The Behavioral Dimension of Transport Decarbonization

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1 Introduction

Designing and implementing actions for decarbonization necessitates a comprehensive understanding of human behavior. While technological advancements are essential, they alone cannot resolve the multifaceted challenges of eliminating greenhouse gas emissions. Behavioral change is also necessary, and achieving it requires the use of targeted interventions or behavior change strategies that address individual and contextual factors influencing decision-making. Effective decarbonization strategies must integrate behavioral insights pertaining to multiple actors, including individuals/households, businesses, and government organizations — all of whom experience uncertainty in their decision-making. Behavioral choices significantly influence final consumer demand, mobility patterns, energy choices, and the adoption and use of new technologies. For instance, promoting sustainable mobility behaviors requires not only the availability of ecofriendly transportation options but also the willingness of individuals to adopt and use these options. Understanding these behavioral aspects is critical for designing climate policies that are technically sound, socially acceptable, and balance the dual objectives of achieving zero carbon emissions while enhancing well-being and happiness.

Our workshop participants, authors of this paper, who include experts in transportation and energy research and have disciplinary backgrounds in engineering, economics, econometrics, environmental psychology, applied math and data collection, identified a range of strategies influencing climate mitigation actions, including technology development, policy and regulation, information and education, compensation and redistribution of the costs and benefits, as well as strategies that account for key aspects of behavior. One such aspect is behavioral heterogeneity. Individuals have different beliefs, preferences, needs and constraints that will affect their responses to emissions mitigation measures. Other overarching behavioral factors include willingness to pay and public acceptance, and the role of emotions and seemingly "irrational" responses.

Designing decarbonization policies presents several significant challenges. The objective of achieving zero carbon emissions requires substantial changes in energy production, consumption, and overall societal behavior. Simultaneously, policies must account for adverse impacts on well-being and happiness, ensuring that transitions to low-carbon systems do not adversely affect quality of life, which is also important to secure public support. Additionally, minimizing costs of new technologies and energy is crucial to make decarbonization economically viable and politically acceptable. Furthermore, forecasting and assessing the impact of individual and combined climate change mitigation actions is complicated by deep uncertainty. This uncertainty arises from various sources, including unpredictable technological advancements, variable economic conditions, complex human behavior and contextual factors, and uncertainties about how the climate system will develop. Deep uncertainty makes it challenging to predict long-term outcomes and to design robust policies that remain effective under a wide range of future scenarios. Therefore, policymakers must adopt flexible, adaptive approaches and continuously update their strategies based on new information and insights.

This complexity is illustrated in Figure 1, where the x-axis represents the range of all possible solutions, ranked from the least to the most expensive. The left y-axis shows the effects of each policy on decarbonization, while the right y-axis indicates the corresponding level of well-being or happiness. The shaded areas around the curve represent the level of uncertainty associated with the estimation of those indicators.

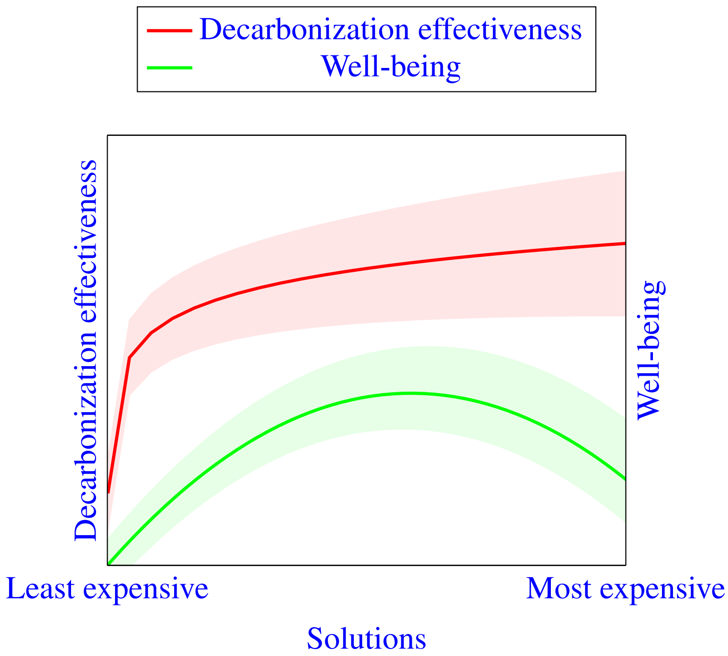

Figure 1: Impact of solutions

We propose a methodological framework to help policymakers deal with uncertainty; design policies and regulations; understand public responses; and forecast the impact of policies and technologies on behavior, while identifying effective strategies for communicating these impacts to stakeholders. The framework includes surveys of human behavior, choice models of technology and policy adoption, choice of energy sources and consumption behavior. Bundles of decarbonization measures can then be evaluated using agent-based simulations where behavioral models predict the reactions by different stakeholders and the consequent reduction in emissions. We focus on decarbonization of the transport sector for the remainder of this paper; however the framework we employ is applicable to other sectors as well.

2 Kaya Identity for Transport Sector Decarbonization

The Kaya identity (Kaya and Yokobori, 1997) is a simple generalized formula that expresses carbon emissions as the product of three factors.

The total CO_2 emissions of the transport sector can be decomposed using the Kaya identity as follows:

$$CO_2 = \sum_m \left(\frac{CO_2}{E}\right)_m \cdot \left(\frac{E}{PKT}\right)_m \cdot PKT_m, \tag{1}$$

where the sum runs over all transport modes m, E is the amount of energy consumed, and PKT stands for passenger kilometers traveled. Reducing the total CO_2 emissions can therefore be achieved by addressing each of these three factors:

- $\left(\frac{CO_2}{E}\right)_m$ represents the fuel choice for mode m. This factor can be reduced through the adoption of energy carriers with a lower carbon content, such as electricity, biofuels, synthetic fuels, or hydrogen. Importantly, this ratio needs to be evaluated on a lifecycle basis.

- $\left(\frac{E}{PKT}\right)_m$ represents mainly the technology choice for each mode m, indicating how efficiently energy is used per unit of transport activity. Enhancing fuel efficiency through technological advancements in vehicle design and improving traffic flows to minimize congestion lead to lower values of this factor. In theory, this factor also includes a behavioral element, that is, the occupancy level. However, multiple studies have shown that increasing vehicle occupancy is extremely challenging (Klinich et al., 2021, Lowe and Piantanakulchai, 2023). Still, supportive policies and measures that facilitate and encourage shared mobility — such as incentives for carpooling, improved ride-sharing platforms, and flexible mobility services that address concerns around convenience, privacy, and reliability — have a potential to create favorable conditions for individuals to adopt higher-occupancy travel behaviors.

