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Behavioral and Neuroeconomics of Environmental Values

Phoebe Koundouri

Barbara Hammer

Ulrike Kuhl

Alina Velias

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Phoebe Koundouri[1], Barbara Hammer[2], Ulrike Kuhl[2], and Alina Velias[3]

[1]School of Economics and ReSEES Laboratory, Athens University of Economics and Business; Department of Technology, Management and Economics, Technical University of Denmark; Sustainable Development Unit, ATHENA RC; Sustainable Development Solutions Network-Europe; Academia Europea email: pkoundouri@aueb.gr

[2]Machine Learning Group, Faculty of Technology, Bielefeld University, 33615 Bielefeld, Germany

[3]Research laboratory on Socio-Economic and Environmental Sustainability, Athens University of Economics and Business, Athens, Greece

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Abstract

Identifying mechanisms of real-life human decision-making is central to inform effective, human-centric public policy. Here, we report larger trends and synthesize preliminary lessons from behavioral and neuroeconomic investigations focusing on environmental values. We review the currently available evidence at different levels of granularity, from insights of how individuals value natural resources (individual level), followed by evidence from work on group externalities, common pool resources, and social norms (social group level), to the study of incentives, policies, and their impact (institutional level). At each level, we identify viable directions for future scientific research and actionable items for policy-makers. Coupled with new technological and methodological advances, we suggest that behavioural and neuroeconomic insights may inform effective strategy to optimize environmental resources. We conclude that the time is ripe for action, to enrich policies with scientifically grounded insights, making an impact in the interest of current and future generations.

Contents

homo economicus: model of human agents as rational maximizers of self-interest, who possess perfect knowledge of costs, benefits, and constraints of all possible actions at any given time

1. INTRODUCTION

Human decision-making "in the wild" falls short of the economically rational *homo economicus* (Persky 1995). Rather, it depends on the way we deal with gains, losses, uncertainty (Alpizar et al. 2011, Jang et al. 2020), and the temporal distance of prospective gains (Ballard & Knutson 2009, Shamosh et al. 2008). Further, emotions (Bechara & Damasio 2005), and even context (Weber et al. 2002, Dolnicar & Grün 2009) impact decision-making. This realization sparked novel interdisciplinary research, commonly subsumed under behavioral and neuroeconomics. These emerging fields benefit from interactions between behavioral studies, psychology, and neuroscience, enriching economic theory to accurately reflect human decision-making in daily life (Kahneman & Tversky 2013).

For instance, behavioral studies highlight the importance of simple heuristics, rather than accurate calculations of various probabilities, (Deryugina 2013). Neuroscience reveals how complementary processes in distinct brain regions interact, supporting decision-making (Ballard & Knutson 2009). Moreover, different disciplines offer new insights into economic drives and motivations (Sawe & Knutson 2015, Moser 2016), ambiguity (Hsu et al. 2005) and risk processing (Weber et al. 2002, Charness et al. 2013, Mohr et al. 2010, Hsu et al. 2005), and temporal discounting (Ballard & Knutson 2009). Consequently, a broader, multidisciplinary approach may not only help to explain individual differences (Gifford & Nilsson 2014) for predicting human decision-making, but also to inform effective policy (Ostrom 2008, Hepburn et al. 2010, Fischhoff 2021, Ranney & Velautham 2021). Considering this vast potential for societal impact by translating behavioral and neuroeconomic findings into policy may help to answer one of the ultimate pressing question of our time: How can we build a sustainable future, and how can we engage the public effectively to achieve this end?

The current review gives an overview of state-of-the-art findings of relevant cognitive processes underlying human economic decision-making, with a special focus on environmental valuation. While behavioral research increasingly focuses on protecting natural resources (Fischhoff 2021), neuroeconomic investigations with explicit environmental focus remain sparse (see Sawe & Knutson 2015, Khaw et al. 2015, Vedder et al. 2015, Vezich et al. 2017, Brevers et al. 2021, for the few examples). Consequently, where suitable, we discuss complementary neuroeconomic insights derived from more general decision-making research. Further, we offer an enriched view of how individuals reach economic decisions with regard to common pool resources, public goods, and institutional incentives. Finally, in the face of growing environmental crises, we will highlight the exciting opportunity for effective 'green' action informed by research and advanced technological innovation, steering the world towards more sustainable development.

'Green' action: any action aiming to minimize an otherwise negative footprint on the environment

2. METHODOLOGICAL FRAMEWORK

2.1. Behavioral economics

Behavioral economics combines psychological insights with economic models to explain and predict human behavior. Specifically, behavioral theory departs from standard axioms of economics in three major ways (Mullainathan & Thaler 2000):

- **Bounded Rationality:** deviations from rational solution due to cognitive errors
- **Bounded Willpower:** self-control failures
- **Bounded Self-Interest:** concerns for others' welfare (as opposed to purely selfish motives)

These adjustments to the baseline assumptions of rationality form the foundations of theoretical predictions of behavioral economic models. Putting predictions of models to empirical tests allows to evaluate the theory. Empirical studies in behavioral economics strongly draw on methods from experimental economics (Loewenstein 1999). Table 1 illustrates prominent empirical designs, from lab to field settings (Harrison & List 2004). Laboratory studies provide controlled settings, keeping potential confounding variables fixed between groups under consideration. Varying only the aspect of interest, one may attribute differences in participant's behavior to this aspect. This approach grants causal conclusions (*internal validity*; Lonati et al. 2018).

Extensive control, however, comes at the cost of reduced *external validity*. The gap separating controlled designs and 'real life' likely explains systematic differences between lab settings and natural environments (Galizzi & Navarro-Martinez 2019), questioning whether lab studies may truly provide quantitative conclusions (Loewenstein 1999). However, the linchpin of empirical findings is their applicability in real-life, as economics aims to inform about the best course of action. Consequently, field experiments alleviate this issue by moving investigations from the lab to more realistic contexts (see Table 1; Harrison & List 2004). However, the distinction between lab and field is not necessarily synonymous with a trade-off between internal and external validity (Lonati et al. 2018): experimenters applying scientific rigour and careful designs may succeed to preserve both also in field settings (Harrison & List 2004).

Ensuring *incentive compatibility* is a challenge in behavioral economics (Chen 2008). In fact, contingent valuation – the established way to assess environment valuation (Table 1 Hanemann 1994) – has drawbacks commonly associated with non-incentive compatible methods (Rakotonarivo et al. 2016). Recorded responses reflect true preferences only if participants may maximize their outcome by acting solely according to them. In experimental reality, true incentive-compatibility is difficult – if not impossible – to achieve. First, participant biases (e.g., aligning behavior with assumed expectations; non-compliance) impede conclusions from observed behavior to true preferences (Lonati et al. 2018). Therefore, studies relying purely on self-reported preference are typically weaker in terms of internal and external validity. To remedy bias, we may extending self-reported preference measures

confounding variable: unobserved variable introducing spurious associations by influencing both the supposed cause and the supposed effect

internal validity: the level of confidence for drawing causal conclusions from a study's results

external validity: the level of generalizability of findings in a research setting to the environment the study approximates

incentive compatibility: state reached if an individual achieves the best outcome just by acting according to their true preferences

field study: studies taking place in the setting of interest

Table 1 Overview of behavioral experimental designs.

