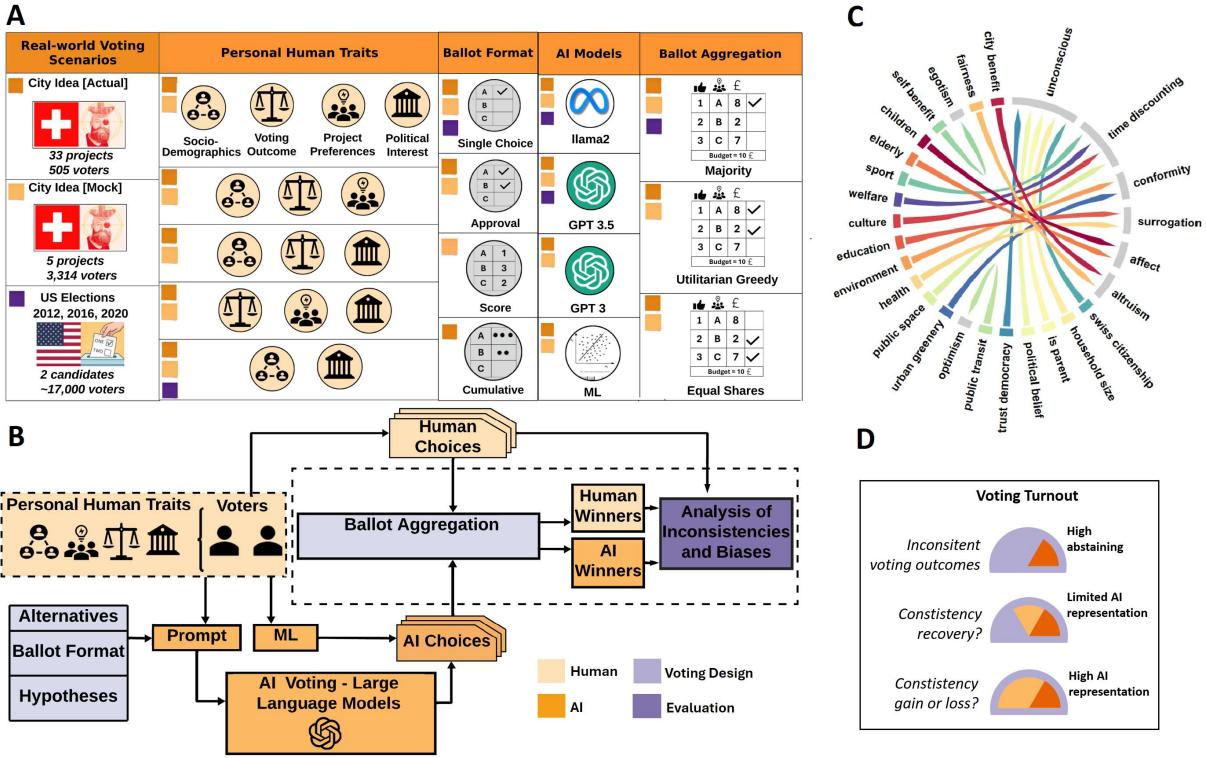


Figure 1: An overview of the generative AI framework, along with the factorial design and the biases studied in this article. (A) The factorial design with the 5 studied dimensions: (i) real-world voting scenarios in the context of participatory budgeting and national elections. (ii) Various combinations of persona human traits based on which AI personas are created. (iii) Four voting input methods. (iv) Four AI models, three large language models and a predictive machine learning model (benchmark). (v) Voting aggregation methods for elections and participatory budgeting. The studied combinations for each voting scenario are marked with different colors, see also Table 1. (B) The framework of generative AI voting. For each voter in the real-world voting scenario, a prompt is given to large language models to construct the voting persona. The input is the personal human traits, the voting options and the ballot format with instructions for the voting persona about how to make a choice. This choice is the output of the persona. Both human and AI choices are aggregated using a voting aggregation method. The inconsistencies of individual and collective choices for humans and AI personas are assessed, along with potential biases that explain these inconsistencies. (C) The personal human traits are mapped to cognitive biases. Section 4.4 illustrates choice inconsistencies and their origin to potential cognitive biases. (D) Hypothesizing for a recovery of consistency in voting outcomes under low voters turnout using AI representatives for abstained human voters.

## 2.1 Fair collective choice is resilient to human-AI inconsistencies

Figure 2 illustrates the human-AI consistency in individual and collective choices. The consistency of individual choice remains poor in complex ballot formats with several alternatives. On average, it is 4.5% and 27.2% for the actual and mock voting in participatory budgeting, yet it is 82.3% for the binary majoritarian US

elections. GPT 3.5 shows the highest consistency of individual choice among the large language models, which is 5.2% and 5.31% higher than GPT 3 and Llama2. On the contrary, the consistency of the collective choice increases by 51.2% in total. Strikingly, the consistency of equal shares is on average 80.8%, which is 32.8% higher than utilitarian greedy. Even when reducing the number winners of equal shares to the 8 of utilitarian greedy, the consistency remains 29.4% higher.

Compared to large language models, the machine learning model shows 3.6% higher consistency in individual choice and 6.6% higher in collective choice. All consistency values are the maximum ones derived with all personal human traits as shown in Figure 1a. The removal of project preferences shows the highest consistency reduction of 19.7%, while political interest shows the lowest consistency reduction of 3.4%.

Figure 3 illustrates the transitivity of preferences in different large language models by measuring the consistency of individual choice among different pairs of ballot formats. ‘Approval - cumulative’ voting shows the highest consistency, which is 1.8% higher than ‘single choice - approval’ and 3.5% higher than ‘single choice - cumulative’.

GPT 3.5 shows 21.1% higher consistency than GPT 3 and 20.2% higher than Llama2. While human transitivity approaches 95.2% on average, AI transitivity remains at 70.1% for GPT 3.5. The mock voting with only 5 alternatives achieves on average 65.5% of consistency, while the actual voting with 33 alternatives shows a consistency of 43.4%.

## 2.2 AI representatives to recover from low voters turnout

Figure 4a illustrates the capability of AI representatives to recover the consistency of voting outcomes lost by low voters turnouts. Strikingly, up to 50% of AI representatives are sufficient for a maximum consistency recovery of 53.3% under voting turnouts lower than 80% when equal shares is used. This significant recovery is despite the very low consistency of human-AI individual choices in complex ballot formats with several options (Figure 2a). The recovery is also confirmed for equal shares with the top-8 winners, which is equal to the number of winners with utilitarian greedy (on average 18.1% lower consistency recovery). However, AI representatives fail to recover consistency with utilitarian greedy as the voting aggregation method.

Figure 4b shows that the recovery of consistency is more robust for both voting aggregation methods under low number of alternatives. Consistency is recovered with up to 75% of abstained voters represented by AI under a maximum of 60% voters turnout, after which 50% of AI representatives are sufficient for consistency recovery.

Under the voting scenario of the US elections that comes with highly consistent human-AI individual choices, consistency is fully recovered for  $\geq 25\%$  of abstained voters represented by AI under a minimum of 50% voters turnout. However, below 50% of voters turnout, election results are very sensitive and consistency recovery is guaranteed only for 100% of abstained voters represented by AI. More detailed results on mixed populations of humans and AI representatives, including the consistency loss when human voters abstain are shown in Figure S2.

## 2.3 Biases explaining AI inconsistencies in choice and preference transitivity

To explain the origin of (in)consistencies in human-AI choice and different voting input methods, a prediction model is designed for each voting scenario. The personal human traits, mapped to different cognitive biases, become the independent variables and the consistency the dependent variable. The prediction model is built using a neural network (see Section 4.4). The relative importance of the personal human traits that explain the AI consistency is calculated using shapley additive explanations (see Section 4.5).

In the case of participatory budgeting in Figure 5a and 5b, the preference for environmental projects (potential conformity bias [40, 41, 42]) shows an average importance of 26.5% ( $p=0.0258$ ) in explaining human-AI choice consistency (25% and 12% higher consistency among environmental supporters, with  $p=0.038$  for the