- PKT_m reflects the total travel demand in passenger-kilometers of each mode, that is, travel behavior.

Strategies to reduce this component involve promoting modal shifts to more fuel-efficient modes of transport, encouraging travel at different times of the day to avoid congestion, reducing the overall need to travel (e.g., through telecommuting or digital services), combining trips to improve efficiency, and supporting active mobility options such as cycling and walking, which do not rely on fuel consumption.

Using this framework, our paper discusses various behavioral factors affecting CO_2 emissions. For example, individuals exhibit different travel behaviors based on trip purpose, trip length, traveling party size and composition, household characteristics, socio-economic factors, social influence, and many other factors. Transport providers manage diverse business models, network configurations, fleet compositions, and operational costs, leading to different technology and fuel choices, which are also influenced by technological advancements. These providers experience uncertainties including fuel price volatility, availability and performance of new technologies, and differ in their willingness and ability to adopt them. Governmental policy also shapes behavior. Transport firms may be influenced by infrastructure investments and regulations, while the behavior of individuals may be influenced by information campaigns, educational initiatives, pricing signals, and mechanisms for compensation and emissions redistribution, jointly affecting all three of the right-hand side factors in the Kaya Identity. Understanding and integrating these factors into decision-making tools enhances the efficiency and effectiveness of government policy and industry strategies, promoting sustainable practices and reducing carbon footprints in the sector and thus affecting the dependent variable in the Kaya identity, that is overall CO_2 emissions.

In Section 3, we discuss key considerations in modeling human behavior, including behavioral heterogeneity, social influences, and the introduction of new technologies. Section 4 focuses on various government actions that can influence each factor in the Kaya identity. And in Section 5, we describe a comprehensive modeling and simulation framework that can be used by policy-makers to design, test and refine decarbonization strategies.

3 Considerations in Modeling Human Behavior

3.1 Behavioral heterogeneity

The extent to which people engage in pro-environmental behavior varies, depending on individuals' capacities and motivation to engage in the behavior (Steg and Vlek, 2009, de Coninck et al., 2018, IPCC, 2022). Behavioral heterogeneity thus depends on contextual factors, differences in personal ability to act, and the motivation to act. Contextual factors include available infrastructure, technology, market design, price regimes, and regulations (we elaborate on these below). For example, individuals are more likely to drive an electric car if they have access to a fast and reliable charging infrastructure and when electric cars are affordable (e.g., via subsidies), and people can only use public transport when convenient public transport is available.

Differences in personal ability to act are another factor leading to behavioral heterogeneity. Perceived ability depends on personal characteristics such as education level, knowledge, income and family situation. For example, perceived ability to act pro-environmentally will be higher when people have better knowledge of the causes and consequences of environmental problems, and understand how to mitigate these problems (de Coninck et al., 2018). Also, higher income groups may feel more able to act pro-environmentally (Du et al., 2024), particularly when such actions are financially costly, e.g., investments in home insulation or PV (de Coninck et al., 2018), or adoption of electric vehicles (Best and Nazifi, 2023). Further, the family context can restrain some behaviors (e.g. people may need a car to pick up children after work).

The third motivation to act affects behavioral heterogeneity. People consider various costs and benefits of actions, and weigh these consequences differently depending on the values they endorse (de Coninck et al., 2018). Values reflect general goals that people strive for in their life, which affect how they weigh different costs and benefits of actions, and which choices they make (Dietz, 2015; Steg, 2023). Four types of values are particularly important to understand environmental choices: hedonic values (i.e., striving for pleasure, reducing effort), egoistic values (i.e., striving to enhance and secure one's resources such as money and status), altruistic values (i.e., striving to enhance the well-being of others) and biospheric values (i.e., striving to protect nature and the environment; Steg, 2016a). In general, people with strong hedonic and egoistic values are less likely to act pro-environmentally, as doing so is oftentimes somewhat costly (e.g., buying an electric vehicle) or less comfortable (e.g, traveling by bus rather than by car). In contrast, stronger altruistic and particularly stronger biospheric values generally promote pro-environmental actions, as such actions benefit nature, the environment and the well-being of others, including future generations.

People consider a range of individual, collective, social, and emotional costs and benefits when making decisions (de Coninck et al., 2018). First, they are more likely to act pro-environmentally when such actions offer individual benefits at low cost (Wolske and Stern, 2018). Second, people are more likely to engage in pro-environmental behavior when they are concerned about environmental problems, feel a sense of responsibility to reduce them, and view themselves as supportive of the environment (de Coninck et al., 2018). Third, social norms, i.e., the expectations and behaviors of others, can significantly influence individual choices. People tend to follow such norms to gain social approval, avoid disapproval, or because they believe it is the right thing to do (de Coninck et al., 2018). For example, people are more likely to install solars when many neighbours already did so (Graziano and Gillingham, 2014). Fourth, people are more likely to act pro-environmentally when they anticipate that such actions will generate positive emotions, such as a sense of pleasure or moral satisfaction, and may avoid certain behaviors if they expect these to result in negative feelings (Steg, 2023; Creutzig et al., 2022; Zawadzki et al., 2020).

Our discussion indicates that many factors affect individual choices and the likelihood that people act pro-environmentally. These factors vary across individuals, explaining the heterogeneity in choice behavior. It is important to understand these different factors and their impacts on individual choices and behaviors, so that policies can be appropriately designed to mitigate climate change. Table 1 summarizes exemplary choices with respect to each of the Kaya identity-based factors that relate to the three components representing behavioral heterogeneity. Integrating these factors and choices into transport models would increase the representation of consumer and producer heterogeneity.

3.2 Technology adoption and infrastructure requirements

The introduction of new technologies can bring about challenges, such as increased demand for energy or travel (known as induced demand) and hidden economic, environmental, or social costs that may not be immediately apparent. These factors necessitate careful consideration to prevent unintended consequences.

For instance, the rapid uptake of EVs will increase electricity demand, requiring infrastructure upgrades and potentially worsening environmental impacts if the additional electricity is not sourced from renewables and the transition is not effectively managed (Daina et al., 2017, Pawlak et al., 2023). Broader infrastructure considerations are thus essential when implementing decarbonization strategies, as they provide the physical framework to transition towards sustainable technologies and practices. For example, a transition to electrified road vehicles is severely hindered if there is no charging infrastructure to support them (Hardman et al., 2018). Table 2 provides an example of propagating infrastructure requirements for each of the three Kaya identity factors.