Description	Example[a]	IV	EV	Comment	Key studies with environmental focus
Incentive compatible					
Laboratory experiment (LAB)					
laboratory setting, typically with student samples and abstract framing of task	Students decide how much money to donate to an anonymous peer, and how much to keep themselves.	↑	↓	Pro: - highest exp. control Con: - GOF from lab to field / student to other unclear	Harbaugh et al. (2007)*
Artefactual field experiment (AFE)					
LAB with specific target population	Coffee farmers in Costa Rica decide how much money to donate to an anonymous peer, and how much to keep themselves.	↑	→	Pro: - improved GOF to target group Con: - hard to recruit representative sample	Menges et al. (2005)
Framed field experiment (FFE)					
AFE extended by field setting (i.e., realistic commodities, outcomes, information, and stakes)	Coffee farmers in Costa Rica make investment decisions for adapting their farms to extreme weather events, with decisions determining monetary payoff.	→	↑	Pro: - improved GOF to target group + setting Con: - hard to recruit representative sample	Alpizar et al. (2011) Anderson et al. (2017) Galizzi & Navarro-Martinez (2019) Werthschulte & Loschel (2021)
Natural field experiment (NFE)					
FFE within natural task environment; participants kept unaware of experiment	Crop insurance provider analyses numbers and worth of insurance contracts of coffee farmers in Costa Rica, before and after extreme weather events.	↓	↑	Pro: - most naturalistic setting - reduced Hawthorn effect [b] Con: - little control of confounds	Clot & Stanton (2014)
Not incentive compatible					
LAB / AFE / FFE / NFE with hypothetical stakes					
Respective designs with hypothetical outcomes	Coffee farmers in Costa Rica make hypothetical investment decisions for scenarios such as adapting their farms to extreme weather events.	→	↓	Pro: - easy and cheap Con: - low consistency / reliability of hypothetical valuation	Hardisty & Weber (2009) Deryugina (2013)
Discreet choice experiment (DCE)					
Participants choose hypothetical alternatives differing on multiple dimensions along attributes of interest.	Coffee farmers in Costa Rica choose potential plans for extreme weather adaptation, described by respective cost increase, reduced risk of crop failure, and expected change in crop yield.	→	↓	Pro: - capture multidimensionality of environmental outcomes Con: - low consistency / reliability of hypothetical valuation	Boeri & Longo (2017) Mao et al. (2020)
Contingent valuation study (CVS)					
Participants answer surveys assessing valuation of non-market commodities like environmental resources	Survey respondents state their maximum WTP for a change in the provision of the goods or service, or their minimum compensation (WTA) if the change is not carried out.	→	→	Pro: - grants value estimates for non-monetary resources Con: - response bias / protest answers	Khaw et al. (2015)* Lopez-Mosquera & Sánchez (2011)

[a]Examples constructed around the FFE by Alpizar et al. (2011)
[b]Hawthorn effect: participants changing their behavior due to the fact of being observed
Symbols: ↑ = high; → = medium; ↓ = low; * = studies using behavioral design, combined with neuroscience method
Abbreviations: IV = internal validity; EV = external validity; GOF = generalizability of findings; WTP = willingness to pay; WTA = willingness to accept

with observational data reflecting true behavior. Second, practical reasons often hinder incentive compatibility. For example, policy outcomes can only be considered as hypothetical alternatives: One may ask people whether they prefer an increase in taxation to ameliorate the risk of flooding, but one cannot enforce these outcomes in real life.

Finally, Discreet Choice Experiments (DCEs) are increasingly used to evaluate environmental policy options (Rakotonarivo et al. 2016, Boeri & Longo 2017, Mao et al. 2020). A DCE elicits participant's preferences over complex goods through presenting them with a sequence of choices that differ on multiple dimensions along attributes of interest (e.g., different policies for renewable energy, described by the respective reduction in greenhouse gas emissions, number of power outages, jobs lost / created, and cost increase; Boeri & Longo 2017). Given the multifaceted nature of many environmental outcomes, DCE reveal the most important attributes determining people's preferences and their respective trade-offs, even enabling forecasts of demands and behavior. However, a systematic meta-analysis of

Table 2 Overview of neuroscience methods.

Explanation	Signal	Spatial resolution	Temporal resolution	Comment	Key studies with environmental focus
Lesion studies					
Studying behavioral/cognitive deficits of patients with focal brain damage	behavioral	variable	–	Pro: - allows to directly relate dysfunction to brain region Con: - small, heterogeneous samples - large variability lesion size/extent	–
Electroencephalography (EEG)					
Electrodes placed on scalp	electric	40mm	0.001-0.01s	Pro: - mobile, non-invasive, cheap Con: - poor spatial resolution, noisy data	Lee et al. (2014)
Local field potentials (LFP); Single unit recordings					
Implanted micro-electrodes	electric	0.4mm	0.01s	Pro: - excellent temporal & spatial resolution Con: - invasive	–
Functional magnetic resonance imaging (fMRI)					
Recording of magnetic signal variations of (de-)oxygenated blood within the brain	hemodynamic	1mm	1s	Pro: - excellent spatial resolution Con: - expensive - stationary	Linder et al. (2010) Khaw et al. (2015) Sawe & Knutson (2015) Vedder et al. (2015) Vezich et al. (2017) Brevers et al. (2021)
Positron emission tomography (PET)					
Visualization of metabolic processes after injection of radioactive tracers	metabolic[a]	5mm	100s	Pro: - focus on specific processes Con: - invasive, expensive - participants subjected to radiation	–
Functional near infrared spectroscopy (fNIRS)					
Near-infrared light projected through the scalp to record intensity of refracted light	hemodynamic	5-10mm	0.001-0.01s	Pro: - mobile Con: - poor spatial resolution	–
Magnetoencephalography (MEG)					
Highly sensitive magnetometers record magnetic fields at scalp, generated by underlying neural activation	electro-magnetic	2-3mm	0.001-0.01s	Pro: - excellent temporal resolution Con: - effortful to eliminate environmental magnetic interference	–
Transcranial magnetic stimulation (TMS); Transcranial direct current stimulation (tDCS)					
A magnetic field/electric current applied at the scalp targets specific brain regions, stimulating/interfering with processing	stimulation/ interference	$25mm^2$-$2500mm^2$	[b] 0.001-1s	Pro: - non-invasive Con: - poor spatial resolution - stimulation/interference non-specific - (low) risk of seizures	Langenbach et al. (2022)

[a] use of tracer determines targeted metabolic process (e.g., regional tissue composition, absorption, blood flow).
[b] timing largely depends on the TMS / tDCS protocol / method (e.g., single pule is quick, repeated TMS rather slow)

DCEs found low consistency between valuations and low reliability of hypothetical valuation when compared to non-hypothetical cases (Rakotonarivo et al. 2016).

2.2. Neuroeconomics

Neuroeconomics complements behavioral economics by revealing the biological basis of economic decision-making: researchers investigate the properties and interactions of brain activity during economic tasks using appropriate tools (Table 2).

Most established methods in neuroscience focus on patients with focal brain lesions (Vaidya et al. 2019), or electrodes implanted in animal models at sites of interest (local field potentials, LFP; or single unit recordings, Herreras 2016). Modern neuroscience predominantly relies on minimally or non-invasive neuroimaging techniques, combined with sophisticated experimental designs and appropriate data analyses. These methods reveal brain activation during task performance, like positron emission tomography (PET), functional near infrared spectroscopy (fNIRS), magnetoencephalography (MEG). Most prominently used, however, are electroencephalography (EEG) and functional magnetic resonance imaging (fMRI).

During an EEG recording, electrodes placed on the scalp measure electric potentials originating from the underlying brain tissue (Michel & Murray 2012). Thus, EEG signals serve as a direct estimate of collective neuronal activity, providing an excellent temporal resolution in the millisecond range (Michel & Murray 2012). An fMRI assessment requires participants to lie in a long, tubular MRI scanner detecting small changes in the brain's regional blood flow. These are taken to reflect the increased oxygen consumption by active neurons (Logothetis et al. 2001). With their three-dimensional images, fMRI measurements offer an excellent spatial scale. However, the temporal resolution is inferior to that of electrophysiological tools as activity is only indirectly inferred (Bolton et al. 2020).

A final critical addition to the neuroscientific toolbox are non-invasive neuromodulation techniques. transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS) induce electrical currents in the brain, thus facilitating or inhibiting neural activity in target regions (Priori et al. 1998, Zhengwu et al. 2018). Modulating neural activity, these methods promise causal inferences about relationships between brain regions and their respective functions.

