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Climate Change, Intergenerational Fairness, and the Promises and Pitfalls of Artificial Intelligence

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Abstract

Among his many achievements, Daniel Kahneman will be remembered for his fundamental contribution to the economics of fairness with its many far-reaching applications. In this paper, I focus on intergenerational fairness and its importance in tackling climate change, a high-stakes example of an intergenerational dilemma. Drawing on recent technological advances, I explore how artificial intelligence (AI) can be applied to promoting fairness and cooperation in intergenerational dilemmas. An intergenerational dilemma is characterised by three key features: asymmetry in decision power and outcomes, no possibility for reciprocity between generations, and the global nature of the problem. Building on the literature of (contemporary) economic games, I discuss how AI has the potential to change "the rules of the game" by acting as a market participant or a market maker (i.e., social planner). I outline several directions for future research, where applying AI to the problem of intergenerational dilemmas shows promise, including intra- and intergenerational fairness, long-term preferences, and mechanism design. However, while AI holds the potential to help us tackle major societal issues like climate change, I conclude with a cautionary note that excessive use of AI today—even if well-intended to benefit future generations—could further accelerate the very problems, including climate change, that we set out to tackle.

Keywords Intergenerational dilemma · Cooperation · Artificial intelligence (AI) · Climate change · Mechanism design

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1 Introduction

Much of Daniel Kahneman's ground-breaking work will be remembered for its influence on heuristics and biases in decision-making. But while this programme of work has received considerable attention, just as much could be said about his lasting influence on our understanding of fairness– the idea that markets and society are fundamentally shaped by people's preferences for "for being treated fairly and for treating others fairly" (Kahneman et al. 1986b, p. S285).

In a now seminal paper Kahneman et al. (1986a) demonstrate across a series of vignette studies that participants view fairness as a central tenet of market behaviour, constraining the profits that firms are able to make as they need to conform to market participants' expectations of fairness. For example, one of the vignettes reads: "A hardware store has been selling snow shovels for $15. The morning after a large snowstorm, the store raises the price to $20. Please rate this action as." Despite the increased demand clearly offering an opportunity for the hardware store to increase profits, 82% of participants responded that it would be unfair for the store to raise the price of shovels. The authors go on to show perceptions of fairness matter across various settings (e.g. consumer prices, wage setting, rents), but also various factors—such as reference dependence, context and history, framing effects, monopoly power and some forms of price discrimination—impact fairness perceptions and that unfair market behaviours are punished by customers at their own cost, such as punishing unfair allocations in ultimatum games or avoiding businesses that do not act fairly. The implications of Kahneman et al. (1986a) are notably wide-ranging, covering all aspects of economic exchanges, markets and public good settings.

Indeed, this seminal study was shortly later followed by various demonstrations of fairness and equity principles in many other settings, including in distributive and non-market settings (Selten 1988; Konow 1996). Fairness principles have also been applied to environmental economics and intergenerational scenarios: Wade-Benzoni et al. (2008) introduce fairness considerations into intergenerational allocation decisions by showing that the level of uncertainty about future generations involved and the power dynamics that shapes attitudes towards intergenerational stewardship versus short-term self-interest. Johansson-Stenman and Konow (2010) argue that fairness also plays an important role in biasing people towards their own benefit, while Wade-Benzoni et al. (1996) demonstrate that self-serving bias is exploited in asymmetric settings that are prevalent in intergenerational dilemmas.

Acting fairly usually does not come "free" but instead fairness—and specifically, altruism and cooperation—comes at a cost to the decision-maker that leads to (greater) benefits for others. In other words, fairness relies on social preferences (Charness and Rabin 2002; Fehr and Charness 2023), including the willingness to cooperate with others and act altruistically. In the context of future generations, cooperation means for one party to pay a cost today (e.g. reducing GHG emissions) to benefit another party in the future (e.g. sustaining a thriving planet to live on) (Hauser et al. 2014). As outlined in Sect. 2, entitled "Cooperating with the future" (adopted from the paper title in Hauser et al. (2014)), this literature shows that humans are often willing to sacrifice some of their own payoff for the benefit of future generations, but that cooperation can be derailed by a minority of defectors.

Pundits often invoke the idea that future technologies, including through the rapid advances in artificial intelligence (AI), will be able to help us to come up with new solutions that are able to meet necessary climate goals. One option is that new technologies are discovered, making it considerably easier for us to live our lives today without needing to adjust our behaviour or pay a cost to cooperate with future generations. While this is possible, it relies on some technological breakthrough that is hard to anticipate whilst, for now, the need for action to reduce emissions remains. An alternative scenario involving technology is one in which we need to learn to cooperate with AI so that we can find solutions—technological or societal—to sustain our planet.

In Sect. 3, under the heading "Cooperating with machines" (inspired by the paper title of Crandall et al. (2018)), I discuss how advances in AI, including state-of-the-art reinforcement learning (RL) algorithms, may help us by cooperating more with other humans or by designing institutions (through AI-led mechanism design) that may be able to foster more cooperation among humans. The nascent literature on AI and cooperation suggests that AI can be both a cooperative partner and a social planner in strategic settings, enabling cooperation.