Another challenge of innovative and sustainable infrastructure projects can be the time to impact, as these projects are influenced by a complex chain involving regulatory approvals, funding allocations, stakeholder consultations, and end-user behavior. For instance, the scalability of EV charging infrastructure hinges on industry partnerships and governmental support to expand access and adoption

	Fuel Choice	Technology Choice	Travel Behavior
Contextual factors	Availability of electrical infrastructure allows replacing electric for diesel buses	Availability of HOT lane leads to less stop-and-go traffic and reduced energy intensity	Reduction in vehicle use, driven by favorable weather and safe cycling infrastructure encouraging greater bicycle use, along with a well-developed public transport system.
Differences in personal ability to act	Ability to afford EV	Better knowledge of environmental problems leading to enhanced use of more energy-efficient vehicles	Physical fitness to enable more cycling
Motivation to act	Dominance of biospheric values leading to purchase of EV	People w. dominant hedonic or egoistic values choosing more energy-intensive vehicles	People with stronger biospheric values more likely choosing public transport.

Table 1: Exemplary consumer and producer choices of the Kaya identity factors for each of the three components representing behavioral heterogeneity

across diverse geographical regions (Li et al., 2017).

The uptake of any new technology, and the infrastructure accompanying it, typically begins with early adopters. In contrast to early adopters, later adopters are more strongly consider perceived usefulness, affordability, accessibility, and policy incentives (Rogers, 2003). However, early adopters on their own are seldom enough to make something financially viable. To scale up, funding mechanisms are required, with initiatives ranging from private-public partnerships to support from charities and foundations such as the Solar Impulse Foundation, which advocate for sustainable solutions.

Finally, public willingness to pay for both the additional costs of using infrastructure (marginal costs) and the larger upfront investments (capital expenditures) is essential to ensure that innovative infrastructure projects are financially secure

	Fuel Choice	Technology Choice	Travel Behavior
Infrastructure requirements	Rapid adoption of EVs may require electrical infrastructure upgrade	Requirement for skilled technicians to maintain advanced, more fuel-efficient engines	Availability of bicycle lanes when promoting shift to bicycle use

Table 2: Exemplary infrastructure requirements to enable choices related to the Kaya identity factors

and can sustain themselves over time.

The time it takes for traditional infrastructure to have an impact ("time-to-impact") can be shortened if it is designed to address an existing demand for public transportation or to encourage people to shift from using polluting cars to cleaner public transport. This is the case, for example, of the Crossrail project in London, or the Grand Paris Express intended to improve Paris accessibility and attractiveness, and to make Paris region a polycentric city (Enright, 2016). However, funding such large infrastructures also raises challenges.

Finally, uncertainties regarding the environmental and societal impacts of infrastructure projects necessitate careful consideration. Issues such as their effects on bio-diversity and human communities, alongside local and global perceptions of these impacts, can spark social protests and influence decision-making (see Heathrow's 3rd runway (The Guardian, 2020a; The Guardian, 2020b), or the UK national grid upgrade (BBC News, 2024), or the local opposition to the Grand Paris Express project in the most productive agricultural lands around Paris (Mouterde, 2023)).

4 Government actions

Policies, programs, rules and regulations enacted at all levels of government are obviously designed to influence the behavior of individuals, households and business establishments as described in the following subsections.

4.1 Market-based policies

Market-based environmental policies encourage behavior change (in firms and/or individuals) through market signals by leaving economic agents a choice, as opposed to explicit regulatory directives or 'command' and 'control' regulation (technology-based or performance-based standards). Broadly, market-based policies include pollution charges and deposit-refund systems (e.g. carbon taxes enacted in European countries in the 1990s), tradable permits and cap-and-trade schemes (e.g., the U.S EPA's 1986 Clean air act which mandated an emission trading policy for 'criteria' pollutants; the EU ETS), subsidies to reduce pollution, and market barrier reductions (removing explicit or implicit barriers to market activity). As such, they can affect all factors forming the Kaya identity.

Although governments at all levels are starting to implement market-based instruments (Stavins, 2020; Lindsey and Santos, 2020), they have in general been slow to do so. A key challenge has been resistance from interest groups and the public for a variety of reasons. There is the legitimate concern that market-based instruments may lead to adverse distributional impacts, exacerbate existing inequalities, and give rise to environmental injustice. This is particularly problematic when the financial burden of such policies—such as carbon pricing or energy taxes—falls disproportionately on vulnerable groups, who often have fewer resources to absorb additional costs or adapt their behavior. These same groups are also frequently the most exposed to environmental risks, making them doubly disadvantaged by both economic and environmental harms. For example, a carbon tax often places a heavier burden on lower-income households, as they spend a larger share of their income on energy and everyday goods affected by the tax, especially before any compensation or revenue redistribution is applied (Goulder et al., 2019; Stavins, 2022; Mathur and Morris, 2014).

Market-based tools like carbon pricing and emissions trading have often been introduced too weakly to be effective. In many cases, carbon prices have been too low or pollution limits too loose to drive meaningful change (Lindsey and Santos, 2020). Participation has sometimes been limited, and the expected cost savings have not materialized (Johnson, 1999). These outcomes are partly due to unrealistic assumptions about how people and companies behave, flaws in policy design, and the fact that many companies lack the internal capacity to take full advantage of these systems (Stavins, 2010).

The effectiveness of market-based policies strongly depends on how individuals and firms respond to price signals, making it especially important to understand and anticipate behavioral reactions, which are often uncertain and context-dependent. At the same time, generating accurate predictions about the likely impacts of the policy is critical in garnering public acceptance and underscores the role of behavioral models. For instance, the Stockholm congestion charging scheme is instructive; initial public skepticism changed after the scheme was introduced largely due to the evident reduction in congestion (Eliasson, 2008; Eliasson and Jonsson, 2011) and in environmental problems (Schuitema et al., 2010).

Suitable approaches to address the dual challenge of anticipating behavioral responses and fostering public support (in the context of both environmental and congestion externalities) include recycling/dividend schemes to address welfare and distributional impacts, the use of behavioral modeling and optimization to design policies that account for likely public reactions, careful framing of policy instruments (for example, users in Stockholm were more receptive when the term "environmental charges" was used instead of "congestion charges"), and information campaigns. More broadly, no single policy instrument is likely to offer a complete panacea towards decarbonization, as no single instrument can address all barriers of change.

Table 3 provides two examples of market-based policy measures and their potential impact on each of the Kaya identity factors. As visible, the impact of the two policies on travel behavior can lead to opposite directions.