While neuroeconomics promises a window into the human mind, some issues may spark justified scepticism. For instance, neuroeconomic data is often sparse, and conclusions are drawn from few participants in very specific settings (Harrison 2008). More fundamental methodological criticism points to poor test-retest reliability of fMRI (Elliott et al. 2020), inappropriate statistical handling of the data (Eklund et al. 2016), and limited capacity to establish causal links between observed brain activity and psychological processes under study (Poldrack & Farah 2015). Moreover, technical requirements of the equipment often dictate the scope of investigations: There is only so much a person can do while lying motionless in a stationary MRI-scanner. However, it is often difficult to increase realism in neuroimaging studies, calling into question the generalizability of results. Thus, more flexible psychophysiological measures like electrodermal activity, electromyographic data, or respiration rate may complement contemporary neuroimaging methods, contributing insight into somatic states of cognitive processing (Bechara & Damasio 2005). Last, next-generation neuroscientific technology promises mobile and wireless options for studies in more naturalistic settings outside the lab (Chi et al. 2013), making these tools particularly interesting in the domain of environmental valuation.

willingness to pay: the maximum price a consumer is willing to pay for a product or service

willingness to accept: the minimum monetary amount that a person is willing to accept to sell a good or service

3. EMPIRICAL EVIDENCE ON ENVIRONMENTAL VALUATION

Given this diverse repertoire of methodologies, emerging literature highlight behavioral and neural aspects of environmental valuation.

First, behavioral evidence reveals a striking disconnect between *Willingness To Pay (WTP)* and *Willingness To Accept (WTA)*. Consumers likely name a much higher price for giving up existing access to clean water (WTA), than for gaining access (WTP). Research shows that the WTP - WTA disparity is greatest for environmental goods, compared to health, safety, or ordinary private goods (e.g. cars and houses) (Tunçel & Hammitt 2014), but consistently smaller in incentive-compatible designs. Consequently, studies measuring value of environmental goods need to account for this disconnect in incentive-compatible settings. Second, environmental outcomes are non-deterministic - they happen with some probability that is either known (risk) or unknown (ambiguity). Brain imaging reveals fundamental differences how humans represent and process choices under risk and ambiguity (Hsu et al. 2005, see Section 3.1.1). Third, people prioritize immediate over temporally distant gains. Environmental interventions tend to take effect in the remote future, while current generations bear their costs. Behavioral economics highlights the systematic disconnect between valuations of present and future outcomes, and neuroeconomics reveals distinct neural systems related to magnitude and delay of future rewards (Ballard & Knutson 2009, see Section 3.1.2). Fourth, environmental outcomes affect the whole of society. Thus, considerations of fairness and perceived intentions of other stakeholders affect individual action (Anderson et al. 2017). Similarly, recent evidence points towards perspective-taking and mentalizing for sustainable action, akin to cooperation behavior (Langenbach et al. 2022, see Section 3.2). Last, the impact of environmental valuation also affects institutional stakeholders like companies, governmental, and non-governmental organisations. These parties rely on empirical insights to realize appropriate – and effective – policies. In turn, political initiatives, taxation and regulations may shape individual and societal valuation of environmental resources.

mentalizing: understanding the mental states of oneself and others

In the light of these challenges, we will present behavioral and neuroeconomic evidence along three interconnected levels, specifically relevant to environmental valuation (see Figure 1 List & Price 2013):

- **Individual level:** Studying behavioral particularities of human valuation, that may affect societal norms.
- **Social group level:** Exploring typical problems of group externalities / social dilemmas associated with common pool resources.
- **Institutional level:** Addressing how incentives and institutions affect decisions and outcomes.

3.1. Individual level

3.1.1. Gains, losses and uncertainty in environmental outcomes. Economics examines how humans choose to use limited resources to maximize satisfaction. How do humans construct value concerning environmental resources? Different methods eliciting environmental values arrive at different results, pointing towards on-the-spot processing rather than stable underlying constructs (Schkade & Payne 1994). Despite methodological drawbacks associated with environmental valuation studies (cf. Section 2.1 Rakotonarivo et al. 2016), behavioral evidence suggests higher WTP for organic food (Linder et al. 2010) or environmental proposals (Khaw et al. 2015), indicating that participants inherently value green commodities. One exciting behavioral variant of valuation studies focuses on subjective well-being. Welsch & Kühling suggest assessing the trade-off between income and environmental conditions techniques of valuation, based on self-reported happiness, to approach environmental valuation. Strikingly, related psychological parameters such as emotional experience and satisfaction have been shown to correlate with the WTP for environmental resources (López-Mosquera & Sánchez 2011), paving the way to richer valuation models accounting for the multitude of environmental services.

While behavioral economics infers how humans construct value from their actions, neuroeconomics aims to identify the neural basis of economic decision-making (Figure 2; for a recent review, see Serra 2021). Specifically, this concerns the neural representation of gains

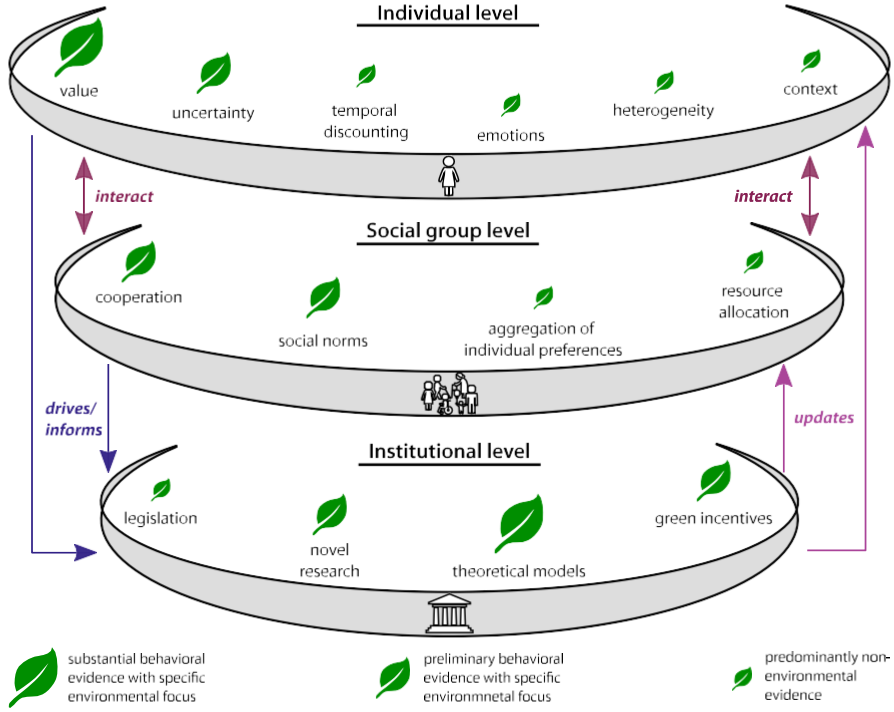

Figure 1

Schematic figure highlighting the three levels and corresponding aspects considered in this review. Size of leaf icons indicates the amount of behavioral literature available. Arrows highlight inter-dependencies between levels.

and rewards, losses, and uncertainty.

Single unit recordings in non-human primates demonstrate that neural responses reliably depend on reward magnitude (for a review, see Haber & Knutson 2010). Candidate brain regions include midbrain cells relying on the neurotransmitter dopamine, the lowermost part of frontal cortex (orbitofrontal cortex, OFC), a small cluster of neurons found deep within the brain (the striatum), and the area spanning the brain's medial midline (cingulate cortex). In human participants, similar regions show reward-related activity in response to monetary gains (Knutson et al. 2001) and rewarding social acts (Harbaugh et al. 2007). Importantly, besides reward magnitude, signalling in this circuity reflects relative preference among available options (Kable & Glimcher 2007). Additionally, reward prediction relies on signals from the amygdala, typically associated with emotion and motivation (Knutson et al. 2001). Located deep within the brain, it mediates general reward-related arousal, and links sensory cues to the affective value of their anticipated outcome (Murray 2007).