I will discuss in Sect. 4 several opportunities for AI to be used in intergenerational dilemmas, including developing AI agent's capacity for fairness, grounding our understanding of fairness principles towards future generations in either a normative or empirical debate, and using AI to lead mechanism design in the context of intergenerational dilemmas. However, deploying ever more powerful AI to help us solve intergenerational dilemmas is not a straightforward solution. While the use of AI might help us find new solution to benefit future generations, this search might present in itself a social dilemma: By investing more heavily in AI, our demand for more energy that is needed to power ever more powerful AI also increases the costs to the future. Paradoxically, using AI to help us solve intergenerational dilemmas may become a social dilemma today which can come at the cost of a more sustainable future.

This paper seeks to review promising advances in the AI and intergenerational dilemmas literatures, and encourage environmental economists to get involved in this debate. From mechanism design to moral principles, environmental economists will be needed, building on the seminal insights in Kahneman et al. (1986a) that human fairness plays an important role in contemporary markets. Now, we are called upon to apply our understanding of markets, fairness and mechanism design to the development of AI to help us solve intergenerational dilemmas, such as climate change.

2 Cooperating with the Future

Human-induced climate change has been shown to contribute to the warming of the planet with long-term consequences for future generations (Stern 2006). While the warming of the planet is inevitable at this point, researchers and policy-makers alike agree that reductions in today's greenhouse gas (GHG) emissions (including carbon dioxide and methane emissions) could decrease the severity of consequences for future generations. The greater the reductions today, the greater the benefits to future generations. As the *Stern Review* concludes, "There is still time to avoid the worst impacts of climate change, if we take strong action now" (Stern 2006, p. xv). However, achieving a sizeable reduction in GHG emissions is challenging for multiple reasons.

First and foremost, like all social dilemmas, solving an intergenerational dilemma requires cooperation. Cooperation is defined as paying a cost to benefit someone else

(Nowak 2006). In the context of an intergenerational dilemma, this implies that a present-day decision-maker pays a cost to benefit someone in a future generation (Hauser et al. 2014). As is widely acknowledged in economics and the social sciences, getting people to change their behaviour is often far from straightforward, especially when incentives to do so are not aligned. In the case of social dilemmas as well as intergenerational dilemmas (including the example of reducing GHG emissions), those incentives are usually not aligned, at least in the short-term. In economic models and economic games, reducing GHG emissions relative to the status quo is usually viewed as a costly action (Diederich and Goeschl 2014; Fornwagner and Hauser 2022). This is because it is assumed that people's current choices and lifestyle (in addition to behavioural biases such as inertia, status quo bias, and habitual behaviours) are reliant on certain amenities and comforts, to which individuals have habituated. To maintain this lifestyle, a certain level of energy consumption—often enabled through the burning of fossil fuels that power households, industries, and supply chains—is required. Any change requires taking action that is costly to the individual, either as an upfront cost (e.g. in changing energy source, such as investing in solar panels or other renewable sources) or a long-term behavioural change (e.g. less international air travel, more efficient energy use at home, or using more environmentally friendly products). A self-interested individual (i.e. an agent without any fairness considerations or social preferences) will choose not to pay those costs and therefore not to cooperate for the benefit of future generations.

The costliness of taking action to cooperate applies to all social dilemmas, and is not unique to intergenerational dilemmas. But an intergenerational dilemma—especially in the climate and environmental context—can be described as a social dilemma with three key characteristics: asymmetry of decision power and beneficial outcomes; no possibility for reciprocity; and, typically, the global nature of the intergenerational problem.

2.1 Asymmetry

Achieving intergenerational cooperation is an asymmetric social problem. The asymmetry between those holding decision power and those benefiting from (positive and negative) outcomes in intergenerational exchanges can be very large (Wade-Benzoni et al. 1996).[1] The costs of taking actions are often borne solely by decision-makers today, while the benefits are heavily concentrated in, and accrued by, future generations (Heath 2013). The fact that the costs are felt solely by today's generation makes the challenge of getting them to cooperate substantially harder than in an 'traditional' social dilemma. A traditional social dilemma (such as the Prisoner's Dilemma or the Public Goods Game; see Nowak (2006)) is defined by a specific misalignment of individual and group-level behaviours, whereby everyone would be better off cooperating but each individual decision-maker has an incentive to defect, leading to the tragedy of the commons (Hardin 1968). The challenge is even more pronounced in an intergenerational dilemma: whereas individual decision-makers in a traditional social dilemma may be incentivised to defect, they would still receive back *some* payoff from the public good to which they can choose to contribute. In contrast, the inherent

[1] Note that existing models of asymmetry (e.g. Hauser et al. 2019) are typically applied to contemporary social dilemmas where asymmetry exists between endowments, productivities or other identities of current player. However, a more general form of a social dilemma is needed to capture the intergenerational dimension of asymmetry currently missing in many social dilemma models.

asymmetry in an intergenerational cooperation is very large and therefore cooperation is very costly to today's decision-makers. Thus, expecting cooperation to arise among today's decision-makers in an intergenerational dilemma requires stronger assumptions about altruistic preferences than in traditional social dilemmas.