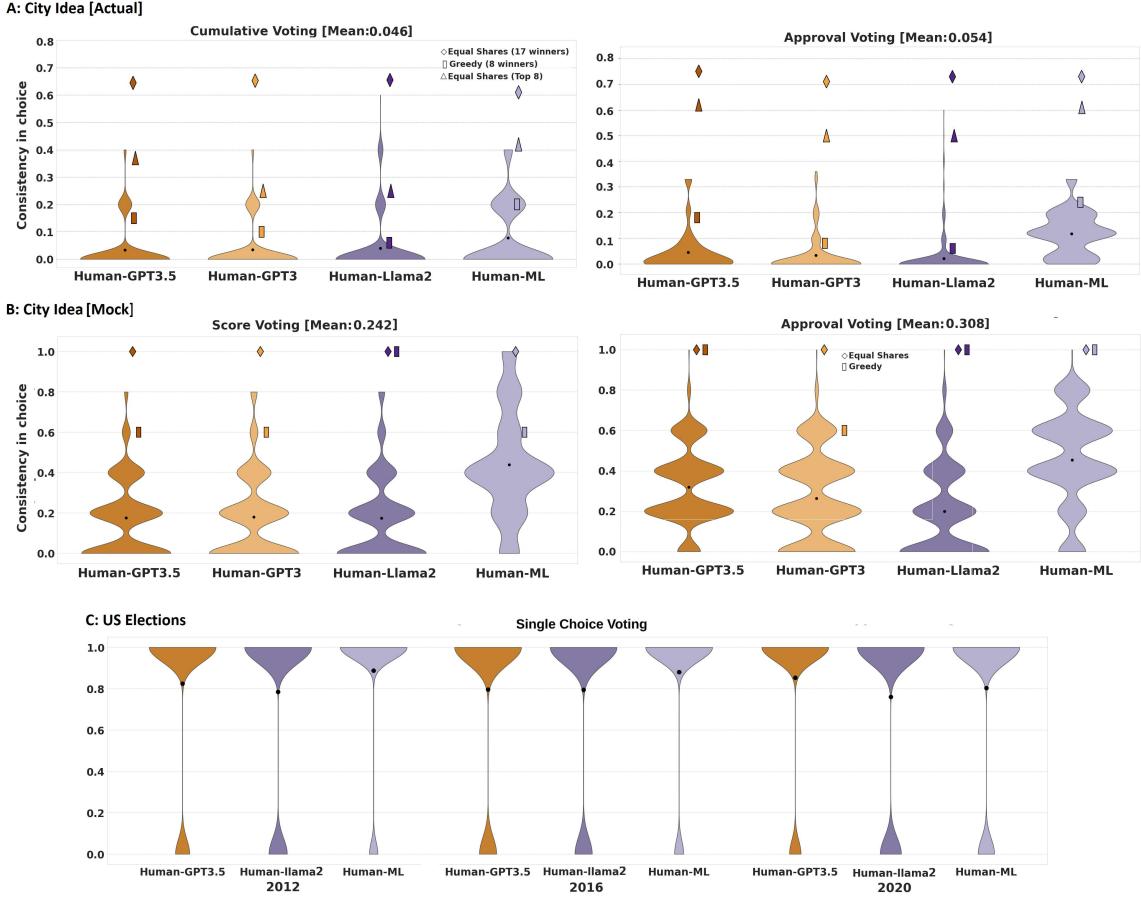


Figure 2: **Choice by large language models is consistent to humans for single-choice majoritarian elections, however consistency drops for more complex ballots with larger number of alternatives as in the case of participatory budgeting.** Strikingly, consistency of collective choice is significantly higher than individual choice, particularly for the fairer voting aggregation rule of equal shares. GPT 3.5 shows the highest choice consistency and Llama2 the lowest among the large language models, which though remain inferior to a predictive machine learning model. The consistency (y-axis) in individual and collective choice is shown for different AI models (x-axis) across three real-world voting scenarios: The participatory budgeting campaign of City Idea, (A) actual and (B) mock, and (C) the US national elections of 2012, 2016 and 2020. The consistency in the participatory budgeting scenarios is shown for different voting input methods (left and right). The consistency of collective choice with the two voting aggregation methods of utilitarian greedy and equal shares is also shown. For the actual voting of City Idea, the consistency of equal shares is calculated for all winners and 8 winners (as many as greedy) for a fairer comparison.

actual voting scenario). Political belief and ideology are strongly correlated with the actual two alternatives in the US elections (right/conservative for republicans and left/liberal for democrats), therefore, they strongly

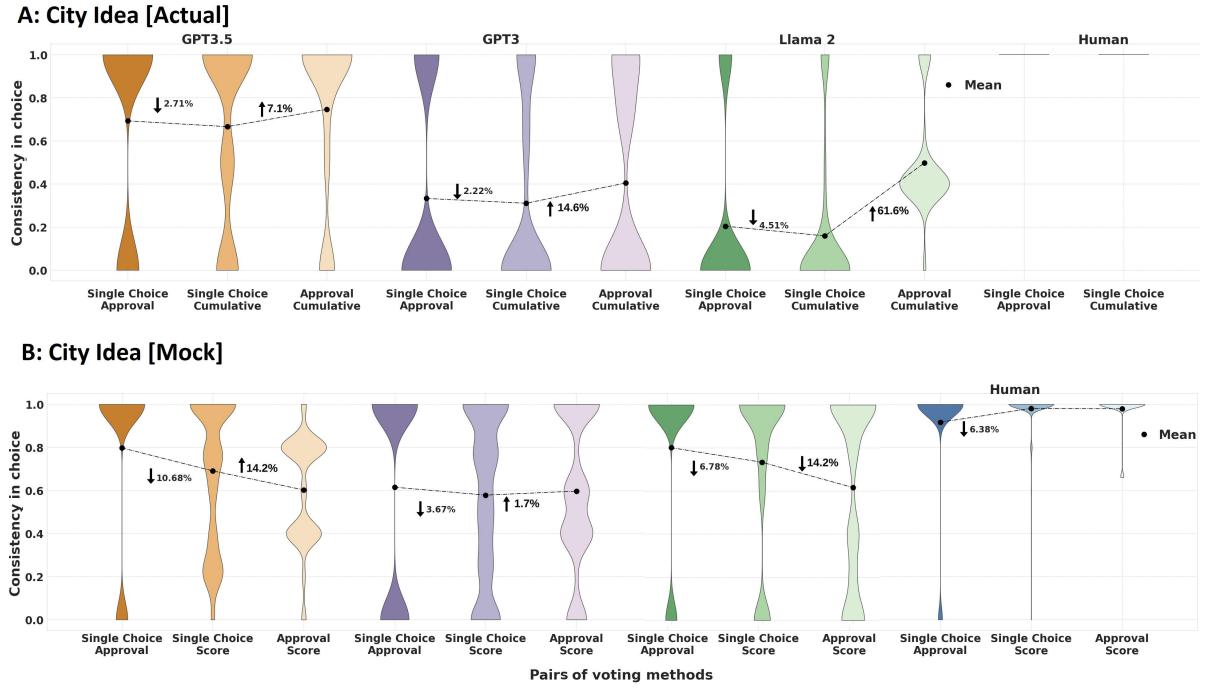


Figure 3: Voting personas based on GPT 3.5 show transitivity of the preferences over the different voting input methods in the actual complex voting scenario. However, GPT 3 and Llama2 remain with a low consistency  $<0.5$ . The simpler mock voting scenario shows higher transitivity among all language models. The consistency (y-axis) in individual choice among different pairs of ballot formats (x-axis) is shown for different large language models, humans and the two voting scenarios in the participatory budgeting campaign of City Idea: (A) actual vs. (B) mock.

explain the consistency of human-AI choice (mean relative importance of 98.7%,  $p<0.02$  and 4.8%,  $p<0.03$  respectively). However, this is not the case in participatory budgeting as it is political belief that rather explains inconsistency (relative importance of -51.2% with  $p<0.02$ ). This demonstrates that the underlying participatory budgeting choices remain politically neutral to a high extent, despite the fact that the City Idea campaign mainly attracted left-wing voters (42.5% versus 31.5% of right wing voters). In contrast, race and discussion of politics explain inconsistencies in the US elections with a mean relative importance of -48.1% ( $p<0.04$ ) and -64.7% ( $p<0.04$ ) respectively. Inconsistency is 33% higher than consistency among white people ( $p<0.019$ ), while for people who discuss politics inconsistency is 63.2% higher than the ones who do not ( $p=0.046$ ).

The consistency among the voting input methods is explained by preference towards time discounting factors [41] in participatory budgeting, such as sport and welfare projects. The average relative importance is 25.6% and 17.5% respectively (all with  $p<0.03$ ), with 48.53%, and 37.5% of higher consistency among supporters in the actual voting ( $p<0.044$ ). Affect heuristics such as preference for projects that benefit families with children also strongly contributes to the consistency with 58.9% higher consistency among supporters in the actual voting ( $p<0.032$ ). Figures, S3, S4, and Table S8 illustrate additional insights about how personal human traits explain the AI top choice and the human-AI consistency of the individual choices.

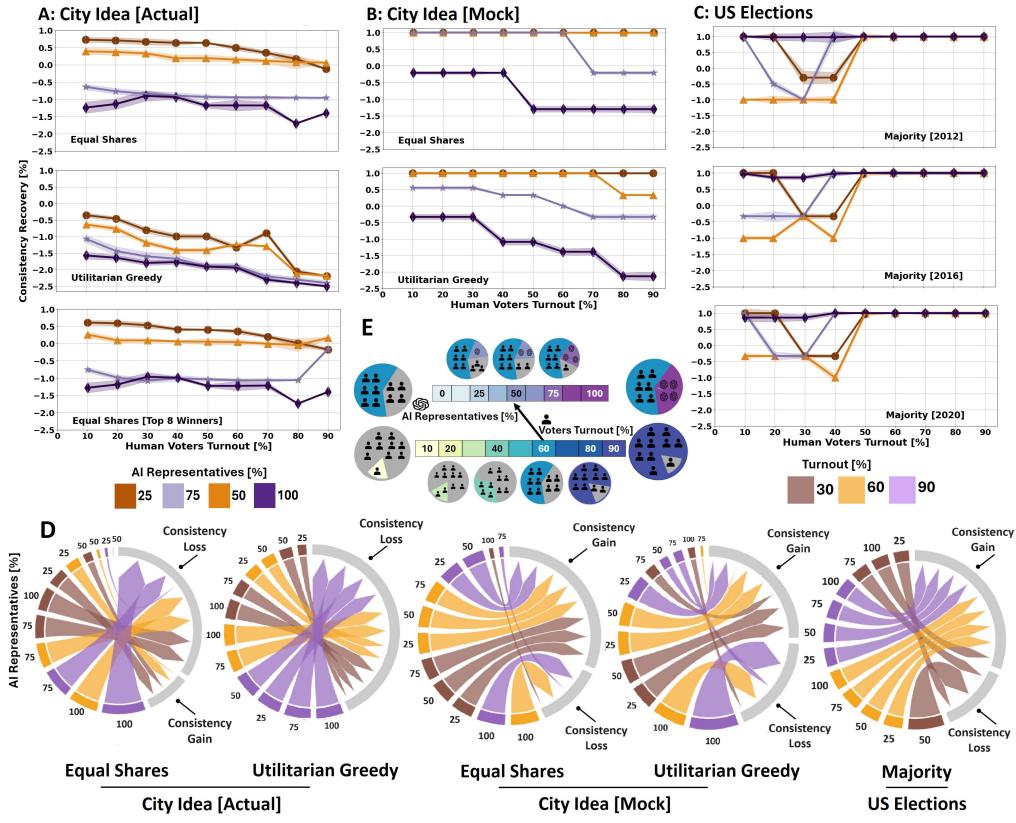


Figure 4: By representing up to half of the human voters who abstain from voting with AI, a significant lost consistency in the collective choice is recovered in participatory budgeting under fair voting aggregation methods such as equal shares and under low number of alternatives. However, further consistency loss is observed under a large number of alternatives with the standard utilitarian greedy method as the number of AI representatives increases. In contrast, single-choice majoritarian elections with highly consistent human-AI individual choice maximize consistency recovery for the whole spectrum of voters turnout by maximizing the AI representatives for the voters who abstain. Nevertheless, for more than 50% of voters turnout, consistency is fully recovered by representing at least 25% of abstained voters with AI. The consistency loss in the voting outcome by low voters turnout (x-axis) is emulated by removing different ratios of human voters. A recovery of consistency (y-axis) is hypothesized by different ratios of abstained voters represented by AI: 25%, 50%, 75% and 100%. The consistency recovery values are the means of all three large language models (see Figure S1 for the results of each large language model). The (A) actual and (B) mock voting in the participatory budgeting campaign of City Idea are shown with two voting aggregation methods: utilitarian greedy and equal shares, with all winners and the top-8 (as many as greedy) for a fairer comparison. (C) US elections. (D) Chord visualizations summarizing how the interplay between voters turnout and AI representation yields voting outcomes with consistency gain or loss. (E) Visualizations summarizing the mechanism of consistency recovery through AI representatives for the voters who abstain.