While still vastly understudied, first neuroeconomic evidence reveals neural correlates of environmental value. For instance, Linder et al. demonstrate higher WTP for organically-produced food, together with increased activity in the ventral portion of the striatum (VS, i.e., the economic reward hub; Linder et al. 2010). Khaw et al. show comparable brain activation in participants when they contemplate their WTP for environmental proposals (e.g., protecting sea turtles, increasing the proportion of renewables), and during valuation

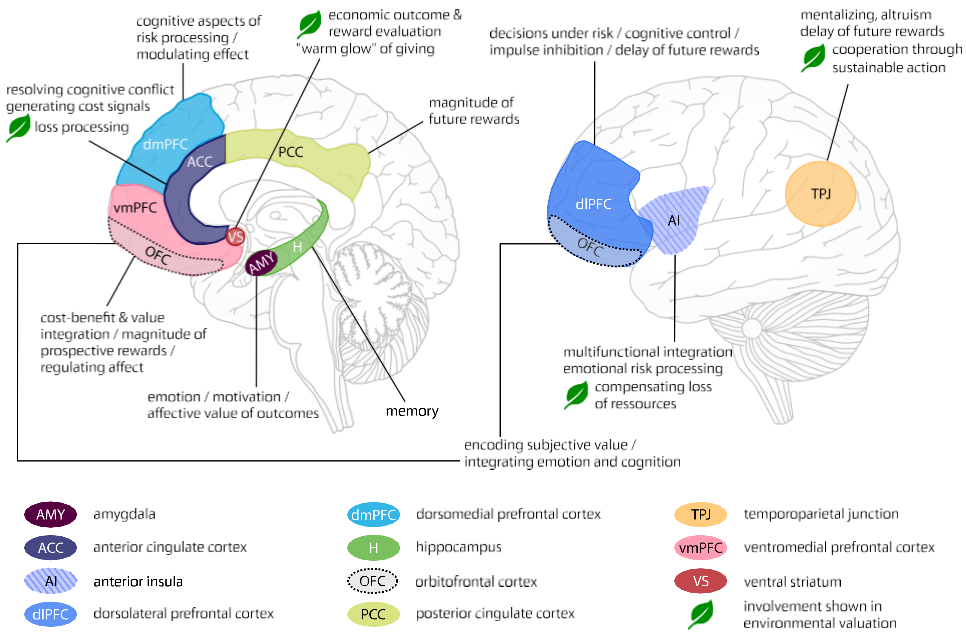

Figure 2

Schematic figure highlighting brain areas supporting aspects of economic decision-making. Hatched areas lie beneath the brain's surface. The leaf icon signifies functional associations that have been identified specifically in the context of environmental valuation.

processes for consumer items, snack foods or activities (e.g., dorsomedial prefrontal cortex (dmPFC), PCC, and VS; Khaw et al. 2015). In stark contrast to previous literature on economic valuation, this study failed to show a linear relationship between the degree of brain activity in prefrontal cortex or VS, and behavioral preferences. This may suggest distinct neural underpinnings in the translation process from internal valuation to behavioral preference for environmental economic decisions.

Complementary to processing positive rewards, distinct brain regions encode negative utility, e.g., in response to monetary loss (for a review, see Dugré et al. 2018). A common pattern emerging from corresponding work points to three major players in loss processing. First, increased activity of the striatum – also typically observed in positive reward processing – highlights its more general role in economic outcome evaluation. Second, the anterior part of the brain's midline region (the anterior cingulate cortex, ACC) presumably generates cost signals that exert control on decision-making to minimize losses while maximizing gains (Brown & Alexander 2017). Third, the anterior insula (AI), hidden within the brain's prominent lateral fissure, acts as a multi-functional integration area, putatively relaying information between different cognitive and social-emotional systems (Kurth et al. 2010).

In terms of loss-processing, striking similarities between the neural processing of economic loss and loss of natural resources seem to exist. Sawe & Knutson assessed participants' WTP to prevent destructive land use in national parks while recording fMRI. Interestingly, imagery of park lands reliably increased activity within the VS, consistently associated with economic valuation. Destructive land use, however, triggered negative arousal supported by regions related to economic-loss processing (AI, ACC). This effect was especially prominent in individuals who endorse more pro-environmental attitudes. Importantly, the extent of AI activation predicted individual WTP. In line with this, behavioral evidence suggests that losses loom larger than gains of the same expected value (Kahneman & Tversky 2013), and trigger more negative emotions relative to gains (Jang et al. 2020). Consequently, framing environmental outcomes as losses may elicit a drastically different preference compared to the gain framing.

A realistic account of gain- and loss-processing needs to account for the probabilistic nature of most real-life action: Time and again, humans face decisions leading to consequences with a certain likelihood, rather than absolute certainty. Consequently, on a neural level, economic decision-making relies not just on a reliable representation of value, but also of probability – i.e., risk. Single unit studies in non-human primates reveal individual neuronal populations in midbrain and frontal regions, encoding expected value and likelihood of prospective rewards as a potential physiological correlate for economic risk processing (Haber & Knutson 2010). Human brain imaging points to the striatum representing probabilities of rewards (Hsu et al. 2005), corresponding to its canonical role in economic valuation. Moreover, risk processing in humans relies on regions involved in cognitive (dmPFC), and emotional control (e.g., AI), jointly informing decision processes in the prefrontal brain (dorsolateral prefrontal cortex, dlPFC; Mohr et al. 2010).

risk: uncertain situation with known probabilities of potential outcomes

ambiguity: uncertain situation with unknown probabilities of potential outcomes

Intriguingly, inter-individual differences modulate activation of regions within this network: i.e., risk-averse individuals show stronger responses to risky decisions in AI, linking cognitive and affective processes (Kurth et al. 2010). Individuals prone to sensation, conversely, show blunted AI-responses to both monetary gains and losses (Zheng & Liu 2015).

Mirroring the complexity of neural risk processing, individuals exhibit variable and sometimes even contradictory behavior when facing risky decisions. For instance, attitude towards risk varies between individuals, and may depend on the outcome's domain (Weber et al. 2002) and elicitation method (Charness et al. 2013). In practice, this means that people may require different incentives for taking health-related than for taking environmental risks, or for reducing risk compared to removing it completely (Hansson & Lagerkvist 2012). Moreover, people underestimate the probability of high-magnitude outcomes, an effect potentially remedied by adjusting the language used to communicate probability (Patt & Schrag 2003).

In contrast to situation with known probabilities, likelihood cannot be assigned in ambiguous outcomes (Knight 1921). In relation to environmental aspects, we may distinguish between ambiguity of outcomes (occurrence of floods, droughts, hurricanes) and ambiguity of costs and benefits of different actions addressing these outcomes (Heal & Millner 2018). Field experiments show that farmers' risk aversion in regards to climate change increases under ambiguity (Alpizar et al. 2011). Notably, adaptation cost influences individual choices, fostering coordinated action to reduce costs.

Brain imaging studies with human participants reveal differing activation patterns for risky and ambiguous choices (Hsu et al. 2005). Specifically, ambiguous conditions activate regions associated with emotion and motivation (i.e., amygdala), regulation of emotional responses (dmPFC), and integration of emotion and cognition to generate subjective value (OFC; Hsu et al. 2005). Consequently, behavioral and neuroeconomics highlight important differences concerning human decision-making under risk and ambiguity, in stark contrast to classical decision theory failing to account for such distinction.

3.1.2. Temporal discounting of environmental outcomes. Environmental decision-making involves high stakes alongside large spatial and temporal scales. Specifically, humans tend to discount temporally-distant outcomes, valuing near rewards more than future ones (myopia, Hepburn et al. 2010). This also affects decision-making in the domain of environmental values, such as perceptions of climate change(Weber 2010), rate of energy consumption (Werthschulte & Loschel 2021), or payment for environmental services (Clot & Stanton 2014). While is yet unclear whether general time-discounting models apply to environmental outcomes, the initial evidence suggests similar discounting mechanisms for environmental and financial outcomes for hypothetical scenarios. (Hardisty & Weber 2009).

myopic decision-making: prioritizing immediate over temporally distant events, while discounting future consequences

Much like risk preference, delay discounting varies between individuals as a function of intelligence and working memory, mediated by activity in prefrontal control regions (i.e., dlPFC; Shamosh et al. 2008). The brain basis of temporal discounting in financial contexts has been thoroughly investigated in neuroeconomics: Ballard & Knutson distinguish neural systems related to magnitude and delay of future rewards. Specifically, larger prospective gains elicit greater signal changes in areas typically linked to economic outcome evaluation (VS, PCC), and cost-benefit integration (ventromedial prefrontal cortex, vmPFC). These insights extend earlier work by McClure et al., who provided thirsty participants with small amounts of liquid to demonstrate that the mesolimbic dopamine system (VS, PCC, ACC, and OFC) additionally responds to immediate, primary rewards. The limbic system's integral part in associating emotion with cognition via its connectivity with the amygdala and OFC (Catani et al. 2013) may explain the strong human preference for immediate outcomes.