	Fuel Choice	Technology Choice	Travel Behavior
Carbon tax	Depending on size of tax, diversion from petroleum-fueled vehicles to EVs	Uptake of more energy-efficient vehicles	Decline in petroleum-fueled automobile travel demand due to higher fuel prices and shift to public transport
Subsidy for EVs	Enhanced adoption of EVs	Electric technologies, such as electric drivetrains, can be much more efficient than internal combustion engines, because they aren't restricted by the same physical limits.	Reduced marginal cost of EVs may cause increase in EV driving (rebound effect)

Table 3: Exemplary consequences of two market-based policy measures for the Kaya identity factors

4.2 Regulations

Regulations serve as policy tools that force behavioral change to address environmental challenges. They can be categorized into supply-oriented and demand-oriented approaches. Supply-oriented regulations, such as mandates for minimum sustainable aviation fuel mixes (affecting CO_2/E in the Kaya identity), directly influence the composition and availability of products in the market by placing rules on the supplier. Demand-oriented regulations are placed on the end-user/consumer. Measures like establishing low-emission zones in urban areas, setting speed limits, or banning the use (rather than the production) of internal combustion engines are examples of policies designed to reduce emissions and improve air quality by prohibiting some types of targeted user behavior.

As with market-based policies, regulations can affect each factor of the Kaya identity. Regulations aiming at fuel specifications affect $\mathsf{CO_2/E}$, whereas those aiming at vehicle fuel economy impact $\mathsf{E/PTK}$ and PKT. However, in contrast to market-based measures, the lower marginal costs of driving associated with a more fuel-efficient vehicle can result in an increase in vehicle travel and thus traffic congestion, air pollution, and other externalities. For the industrialized world, this rebound effect was estimated to be around 12% in the short run, increasing to 32% in the long run (Dimitropoulos et al., 2018).

While regulations can be enacted quickly and have immediate legal effect, their environmental impact often unfolds gradually. First, considerable time is needed to build support among stakeholders and reduce public and political resistance. Once passed, the regulation must be aligned with existing legal frameworks and implemented in a way that meets all legislative requirements. Industries may also require a substantial lead-in time to adjust and comply with new standards. For example, if a regulation affects vehicle design, long fleet turnover times must be taken into account, meaning that the full environmental impact of such measures may not be realized for decades (e.g., Schafer et al., 2009). Furthermore, behavioral adaptation must occur in response to the regulation, which also takes time. While these challenges are often associated with regulatory instruments, they also apply to other policy tools that aim to influence long-term technology choices, such as vehicle adoption, and should be considered when evaluating short-term versus long-term effectiveness. Skipping any of these steps risks undermining a regulation's durability, early uptake, or overall impact.

Table 4 presents two examples of regulatory policy measures along with their impact on each of the Kaya identity's factors. As with regulatory measures, depending on the implemented policy, the outcome on travel behavior can be fundamentally different.

4.3 Information and education

Providing information and education on the causes and consequences of environmental problems or on ways to reduce these problems generally increases people's knowledge. However, it often does not encourage pro-environmental actions (de Coninck et al., 2018), as people typically face other barriers to act as well. Indeed, informational strategies are especially effective when the targeted behavior

	Fuel Choice	Technology Choice	Travel Behavior
Fuel economy regulations	No direct impact on fuel choice	Adoption of more fuel-efficient vehicles	Rebound effect leads to more driving
Sustainable Aviation Fuel (SAF) mandate	Mandatory uptake of SAF	More expensive fuel can lead to accelerated adoption of more fuel-efficient aircraft	At least part of fuel cost increase will be passed on to consumers depressing travel demand

Table 4: Exemplary consequences of two regulatory policy measures for the Kaya identity factors

is not very inconvenient or costly (in terms of money, time, effort and/or social disapproval), and when individuals do not face important external constraints on behavior (Steg and Vlek, 2009).

Social influence approaches that communicate what other people do or think can encourage mitigation actions, as can social models of desired actions. For example, information on what others do or expect one to do, providing role models, and community approaches that promote behaviour change from the bottom-up can encourage pro-environmental actions (de Coninck et al., 2018). Other interventions that utilize the social context are spreading awareness of environmental impacts through social media (Manca, Sivakumar and Polak, 2022), leveraging 'social marketplaces" where people encourage each other in myriad ways (Manca, Daina, Sivakumar, Yi, Zavitsas, Gemini, Vegetti, Dargan and Marchet, 2022), or mobile app-base games to connect with communities (Cellina et al., 2020; Di Dio et al., 2018; Sottile et al., 2021).

Information and education programs can complement and enhance the impact of regulatory and market-based measures by communicating the need for and the goals of these policies, and fostering understanding of their positive impacts (Steg and Vlek, 2009). For instance, explaining the rationale behind and positive impacts of carbon pricing can enhance public support and compliance with these measures. Hence, by integrating information campaigns with regulatory frameworks and market incentives, policymakers can reinforce the effectiveness of these policies, encouraging broader societal participation and support. Such integrative policies are likely to address multiple barriers to change, thereby catalyzing sustainable behavioral change.

Information and education campaigns can also support the introduction of cleaner technologies. For example, electric vehicles (EVs) illustrate how factors like drivetrain options, costs, and driving range can significantly influence consumer choices (Daina et al., 2015). Awareness campaigns and educational efforts can play an essential role in disseminating information about these parameters, ensuring consumers can make informed decisions (Haghani et al., 2024). Additionally, marketing initiatives that highlight options like battery leasing for EVs can help inform consumers about ways to reduce upfront costs, thereby encouraging broader adoption (Budde Christensen et al., 2012).

Table 5 presents the example of automobile CO2 emissions labeling and the potential consequences for each of the three Kaya identity factors.

	Fuel Choice	Technology Choice	Travel Behavior
Automobile fuel consumption and CO_2 emissions labeling	Mandatory CO_2 car labeling (Haq and Weiss, 2016)	Greater awareness of CO_2 emissions when comparing vehicle models for purchase	Potentially more environmentally conscious mode choice in daily travel

Table 5: Exemplary consequences of an information and education policy measure for the Kaya identity factors