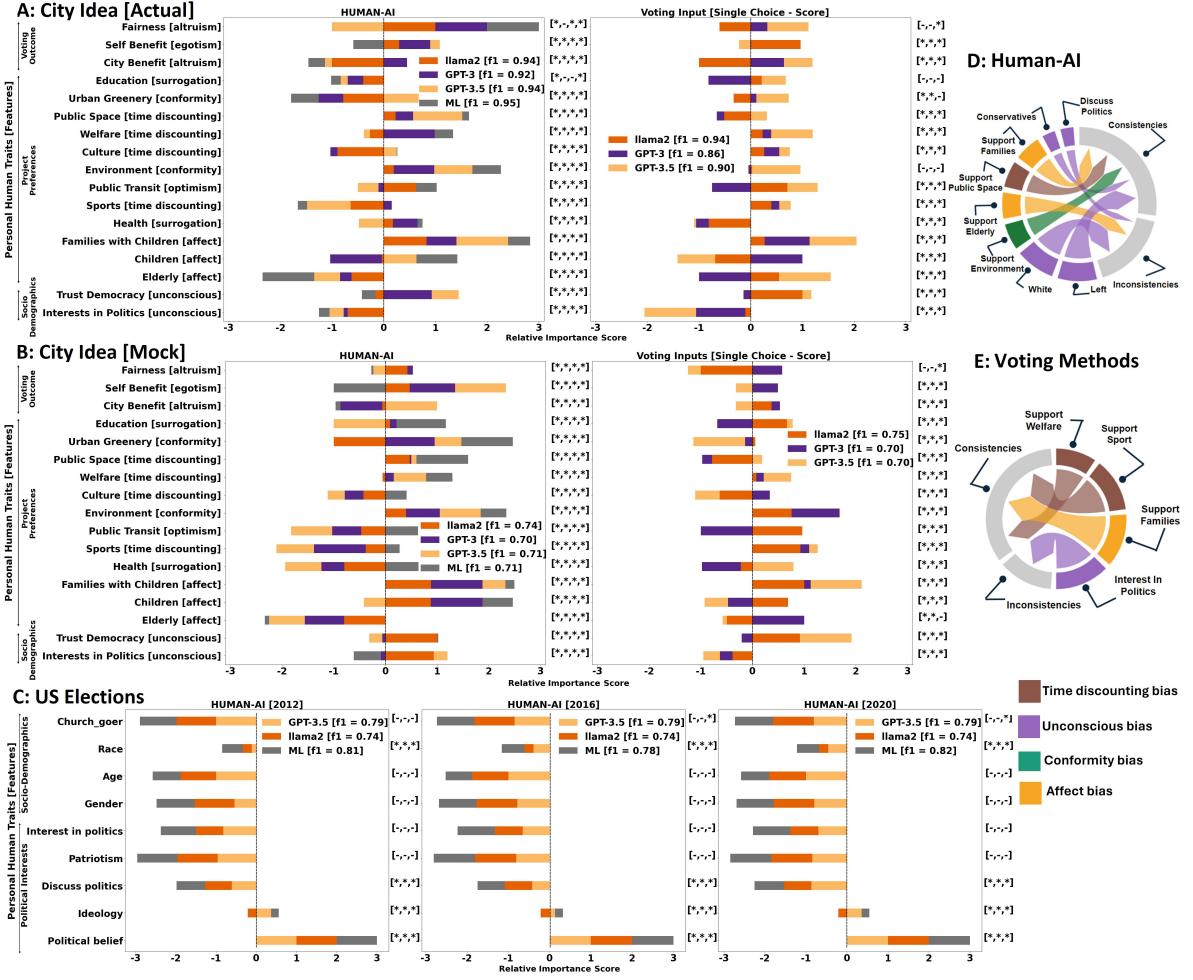


Figure 5: Conformity bias, such as preference for environmental projects, positively contribute to the consistency of human-AI choice. On the other hand, unconscious biases such as race and discussion of politics cause inconsistencies. For US elections though, political belief and ideology strongly contribute to consistency. Time discounting factors such as preference for sport, and welfare projects as well as affect heuristics such as preference for projects that benefit families positively contribute to the consistency of choice among the voting input methods. The relative importance (x-axis) of the personal human traits (y-axis) to predict the consistency of choice and consistency between voting input methods (single choice vs. cumulative/score) is shown for different large language models and the machine learning model. This is calculated using Shapley Additive Explanations. The (A) actual and (B) mock voting in the participatory budgeting campaign of City Idea is shown along with the (C) US elections. The '\*' denotes that the feature is statistically significant ( $p < 0.05$ ) for each of the AI models of Llama2, GPT 3, GPT 3.5 and ML respectively. The chord visualizations summarize the biases that explain the (in)consistencies of (D) human-AI choice and (E) voting input method.

### 3 Discussion

**Generative AI voting: an inevitable race to safeguard democracy.** Generative AI voting is likely to emerge as an inevitable technological convergence of AI and e-voting solutions currently adopted in real-world. On the one hand, generative AI and large language models are expected to become more open, pervasive and accessible to citizens [43, 15]. AI personal assistants are already part of everyday life [44, 45, 46], with their generative version expected to follow. On the other hand, the mandate of more direct, secure and active participation in decision making for public matters is expected to further scale up electronic voting solutions and digital platforms. For instance, participatory budgeting elections are mainly conducted digitally, while Estonia has already institutionalized a digital identity for 99% of its citizens as well as electronic voting since 2005 [47]. As Toomas H. Ilves, former president of Estonia, emphasized "*with the digital signature and the machine-readable ID card, we created the e-citizen*". In the light of these converging advancements, the inter-operation of a generative personal voting assistant with a digital voting platform becomes technologically feasible along with the citizens' need to have a more direct saying in several public matters and consultations. Therefore, the findings of this study become spot on to understand the implications of such a future, while they are significant to prepare safeguards for digital democracy.

**Fair voting design as a safeguard for generative AI voting.** Large language models prove not ready yet to accurately represent humans in complex voting scenarios such as participatory budgeting. However, a striking finding of this study, built upon our demonstrated real-world evidence in Aarau, is that consistency of large language models becomes significant under fair voting aggregation methods that promote a proportional representation of voters' preferences. This motivates a huge opportunity to get democracy "right" in the digital era of AI: move to alternative voting methods that yield fairer voting outcomes for all, while shielding democratic outcomes from AI biases and inconsistencies. The momentum for this win-win paradigm shift is tremendous, which would not be possible otherwise to demonstrate without the real-world empirical evidence based on which this study unfolds: fair voting rules such as the method of equal shares promotes under-represented projects and yield more winning projects with higher proportional representation of citizens' preferences [39, 22]. Nevertheless, how to scale up these democratic blueprints remains an open question, but AI can play a key role here.

**Why fair collective choice is resilient to AI biases and inconsistencies.** We provide an explanation of this significant and striking finding. There is evidence that the method of equal shares has an inherent stability in the resulting voting outcomes [22]. For instance, even with 25-50% of the voters, the elected projects do not significantly change [22]. This is despite the fact that projects may end with very different number of total votes, as low and middle-cost projects require a very minimal support to get elected, and as a result, these winning projects are likely to be retained in the winning set, even with different choices or set of voters. Such projects are expected to be an origin of consistency. Indeed, this effect is also observed in the real-world voting scenario of City Idea, as with 80% abstaining voters, 84% of the winners are retained with equal shares, see Figure S2. As City Idea promoted equal shares already in the project ideation phase and made apriori use of equal shares for the aggregation of the ballots, this study becomes the first of its kind and comes with compelling realism and merit for the validity of our significant findings. This comes in stark contrast to other earlier studies [22, 39] that hypothesize the application of equal shares over proposed projects and ballots aggregated with the standard method of utilitarian greedy.

**Mitigating low voters turnout: AI representation is not enough, voting design matters.** This perspective is assessed for the first time in this study by emulating voting scenarios with varying voters turnout, while letting voters who abstain to have a representation by generative AI to restore the lost consistency of abstaining. Nevertheless, the inherent inconsistencies of generative AI can hinder the effectiveness of AI representatives. Therefore understanding these opposing dynamics comes with significant merit to mitigate the impact of AI biases and inconsistencies in collective decision making. This is by showing striking evidence

that voting design has a determining role on how much consistency can be recovered and what effect this can have for the legitimacy of the voting process and outcomes. Recovering the lost consistency under very low voting turnouts in single-choice majoritarian elections requires populations with very high majorities of AI representatives, which turns out to be illegitimate. In contrast, the lost consistency under higher voting turnouts can be restored even with low proportions of AI representatives. The fair method of equal shares is also here a prominent accelerator for the consistency recovery: fewer AI representatives are sufficient to restore consistency even under very low voter turnouts. It is also evident that such consistency recovery could not be achieved with the standard voting aggregation method.

**Trustworthy generative AI voting: a call for research and policy action.** What information large language models use to reason about voting decisions is influential for different types biases to manifest. Unconscious and conformity biases, related to political belief, race and environment reinforce human choices or yield inconsistencies. Time discounting biases, related to the support of projects on welfare and sport, explain preference transitivity among different ballot formats. These significant findings demonstrate that training data in generative AI voting are expected to be highly impactful for the representation of the voting outcomes in the population. Ethical and democratic guidelines are urgently needed, particularly for the use of (generative) AI in voting processes. For instance, who shall determine the input training data of AI representatives? Should the training data involve only self-determined personal information of voters, or shall these be augmented with more universal knowledge and experts' opinions? How to protect the privacy and autonomy of voters when training such AI representatives [46]? Will citizens retain power to control AI representatives that reflect their values and beliefs, while remaining accountable? These are some key questions as a basis of a call for action on research and policy in an emerging era of generative AI voting.