Beyond reward magnitude, varying the delay modulates activity (i.e., longer delays decrease responses) in cognitive control regions (dorsolateral prefrontal cortex, dlPFC), and parietal areas (e.g., temporoparietal junction, TPJ; Ballard & Knutson 2009). Strikingly, deactivation of delay-sensitive regions in response to longer temporal offsets is greater for more impulsive individuals (Ballard & Knutson 2009). In line with this, stimulation of the left dlPFC via tDCS decreases temporal discounting in participants choosing between smaller-but-sooner and larger-but-later rewards, marking its crucial role in mediating temporal discounting (He et al. 2016).

However, it is yet unclear whether similar temporal discounting mechanisms apply to environmental valuation. In fact, there is some behavioral indication of domain-specificity: Richards & Green found significantly lower discount rates for environmental compared to financial outcomes (Richards & Green 2015). As this effect could not be consistently shown in previous research (Hardisty & Weber 2009), future investigations will need to study temporal discounting across the domains and, specifically, assess whether general models also hold for environmental scenarios.

The fundamental bias towards the present in human decision-making may severely impede concrete action reducing the long-term impact of environmental challenges like climate change. Thus, policies need to account for and overcome this critical myopia to alleviate potentially catastrophic consequences of present choices.

3.1.3. Impact of emotions on decision-making. Emotions may affect preferences and decisions (Bechara & Damasio 2005), occasionally leading to biases of judgement, and systematic errors in predicting emotional outcomes (Nisbet & Zelenski 2011). For instance,

affective forecasting: prediction of future emotions

individuals may fail to maximise the hedonic benefit from simple acts like talking a walk outdoors (Nisbet & Zelenski 2011). Consequently, active exposure to environmental stimuli may improve experiental learning, thus circumventing such errors in affective forecasting.

The interplay between emotion and decision-making has been a prominent subject of neurocognitive investigation, culminating in the so-called *somatic marker hypothesis* (Bechara & Damasio 2005). In short, this theory considers decision-making to be subject to biasing signals (somatic markers) arising from autonomic bodily states, including feelings and emotions. These markers consequently guide decision-making, pointing towards the most relevant alternatives based upon the individual's previous experiences. While not devoid of criticism (for a critical evaluation, see e.g., Dunn et al. 2006), this theory potentially explains how emotions affect decision-making.

In line with the somatic marker hypothesis, neuroeconomic investigations reveal mechanisms that may lead to biased judgement through emotions. For instance, anticipatory anxiety has a striking impact on how the brain valuates different choices. Specifically, anticipatory anxiety changes the neural signatures for economic valuation, away from the typical pattern involving VS and ventromedial prefrontal cortex (vmPFC), towards a stronger contribution of the AI, potentially shifting valuation focus to possible negative outcomes (Engelmann et al. 2015).

However, beyond the view of emotion as a stumbling block for cognition, affect may also guide decision behavior, thus producing strategies aligned with economic notions of rationality. One particularly illustrative emotion relevant to human decision-making is regret. First and foremost, engaging in counterfactual thinking, i.e., deliberating about what could have been may invoke regret. Instead of purely maximizing expected utility, a person's choice is often motivated to avoid this highly unpleasant emotion (Zeelenberg et al. 1996), with profound impact on decision-making (Loomes & Sugden 1982, Zeelenberg & Pieters 2007). Regret-minimization guides human choice in important and challenging situations, or when the decision-maker believes that they will face consequences for their actions (Zeelenberg & Pieters 2007).

A fundamental player mediating emotions like regret is the vmPFC. In their seminal line of studies taken to support their somatic marker hypothesis, Bechara & Damasio employed a gambling task to investigate individual aptitude for risk taking, impulsivity, and resistance to immediate gratification in neurotypical controls and patients with brain lesions. Strikingly, while intellectual and cognitive abilities appear intact, patient groups with either frontal lesions, or impairments of the amygdala consistently prefer short-term gains, despite larger net losses (see Section 2 of Bechara & Damasio 2005, for a concise review of the corresponding experimental data). Similarly, individuals with vmPFC lesions may feel disappointment, but no regret after high-risk choices with adverse outcomes (Camille et al. 2004). Newer evidence suggests a more fine-grained differentiation of frontal regions, with lack of regret stemming from lesions confined to the lowermost part of the lateral frontal lobe, the lateral OFC (Levens et al. 2014). Thus, the vmPFC may guide future decision-making, integrating choices with anticipated emotional responses, while the lateral OFC mediates after-choice emotional signalling associated with subsequent behavioral modification. Further neuroimaging work with neurotypical participants confirms vmPFC activity as a strong correlate of anticipating and feeling regret (Coricelli et al. 2005). Additionally, regret triggers enhanced activity in the ACC, and within hippocampal memory structures (Coricelli et al. 2005). While the ACC is a major player in processing losses more generally (see Section 3.1.1), hippocampus activity may indicate avoidance learning based on emotional experience (Coricelli et al. 2007).

What are potential implications of regret critically influencing decision-making in the context of environmental value? On the one hand, incorporating risk-aversion in choice modelling may introduce greater behavioral realism (Chorus 2010). In fact, random regret minimization models show higher explanatory and predictive power for individual choice behavior in the context of renewable energy programs (Boeri & Longo 2017), and air quality improvement policies (Mao et al. 2020). On the other hand, putting a strong focus on the highly regretful future outcomes of environmentally destructive behavior may improve efficiency of public campaigns promoting pro-environmental behavior (Brosch 2021).

3.1.4. Heterogeneity of preferences & attitudes towards environment. Humans differ in terms of many factors, including their pro-environmental attitudes. Considering socio-demographic and psychometric factors, participants that actively take pro-environmental initiative seem to have higher education and income, while being more oriented towards outdoor activities (Bodur & Sarigöllü 2005). However, concerned and unconcerned individuals do not statistically differ in terms of age, gender, and occupation. Cross-cultural studies are in line with this finding, demonstrating limited evidence of heterogeneity in environmental regard driven by factors such as gender (Chan et al. 2019), or personality traits (Milfont et al. 2006). The role of age is less clear, with some studies suggesting no effect (Gray et al. 2019), while more recent accounts show higher pro-environmental behavior in old compared to young individuals (Wang et al. 2021, Xu et al. 2021). In contrast, socio-economic aspects like rural-urban residence, or political orientation seem to affect environmental concerns (see Gifford & Nilsson 2014, for a comprehensive review of relevant factors).

From a psychological perspective, individual beliefs are profound motivational factors impacting the environmental decision-making heuristic (Deryugina 2013). A large scale survey of over 1,760 German households revealed that self-interested beliefs about e.g., health value and sustainability strongly motivate the choice for organic products (Moser 2016). Intriguingly, though, this effect seems to vary depending on product type, affecting healthy products more profoundly than products that tend to be more unhealthy, but offer instant gratification (Van Doorn & Verhoef 2011).

Beyond individual beliefs, human economic valuation also depends on subjective appraisal of environmental beauty (Fanariotu & Skuras 2004). Specifically, economic valuation models predicting participants' WTP to prevent forest fires are significantly improved when including individuals' ratings of scenic beauty. Thus, opening the public's eye for scenic beauty may be a worthwhile strategy to increase public investments for preserving natural resources.

Whatever reason sparks regard about ecological issues, environmental concern shapes human perception (see Luo & Zhao 2021, for a review). Based on studies suggesting stronger attentional biases towards climate-related stimuli in individuals showing initially stronger concern Luo & Zhao speculate a two-way interaction: Larger attention to environmental issues may induce greater concern, leading in turn to greater attention, and so on. Bergquist recently provided further intriguing insights about the human 'green' psyche: a majority of humans across samples and countries tend to perceive themselves as being more environmentally friendly than others (Bergquist 2020). While this conception did not reduce participants' perceived obligation to act environmentally friendly, it weakly reduced pro-environmental intentions. Thus, negative spillover effects may have a detrimental effect in environmental cognition, with (perceived) pro-environmental actions subsequently warranting less environmentally friendly behavior (Carrico 2021). In contrast, recent work also reveals evidence for positive spillover, with present pro-environmental actions motivating subsequent pro-environmental behavior (Carrico 2021).