4.4 Compensation and redistribution

A 'just transition' entails that climate change policies address the inequitable distribution of both the impacts of climate change and the costs and benefits of mitigation efforts. Marginalized and low-income populations — who are least responsible for past greenhouse gas emissions and have benefited the least from carbon-intensive economic development or decarbonization policies (such as subsidies or incentives mostly used by higher-income groups) — are often the most vulnerable to climate impacts and possess the fewest resources to adapt. It is also essential to consider the potential regressive effects of climate policies, particularly market-based instruments like carbon pricing, which can disproportionately burden low-income households and exacerbate existing social and economic inequalities. The political economy of a 'just transition' is complex. It involves questions of recognition — ensuring that the concerns and identities of all social groups are acknowledged and respected — alongside procedural justice, which relates to fair and inclusive decision-making processes, and distributive justice, which concerns the fair allocation of resources and responsibilities. It also requires attention to distributional outcomes, meaning the actual, measurable impacts of climate policies on income, ethnicity, gender, and other forms of inequality, both within and across countries (Newell and Mulvaney, 2013; Markkanen and Anger-Kraavi, 2019). For instance, transition-related job losses (for example, from the closure of coal mines, fuel and gas plants) are likely to be concentrated in areas and social groups that already have been affected by deindustrialization and globalization (Vona, 2019). Ethnic inequalities arise when large-scale renewable energy infrastructure projects (e.g., hydroelectricity) or forest protection initiatives lead to forcible relocation and the loss of traditional livelihoods (Markkanen and Anger-Kraavi, 2019; Hess and Fenrich, 2017)

Addressing distributional justice towards a just transition requires appropriate measures of compensation and redistribution. For instance, in the case of market-based policies such as a carbon tax or a congestion toll, this would involve dedicating or earmarking revenues in ways that benefit 'losers' (for example, lump-sum transfers have been adopted for the federal carbon tax in Canada (Lindsey and Santos, 2020)). Other compensation schemes for climate policies include environmental tax reforms that reduce labor taxation, green deal plans (investments in areas of the green economy that could stimulate job creation), place-based policies (a local targeted version of green deal plans that focuses on spatial inequalities induced by the green transition), and progressive green subsidies (i.e., to remove financial constraints for the poor and accelerate the adoption of green technologies) (Vona, 2023). Public support for these policies tends to increase when revenues are used in ways perceived as fair and beneficial—for example, through direct rebates to households, investments in public services, or targeted support for vulnerable groups, rather than across-the-board tax cuts or general budget spending (Klenert et al., 2018).

However, there are several challenges associated with direct refunds and compensations. First, it is challenging to determine an adequate compensation since it requires quantifying exactly benefits and losses at the individual level. For this reason, achieving a Pareto improvement (where no individual is worse off) is often considered a near impossibility by economists (Lindsey and Santos, 2020). Another challenge is that refunding schemes may create undesirable incentive effects (e.g., users trying to overstate losses) and open the door for strategic behavior that undermines efficiency gains from the policy (Lindsey and Santos, 2020). Finally, administrative and transaction costs could be prohibitive, but these can conceivably be minimized through technology.

4.5 Joint effect of policies

When policies fail to consider the presence of other corrective instruments, market failures can occur. For instance, implementing congestion pricing without investing in a good public transportation alternative may lead to distortions in urban mobility patterns.

An illustrative example can be drawn from the electricity sector, where different pricing policies for road usage and dynamic energy pricing for electric vehicles (EVs) can have interlinked implications. Road pricing policies designed to manage traffic congestion may influence the adoption of EVs and subsequently impact energy demand and grid operations. Conversely, dynamic energy pricing can influence transportation decisions by altering the cost structure of using EVs compared to conventional vehicles. Developing and implementing an optimal joint pricing model that considers both energy and transportation sectors could lead to synergistic benefits, such as reduced traffic congestion and optimized energy use.

Managing the joint effects of multiple policies also requires careful consideration to avoid contradictory regulations or excessive regulatory burdens. Conflicting policies can create uncertainty and hinder compliance, while an accumulation of regulations may overwhelm stakeholders and undermine policy objectives. Effective coordination and stakeholder engagement are essential to streamline regulatory frameworks and ensure coherent policy outcomes across different sectors.

Furthermore, using the revenues generated from regulatory fines or fees to support socially and environmentally beneficial initiatives can enhance both the effectiveness and public acceptance of climate policies (Schuitema and Steg, 2008). For example, proceeds from carbon pricing schemes or environmental fines could be directed toward compensating low-income households affected by higher energy prices, or invested in renewable energy projects and climate adaptation measures—uses that are generally perceived as fair and aligned with environmental goals.

To mitigate inequity, targeted policies could redirect public charging infrastructure investments to under-served exurban and rural areas, as well as multi-family residences where charging options are limited. In addition, EV subsidies combined with energy demand management policies lead to the prevalence of residential Battery Energy Storage Systems in high-income households (due to the costs involved) which can lead to significant cost savings over time that will not benefit lower income households suffering from energy poverty.

In conclusion, addressing the joint effects of policies requires a holistic approach that integrates diverse policy instruments and sectors. By fostering synergies and minimizing conflicts, policymakers can maximize the effectiveness of regulatory interventions and achieve sustainable outcomes across energy, transportation, housing, and other critical areas of societal development.

4.6 Public acceptability

The extent to which options are evaluated (un)favorably by the public plays an essential role in the implementability of proposed policy measures. Hence, it is critical to understand which factors affect the acceptability of policies, as this provides important insights into which strategies could be implemented to address public concerns. Four factors appear to affect public acceptability of options: perceived costs and benefits of options, distributive fairness, procedural fairness, and trust in responsible actors.

First, acceptability is higher when people believe options have more positive and less negative effects for self, others, or the environment (de Coninck et al., 2018). Because of this, policy 'rewarding' pro-environmental actions are more acceptable than policy 'punishing' actions that increase environmental problems. Pro-environmental options and policies are evaluated as more acceptable when people strongly value the well-being of other people and the environment, when they are more concerned about environmental problems, and when they feel more responsible and capable to help reduce these problems, probably because this increases the likelihood that people recognize and value the environmental benefits of options and policies (de Coninck et al., 2018). Further, the more people are aware of environmental problems, the more strongly they prefer governmental regulation and behavior change rather than free-market and technological solutions (Poortinga et al., 2002). Acceptability can increase when people experience that an option or a policy has more positive effects then they expected, which suggests that effective policy trials or being able to try out an option can build public support for sustainable options and policy (de Coninck et al., 2018).

Second, public acceptability depends on how the costs and benefits of options and policies are distributed across group (i.e., distributive fairness): sustainable options and policies are more acceptable when their costs and benefits are distributed equally across groups, and when vulnerable groups, future generations, and nature and the environment would be protected (Steg, 2023). Distributive fairness can be enhanced by compensation schemes, for example by offering additional benefits to people that would be negatively affected by the proposed changes. For example, public acceptability of pricing policies is higher when redistributing revenues towards those affected (Schuitema and Steg, 2008), and when earmarking revenues for environmental purposes (Steg, 2016b, Steg, 2023, Sælen and Kallbekken, 2011).