## 4 Methods

We show here how AI representatives are emulated and the real-world data based on which the voting scenarios are constructed. We also illustrate the evaluation approach and the studied human cognitive biases. Finally, the approach to explain the inconsistencies and biases of generative AI is outlined.

### 4.1 Emulating AI representatives

We introduce a generalized design to create AI representatives using three large language models and a predictive AI method as a benchmark (referred to as ML) to generate choices (ballots) and emulate AI voting representation.

**Input to ballot generation.** This comprises of (i) defining the voting scenario, the voting alternatives and the personal human traits of the voter as the input context (LLMs) or features (ML) to inform the ballot choice, (ii) generating the ballots and (iii) aggregating the ballots into a collective decision (see Figure 1).

- (i) *Personal human traits:* Voter's information is used to define an AI *persona* of a human voter, i.e. the AI representative (more information in Tables S3 and S4 in SI). This includes (i) *socio-demographic characteristics* (e.g., gender, age, education, household size), (ii) *political interests* (e.g., ideological profile, political belief), (iii) personal attitude towards *project preferences* (e.g., prioritization for green initiatives, sustainable transport, elderly care facilities) and (iv) preferences for the qualities of *voting outcomes* (e.g., favoring cost-effective winning projects vs. popular ones vs. winning projects with proportional representation of citizens' preferences). These traits are extracted from feedback surveys of voters, who also cast ballots in the voting scenarios and therefore the survey data are linked to the actual voting behavior (see field study design in Section 4.2).

- (ii) *Voting alternatives*: The three real-world voting scenarios determine the voting alternatives given as input to the AI representatives. They are illustrated in detail in Section 4.2. The actual City Idea scenario comes with 33 project alternatives and their cost, while the mock scenario comes with 5 costed project alternatives. The US elections comes with two alternatives. These three scenarios provide a broad spectrum of decisions spaces to assess the AI representatives.
- (iii) *Ballot formats*: The two participatory budgeting scenarios are either approvals (*n*-*approval* ballot where ‘n’ is the number of projects approved) or cardinal preferences (score or cumulative) [48, 49]. In the case of *score* ballots, the voters provide a score to a project from a specified range such as 1 to 5 with 1 being the lowest preference and 5 being the highest. In the case of *cumulative* ballots, the voters distribute a number of given points among the projects. Single-choice ballots are derived from single approvals, top scores or top points distributed to a project.

**Generative AI.** We use proprietary models such as GPT 3.5, GPT3 [50] and the open-source Llama2-13B [51]. GPT 3.5 and GPT 4 have similar performance for these tasks [52], hence we resort to GPT 3.5 for the analysis. Furthermore, both GPT 3.5 and GPT 4 use the “*Let’s think step by step*” to evaluate a prompt and find a solution that mimics human reasoning [52]. For each of the large language models, predictions are made based on the five combinations of personal human traits (see Figure 1), however the predictions with all models have the highest consistency to human choices, which we use for the analysis.

**Predictive AI benchmark.** The personal human traits are set as features to predict the ballots using classification methods [53]. We sample 40% of the data and use synthetic minority oversampling [54] to augment the data. This 40% is decided empirically based on the performance of the neural network models. We also divide the prediction into multiple sub-problems, which predict the approvals or assigned scores for every option and then compile the final ballot. This model is then used to predict 60% of the unknown ballots and 40% of the known ballots.

**Ballot aggregation.** For the US elections, majority determines the winner. For the two voting scenarios of participatory budgeting, the generated ballots by the AI representatives are aggregated using either the utilitarian greedy method or the method of equal shares. *Utilitarian greedy* simply selects the next most popular project, the one with the most received votes, as long as the available budget is not exhausted. *Equal shares* provides a proportional representation of voters’ preferences by dividing the budget equally among voters as endowments. This part of the budget can only be used to fund projects that the voter has voted for. The method goes through all project options, beginning from the projects with the highest number of votes. It selects a project if it can be funded using the budget shares of those who voted for the project. A full explanation of the is out of the scope of this article and can be found in earlier work [38, 48, 49]. In practice, the method of equal shares is likely to sacrifice an expensive popular project to select instead several low-cost projects, which, in combination, satisfy the preferences of more voters [39, 22]. As a result, equal shares tends to elect more winning projects. Because of this effect, it likely that consistency measurements based on the Jaccard similarity yield higher values for equal shares. This is the reason we control for the number of winning projects in equal shares by counting a subset of the most popular winning projects which is equal in number with the winners of the utilitarian greedy method.

**Emulated voting processes with human voters and AI representatives.** We emulate the following voting processes: (i) Human voters exclusively with 100% turnout. (ii) Human voters exclusively with varying turnout in the range [10%,100%] with a step of 10%. (iii) Mixed populations of human voters and AI representatives assessed of whether they can recover the consistency of voting outcomes lost by different human voters turnouts in the range [10%,100%] with a step of 10%. The ratio of AI representatives for the abstained voters varies in the range [25%,100%] with a step of 25%. (iv) AI representatives exclusively.

Each scenario of voters turnout is repeated 10 times by selecting a random subset of voters who abstain. For each turnout level, the AI representation of abstained voters is also repeated 10 times by selecting a

random subset of the abstained voters to represent by AI.

**Data collection infrastructure.** Generative AI choices are collected via API prompts to large language models from 16th of June 2023 to 8th of November 2023. We prompted the large language models using the zero-shot learning feature [50], which does not require any specific fine-tuning. We use chain of thought prompting [55] to provide a comprehensive and systematic flow of information for better interpretability. The large language models run with temperature settings of 0.2 to 0 (20 runs for each temperature setting), for a focused decision with less randomness [56]. As we are dealing with a significantly large decision space, particularly the 33 projects in the actual voting, running with a high-temperature setting can lead to random decision-making. To maintain consistency, we retain the projects that are approved at the deterministic temperature setting (the responses are easily reproducible at temperature setting = 0). Furthermore, if a project is selected both in 0.1 and 0.2, we include the approval for that project in the ballot to also incorporate diversity. In the case of score voting, we take the frequency of the distinct scores assigned to a project across different temperature setting and add the score with the highest frequency. However, for the actual City Idea scenario for which we emulate cumulative voting, the total score provided in a ballot should be lower than the total number of points. Therefore, it would not be accurate to derive a score for a project from multiple outputs corresponding to different temperature settings, hence we conducted experiments only with the temperature setting of 0.2. The decoding algorithm for the large language model is set to the nucleus sampling approach [55]. Compared to purely random sampling, it avoids generating outliers or improbable sequences of choices.

For the predictive AI choices, we use neural networks with 3 hidden layers and the *relu* [57] activation function for the sub-networks in the neural network. We employ the ensemble method [58] of designing multiple neural networks with different parameters and merging in the final layer with cross entropy loss [59]. This helps to generalize on different sizes of datasets and improve the prediction scores on unseen data.

## 4.2 Voting datasets

Table 1 outlines the settings of the emulated voting scenarios.

**US elections.** The 2012, 2016, and 2020 survey waves of the American National Election Study (ANES) [60] are used. They encompass 4,500 votes together with the respective voter information for each of these three years. This mainly includes socio-demographic characteristics: (i) racial/ethnic self-identification, (ii) gender, (iii) age, (iv) conservative-liberal ideological self-placement, (v) party identification (political belief), (vi) political interest, (vii) church attendance, (viii) discussion of politics with family/friends, (ix) feelings of patriotism associated with the American flag, and (x) state of residence. A total of 9 elections are emulated using Llama, GPT-3.5 and the predictive ML model based on single-choice ballots, with winners decided by majority for the three years. We extracted information from 20,650 voters of the ANES dataset [60] and after pre-processing (removing voters with missing values in more than 5 of the personal traits), a set of 17,010 voters is used. The examples of the prompts used to generate the AI choices can be found in Table S5.

**City Idea: Participatory budgeting campaign in Aarau, Switzerland.** The data from a recent innovative participatory budgeting field study are used [32, 39], which was conducted with ethical approval from University of Fribourg (#2021-680). It run in 2023 and is rigorously designed to assess the application of equal shares for the first time in real world, in combination with cumulative voting, using the open-source Stanford Participatory Budgeting platform [33]. As such, the field study includes a survey conducted before voting linking the choices of survey respondents and voters. We use the following personal human traits from the survey (more information in Tables S3 and S4): (i) 9 key socio-demographic characteristics (e.g., age, citizenship, education) and 2 political interests (political beliefs and trust in democracy), (ii) preferences for 9 different types of projects and 6 beneficiaries and (iii) 4 types of preferences for qualities of the voting outcome.

Two participatory budgeting voting scenarios are studied in the context of the real-world campaign of City Idea:

Table 1: The studied dimensions across three real-world voting scenarios. They provide the necessary diversity to generalize the findings of this study as they include different scales in number of voters, different ballot formats and aggregation methods, low and high numbers of alternatives, different personal human traits for studying a broad spectrum of biases including both generative and predictive AI methods.

Studied factors	US Elections 2012, 2016, 2020	City Idea [Mock]	City Idea [Actual]
<b>Ballot Input</b>			
<b>Personal human traits</b>			
Socio-demographics	✓	✓	✓
Preference for voting outcome qualities	✗	✓	✓
Project preferences	✗	✓	✓
Political interests	✓	✓	✓
<b>Ballot format</b>			
Single-choice	✓	✓	✓
Approval	✗	✓	✓
Score	✗	✓	✗
Cumulative	✗	✗	✓
<b>Alternatives for voting</b>	2	5	33
<b>Ballot Generation</b>			
<b>Generative AI</b>			
GPT 3	✗	✓	✓
GPT 3.5	✓	✓	✓
Llama2-13B	✓	✓	✓
<b>Predictive AI</b>			
Neural Networks	✓	✓	✓
<b>Ballot Aggregation</b>			
Majority	✓	✗	✗
Utilitarian greedy	✗	✓	✓
Equal shares	✗	✓	✓
<b>Voters</b>	~17,000 (across 3 years)	3,134	505
<b>Emulated elections</b>	9	91	27

- (i) *Mock Voting*: Five hypothetical costed projects belonging in different categories are put for mock voting as part of the initial survey. Table S1 illustrates the project alternatives and their cost. The choice of 3134 voters over the same alternatives is tested with three different ballot formats in a sequence, starting with the simplest one of single choice to the most complex ones of approvals and score voting. This allows us to emulate a total of 45 elections = 3 ballot formats x 2 ballot aggregation methods x 3 AI models x 5 personal traits + 1 for the predictive ML model.
- (ii) *Actual Voting*: Using the Stanford Participatory Budgeting platform [33], 1703 voters cast their vote using cumulative ballots by distributing 10 points to at least 3 projects of their preference, out of 33 projects in total (see Table S2 for project descriptions). A subset of 505 of these voters, which participated in the initial survey and provided their personal human traits, are used to construct the AI representatives. The ballot formats of single choice and approvals are derived from the cumulative ballots by taking the project with the most points and the projects that received any point respectively. This allows us to emulate a total of 91 elections = 3 ballot formats x 2 ballot aggregation methods x 3 AI models x 5 personal traits.