From a social planner perspective, it is worth noting that if today's generation held strong altruistic preferences for people in the future alongside low discount rates for outcomes occurring in the future, the expected value of (intergenerational) social welfare across many generations is extremely large (Fischer et al. 2004; MacAskill 2022). At a relatively small cost to an individual today, the benefits will accumulate in the very long term, positively affecting many lives and livelihoods. Indeed, evidence for people's willingness to value future generations has been documented both in hypothetical surveys with long time horizons (Steinke and Trautmann 2021) and incentivised experiments varying shorter-term discount rates (Hauser et al. 2014). Furthermore, there are also examples of communities—including some effective altruists who are focused on longtermism—that have coalesced around the unified purpose that the future should be discounted very little with a view towards improving the welfare of humanity in the long-term (Ord 2020; MacAskill 2022). If greater numbers of people were to share this view, it is possible the inherent asymmetry in intergenerational dilemmas becomes less of a problem. That said, there is also evidence that a unbudging minority of people is often unwilling to pay the costs today to benefit future generations, which can undermine collective action and harm social welfare across generations (Hauser et al. 2014).

2.2 No Possibility for Reciprocity

A corollary arising from the asymmetry in an intergenerational dilemma is that mechanisms previously identified in the literature (see Nowak (2006)) for solving contemporary social dilemmas and increase cooperation are difficult—or even impossible—to apply in intergenerational contexts. One of the key mechanisms in establishing cooperation in traditional social dilemmas is direct reciprocity (Nowak 2006; Rand et al. 2009; Hauser et al. 2016). In a simple model of an intergenerational dilemma, direct reciprocity from future generations may simply not be possible (Hauser et al. 2014).[2] This is because any positive decision (such as GHG emissions reduced) being taken today may only benefit generations far in the future (Heath 2013), by which point the previous generation who made the sacrifice is no longer around to become the recipient of reciprocity even if future generations were inclined to "pay back" the favour. Without the standard mechanisms for cooperation available to increase cooperation, scholars and policy-makers need to look for new mechanisms.

2.3 Large-Scale Cooperation

The third challenge in many (but arguably not all) intergenerational dilemmas is that they require large-scale collective action. Combating climate change and reducing GHG emis-

[2] When intergenerational exchange is modelled with overlapping generations, some form of reciprocity becomes possible: Rangel (2003) shows theoretically that, under strong assumptions, self-interest can maintain cooperation in an overlapping generations framework. Freitas-Groff et al. (2024) explores this question experimentally, finding more limited evidence for self-interest maintaining cooperation across overlapping generations; They show that overlapping generations can help to contribute to cooperation due to a combination of altruism, some form of expected reciprocity, and further other-regarding preferences.

sions is a global problem and requires a global response (Nordhaus 2019). It is not sufficient for just a handful of people, several communities or even a few willing countries to cooperate to overcome the problems associated with climate change. Promoting large-scale cooperation is difficult to achieve (Panchanathan and Boyd 2004; Schnell and Muthukrishna 2024), although some interventions based on pairwise reciprocity have been found to aid cooperation in very large groups (Hauser et al. 2016).

To achieve a major shift in the world's GHG emissions, however, substantial levels of cooperation from a broad group of decision-makers from across the world will be required. In a recent survey involving 73,000 respondents from 50 countries, the United Nations Development Programme documented broad agreement, in that 80% people would like their governments to take stronger action to address climate change (UNDP 2024). While this agreement for action being taken is encouraging, is less clear whether the same levels of support would be obtained if individuals were asked to take an action to address climate change *themselves*. Talk is cheap. Action is costly.

Incentivised economic experiments conducted by Andre et al. (2024) provide some evidence in a US sample for people's willingness to pay for fighting climate change, but also that the social norms around the willingness to fight climate change are misperceived.[3] These misperceptions—and correcting them—matter in settings involving actual GHG emissions, such as reducing energy use (Jachimowicz et al. 2018) and installing solar panels (Kraft-Todd et al. 2018). Raising awareness of social norms can lead to meaningful behaviour change to reduce GHG emissions (Constantino et al. 2022). However, social norms alone may be a weak form of a mechanism, especially if many misperceive them.

2.4 Summary

Intergenerational cooperation requires individuals to take costly action, which will mostly (if not solely) benefit future generations but not themselves, and which requires a global collaborative response. In sum, these characteristics create a perfect storm for a particularly challenging social dilemma. However, as Kahneman et al. (1986a) found early on, fairness concerns among participants are prevalent even in settings where it is payoff-maximising to be selfish. Since then, ample work has demonstrated the importance that fairness considerations—and social preferences more broadly—play in market settings, including in intergenerational dilemmas (e.g. Wade-Benzoni and Tost 2009; Hauser et al. 2014; Freitas-Groff et al. 2024).