Third, public acceptability of sustainable options and policy depends on which decisions procedures were followed, as reflected in perceptions of procedural fairness. The implementation of sustainable options and policies is perceived as more fair and acceptable when transparent procedures have been followed, when the public or public society organizations could participate in the decision-making, and when people feel that their interests and concerns have been taken seriously (Steg, 2023).

Fourth, public support is higher when individuals trust responsible parties (de Coninck et al., 2018). Trust in responsible parties is important as the general public typically does not have sufficient expertise nor the capacity to understand all aspects of options, and thus need to rely on the expertise and good intentions of agents who are responsible for designing and implementing the options. Public acceptability appears to more strongly depend on trust in the integrity of responsible actors (i.e., whether they are believed to be transparent and honest) than on the perceived competence of responsible actors (Liu et al., 2020).

4.7 Policies and Kaya Identity

To conclude this section on policies, the following lists present a selection of climate mitigation policies categorized according to the three components of the Kaya identity applied to the transport sector. Each policy aims to reduce total CO_2 emissions by targeting either the carbon intensity of energy use (CO_2/E), the energy efficiency of transport activity (E/PKT), or the overall travel demand (PKT).

$\left(\frac{\mathbf{CO_2}}{E}\right)_m$ **— Fuel Choice**

- Carbon taxes to shift demand toward lower-carbon energy sources.
- Emissions trading systems (cap-and-trade) to limit total emissions from fuels.
- Sustainable Aviation Fuel (SAF) mandates to promote low-carbon aviation fuels.
- Fuel specifications requiring cleaner energy carriers.
- Subsidies for electric vehicles (EVs) to support low-carbon fuel adoption.
- Public investment in renewable energy funded through climate policy revenues.
- Information campaigns promoting adoption of lower-carbon fuels.

$\left(\frac{E}{\mathbf{PKT}}\right)_m$ **— Technology Choice**

- Fuel economy regulations requiring more efficient vehicles.
- Emissions labeling for vehicles to inform technology choices.
- Congestion pricing to improve traffic flow and reduce energy intensity.
- Green deal plans to invest in efficient mobility technologies.
- Place-based policies targeting energy-efficient infrastructure investments.

- Progressive green subsidies to improve access to efficient technologies.
- Education campaigns highlighting cost and performance of clean technologies.

PKT_m — Travel Behavior

- Low-emission zones restricting high-pollution travel in cities.
- Speed limits and bans on internal combustion engine use.
- Congestion tolls to discourage excessive car use in peak hours.
- Modal shift incentives encouraging use of public or active transport.
- Social influence campaigns promoting sustainable mobility norms.
- Gamification and mobile apps to engage communities in behavior change.
- Compensation schemes for low-income travelers affected by pricing policies.
- Revenue recycling to support users affected by behavioral regulations.
- Electric vehicle cost-sharing (e.g., battery leasing) to broaden adoption.

5 Methodological Framework

The complexity of behavioral dimensions in response to climate change actions necessitates the design and development of decision-aid tools. These tools aim to assist policymakers in designing, optimizing, and anticipating the impacts of various measures. This section introduces a methodological framework for developing such tools, that involves the collection of behavioral data and the design of a modeling framework.

As illustrated in Figure 6, the methodological framework integrates policy design, behavioral modeling, performance measurement, and optimization in a continuous, iterative process. This approach utilizes a diverse range of input data, including exogenous data such as energy prices and economic conditions (Berk and Yetkiner, 2014); behavioral data (including factors influencing behavior) collected through experiments and surveys (see Section 5.2); and a global typology of individuals and households representing different demographic, socio-economic, and geographic segments. This typology also represents the population of business establishments. Within such a typology, synthetic populations of individuals, households and establishments with the same statistical properties of the actual populations can be created (Chapuis et al., 2022, Kukic et al., 2024).

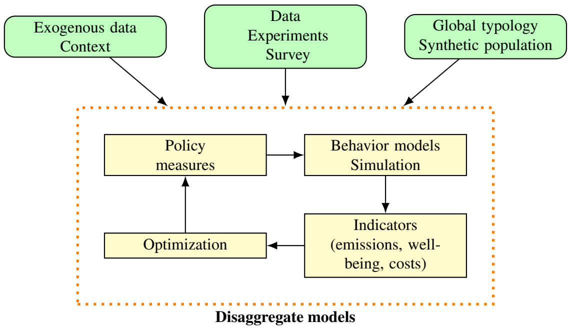

Table 6: Methodological framework

5.1 Behavioral models and simulation

The role of behavioral models and simulations is to predict individual and group responses at a disaggregate level. These models can simulate various scenarios to understand potential outcomes of the policy measures. They generate various numerical indicators that characterize the behavioral responses for each of those scenarios.

Individuals make numerous choices that are relevant for analyzing decarbonization policies. These choices pertain to their activities, travels, and energy consumption, among others. Some decisions are long-term, such as house location, the type of heating system, or vehicle ownership, while others are short-term, like travel mode and destination for specific activities. These decisions may be modeled simultaneously, as proposed by Pougala et al. (2022), Pougala et al. (2023), and Rezvany et al. (2023) or they may be modeled sequentially (e.g., Jing et al., 2024). An example of a behavioral modeling and simulation platform for urban transportation that adopts a sequential approach is shown in Figure 2 (Jing et al., 2024).

The behavioral dimensions explicitly represented include:

Individual characteristics: Measurable variables about each individual, including age, income, gender, or health status.

Latent Characteristics: Individual characteristics—such as perceived costs and benefits of options and policies, attitudes, social norms, values, perceptions, and emotions—play an important role in shaping behavior. These include factors like skepticism, denial, or guilt, as well as perceptions of inequity, moral licensing (e.g., "I am already doing enough"), or overconfidence (e.g., "technology will solve everything").