The examples of the prompts used to generate the AI choices in both mock and actual voting can be found in Table S6.

### 4.3 Evaluation of choices by AI representatives

The emulated elections with AI representatives are compared to the real-world elections of human voters at two levels: (i) *individual choice*, i.e. the ballots, and (ii) *collective choice*, i.e. the resulting voting outcomes. Consistency is the main measure of assessment.

**Consistency of individual choice.** Consistency is assessed at two levels:

- (i) *Human-AI consistency of individual choice*: This is the Jaccard similarity [61] of individual choices made by AI representatives with the original choices of the humans they represent. For single-choice ballots, this is either 1 (consistent) or 0 (inconsistent) for each voter and the respective AI representative. For approval voting, the AI and human choices are binary sequences representing the ballot, containing 1 (approved) or 0 (not approved) for each alternative. The Jaccard similarity between these sequences is the ratio between the number of alternatives approved by both the human and the AI representative over the number of alternatives approved by at least one of them. For score and cumulative voting, projects are ranked based on the scores and points received respectively. Each top-k project of a human voter is compared to the respective top-k project by its AI representative. Matching is indicated by 1 (consistent), otherwise 0 (inconsistent) indicates no matching. The mean number of matchings among all ranked projects measures the consistency for these ballot formats.
- (ii) *Consistency of AI and human individual choice across ballot formats*: We consider the consistency between different pairs of ballot formats. For ‘single choice - score’ and ‘single choice - cumulative’ voting, consistency is measured as  $1 - (\text{top score} - \text{score} [\text{single choice}])$ . The top score represents the highest score provided in the score or cumulative ballot. The score of the single choice is the score given under the score ballot format to the project selected by the single-choice ballot format. For ‘single choice - approval’ ballots, consistency is either 1 (single choice is approved) or 0 (single choice is not approved). For the ballot pairs ‘approval - score’ and ‘approval - cumulative’, score and cumulative voting are first represented as 1 (score/points >0) or 0 (no score/points) for each alternative. The Jaccard similarity is then used to calculate consistency.

**Consistency of collective choice.** It is defined for two voting processes that elect winners from the same alternatives, but have different voters (human, AI representatives, mixed), and, as a result, can yield different voting outcomes. The voting outcomes with the winners are first calculated using one of the ballot aggregation methods, i.e. majority, utilitarian greedy or equal shares. These outcomes are represented as binary sequences containing either 0 (not winner) or 1 (winner) for each alternative. Consistency is calculated using the Jaccard similarity [61] between these binary sequences.

**Consistency recovery in collective choice with AI representatives.** It is determined here for voting processes with varying voters turnout, in which abstained voters result in consistency loss, which can be recovered if a portion of these abstained voters are represented by AI. It is measured as follows:

$$\frac{\text{consistency} [\text{human voters} - \text{abstained voters} + \text{AI representatives}] - \text{consistency} [\text{human voters} - \text{abstained voters}]}{1 - \text{consistency} [\text{human voters} - \text{abstained voters}]},$$

where the voters turnout  $\frac{\text{human voters} - \text{abstained voters}}{\text{human voters} + \text{abstained voters}}$  varies in the range [10%,90%] with a step of 10%, and AI representation  $\frac{\text{AI representatives}}{\text{abstained voters}}$  varies in the range [25%,100%] with a step of 25%.

#### 4.4 Human cognitive biases in AI collective decision making

Human choices are significantly influenced by potential cognitive biases that are often a manifestation of socio-economic characteristics, conditions of life quality, satisfaction with the available public amenities and the overall life experiences of an individual [41]. Here we map self-reported personal human traits with which large language models are prompt to potential underlying human cognitive biases, as a way to explore whether they are reinforced by the language models and become more likely to manifest in the AI choices. Figure 1c outlines the mapping we study based on a systematic and comprehensive review of relevant literature. The following types of biases are determined:

**Time-discounting biases.** These are characterized by the tendency to receive immediate gratification over a larger but future reward. Projects related to the public space, culture, or welfare are often one-off projects, such as an annual festival, a cinema night, or educating asylum children (alternatives proposed for the participatory budgeting campaign in Aarau [32]), where expected benefits are experienced in the short term. Therefore, such project are subject of time-discounting biases [41]. In contrast, the construction of a road, for example, incurs investment costs several years before the actual project implementation. Such investments create a sustainable reform that benefits all in the long run. Even though 72% of the public transportation infrastructure in European cities ends up in cost overruns, people still vote for these projects due to an underlying necessary optimism to improve transport [41, 39]. We refer to this economic discounting over a long-term sustainability impact as ‘optimism’ [62, 63].

**Surrogation biases.** This reflects how humans favor simpler measures to assess the impact over ones that are more precise and harder to evaluate. Korteling et al. [41] argue that these biases manifest when deciding projects with large societal impact such as health or education, while their outcome is subject of different satisfaction levels among citizens. The project outcomes may be perceived as successful by part of society using easy-to-evaluate metrics instead of looking at long-term effects on the community. For instance, a timely vaccination drive may be preferred over significant changes to vaccination protocols or health insurance policies covering vaccination. Hence these projects are likely to be more preferred as they come with more intuitive ways to assess for the broader population. This is reflected by the average winning rate of the health and education-related projects of 38.1% and 36.2% respectively in Poland [39], where participatory campaigns have been actively hosted in the last decade.

**Conformity biases.** These biases arise out of group pressure under which people make decisions to be socially desirable [40, 42]. It is argued that a conformity bias may induce voting for green alternatives [41]. Green-themed participatory budgeting campaigns have been adopted in European cities such as Lisbon [64], to promote green initiatives, aligning to a culture for more sustainable behavior. Poland runs participatory budgeting campaigns at large scale, which include environment and urban greener projects. These are within the top-5 most popular projects with an average of 22.5% and 26.5% respectively [39]. Even in Aarau we observe the same trend wherein, environmental friendly projects account for the top-10 most popular projects [32].

**Affect heuristic biases.** This defines the tendency to make decisions based on what intuitively or emotionally feels right. Affect biases have been studied to analyze the inclusive attitudes most people show towards elderly people [65]. Similar biases also manifest in welfare of children and in inter-generational communication [41, 66]. In Aarau, we observe that 71.3% of the voters prefer projects for younger and elderly people.

**Biases for altruism and egotism.** Individual interest is often in conflict with the community interest in participatory and collective decision-making processes. While voting, the intrinsic altruism of citizens strongly influences choices. As a result, altruism and egotism are influential for the fairness of voting outcomes and how these outcomes benefit the city in overall [67, 41, 66]. In Aarau, we observe that 67.1% of the voters, who prefer better representation in the outcome are prosocial and prioritize the city-wide benefit (altruism bias) over individual benefit (egotism bias).

**Unconscious biases.** Human choices are influenced by socio-economic and demographic traits such as race, ethnicity, citizenship, household size and income [68]. Specifically, political ideology and belief shape to a high degree decisions for candidates in elections [69].

#### 4.5 Explainability of generative AI voting

The consistency of the individual AI choices (see Section 4.3) is modeled as the dependent variable in a predictive machine learning framework. Causal relationships that explain how personal human traits (independent variables) contribute to consistency are studied. We model the problem of explaining inconsistencies as a classification problem, where 10 uniform consistency levels are defined as  $[0.0, 0.1], (0.1, 0.2], \dots, (0.9, 1.0]$ . Further details about how we account for imbalances of features, their collinearity and hyperparameter optimization of the model are illustrated in Section S2 and Table S7. We also assess prediction models with different dependent variables, see Figure S4 for more details.

**Explainability of choices.** We introduce a two-dimensional feature importance analysis framework to determine the impact of the personal human traits on the consistency of individual choice. We use model agnostic Shapley Additive Explanations [70] to extract individual contributions of each trait. Results are shown in Figure 5. Feature ablation study [71] is used to calculate the error (loss) in the overall prediction accuracy of the model when a feature is removed (results in Table S8).

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## Acknowledgements

This work is funded by a UKRI Future Leaders Fellowship (MR/W009560/1): *Digitally Assisted Collective Governance of Smart City Commons–ARTIO*. The participatory budgeting data were earlier collected in the context of the City Idea campaign with support from Swiss National Science Foundation NRP77 ‘Digital Transformation’ project (#407740\_187249): *Digital Democracy: Innovations in Decision-making Processes*. The authors would like to thank Thomas Wellings, Regula Häggli and Dirk Helbing for constructive discussions.

## Supplementary Material

Supplementary material is available below.

## Author contributions statement

S.M. wrote the manuscript, collected the data, designed and developed the AI models, and analyzed the data. E.E. edited the manuscript and analyzed the data. E.P. wrote the manuscript, conceived the study, designed the AI models and analyzed the data.

## Data Availability

The data for US elections are available in the link [https://figshare.com/collections/Generative\\_AI\\_Voting\\_-\\_ANES/7261288](https://figshare.com/collections/Generative_AI_Voting_-_ANES/7261288).

## Code Availability

The codes are available in the link <https://github.com/TDI-Lab/Generative-AI-Voting>

# Generative AI Voting: Fair Collective Choice is Resilient to LLM Biases and Inconsistencies

## Supplementary Information

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## S1 Field Study for Multi-Winner Voting

This section outlines the inputs to the ballot generation which includes the pre-voting survey questions specifically used in the City Idea mock and actual participatory budgeting campaign for capturing the personal human traits and the voting scenario such as the alternatives and their descriptions. We also provide examples of the prompt design for ballot generation in all datasets.