Building on the fact that participants often exhibit some level of fairness considerations, economists, psychologists, political scientists, sociologists and other social scientists have long debated and tested interventions to promote cooperation in maintaining public goods, including in the context of intergenerational dilemmas, such as legacy building (Wade-Benzoni et al. 2010), voting (Balmford et al. 2024; Hauser et al. 2014), punishment (Lohse and Waichman 2020), and future-generation forecasts (Bosetti et al. 2022); for a full review of

[3] On average, participants in a US study were willing to donate \$225 out of a \$450 windfall endowment to a charity fighting climate change, with 6% donating \$0 and 12% donating the full \$450. Participants believed that 51% other participants were willing to fight climate change, while the actual share in the study was 62%. Informing participants of the true share and of the share of people who believe that climate change should be addressed increased donations to the charity.

the literature and interventions, see Colaizzi et al. (2025). The next section introduces a new player to the conversation of the (intergenerational) commons: artificial intelligence.

3 Cooperating with Machines

Much faith is being placed in artificial intelligence (AI) to identify new technological and societal solutions, or optimise existing policies, to address climate change (alongside other UN Sustainable Development Goals; see Vinuesa et al. 2020). Given that reducing GHG emissions is both a technological and social endeavour, AI could be applied to both areas.

Technological advances in the field of AI are numerous, from recent scientific breakthroughs in the medical sciences (e.g. AlphaFold Jumper et al. 2021) to material science (Merchant et al. 2023), some of which may well lead to breakthroughs in dealing with GHG emissions and in improving climate change adaptations. Technological transformations have also featured in economic models of climate change, including moving from "dirty" energy to clean energy and the challenges associated with this transition (Acemoglu et al. 2016). There are also more unusual (and arguably far-fetched) proposals that hypothesise that new technologies will be developed (potentially with the help of AI) in due course that will deal with emissions and other pollutants associated with climate change. These proposals have included large carbon-removal machines, wind-powered pumps for ice restoration, and stratospheric aerosols which can reflect solar radiation (McLaren and Markusson 2020). While it is possible that such transformative technology is discovered and that this removes the need for behaviour change for any individual member of society, it would seem overly optimistic to hold out for such "miracle" technology to solve our problems. Indeed, as McLaren and Markusson (2020) put it in their review of the last 40 years of climate politics, "this history (…) is indicative of an overall dynamic which should give climate scientists and policy makers pause for thought before pursuing yet another round of technological promises without social transformation in the hope of averting dangerous climate change" (p. 392). Moreover, an overwhelming focus on (miraculous) technological innovation to solve intergenerational dilemmas can simply also be a strategy (e.g. decoy or distraction) employed by some members of the current generation to avoid having to pay costs today to benefit future generations.

Therefore, I focus instead on the potential of AI to help us address the *societal* challenges associated with climate change and, more broadly, intergenerational dilemmas. In the past, intergenerational dilemmas were shaped entirely by individual decision-makers' actions based on their fairness principles, including self-serving and altruistic tendencies (Wade-Benzoni and Tost 2009). Now, AI is a new player is being introduced to the game of intergenerational exchange, both as a market participant and a market maker.[4]

While the number of studies investigating AI-human interactions are growing fast with several paper studying cooperative or public goods challenges, there has not yet been a focus on AI-human interactions in the context of climate change or intergenerational dilem-

[4] Another role AI could play that is not being discussed here is in how it might augment and extend real people's understanding and perception so that it might change their behaviour around intergenerational dilemmas and sustainability challenges. For example, Dubey et al. (2024) show that generative AI images of re-imagined US cities without cars leads to more support for a hypothetical sustainable transport bill. Similarly, Wang et al. (2025) show that Virtual Reality can be used to test policy interventions, such as nudges, to encourage more sustainable modes of transport.

mas. The extant evidence is so far mainly based on contemporary public goods problems[5]; however, some key themes have emerged that are instructive later for intergenerational dilemmas.

3.1 AI as a Market Participant

Markets and other exchanges (e.g., public goods) are made up of participants who employ strategies to maximise their utility. As Kahneman et al. (1986a) noted, participants are often motivated by fairness considerations, which consequently shape their own behaviours and the equilibrium behaviours observed in markets.

In contrast, unless specifically instructed, AI agents do not come endowed with fairness principles. In general, AI agents are designed to achieve certain objective functions. This objective function can take any form, including that, for example, the algorithm is cooperative and trusting; however, it cannot be assumed *a priori* that algorithms that will take part in market or public goods settings, let alone in intergenerational dilemmas, will be designed to cooperate for the benefit of humans or other AI agents. Typically, an AI agent in these settings is assumed to maximise its own payoff—as is the prevailing assumption in human decision-making models—but in more sophisticated cases, doing so whilst also considering that other participants may have fairness principles (e.g. punish unfair behaviour) that the AI agent needs to consider. Given the complexity of human and AI interactions, it is far from straightforward to know what type of AI agents will do well in engaging with human decision-makers.