These behavioral investigations begin to form a comprehensive picture of the heterogeneity in pro-environmental attitudes. This emerging view, however, lacks substantial neuroeconomic evidence identifying neural correlates and characteristics of observed individual differences. First sparse data suggests that consumers favoring environmentally-friendly products show differential frontal activity when engaging with green product messages (Lee et al. 2014). Similarly, individuals who endorse pro-environmental attitudes show greater AI activity in response to destructive land use (Sawe & Knutson 2015), and a greater buying preference for organic food is reflected by increased economic valuation in terms of VS activity (Linder et al. 2010). Fully revealing the neural basis for 'green' behavior will be an exciting avenue for future research.

3.1.5. Effects of decision context. So far, we have seen the complexity of human decision-making, subject to various factors beyond magnitude and probability of prospective rewards and losses. To make matters even more complex, neuroeconomic evidence suggests a particularly strong influence of decision context on the neural mechanisms of environmental evaluation. Brevers et al. recently showed fundamental differences when participants contemplate to be more sustainable by 'doing more' or 'doing less'. Behaviorally, 'doing more' was judged as more feasible than reducing unsustainable actions.

Additionally, thinking about increasing the amount of sustainable behaviors engaged regions connected to processing subjective economic value (OFC), together with areas typically supporting episodic memory (hippocampus). Conversely, thinking about decreasing unsustainable behaviors relied on frontal control regions (dorsolateral prefrontal cortex, dlPFC), while hippocampal activity was reduced, potentially marking suppressed memory retrieval of own unsustainable actions (Brevers et al. 2021). Thus, the perspective context elicits distinct neural patterns for environmental cognition. Comparably, differences emerge when imagining either pleasant/beautiful or unpleasant/non-beautiful environments (Vedder et al. 2015). Corresponding fMRI results reveal distinct neural representations for each context, with greater, more wide-spread activation following negative probes.

Further, pro-environmental behavior not only varies between individuals, but also within a person depending on context. Survey data suggest a considerable drop in pro-environmental behavior when on vacation, with only the most environmentally friendly respondents resisting the change of scene (Dolnicar & Grün 2009). These inter- and intra-individual effects need to be taken into account to realize effective green policy.

3.2. Social Group level

3.2.1. Cooperation and environmental outcomes as public goods. Environmental resources are non-excludable and non-rivalrous public goods. While benefiting all members of society, they require coordinated action to maintain.

Financing of public goods is directly linked to social dilemmas. For example, a group of fishermen may cooperate to fish responsibly (i.e., refraining from maximizing profits by fishing excessively), thus allowing the fish to reproduce (Stoop et al. 2012). In this scenario, an over-fishing free-rider would achieve higher profits. However, if everyone followed this same logic, the public good of the fish pond would deplete rapidly. Brain-wise, coopera-

ACTIONABLE ITEMS, INDIVIDUAL LEVEL EVIDENCE

- Environmental valuation models may be enriched by including affective value of natural resources (López-Mosquera & Sánchez 2011, Welsch & Kühling 2009), and accounting for cognitive biases such as myopic temporal discounting (Weber 2010, Clot & Stanton 2014), gain-loss discrepancies (Jang et al. 2020, Ölander & Thøgersen 2014), and suboptimal emotional forecasting (Nisbet & Zelenski 2011)
- Policy-makers need to account for psychological barriers to individual green action, especially human's fundamental bias towards present gains at the expense of the future outcomes (Weber 2010, Clot & Stanton 2014).
- Policies may capitalize on insights into the human green psyche, seizing e.g., positive spillover effects (Carrico 2021).
- Effective incentives must be tailored to the individual, incorporating personal pro-environmental stances Luo & Zhao, and cognitive biases (Bergquist 2020).
- From a research perspective, there is ample room for greater focus of neuroeconomic work on mechanisms of valuation, specifically in environmental contexts.

tive choice elicits activity in a network comprising areas associated with cognitive control (e.g., dlPFC), value computation (VS), emotion processing (AI, amygdala), and mentalizing (TPJ), modulated by fairness, individual social preference, and strategic considerations (for a review, see van Dijk & De Dreu 2021). People care not only about own outcomes, but also how those compare to outcomes of others (*distributional preference*; Fehr & Schmidt 1999, Charness & Rabin 2002, Anderson et al. 2017), exhibiting a general willingness to redistribute outcomes more equally, even at a cost (Durante et al. 2014). Also for environmental outcomes, this distributional preference seems to hold, with WTP dependent on equity of outcomes (Cai et al. 2010). In line with behavioral distributional preferences, neuroeconomic data suggests greater reward signalling in relevant brain regions (vmPFC, VS) for decisions that restore equality in social settings (Tricomi et al. 2010). Likewise, social cues elicit similar value signals as monetary gains within the economic reward hub (VS), suggesting comparable processing mechanisms (Izuma et al. 2008).

There is indicative evidence of differing inequality aversion depending on temporal distance and gain/loss domain of the outcome (Venmans & Groom 2021). In a recent review on neuroeconomic implications for climate change policy, Sawe & Chawla put forward the compelling suggestion that neural processes underlying inequality aversion may be fundamentally modulated by one's individual economic standing (Sawe & Chawla 2021). Building on theoretical considerations of Fehr & Schmidt, they suggest that affluent individuals may experience advantageous inequity aversion, while economically disadvantaged individuals more likely experience disadvantageous inequity aversion. Importantly, both variants result in different behavior, supported by different neural processes (Gao et al. 2018). Advantageous inequity aversion requires sacrifices of own gains in order to balance the scales, associated with stronger activation in regions typically involved in social cognition, i.e., the AI, dmPFC and dlPFC. In contrast, disadvantageous inequity aversion results in behavior that minimizes benefits of others to level the playing field, supported by regions involved

public good: a commodity available to all

social dilemma: a situation that creates a conflict between the individual's interests and the collective's interests

free rider problem: occurs when those who benefit from public goods do not pay for them or under-pay

distributional preference: decision-making under an other-regarding utility, with actions depending on one's own material payoff and the (material) payoffs of other agents in emotion and conflict resolution, i.e., the dorsal ACC, amygdala, and left posterior insula (Gao et al. 2018). Thus, motives for engaging in pro-environmental behavior may exceed intrinsic factors, also including economic circumstances, with critical implications for policy design.

The economic concept of distributional preferences is closely linked to altruism and the concern for others (Menges et al. 2005), thus touching on central topics in the field of social neuroscience. While pro-environmental actions may also stem from less compassionate motives such as peer-pressure (Guagnano 2001), recent studies associate altruism with sustainable behaviors (Xu et al. 2021, Knez 2016). Corresponding neuroeconomic studies suggest that engaging in altruistic behaviors recruits regions associated with empathy and social cognition (the temporoparietal junction, TPJ), value integration and cost-benefit estimation (vmPFC, dmPFC), basic emotions and drives (VS, ACC; see Filkowski et al. 2016, for a review).

Harbaugh et al. demonstrate increased activation of reward-related brain regions (including, e.g., VS, bilateral caudate, and bilateral insula) not just for receiving money oneself, but also when money goes to a charitable purpose. Strikingly, the strength of brain activation indicated the likelihood of donating, and participants with increased responses reported higher subjective satisfaction upon making a donation (Harbaugh et al. 2007). From a network perspective, fMRI results demonstrate interactions between involved brain regions, thus emphasizing the interplay of associated processes. For instance, making charitable donations triggers correlated signals in the TPJ, involved in social cognition, and vmPFC, associated with cost-benefit evaluation (Hare et al. 2010). Moreover, individual differences in behavioral altruism are linked to both structure and function of right TPJ (Morishima et al. 2012), further highlighting the importance of social cognitive processing for altruistic decision-making.

Recently, stimulation studies using TMS and tDCS identified differential contributions of prefrontal and temporoparietal regions during altruistic behavior. Stimulating medial prefrontal cortex induced a boost in altruistic behavior in situations of disadvantageous inequality (Liao et al. 2018, Zhang et al. 2022), while the right TPJ may be more relevant in advantageous inequality (Zhang et al. 2022). In line with this latter notion, recent evidence points towards a crucial role of the TPJ for engaging in sustainable behaviors that have strong cooperative aspects (Langenbach et al. 2022). Specifically, Langenbach et al. let participants play a fishing game and could maximize their own outcome at the expense of following generations and the virtual environment. In this setting, stimulating TPJ via tDCS increases sustainable fishing that – simultaneously – benefits subsequent players.