In the case of American elections, there was no pre-voting survey and the citizens mostly reported some of their demographic data while registering for the voting process. These include - (1) racial/ethnic self-identification [white, black, Asian, Hispanic, or others], (2) gender [male, female, others], (3) age, (4) ideology [extremely liberal, liberal, slightly liberal, moderate, slightly conservative, conservative, or extremely conservative], (5) political belief [democrat, republican, or independent] , (6) political interest [very interested, somewhat interested, not very interested, or not at all interested], (7) church attendance [yes, no], (8) if the respondent reported discussing politics with family and friends [yes, no], (9) feelings of patriotism associated with the American flag [extremely good, moderately good, a little good, neither good nor bad, a little bad, moderately bad, or extremely bad], and (10) state of residence.

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The alternatives (projects) listed for the mock and actual voting have been characterized in Tables S1 and S2 respectively. The complete set of questions used to extract personal human traits such as socio-demographic data, project preferences and voting outcome expectations in the pre-voting survey of Aarau can be found in Tables S3 and S4. The examples of prompts used to create personas both for the mock and actual voting are detailed in Table S6. The prompts used for the US elections are in Table S5.

Table S1: Mock Voting - City Idea. A total of 5 projects were proposed for the mock voting related to urban greenery, public space, public transit and health. The total budget was set to 50000 CHF.

ID	Project Descriptions	Cost (in CHF)
P1	Bins placed in local woodland to reduce litter	5000
P2	Recreational activities for elderly	10000
P3	Refurbishment of local park	30000
P4	Mental health counseling at local school	15000
P5	Bike lane improvements	40000

Table S2: Actual Voting - City Idea. Initially, a total of 100 projects were proposed by the citizens of Aarau. The policymakers then selected 33 projects for voting, mostly related to education, culture, environment, welfare, urban greenery, public space, public transit, and health. The total budget was set to 50000 CHF.

ID	Project Descriptions	Cost (in CHF)
P1	Upgrade Ruchlig soccer field	15000
P2	Boule for all in Telli	2800
P3	Intergenerational project	1600
P4	Wild bees' paradise	20000
P5	Parent-Child Fun and Action Day	3100
P6	Gruezi 2024 - New Year's Party	4000
P7	Children's Disco	4330
P8	Long Table Festival	3400
P9	Let's Play Football	2300
P10	LGBTQIA+ monthly party	20000
P11	Open sports hall	2300
P12	Open closet	7000
P13	Open children's studio	10000
P14	Petanque court	8000
P15	Pfasyl Aargau	3600
P16	Sponsoring a space for Aarau	1000
P17	Seniors gathering 70+	3500
P18	Processing birth	5000
P19	Ways of remembering	500
P20	Bread tour	1500
P21	Public bicycle pumps	4000
P22	CufA - Cultural Festival Aarau	15000
P23	One Place for all	17000
P24	Public herb garden	800
P25	Aarau Future Acre	3600
P26	Summer fun in the Sonnmatt summer garden	1500
P27	New edition of the Telli Map	4000
P28	Climate days for Aarau	24000
P29	A Garden for All	2500
P30	Summery cinema nights in the Badi	10000
P31	Ruchlig water playground	25000
P32	Usable space with a hedge	1000
P33	Playground extension Oehlerpark	20000

For mock and actual voting, a total of 13,256 (3314 personas for each LLM - GPT 4, GPT 3.5, GPT3 and llama2-13B) and 1506 LLM personas (505 personas for each LLM - GPT 3.5, GPT3, and llama2-13B)

have been simulated. Considering 2012, 2016, and 2020, a total of 31,256 LLM (averaged over 3 years: 4500 personas for each LLM - GPT 3.5 and llama2-13B) counterparts for humans have been instantiated for voting.

Table S3: Pre-voting Survey: Socio-Demographics, Political Interests and Voting Outcome Preferences

ID	Question	Type	Options
Socio-Demographic Characteristics			
SD1	What is your gender?	Single Choice	3 [Man, Woman, Various/ Other]
SD2	What is your age?	Number	String
SD3	What is your location?	Text	String
SD4	Are you entitled to vote in Switzerland?	Single Choice	2 [Yes, No]
SD5	What is the highest education you have completed so far?	Single Choice	[School Level, Bachelors, Masters, Doctorate and above]
SD6	Were you born in Switzerland?	Single Choice	4 [No, Yes, Don't know, No answer]
SD7	Did your parents migrate to Switzerland?	Single Choice	5 [Yes both, Only one, No both parents immigrated, Don't know, No answer]
SD8	Do you have children?	Single Choice	3 [No, Yes, No answer]
SD9	Do you have trust in political parties	Single Choice	3 [No, Yes, No answer]
Political Interests			
P1	Where would you place yourself on a scale from 0 to 10, on which 0 means "left" and 10 means "right"?	Ratio Scale	12 [Extremely Left to Extremely Right, Don't know, No answer]
P2	How interested are you in politics in general?	Ratio Scale	6 [Not interested at all, Rather not interested, Somewhat interested, Very interested, Don't know, No answer]
P3	On a scale from 0 (no trust) to 10 (full trust), how much do you trust the following institutions, organizations and groups?	Group of questions	2 questions
P3.1	City council (government)	Ratio Scale	10 [no trust, very low trust, low trust, moderate trust, neutral, moderate trust, moderate high trust, high trust, very high trust, full trust ]
P3.2	Social media	Ratio Scale	10 [no trust, very low trust, low trust, moderate trust, neutral, moderate trust, moderate high trust, high trust, very high trust, full trust ]
Preferences for Voting Outcomes			
VM1	Which method do you prefer for the selection of the projects? Please rank them from 1 to 3. Options Method 1: most votes, Method 2: most of the budget, Method 3: satisfy most voters	Multiple choice	5 [Most preferred, Second most preferred, Third most preferred, Don't know, No answer]
VM2	On a scale of 1 to 5, how important do you think these criteria are for the selection of projects to implement at a local level? (such as measures for climate adaptation or economic promotion)?	Group of questions	4 questions
VM2.1	Cost efficiency	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
VM2.2	Environmental impact	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
VM2.3	Benefit for city	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
VM2.4	Benefit for myself	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]

Table S4: Pre-voting Survey: Project Preferences

ID	Question	Type	Options
SP1	You now see nine thematic areas in which urban projects can be realized. Please choose the three topics that are most important to you and rank them. So from 1 (very relevant to me) to 3 (relevant to me). The nine areas are Education, Urban greenery (e.g. parks, greenery), Public space (e.g. squares), Welfare (for people living below the poverty line), Culture, Environmental protection, Public transit and roads, Sport, and Health	Multiple choice	5 [most relevant, second most relevant, third most relevant for me, Don't know, No answer]
SP2	On a scale of 1 to 5, how important is it to you that the following group benefits from urban projects?	Group of questions	6 questions
SP2.1	Families with children	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
SP2.2	Children	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
SP2.3	Youth	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
SP2.4	Adults	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
SP2.5	People with disabilities	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]
SP2.6	Elderly	Ratio Scale	7 [not important, very less important, moderately important, important, highly important, Don't know, No answer]

Table S5: Prompts for Persona Assignment - American National Studies

Personal Human Traits	Prompts
Socio-Demographics	Which candidate would be most preferred in the US presidential elections for a person with the following profile?  Racially the person is <u>black</u> . Ideologically, the person is extremely liberal. Politically, the person is a <u>Democrat</u> . The person <u>attends</u> church. The person <u>is 86 years old</u> . The person is a <u>woman</u> . The person has <u>no interest</u> in politics. The person feels <u>a little good</u> while seeing the American flag.

## S2 The Machine Learning Framework

The machine learning framework has been specifically devised to forecast the performance of the various personal human traits in predicting the consistencies. We also employ some sampling based techniques to ensure fairness in the prediction of the machine learning models.

### S2.1 Fairness in Machine Learning Architectures

In this section, we discuss the approaches adopted to reduce prediction bias in our machine learning framework, which can arise due to sensitive personal traits such as gender, age, education, and household size [4]. To reduce the impact of the bias from these traits, we augment the approaches suggested by Johnson et al. [4] and formulate an approach based on hyperparameter optimization and synthetic minority oversampling [1].

Table S6: Prompts for Persona Assignment - Actual and Mock Voting, Aarau. The prompts have been shown for some of the ballot formats and personal human traits.

Personal Human Traits	Prompts
Socio-Demographics. Approval Ballot Format	<p>Among the following list of projects: P1: <u>Bins for Litter</u>, cost is <u>5000 CHF</u>; P2: <u>Elderly Fun</u>, cost is <u>10000 CHF</u>; P3: <u>Local Park</u>, cost is <u>30000 CHF</u>; P4: <u>Mental Health</u>, cost is <u>15000 CHF</u>; P5: <u>Bike Lane</u>, cost is <u>40000 CHF</u> with a total budget of <u>50, 000 CHF</u></p> <p><i>Which projects are preferred for a person with the following profile?</i></p> <p><u>male</u>, <u>49.0 years old</u>, <u>lives in Zelgli</u>, <u>citizen of Switzerland</u>, has education at the level of <u>Master's degree</u>, <u>not born</u> in Switzerland, whose both parents <u>were born</u> in Switzerland, does <u>not have children</u></p>
Political Interest. Score Ballot Format	<p>Among the following list of projects: P1: <u>Bins for Litter</u>, cost is <u>5000 CHF</u>; P2: <u>Elderly Fun</u>, cost is <u>10000 CHF</u>; P3: <u>Local Park</u>, cost is <u>30000 CHF</u>; P4: <u>Mental Health</u>, cost is <u>15000 CHF</u>; P5: <u>Bike Lane</u>, cost is <u>40000 CHF</u> with a total budget of <u>50, 000 CHF</u></p> <p><i>Assign a score of 1 to 5, 5 being the highest and 1 being the lowest to the projects for a person with the following profile</i></p> <p>has neutral political orientation (score <u>5</u>), where 1 is left wing orientation and 10 is right wing orientation, <u>not interested</u> in local politics of Aarau, scores the trust in city administration with <u>4</u> (moderate trust), scores the trust in social media with <u>3</u> (low trust) where 1 is no trust and 10 is full trust.</p>
Project Preferences. Single Choice Ballot	<p>Among the following list of projects: P1: <u>Bins for Litter</u>, cost is <u>5000 CHF</u>; P2: <u>Elderly Fun</u>, cost is <u>10000 CHF</u>; P3: <u>Local Park</u>, cost is <u>30000 CHF</u>; P4: <u>Mental Health</u>, cost is <u>15000 CHF</u>; P5: <u>Bike Lane</u>, cost is <u>40000 CHF</u> with a total budget of <u>50, 000 CHF</u></p> <p><i>Which one is the most preferred for a person with the following profile</i></p> <p>considers projects related to education as <u>not important</u>, urban greener as <u>not important</u>, public space as <u>important</u>, welfare as <u>not important</u>, culture as <u>not important</u>, environmental protection as <u>important</u>, public transit as <u>not important</u>, sports as <u>important</u>, health as <u>not important</u></p> <p>scores projects that impact the elderly population with <u>3</u> (moderately important), children with <u>4</u> (important), youth with <u>4</u> (important), the adults with <u>2</u> (very less important), people with disabilities with <u>3</u> (moderately important), elderly population with <u>3</u> (moderately important) where 1 is not important and 5 is highly important</p>

The voter data collected through the field study is first analyzed for unequal distributions. We observe that the distributions are quite balanced for gender, age groups, and household size, but unbalanced for political orientation and basic education.