In an early, wide-ranging demonstration of human-AI interactions in economic games, Crandall et al. (2018) discuss some of the challenges associated with deploying sophisticated AI agents to create long-term cooperation in repeated games, including the need for flexibility across domains and for learning adaptively in short succession based on limited information about their AI or human partners in these interactions. Across 25 state-of-the-art algorithms, the authors identify only a few that do well across a range of tasks and learn to establish successful cooperative relationships. While one AI agent stands out in its ability to forge cooperative relationships with other AI agents (even in complex games), it does not achieve high levels of cooperation when interacting with human decision-makers– however, notably, even humans among themselves fail to achieve cooperative outcomes most of the time. When cheap talk is introduced, levels of cooperation are substantially higher in both human-human and human-AI pairings, suggesting that machines are able to generate and respond to cheap talk in a manner not unlike humans to establish more cooperative relationships.

Further studies have demonstrated that introducing some prosocial preferences into the AI agent's objective function can raise long-term payoffs (Peysakhovich and Lerer 2017), an AI that mimics human behaviour can facilitate cooperation (Hintze and Adami 2024), a small fraction of AI bots introducing "randomness" into a social network can improve cooperation (Shirado and Christakis 2017), and learning from each other plays an important role in human-AI decision-making (Ishowo-Oloko et al. 2014). Conversely, disclosing that the interaction partner is AI (versus human) can reduce other human participants' willingness to cooperate, harming long-term payoffs (Ishowo-Oloko et al. 2019).

[5] I'm not discussing the expanding literature on real-world public goods (e.g. taxation, health or social benefits) where AI can be used to improve policies and decision-making (e.g. Athey 2017; Hofman et al. 2021).

In sum, based on emergent findings from studies where AI is engaged as an active participant in economic games suggest that some algorithms can form long-term cooperative relationships with each other and with other humans. However, two additional observations stand out: First, several papers also found many AI agents that were less effective at creating mutually cooperative outcomes than humans among themselves.[6] In other words, finding an AI agent that is good at cooperating may be hard to come by. The second observation is that none of the existing studies have demonstrated substantial improvements of overall levels of cooperation in the population as a whole when AI agents are introduced as players– at best, the levels of cooperation among human and AI players in the studies were comparable to those with just human players. Thus, we have yet to find an AI agent that propels us—humans—to go beyond the existing boundaries of our willingness to cooperate.[7]

Can AI as a player (i.e., a market participant) be expected to be a driving force in changing societal outcomes in *intergenerational* dilemmas? It remains challenging. When AI is "just" a player, it has not yet been able to act as a catalyst for solving intergenerational cooperation. AI has to play be the existing rules. What if it can be in charge of changing the rules of the game?

3.2 AI as a Market Maker

The second way in which AI may play an important role in markets and public goods settings is as a "market maker"– i.e., a social planner who designs a mechanism that prescribes the "rules of the game" to which participants adhere when they interact with each other (Balaguer et al. 2022). The role of the social planner involves creating, monitoring and, if necessary, changing the rules of the game guided by the social planner's objective function (e.g. to get participants to reach a common goal). This recently emerging stream of work in AI closely relates to what economists refer to mechanism design (Roth 2002).

Whereas in the previous section, AI was constraint to act as a participant, choosing from a specific option set and acting within certain limits set by an existing market, the potential for AI to have a meaningful impact as a market designer may be substantially larger: mechanism design requires both to create the right incentive structure as well as choose the right parameter values in a way that ensure participants respond appropriately to the incentive structure. Given that the wide range of values that each parameter can take, the optimisation task at hand could be a good fit for which AI.

This optimisation problem is not, however, straightforward for AI either: Unlike in some domains, the AI agent will need to explore a wide range of parameters in a dynamic setting where participants respond to both the changes in the incentive structure as well as to other participants' behaviours in the economic game who, in turn, respond to the incentive

[6] This likely does not include a potential file-drawer problem: many studies that found AI agents did not achieve high levels of cooperation with humans may have never been published. In the extant literature, it is notable that, when results of an AI agent not achieving high levels of cooperation were reported, they were usually accompanied by at least one other AI agent that did achieve good levels of cooperation (and thus leading to a higher willingness, or chance, of publication).

[7] This "invisible boundary" of AI-augmented decision-making not achieving levels above those of human-only decision-making may not be limited to the domain of cooperation: Doshi and Hauser (2024) find that AI-augmented story writing leads to small average improvements in creativity, but that writers who are inherently most creative are not helped by AI to go beyond what they were capable of without AI. Dell'Acqua et al. (2023) refer to the separation between where AI enhances versus hinders human decision-making as a "jagged frontier."

structure and each other. To start to address this problem Balaguer et al. (2022) propose a "two-level AI loop" procedure, in which participants learn to best respond to an inner loop for any given mechanism, while an AI agent in the outer loop continues to learn and update based on the experiences of the participants for a given mechanism. To give participants a way to signal their preference for which mechanism they prefer, a democratic voting procedure can be implemented, incorporating an explicit system for gauging the alignment of human values with the AI's objective function (Koster et al. 2022).