Implicit Choice Set: Various types of constraints, including resource constraints

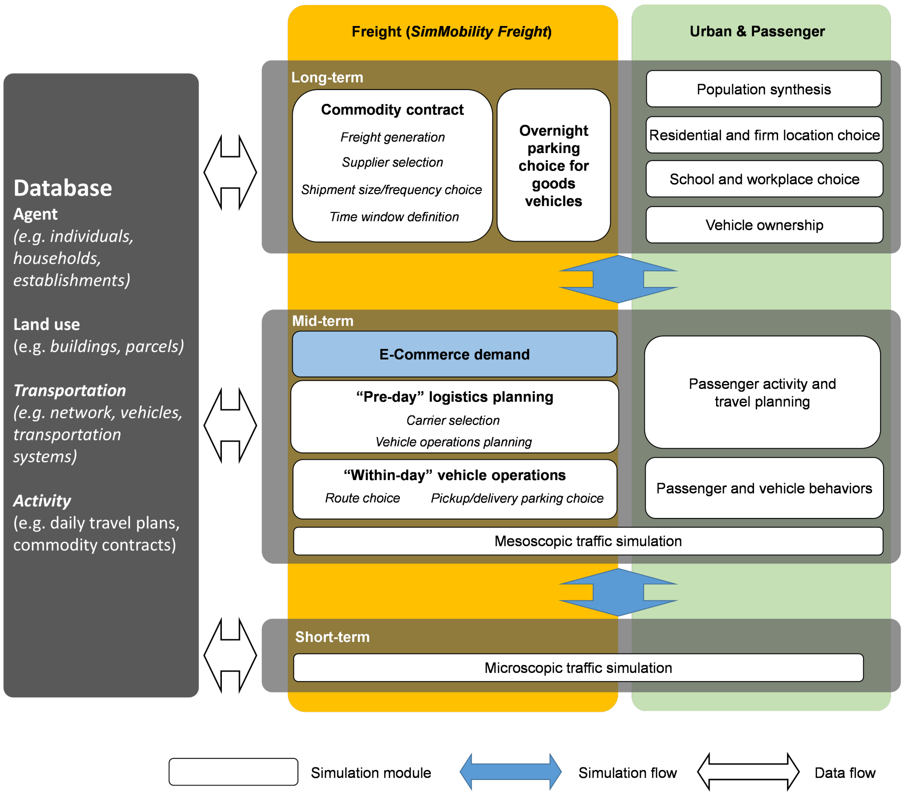

Figure 2: Simulation framework for urban transportation (SimMobility)

(e.g., availability of vehicles in a household), regulatory constraints (e.g., some destinations cannot be reached by carbonized modes of transportation, or heating system with strong GHG emissions are forbidden), and contextual constraints (e.g., extreme weather, floods, earthquakes).

Utility Functions: These combine all the above variables to characterize the preferences of individuals.

The raw output of the simulation is an empirical distribution of detailed schedules, where all modeled choices made by each (synthetic) individual/household and establishment are explicitly represented. Developing behavioral models (using either the simultaneous or sequential approach) requires detailed disaggregate data on the choices of individuals/households and business establishments, as discussed in the following subsection.

5.2 High quality behavioral data

Mobile sensing technologies have revolutionized the collection of behavioral data, enabling the capture of highly accurate, complete, and heterogeneous information that was previously unobtainable. These technologies allow for continuous monitoring of various aspects of human activity and mobility, providing a comprehensive view of behavior patterns. For example, smartphones equipped with GPS, accelerometers, and other sensors can track individuals' movements, modes of transportation, and even physical activity levels. These data offer valuable insights into how people interact with their environment, their travel habits, and lifestyle choices, which can be crucial for developing targeted and effective policies.

The integration of machine learning and inference algorithms with contextual data sources further enhances the value of mobile sensing data. These advanced computational techniques can analyze raw data from sensors and transform it into detailed narratives of human activities and mobility. For instance, combining location data with weather information, public transport schedules, and social media activity can provide a rich, contextual understanding of how and why people move through cities. This comprehensive story-line of human behavior is instrumental in designing urban planning initiatives, transportation systems, and public health Such approaches are being applied in individual — and household — level surveys and data collection programs to obtain higher quality data than conventional surveys can provide (e.g., Hong et al., 2021). These technology solutions can also be used to obtain detailed behavioral data from business establishments providing passenger and freight transport (see, for example, Alho et al., 2018, and Ben-Akiva et al., 2016).

Revealed preferences, derived from observed behaviors, can be leveraged to develop context-specific stated preferences and surveys to assess individual factors influencing behavior, such as attitudes. This approach allows researchers to test consumer reactions to new solutions, scenarios, and policies in a more informed manner. For example, if mobile data reveals that a significant portion of the population cycles to work, policymakers can design targeted surveys to gauge interest in expanding bike lanes or introducing bike sharing programs. This combination of revealed and stated preferences ensures that new initiatives are grounded in actual behavior patterns, increasing their likelihood of success.

Longitudinal data collection, which tracks behavioral dynamics and the factors influencing them over time, is essential for understanding how and why habits and preferences evolve. By merging these data with big data sources, such as telecommunications records, researchers can expand their datasets and gain a multi-sectoral perspective. For instance, combining mobility data with telecom data can reveal how communication patterns influence travel behavior, offering deeper insights into the interconnectedness of different aspects of daily life.

These enriched datasets enable the development of personalized solutions tailored to individual needs and behaviors (Azevedo et al., 2018). For example, individuals with high price sensitivity to a carbon tax can be offered public transportation or active mobility solutions. Such personalized treatments are essential to motivating individuals to provide their data (Xie et al., 2024).

The technology solutions described can also be used to obtain detailed behavioral data from providers of passenger and freight transport with vehicle and shipment tracking (e.g. Alho et al., 2018 and Ben-Akiva et al., 2016).

Despite the potential of high-quality behavioral data, challenges remain, particularly regarding personal data protection policies. Highly restrictive interpretations of these policies can inhibit data controllers' willingness to collect and share personal data. Ensuring robust data protection while facilitating data collection is a delicate balance that requires clear guidelines and trust between data providers and users. Policymakers and researchers must navigate these challenges to harness the full potential of high resolution behavioral data, ensuring that privacy concerns are addressed without compromising the quality and utility of the data collected. context of the Kaya identity factors.

5.3 Indicators

The generated schedules can then be used to measure a wide variety of key indicators. By predicting the decisions of each (synthetic) individual in the population, it becomes straightforward to aggregate individual indicators to obtain their population-level counterparts. For instance, emissions can be derived from travel choices and participation in certain activities. Individual well-being is measured by the utility function within the framework, alongside variables such as health status. Costs are directly derived from the expenses associated with each decision related to activity participation and travel.

5.4 Optimization

These indicators then feed into the optimization phase, where sophisticated optimization techniques are employed to adjust policies and better achieve desired outcomes. The goal is to reconfigure the policies based on the performance of the indicators to enhance their overall effectiveness. This process often involves multi-objective optimization, where improving one indicator may inadvertently deteriorate another.

For instance, increasing subsidy levels for electric vehicles could significantly boost their adoption, reducing emissions and contributing to environmental goals.

However, this might also lead to increased government expenditure, affecting budget constraints and potentially limiting funds available for other crucial sectors like healthcare or education. Similarly, policies aimed at enhancing individual well-being through increased access to recreational activities might lead to higher emissions due to increased travel.