As an example, around 78.3% of the participants are aligned with left-political beliefs, and 66.7% of the participants are at the highest and second highest levels of education for the actual City Idea voting dataset. We mark the data corresponding to individuals with left political orientation as a privileged group and with right political orientation as a non-privileged group. The same technique is applied to segregate high and low education levels.

We employ random sampling and apply hyperparameter optimization to check the effects of data on prediction. Initially, a set of data points (this threshold is decided empirically) are randomly selected to train a decision tree model. Then the model is used to predict the performance measurements of the remaining points. We continue this process for a fixed set of iterations (stopping criterion) to find the set with the highest recall and lowest average odds difference [1]. When we get this set, we employ synthetic minority oversampling [1] which produces synthetic data based on k-nearest neighbors from each minority dataset. The intuition behind this is that we over-sample the unbiased data to reduce the effect of the bias.

Recall is calculated as  $TP/(TP + FN)$  where TP is the true positive, FP is the false positive, TN is the true negative, and FN is the false negative. The average odds difference is calculated as the average difference in the false positive rates and true positive rates for the privileged and non-privileged groups. False positive rates ( $FPR = FP/(TP + FN)$ ) and true positive rates ( $TPR = TP/(FP + TN)$ ) [1].

Apart from addressing the biases for sensitive personal traits, the datasets are also finally checked for a class-wise imbalance, and synthetic minority oversampling [1] is applied for the classes that still remain a minority. This process is helpful for the actual city idea voting dataset where the number of unique classes is over 25, and even after mitigating the possible biases in the protected variables using oversampling, some classes remain a minority, which can impact the overall prediction capability of the model [2].

## S2.2 Incremental Prediction of Choices based on Personal Human Traits Groups

Recurrent neural network sequence solvers are used to causally link the various sets of personal traits to predict the approvals and scores for every project (candidate), from which the ballot is generated. Our approach is characterized by an incremental construction, systematically exploring diverse combinations, such as socio-demographics paired with project preferences or the consideration of project preferences in conjunction with political interests and socio-demographics. The empirical findings assert that the optimization of the F1 score is achievable in both actual and language model (LLM) emulated voting scenarios through the holistic integration of all feature groups (see Table S7).

Consequently, generating a choice becomes a joint probability distribution function ( $\mathbb{P}$ ) based on interpreting the personal human traits:

$$\mathbb{P}(\text{ballot}) = \mathbb{P}(\text{socio-demographics}) \cdot \mathbb{P}(\text{political interests}) \cdot \mathbb{P}(\text{project preferences}) \cdot \mathbb{P}(\text{preference for voting outcome qualities})$$

We use recurrent neural networks [5], which have the capacity to store and remember an interpretation from all the sub-states corresponding to the group of human traits. A human's decision is a combination of socio-demographic characteristics, preferences, political inclination etc [3], which we attempt to mimic using intermediate sub states for all these aspects.

**Data Processing:** The human traits are the independent variables here, which are used to predict the top choices or the overlaps in the choices. Traits that are highly collinear with others are removed to reduce ambiguity and imbalances in the various classes of the dependent variables are handled using synthetic minority class sampling [2].

Table S7: Recurrent Neural Networks to predict i) the individual inconsistencies of the AI choices with humans and ii) within voting methods for the mock and city idea voting. For each dataset, the prediction metrics shown are averaged across both experiments for the datasets. *Parameters of the best model extracted from hyperparameter tuning:* dense layer of 16 neurons; leaky Relu activation function; categorical cross-entropy loss; adam optimiser; synthetic minority oversampling technique to increase 20% data for all classes; epoch: 600.

Personal Human Traits	Model		Mock Voting		Actual Voting
	F1-score	Accuracy	F1-score	Accuracy	
All Traits	llama2	0.781	0.789	0.856	0.860
	GPT 3	0.710	0.711	0.831	0.838
	GPT3.5	0.743	0.755	0.881	0.862
Socio-Demographics and Political Interests	llama2	0.610	0.623	0.616	0.611
	GPT 3	0.561	0.598	0.624	0.601
	GPT 3.5	0.572	0.602	0.676	0.603
Socio-Demographics, Project Preferences and Voting Outcome Preferences	llama2	0.674	0.669	0.750	0.766
	GPT 3	0.625	0.620	0.712	0.705
	GPT 3.5	0.657	0.649	0.721	0.772
Socio-Demographics, Political Interests and Voting Outcome Preferences	llama2	0.661	0.657		
	GPT 3	0.645	0.688	Only Mock Voting	
	GPT 3.5	0.691	0.715		
Socio-Demographics, Political Interests and Project Preferences	llama2	0.581	0.589		
	GPT 3	0.545	0.561	Only Mock Voting	
	GPT 3.5	0.665	0.668		

### S3 Consistency of the AI Choices

In this section, we demonstrate results for (a) consistency recovery for elections involving humans and AI representatives for voters who abstain and (b) analysis of the consistencies of the AI choices considering single choice, approval, and score ballots.

**Emulating elections** The elections are emulated by using AI for m% of the abstaining voters. m is from the range [10%, 100%] with a step of 10%. The winners of these elections are then analyzed for consistency with the winners of the actual election (Figure S2)

**Analysis of the inconsistencies.** The causal link between the self-reported personal human traits of the voters (independent variables) and the consistencies between human and AI choices and also across the voting methods (single choice and approval) is shown in Figure S3.

Table S8: Preference for environmental projects positively contributes to the consistency of human-AI choice. Projects with short-term rewards such as sports and welfare projects positively contribute to the consistency of large language models among the voting input methods. The traits are tested for their relative importance using feature ablation methods to extract the mean decrease in accuracy after removing them from the model. The top 3 important features with high errors and the bottom 2 features with the least errors are noted.

Model	Top 1	Top 2	Top 3	Bottom 1	Bottom 2
	City Idea [Actual]				
Human-AI [Approval]	Public Transit (0.16)	Culture (0.14)	Swiss Citizen (0.10)	Interests in Politics (-0.003)	Have Children (-0.0025)
Voting Input [Single Choice - Approval]	Sport (0.14)	Culture (0.12)	Trust in Democracy (0.11)	Urban Greenery (-0.002)	Have Children (-0.001)
Human-AI [Score]	Public Space (0.08)	Environment (0.07)	Welfare (0.07)	Interest in Politics (-0.002)	Elderly (-0.004)
Voting Input [Single Choice - Score]	Welfare (0.12)	Sport (0.11)	Families with Children (0.09)	Fairness (-0.003)	Interest in Politics (-0.001)
City Idea [Mock]					
Human-AI [Approval]	Public Transit (0.20)	Public Space (0.19)	Household Size (0.18)	Elderly (-0.004)	Sport (-0.003)
Voting Input [Single Choice - Approval]	Environment (0.18)	Public Space (0.18)	Household Size (0.16)	Elderly (-0.005)	Interests in Politics (-0.003)
Human-AI [Score]	Public Space (0.19)	Environment (0.17)	Families with Children (0.16)	Elderly (-0.005)	Interests in Politics (-0.004)
Voting Input [Single Choice - Score]	Families with Children (0.15)	Sport (0.14)	Environment (0.14)	Interests in Politics (-0.003)	Fairness (-0.002)

#### Analysis of the top choices.

The personal traits are also used to predict the top choices of the AI assistants. Preference for public space ( $p=0.02$ ) is also a dominant criterion to predict the top choice of the AI assistants (averaged across Llama2, GPT3.5 and GPT3). If public space is removed from the model, the highest average loss in prediction capacity (0.18) is incurred (Figure S4). The next dominant criteria are preferences for sustainable infrastructure and welfare development such as public transit ( $p<0.01$ , average loss in prediction = 0.164, Figure S4) and welfare ( $p<0.03$ , average loss in prediction = 0.173, Figure S4).