Crucially, group-level models incorporate individual-level behavioral phenomena. For example, pro-environmental behavior typically involves trading-off individual gains for collective benefits. However risky outcomes and uncertainty among cooperators hinders cooperation behavior (Raihani & Aitken 2011). Effective policies to mitigate global environmental crises need to foster cooperation, accounting for both uncertainty and irrational responses that may inhibit collective action.

3.2.2. A strong social motivator: the "warm glow" of giving. What motivates people to engage in pro-social behavior? Participants commonly report feelings of higher subjective satisfaction, e.g., upon making charitable donations (Harbaugh et al. 2007), but also in expectation of engaging in sustainable behavior (Van der Linden 2018).

Recent evidence from over 800 consumers in Germany suggests this positive affect –

often referred to as a “warm glow” – to be a strong motivator for action for specific subgroups of the population, and specific types of action (Iweala et al. 2022, Van der Linden 2018). For instance, while the “warm glow” effect translates to higher WTP only in older, more affluent, respondents, Iweala et al. demonstrate that pro-environmental causes induce positive affect just as much as prosocial causes. Zooming in on concrete sustainable behaviors, “warm glow” seems to be a main driver of simple and small everyday actions (like switching off lights), rather than more-involved behaviors (like buying energy from sustainable sources; Van der Linden 2018). Importantly, the role of “warm glow” appears to go beyond a simple mediator of altruism, strongly motivating pro-environmental behavior as an emotional reward (Hartmann et al. 2017). In line with this view, Harbaugh et al. demonstrate that reward related brain regions (including, e.g., VS) show increased activation for donating to a charity. Strikingly, the strength of brain activation indicates the likelihood of donating, and is related to higher subjective satisfaction (Harbaugh et al. 2007). It remains to be shown whether similar neural processes also mediate positive affect induced by pro-environmental causes.

Policy-makers may capitalize on this preliminary evidence of “warm glow” as an intrinsic social motivator for people who can financially afford to act sustainably (Iweala et al. 2022) in low-cost situations (Van der Linden 2018).

3.2.3. Social norms and social identities. Besides intrinsic drives, extrinsic social motivators influence sustainable action. Considerable behavioral evidence suggests a large impact of norms ascribing “what others do” and “what others think one should do” on individual behavior (see Cialdini & Jacobson 2021, for a review). Field investigations suggest that social norms affect how individuals value incentives, impacting decisions to cooperate or over-extract common-pool resources (Cardenas 2011). Consequently, an effective strategy for promoting green behavior may be to make it a social norm (Kraft-Todd et al. 2015).

However, social norms are no panacea for unsustainable behavior. First, their effectiveness strongly depends on a norm’s alignment with individual social identities: messages in line with norm perceptions of the own reference group have substantial positive impact – but may be rejected if they stand in contrast with the personal in-group (Cialdini & Jacobson 2021). This challenges the effectiveness of group-based interventions, an area with ample room for future research (Masson & Fritsche 2021). Second, if social norms are effective, how to explain gaps between ideal and actual consumer behavior? Consumers commonly report to prefer green products, at odds with their factual purchase behavior (Eurobarometer 2008). To investigate this curious disparity, Vezich et al. analyzed MRI data from participants viewing green and conventional advertisements. While rating green advertisements – as the more socially acceptable ones – more favourably, participant’s brain data revealed greater activation in reward-related regions (vmPFC, and VS) in response to conventional ads. Consequently, self-reports may be confounded by the desire to show socially desirable behavior, not affecting the actual decision process.

3.3. Institutional level

Ideally, scientific insights inform institutional decision-making, e.g., as viable guidelines and policy suggestions. For instance, based on seminal field experimental evidence, Nobel laureate Ostrom formulates suggestions such as placing common resources under management of communities that maximally benefit from them, accompanied by local regulation. Further,

ACTIONABLE ITEMS, SOCIAL GROUP LEVEL EVIDENCE

- Social motives for engaging in pro-environmental behavior include altruism, the concern for others, or establishing social equity - with critical implications for design and effectiveness of policy (Xu et al. 2021, Knez 2016, Cai et al. 2010).
- Effective policies mitigating global environmental crises may benefit from incorporating mechanisms that foster cooperation, if accounting for both uncertainty and irrational responses that may inhibit collective action (Venmans & Groom 2021).
- Policy-makers may capitalize on "warm glow" as a social motivator, leveraging individual intrinsic motivation of people in low-cost situations, who can financially afford to act sustainably (Iweala et al. 2022, Van der Linden 2018).

her basic requirements for sustainable human-resource systems include appropriate infrastructure, advanced technologies unlocking accurate and relevant information, and raised awareness for continuous adaptation and long-term change (Ostrom 2008).

Overall, the institutional level behavioral literature is rich on suggestions and theoretical frameworks like these, but lacks empirical evidence. A wealth of theoretical literature incorporates behavioral phenomena into policy design and evaluation (e.g., integrating temporal discounting in environmental policy, Hepburn et al. 2010). Likewise, abundant recommendations for policy-makers on applications of multiple behavioral principles (e.g., environmental-transport policy, Hepburn et al. 2010), strategies to integrate behavioral science in climate models (Fischhoff 2021), and effective climate education (Ranney & Velautham 2021), exist. However, these numerous drafts of state-of-the-art, scientifically informed interventions seldomly find their way into actual practice.

Consequently, effectiveness of behavioral interventions in environmental public policy is still in its infancy. First evidence suggests that information and attention campaigns positively affect energy consumption (Reiss & White 2008) and the market share of green energy (Litvine & Wüstenhagen 2011). Ölander & Thøgersen showed how targeted nudges based on gain-loss framing, default options, and social norms may increase sustainable energy choices (Ölander & Thøgersen 2014). Conversely, a recent survey in India failed to demonstrate a meaningful impact of government influence on individual green knowledge (Sreen et al. 2020). Similarly, adverse effects of incentives have been reported, indicating common problems of flawed policy design (Bowles & Polania-Reyes 2012). Further, it is yet unclear whether habituation over time may diminish initially positive effects of interventions. Encouraging preliminary evidence suggests that reductions in energy consumption persist even after an intervention's end (Allcott & Rogers 2014), contesting detrimental habituation. Still, there is ample room for future research to explore temporal stability of interventions and their potential for wider application.

4. WHERE DO WE GO FROM HERE? FUTURE OPPORTUNITIES

The advent of interdisciplinary and experimental approaches uncovers how humans value environmental resource, which aspects may be particularly salient, and where to expect

ACTIONABLE ITEMS, INSTITUTIONAL LEVEL EVIDENCE

- Numerous recommendations for state-of-the-art, scientifically informed green interventions exist (Ostrom 2008, Hepburn et al. 2010, Fischhoff 2021, Ranney & Velautham 2021) - it is high time for bringing them into actual practice.
- Behavioral and neuroscientists need more opportunities to work jointly with policymakers to inform interventions that leverage our knowledge of human mind.
- Collaboration beyond the own ’home’ discipline is necessary to account for the complexity of human behavior. This will allow to build up the bulk of much-needed evidence on what behavioral interventions work for environmental outcomes and why (Sreen et al. 2020, Bowles & Polania-Reyes 2012, Allcott & Rogers 2014).

barriers to green action. Going forward, we may continue to leverage the unique potential of experimental economics, harnessing incentive-compatible elicitations in contrast to less reliable self-reports. Similarly, applying neuroeconomic methodology to aspects of environmental valuation promises a more direct view into the human mind.

4.1. Advanced technologies will expand current boundaries

While behavioral economics aims to explain deviations of individual behavior from expected utility theory (Kahneman & Tversky 2013), current models generalize poorly to specific situations and individual heterogeneity (Gifford & Nilsson 2014). Modern techniques, especially artificial intelligence and machine learning (ML), open up new opportunities to approach complex, non-linear dynamics, thus accounting for influential but mutually dependent factors of human decision-making. For instance, ML ensemble technologies leverage linear models to predict nonlinear demand more precisely. (Bajari et al. 2015). Big data practices enable improved analyses of heterogeneous trace-data from game-based assessment (Auer et al. 2022). Moreover, modern ML provides opportunities to exploit naturally occurring data. Social media and information available on the internet characterizing human behavior in realistic settings. As these data are widely unstructured, state-of-the-art natural language processing technologies and image analysis tools constitute crucial prerequisites to automatically access these invaluable sources of information (Vaswani et al. 2017, Chai et al. 2021).