Koster et al. (2025) demonstrate this principle in practice: they design a multi-step AI-led mechanism design process to solve a sustainable resource problem (akin to sustainability problems in the real world, albeit without the intergenerational component). First, the AI agent learns from multiple human trials, in which participants are exposed to one or more existing incentive structures.[8] Once a suitable AI mechanism has been identified through an optimisation process, the AI agent's proposed mechanism is then tested against the standard (i.e., non-AI-designed) mechanisms across various conditions, for example incentive structures that equally or proportionally redistribute gains from the resource. Koster et al. (2025) demonstrate that the AI agent is able to respond and change the incentive structure adaptively in response to both the participants' behaviour and environmental context (e.g. the size of the available common resource). The authors find that cooperation levels are optimised under the AI agent's policy rather than benchmark human-designed mechanisms for sustaining the common resource. Most notably, the AI agent recovers some previously identified principles (e.g. proportional rewards for efficient contributions in settings with unequal endowments, see Hauser et al. 2019) but also identifies policy solutions not previously suggested (e.g. that the redistribution policy should change from proportional to egalitarian as the size of the available common resource increases).

This principle can be applied beyond fixed groups or even beyond social dilemmas. For instance McKee et al. (2023) demonstrate that an AI social planner can be trained to break and make ties between group participants in, raising overall cooperation rates relative to endogenous tie formations. Furthermore, Zheng et al. (2022) show that an AI social planner is able to improve social welfare, equality and productivity above a baseline by optimising taxation, even when players are able to co-adapt their strategies during the process.

3.3 Summary

The use of AI in economic games to solve common resource problems has recently attracted substantial attention. AI can (and likely will) be employed both as a market participant and market maker in the future. While AI's ability to improve cooperation when in the role of a participant have been shown to effective but limited by existing market constraints, AI has shown the capacity to become an effective market maker. By first learning from large

[8] A step in this process includes creating "clones" of human participants. These clones are synthetic versions of real human participants where the clones' behaviours are correlated with real participants' behaviours in the human trials. The clones are then used in potential counterfactual AI mechanism designs with the goal of identifying a mechanism that the clones respond to. However, note that this step is only used for the training process: There is an additional (and necessary) later stage where real participants are put into a setting with a mechanism designed by the AI agent so that their real behaviour can be observed in response to the clones-trained mechanism. For further discussion of synthetic participants in economics research, see Horton (2023); for more about not solely relying on clones to test policies but focus on evaluating the impact of AI on real behaviour, see Hauser and Light (2025).

datasets of human participants' behaviours and subsequently exploring and testing incentive structures and parameter values, AI has shown to improve cooperation among human participants in common resource games and other economic games. These results in contemporary common resource games are encouraging, but the field is still nascent. There are important challenges are ahead if we seek to deploy AI in the search for more solutions to intergenerational cooperation, which I will discuss in the next section.

4 Using AI to Solve Intergenerational Dilemmas

In this section, I will explore several opportunities and challenges that lie at the intersection of "cooperating with the future" (intergenerational dilemmas) and "cooperating with machines" (human-AI interactions). For environmental economists and researchers interested in addressing the social dilemma aspect of climate change—and more broadly of intergenerational dilemmas—the section below outlines some ideas (and their hurdles) with incorporating AI into different parts of this ecosystem.

While this overview is neither comprehensive nor future-proof in light of the fast developments of AI capabilities, it nonetheless seeks to provide a useful roadmap for researchers and policy-makers to address individual, group and societal challenges that will likely remain obstacles to more intergenerational cooperation, even in the presence of ever more powerful AI. It is important for environmental economists to get involved in these debates today, so that this powerful technology is appropriately used to help us solve intergenerational dilemmas, such as climate change.

4.1 Endowing AI with Human Preferences

A challenge with introducing AI into the societal debate around climate change and reducing GHG emissions is that AI usually does not come endowed with a set of moral worldviews of what is "right" or "wrong." One technologically straightforward way to address this problem is to incorporate some form of fairness considerations into the AI architecture and into AI agents' objective functions: When an AI agent acts in the role of a market participant, instead of designing an objective function that maximises a payoff for itself, the agent could be programmed with an objective to contribute to the public good, help the environment, and provide ways for humans to sustainably live on the planet. Peysakhovich and Lerer (2017) find some evidence that endowing AI with some other-regarding preferences can be in the AI's long-term self-interest in some circumstances by raising overall payoffs.