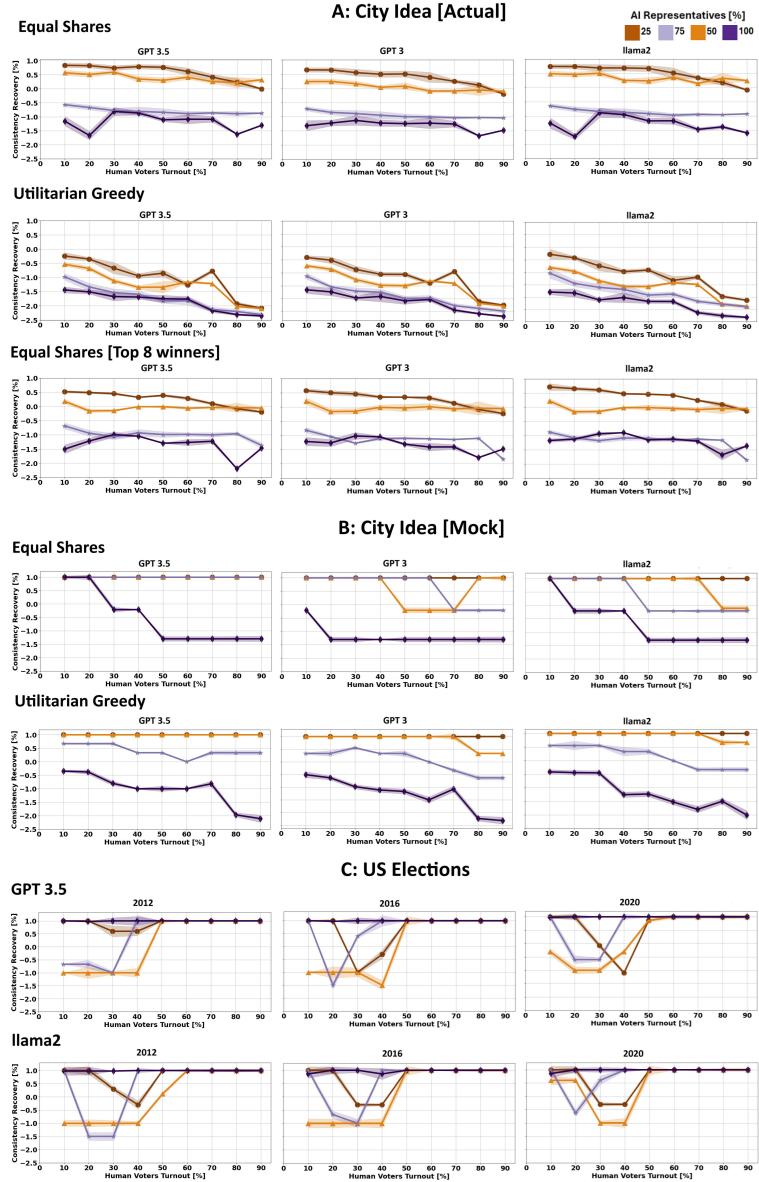


Figure S1: A significant loss in consistency is recovered in participatory budgeting under fair voting aggregation methods such as equal shares by representing up to 50% of the human voters who abstain from voting. Consistency recovery is higher in GPT3.5 compared to GPT3 and **llama2**. The consistency loss in the voting outcome by low voter turnout (x-axis) is emulated by removing different ratios of human voters represented by AI: 25%, 50%, 75% and 100%. The (A) actual and (B) mock voting in the participatory budgeting campaign of City Idea is shown with two voting aggregation methods: equal shares and utilitarian greedy, for three large language models with all winners. Based on the equal shares winners we also calculate the top-8 (as many as greedy) for a fairer comparison. (C) US Elections

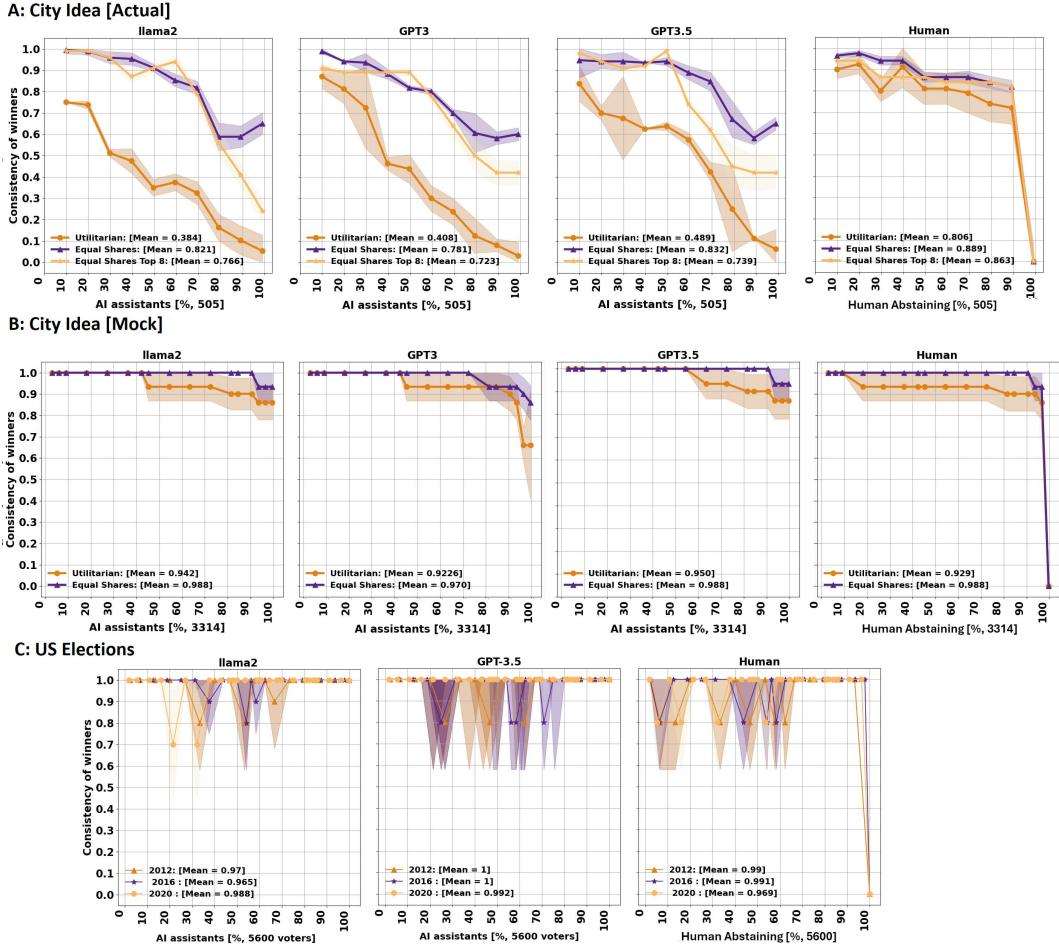


Figure S2: Fair voting methods preserve 83.1% of the winners when 60% voters use AI. When the decision space is limited, 100% of the winners are preserved with up to 80% AI representatives for the voters who abstain (A) and (B): The decision outcomes of the elections based on human turnout and AI representatives for the actual and mock *City Idea* voting in Aarau, Switzerland respectively, (C): US Elections. The abstaining voters are randomly sampled and we use their AI representatives to analyze the change in the overall decision outcomes. Every random sampling instance is repeated 10 times and the average overlap is reported. The human elections are also re-conducted considering only the non-abstaining voters to understand the change in winners.

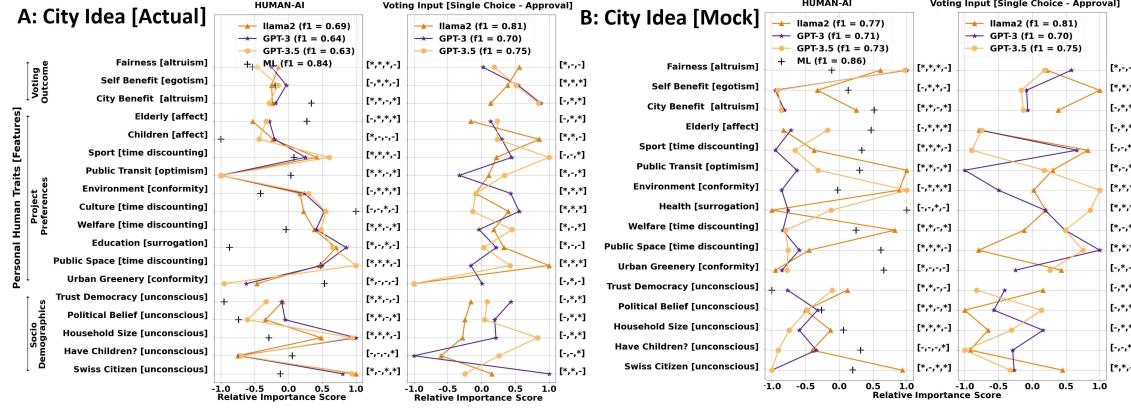


Figure S3: Conformity bias such as preference for environmental projects positively contributes to the consistency of the choices between human and AI based on approvals. On the other hand, unconscious biases such as political belief or general trust in democracy cause inconsistencies. The relative importance (x-axis) of the personal human traits (y-axis) to predict the consistency of choice and consistency between voting input methods (single choice vs. approval) is shown for different large language models and the machine learning model. This is calculated using shapley additive explanations. The (A) actual and (B) mock voting in the participatory budgeting campaign of City Idea is shown. The '\*' denotes that the feature is statistically significant ( $p < 0.05$ ) for each of the AI models of Llama2, GPT3, GPT3.5 and ML respectively.

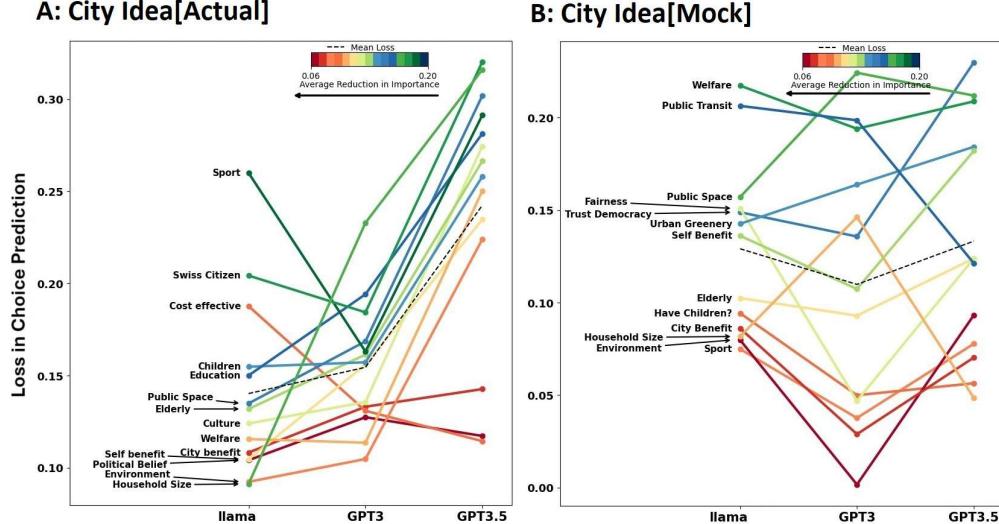


Figure S4: Time discounting factors such as preference for sport, public space and welfare projects significantly contribute to the top choice prediction. (A) shows the feature ablation effect on the AUC ROC scores to explain which traits are relevant to predict the top choice (project) out of the 33 projects in the actual voting in Aarau, Switzerland. A higher loss in AUC-ROC scores when a trait is removed indicates the trait is significant for the assistants in deciding the top choice. (B) shows the feature ablation effect on the AUC ROC scores to explain which traits are relevant to predict the top choice (project) out of the 5 projects in the mock city idea voting in Aarau, Switzerland.

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