Balancing these competing objectives requires a careful and strategic approach. The concept of "Pareto optimality" can be employed to identify solutions that offer the best possible trade-offs between conflicting objectives. This concept is grounded in the principle of dominance. A policy P_1 is said to dominate a policy P_2 if no indicator associated with P_1 is worse than the corresponding indicator for P_2, and at least one indicator of P_1 is strictly better than the corresponding indicator for P_2. A policy is considered Pareto optimal if it is not dominated by any feasible solution.

Once policymakers are presented with the set of Pareto optimal solutions, they can evaluate the relative importance of each indicator and make informed decisions that align with broader societal goals. This approach contrasts with single-objective optimization, where the relative importance of each indicator must be established *before* any analysis, often in an arbitrary and non-transparent manner. Thanks to the multi-objective approach and the *a posteriori* weighting, the trade-offs are more transparent, allowing for a clearer understanding of the implications of each decision.

5.5 Policy measures

Policy measures aimed at reducing carbon emissions encompass strategies such as carbon pricing, subsidies for renewable energy, emission regulations, and infrastructure investments.

For example, implementing a carbon tax to mitigate greenhouse gas emissions is a prevalent policy approach.

In our methodological framework, each measure can affect various factors:

- The value of variables in the utility function: For instance, a carbon tax increases the monetary cost of several options, altering the utility associated with different choices.

- The set of constraints individuals face: For example, a policy restricting access to city centers for carbon-emitting transportation modes would influence the selection of destinations for certain activities.

- Subjective aspects influencing decisions: For instance, a policy that includes transparent communication about the redistribution of carbon tax revenue might alter the public perception of the tax's equity.

The whole process is iterative and dynamic, continuously refining policies based on real-time data and feedback. By leveraging these techniques, it is possible to create a balanced policy framework that maximizes overall benefits while minimizing negative impacts, ensuring a sustainable and equitable approach to societal development.

To illustrate, consider the implementation of a congestion charge in a city. The policy is first modeled to simulate commuter responses using travel survey data. The indicators monitored might include traffic volumes, emissions levels, public transport usage, and economic impacts on commuters. Optimization could involve adjusting the congestion charge rates and timings based on these indicators to balance traffic reduction with economic fairness. Throughout this process, inputs such as fuel prices, public transport availability, and travel patterns from GPS data are utilized, along with synthetic populations representing different commuter types.

By using this comprehensive framework, policymakers can design, test, implement, and refine decarbonization strategies effectively, ensuring they are both efficient and equitable.

5.6 Scientific challenges

The design, implementation and application of such a framework is particularly challenging. We briefly discuss some of those challenges.

Deep Uncertainty One of the primary methodological challenges in developing decarbonization policies is dealing with deep uncertainty. This refers to situations where the probabilities of future events are unknown, and the possible outcomes are numerous and varied. Traditional scenario planning, which involves creating a limited set of detailed scenarios, may not be sufficient to capture the full range of uncertainties. Scenario discovery, on the other hand, uses data-driven techniques to identify and explore a broader array of possible futures. For example, rather than just planning for best-case and worst-case scenarios, scenario discovery might reveal a spectrum of outcomes based on different combinations of policy measures, technological advancements, and societal behaviors (Bryant and Lempert, 2010, Steinmann et al., 2020).

Disaggregate Policy-Sensitive Models Another critical issue is the development of disaggregate policy-sensitive models that can accurately capture the causality of human activities. These models focus on individual or household-level behaviors and decisions, providing a granular understanding of how people respond to specific policies. There is a long tradition of such models in travel demand analysis (Castiglione et al., 2014), where disaggregate choice models (Ben-Akiva and Lerman, 1985) are used in micro-simulation tools (Ben-Akiva et al., 2002, Azevedo et al., 2017).

Multi-Scale Models The integration of models across multiple scales is critical for a comprehensive understanding of the broader impacts of various policies. Multi-scale models synthesize data and insights from microscopic (individual or household level), mesoscopic (community or regional level), and macroscopic (national or global level) scales (Ben-Akiva et al., 2001, Bierlaire et al., 2015). By leveraging these different scales, researchers can perform an in-depth analysis of how local actions accumulate to influence broader trends. For instance, a multi-scale model might combine local traffic data (Pinto et al., 2020) with regional air quality models (Appel et al., 2021) and detailed time use data (Winkler et al., 2023).

Scalability Scalability poses a significant methodological challenge: how to effectively apply microscopic models on a global scale (Lorig et al., 2015). Although microscopic models offer detailed insights, they are often computationally intensive and require vast amounts of data. Scaling these models globally necessitates innovative approaches, such as employing representative samples, leveraging parallel computing, and utilizing machine learning techniques. For instance, scaling an urban transportation model globally might involve selecting representative cities from various regions and extrapolating the results while considering regional differences in behavior and infrastructure.

Propagation of uncertainty The primary role of simulation is to represent the propagation of uncertainty through complex systems. This involves generating empirical realizations of complex random variables, which are often defined on combinatorially intricate state spaces. Advanced techniques, such as variance reduction methods (Ross, 2012) and Markov chain Monte Carlo methods (Hitchcock, 2003, Flötteröd and Bierlaire, 2013), can be particularly effective in this context.

The proposed framework is merely a high-level preliminary concept, and the list of challenges it presents is certainly much longer and more complex than outlined above. This research direction requires an interdisciplinary approach, involving collaboration among engineers, economists, computer scientists, psychologists, climate experts, and other specialists. The richness of this field ensures it will fill the research agendas of numerous research teams.

6 Conclusion

Addressing the global challenge of climate change demands an approach that integrates technological advancements, policy frameworks, and an in-depth understanding of human behavior. This paper emphasizes that decarbonization cannot be achieved solely through technological innovations but requires behavioral insights to design effective, equitable, and socially acceptable policies. The interplay of individual choices, societal norms, and systemic constraints is crucial in shaping responses to climate actions.

Through interdisciplinary collaboration and the contributions of experts across engineering, economics, psychology, and data science, we have outlined a methodological framework to guide policymakers in designing and implementing decarbonization strategies. This framework incorporates high-quality behavioral data, choice modeling, agent-based simulations, and optimization techniques to predict and evaluate the impacts of various climate actions. By addressing challenges such as deep uncertainty, behavioral heterogeneity, and multi-scale modeling, the framework provides a robust foundation for creating adaptive and effective climate policies.

Ultimately, the path to decarbonization requires integrating technical feasibility with behavioral realism and societal values. By fostering collaboration across disciplines and leveraging innovative methodologies, policymakers can craft strategies that not only achieve carbon neutrality but also enhance societal well-being, equity, and resilience in the face of a changing climate. This integrated approach ensures that the transition to a sustainable future is both effective and inclusive, addressing the diverse needs and challenges of global populations.

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