This is not without challenges, however: By deviating from the "rational" self-interest objective function, an AI agent may make itself vulnerable to human or other AI players that do not share more altruistic objective functions and can take advantage of such altruistic preferences. Crandall et al. (2018) systematically study various algorithms that resemble behaviours that players with other-regarding preferences might have; however, they do not make *a prior* assumptions about the agent's altruistic preferences but instead let a competition determine which strategies survive (akin to natural selection in stochastic evolutionary game theory; see Nowak et al. 2004). While these "proximate" behaviours (such as altruism) may emerge from such an evolutionary game, building them straight into an AI agent's objective function may end up leaving them exploited. This approach would therefore benefiting from being combined with a mechanism design policy (see below) that ensures that altruistic (human or AI) players are not taken advantage of.

4.2 Cross-Cultural Examination of Preferences for the Future

What preferences might we want to encode into the AI's objective function? Bonnefon et al. (2024) advocate for a programme of research that is grounded in human psychology that captures fairness principles that people would expect from machines. Such a research programme is exemplified in Awad et al. (2018): Through crowdsourcing 40 million moral thought-experiment decisions from millions of people across 200 countries and territories, the authors map the global moral preferences of the lives that an autonomous car should save. The findings show some consensus in moral preferences but also large heterogeneity by individual demographics and cultural clusters.[9] These moral principles from large-scale survey experiments could provide a foundation for the development of AI morality.[10] Similarly, in economics, Enke (2024) reviews the emerging study of universalism versus particularism in moral preferences (and the relationship with voting and other economic behaviours), which also finds large heterogeneity in the extent to which people value the outcomes of others that are socially closer to them than others (e.g. a relative versus a domestic stranger versus a global stranger). The same logic likely applies to intergenerational dilemmas, where future generations are more socially distant to us than the current needy (Freitas-Groff et al. 2024), let alone than people socially closer to us.[11]

Future environmental economics research could contribute to a common understanding of what kind of moral behaviour towards future generations we think machines should exhibit in the first place, and how we trade off our costs today relative to benefits in the (far) future (e.g. Steinke and Trautmann 2021). However, there are difficulties with this empirical approach. The findings reviewed above paint a picture of some consensus but also diverging preferences across cultures (Awad et al. 2018; Enke 2024; Cappelen et al. 2025). It is unclear to what extent (and how) cultural differences in moral preferences should be accounted for and incorporated into AI agents that seek to address intergenerational dilemmas as participants or market makers.

4.3 Normative Long-Term Preferences for Humanity and the Environment

Another option is to consider a normative approach—irrespective of idiosyncratic preferences to get around the challenge of incompatibility—starting with an acknowledgement that AI could help us to overcome some of our own altruistic shortcomings and biases. As

[9] For instance, Awad et al. (2018) show that people from different backgrounds and different cultures share some similarities in whose life they wish to save (e.g. the lawful over the unlawful) but also disagree on some dimensions, where they feel differently about which life to save (e.g. young versus old, male versus female).

[10] Awad et al. (2022) propose a computational ethics framework, which on the one hand evaluates human and machine morality and on the other hand formalises an algorithm's trade-offs between moral principles and moral intuitions, both of which inform each other in an iterative process.

[11] Fornwagner and Hauser (2022) show that some people are more willing to help the environment at their own cost when their own child is watching their decision relative to other observers, suggesting that our altruistic tendencies are not only affected by the social distance of the receiver, but also the social distance of those who observe our altruistic decisions.

mentioned above, UNDP (2024) documented that most people would like their governments to take stronger action to address climate change: clearly there is agreement to do *something*. But while our tendencies to be altruistic has been extensively documented (starting with early examples in Kahneman, Knetsch and Thaler's seminal 1986a paper), human altruism also has well-known limits, including our insensitivity to the number of people helped or to where our help is most needed (Caviola et al. 2021). Our self-serving bias might get in the way of making costly decisions today that could create more long-term social welfare across many generations.

This is an area where AI could go further than our natural instincts might take us. In theory, an AI agent could be designed to have any interests at heart, including humanity's long-term interests, aiming to maximise the number of lives saved and/or the quality of life on Earth. An AI agent may be able to pursue more long-term, welfare-enhancing policies. The objective function could weight some outcomes more than others, such as a healthy planet for the survival of a diverse ecosystem rather than a more narrowly defined objective function that simply places humanity's survival front and centre. Put differently, while human morality may have evolved to bias their own survival, it is important that we are not constrained by our own moral understanding and preferences when designing the preferences of a potentially more impartial, unbiased and ultimately *fairer* machine.[12] In short, there may be a potential to achieve substantially more intergenerational social welfare than we could have achieved without the help of AI.

4.4 AI as a Mediator and Negotiator

Given the global nature of climate change and other intergenerational dilemmas, the need for consensus among human decision-makers is therefore greater than ever. It may be necessary to first understand and resolve those intra-generational disagreements before we can turn our attention to intergenerational questions. Recent work by Tessler et al. (2024) provides some hope that AI could in fact be useful in bridging the divide between groups, finding that an AI mediator was able to facilitate debate and build consensus on politically divisive issues in democratic citizens' assemblies.

This AI-mediated approach could be applied to intergenerational dilemmas too, especially where generations are at least partially overlapping. For instance, AI agents could be used to reconcile differences between old and young generations' preferences for societal investments today where the asymmetry of costs and benefits are particularly unequally distributed. AI might take on the role of mediator (as in Tessler et al. 2024), or both parties might employ an AI negotiator (Dai et al. 2021) to help them find agreement in a multidimensional, complex intergenerational negotiation. The issues up for debate and negotiation could include forward investments (e.g. reductions in GHG emissions, moving to renewable energy source) and backward investments (e.g. investments into social security and social care).

[12] More generally, Rahwan et al. (2019) caution against excessive anthropomorphism when designing and evaluating machine behaviour.

4.5 AI-Led Mechanism Design

Whether normative or empirically derived fairness principles, a natural place to incorporate these preferences is into the objective function of a social planner– a market maker, not just a market participant. When AI acts as a market maker, the objective function could incorporate a broader set of outcomes across many generations. This approach builds on Koster et al. (2022, 2025) who demonstrated how AI in the role of a social planner can improve social welfare across multiple rounds within the same generation. It is not straightforward to apply the same approach to an intergenerational context, in large part because not having the possibility for reciprocity removes a strong lever for the AI mechanism designer.

One possibility is to endow an AI mechanism designer with levers that have previously only been tested in the context of human decision-makers. For instance, a classic intervention is costly punishment (e.g. in the context of intergenerational dilemmas, see Lohse and Waichman 2020), which could be made more efficient through a dynamic, centralised AI punishment mechanism. Another form of mechanism design could create an institution that comprises of partially overlapping generations (Rangel 2003; Freitas-Groff et al. 2024) so that AI can enforce some chain of reciprocity, or dynamically change the price of forward and backwards investments in this institution. Another possibility is to let AI dynamically identify groups' likely willingness to cooperate with future generations based on the available administrative or behavioural data and consequently design different interventions for different players with varying levels of pre-existing cooperativeness.[13]

4.6 Summary

This section provided the starting points for several directions of how we could use AI to help us solve intergenerational dilemmas. These future directions offer promise but also throw up as many questions as they will answer. How will we deal with designing AI agents' role in sustaining intergenerational goods if people from different socio-economic backgrounds, countries or cultures differ in the weight the put on the welfare of the future? How do we trade-off economic growth today and future prosperity (and survival) in the long term? And where does the role of a paternalistic AI social planner begin and end– when we use AI as a means to an end, what do we owe to the future and what to our current generation? Environmental economists should be encouraged to participate in this debate and design surveys, controlled lab and field experiments and field studies to provide empirical answers to these questions (Falk & Heckman 2009; Lee et al. 2022; Hauser & Light 2025).

[13] Another upside of using AI predictions to estimate cooperativeness is that a well-designed and well-trained AI agent is less likely to fall prey to common human biases that misperceive cooperativeness based on physical, demographic or other stereotypical traits (Rossetti et al. 2022). For example, a commonly held misperception is that women are more generous and cooperative, whereas data from various economic games shows no consistent gender differences (Exley et al. 2025).

5 Conclusion

In this paper, I have summarised recent developments in two separate literatures—cooperating with the future, drawing on the literature of intergenerational public goods games, and cooperating with machines, drawing on the literatures in moral psychology and economic mechanism design—and argued that it is time to bring them together with the goal of applying AI to help us solve intergenerational dilemmas.

As Kahneman et al. (1986b) have previously argued, markets (with previously just human decision-makers) have arrived at an equilibrium in which fairness plays a fundamental role. Building off this early insight, environmental economists have an important role to play in studying intergenerational fairness and expanding our understanding of how people from across the world trade-off their own welfare and future generations' welfare. Such considerations can be used to inform the fairness considerations that should be incorporated into the development of AI agents to help us identify solutions to intergenerational dilemmas.

However, a final challenge remains. Up to this point, I have made the assumption that AI will be an ally in our quest: A way to help us find new solutions to old policy problems. There clearly is scope for AI to be a game changer. It is plausible that—in addition to any technological advances AI will bring—we can deploy ever more capable AI to help us find more effective and fairer ways to help us solve intergenerational dilemmas. If we arrive at solutions quickly and efficiently, this is likely to improve social welfare across many generations.

But there is a latent risk which has all the makings of another intergenerational social dilemma emerging: While it is possible that increased development and use of AI today will help us solve intergenerational dilemmas (which, in the long run, would maximise the welfare across generations), it is also possible that each generation—including our current one—will deploy more AI, excessively increasing our energy consumption (Lorentz and Tuff 2024), both for our own benefit and in search of solutions for the future without succeeding, whilst simultaneously depleting our planet's non-renewable resources ever more quickly. While our intentions may be good, future generations may judge us by our results (or lack thereof). As environmental economists, we should therefore remember that it is our responsibility to balance the benefits and costs carefully when incorporating AI as an ally in our search for fair, intergenerational solutions. The more AI we use today, the greater the costs to future generations.

The future hangs in the balance. We must learn—quickly—how best to cooperate, both with machines, and with the future.

Declarations

Conflict of Interest Nothing to declare.

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