Yet, artificial intelligence does not only provide powerful analysis tools, it may also severely influence human decision-making: by providing rich information from big data sources in human-accessible form, modern technologies reduce information asymmetry, thus supporting more transparent and rational decision-making (Rasetti 2020). ML-based agents interacting with humans make autonomous decisions, directly influencing choice dynamics and human behavior (Parkes & Wellman 2015).

Despite their promise, a word of caution is unavoidable: artificial intelligence models often act as “black boxes”, vulnerable to unexpected attacks or adversarial behavior (Subrahmanian & Kumar 2017). Further, they directly mirror biases present in data used for training, leading to decisions that might be at odds with human moral values (Mehrabi et al. 2021). Last, limited public availability of critical ML-models may foster asymmetrical economic power and unfairness (Luitse & Denkena 2021). The potentially broad impact of these factors calls for suitable regulations of artificial intelligence technology(Huang et al. 2021).

4.2. Word of caution: i-frame vs s-frame

A rising concern among behavioral economists concerns the focus of interventions. Chater & Loewenstein criticize that current interventions predominantly address changes in individual behavior (referred to as "i-frame"), rather than changes of the system in which they operate, such as regulation or taxation (an "s-frame"). Critically, providing small i-frame interventions may crowd out people's support for more effective, system-level policies (Werfel 2017, Hagmann et al. 2019). Serving the interests of corporations, this may convey the false hope of small steps being enough, deflecting from wider, costlier, and much more effective, policies.

Going forward, scientists need to heed this discrepancy of falsely valuing individual over government action, and consider the potential for system-level change in their investigations.

5. THE TIME IS RIPE FOR ACTION

The dramatic effects of climate change become a dangerous reality for more and more humans on earth. Consequently, we live in a time with unprecedented international awareness for environmental issues, and demand for effective environmental policy. In fact, all member states of the United Nations adopted the 2030 Agenda for Sustainable Development (Desa et al. 2016), committing themselves to a transformative vision for environmental, economic, and social development. It is of vital importance to use this momentum to enrich policies with scientifically grounded insights to make an impact now and fast.

While the time is ripe for policy action, it is also ripe for much more concentrated research efforts. We report larger trends and preliminary lessons emerging from behavioral and neuroeconomic studies, however, very little is known regarding the potential and efficacy of policy interventions at much larger scales and more economically involved domains (Velez & Moros 2021).

Integrating behavioral and neuroeconomic findings paves the way for more comprehensive and powerful economic models, providing economists with the means to answer fundamental questions that have so far been inaccessible.The evidence presented in this work – together with ample work distilling human-grounded recommendations for policy-makers (Ostrom 2008, Hepburn et al. 2010, Fischhoff 2021, Ranney & Velautham 2021) – gives clear pointers for suitable action. This includes accounting for inter- and intra-individual particularities of individuals (e.g., individual economic circumstance), fostering cooperation, leveraging intrinsic motivations and extrinsic social drives.

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LITERATURE CITED

Allcott H, Rogers T. 2014. The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review* 104(10):3003–37

Alpizar F, Carlsson F, Naranjo MA. 2011. The effect of ambiguous risk, and coordination on farmers' adaptation to climate change—a framed field experiment. *Ecological Economics* 70(12):2317–2326

Anderson B, Bernauer T, Balietti S. 2017. Effects of fairness principles on willingness to pay for climate change mitigation. *Climatic Change* 142(3):447–461

Auer E, Mersy G, Marin S, Blaik J, Landers R. 2022. Using machine learning to model trace behavioral data from a game-based assessment. *International Journal of Selection and Assessment* 30(1):82–102Funding Information: Participant payments in this study were funded by Revelian Pty Ltd. Publisher Copyright: © 2021 John Wiley & Sons Ltd.

Bajari P, Nekipelov D, Ryan SP, Yang M. 2015. Machine learning methods for demand estimation. *American Economic Review* 105(5):481–85

Ballard K, Knutson B. 2009. Dissociable neural representations of future reward magnitude and delay during temporal discounting. *NeuroImage* 45(1):143–150

Bechara A, Damasio AR. 2005. The somatic marker hypothesis: A neural theory of economic decision. *Games and economic behavior* 52(2):336–372

Bergquist M. 2020. Most people think they are more pro-environmental than others: A demonstration of the better-than-average effect in perceived pro-environmental behavioral engagement. *Basic and Applied Social Psychology* 42(1):50–61

Bodur M, Sarigöllü E. 2005. Environmental sensitivity in a developing country: consumer classification and implications. *Environment and Behavior* 37(4):487–510

Boeri M, Longo A. 2017. The importance of regret minimization in the choice for renewable energy programmes: Evidence from a discrete choice experiment. *Energy Economics* 63:253–260

Bolton TA, Morgenroth E, Preti MG, Van De Ville D. 2020. Tapping into multi-faceted human behavior and psychopathology using fmri brain dynamics. *Trends in Neurosciences* 43(9):667–680

Bowles S, Polania-Reyes S. 2012. Economic incentives and social preferences: substitutes or complements? *Journal of Economic Literature* 50(2):368–425

Brevers D, Baeken C, Maurage P, Sescousse G, Vögele C, Billieux J. 2021. Brain mechanisms underlying prospective thinking of sustainable behaviours. *Nature Sustainability* 4(5):433–439

Brosch T. 2021. Affect and emotions as drivers of climate change perception and action: A review. *Current Opinion in Behavioral Sciences* 42:15–21

Brown JW, Alexander WH. 2017. Foraging value, risk avoidance, and multiple control signals: How the anterior cingulate cortex controls value-based decision-making. *Journal of Cognitive Neuroscience* 29(10):1656–1673

Cai B, Cameron TA, Gerdes GR. 2010. Distributional preferences and the incidence of costs and benefits in climate change policy. *Environmental and Resource Economics* 46(4):429–458

Camille N, Coricelli G, Sallet J, Pradat-Diehl P, Duhamel JR, Sirigu A. 2004. The involvement of the orbitofrontal cortex in the experience of regret. *Science* 304(5674):1167–1170

Cardenas JC. 2011. Social norms and behavior in the local commons as seen through the lens of field experiments. *Environmental and Resource Economics* 48(3):451–485

Carrico AR. 2021. Climate change, behavior, and the possibility of spillover effects: recent advances and future directions. *Current Opinion in Behavioral Sciences* 42:76–82

Catani M, Dell'Acqua F, Thiebaut de Schotten M. 2013. A revised limbic system model for memory, emotion and behaviour. *Neuroscience & Biobehavioral Reviews* 37(8):1724–1737

Chai J, Zeng H, Li A, Ngai EW. 2021. Deep learning in computer vision: A critical review of emerging techniques and application scenarios. *Machine Learning with Applications* 6:100134

Chan HW, Pong V, Tam KP. 2019. Cross-national variation of gender differences in environmental concern: Testing the sociocultural hindrance hypothesis. *Environment and Behavior* 51(1):81–108

Charness G, Gneezy U, Imas A. 2013. Experimental methods: Eliciting risk preferences. *Journal of economic behavior & organization* 87:43–51

Charness G, Rabin M. 2002. Understanding social preferences with simple tests. *The quarterly journal of economics* 117(3):817–869

Chater N, Loewenstein G. 2022. The i-frame and the s-frame: How focusing on the individual-level solutions has led behavioral public policy astray. *Available at SSRN 4046264*

Chen Y. 2008. Incentive-compatible mechanisms for pure public goods: A survey of experimental research. *Handbook of experimental economics results* 1:625–643

Chi YM, Wang Y, Wang YT, Jung TP, Kerth T, Cao Y. 2013. A practical mobile dry eeg system for human computer interfaces, In *International Conference on Augmented Cognition*, pp. 649–655, Springer

Chorus CG. 2010. A new model of random regret minimization. *European Journal of Transport and Infrastructure Research* 10(2)

Cialdini RB, Jacobson RP. 2021. Influences of social norms on climate change-related behaviors. *Current Opinion in Behavioral Sciences* 42:1–8

Clot S, Stanton CY. 2014. Present bias predicts participation in payments for environmental services: Evidence from a behavioral experiment in uganda. *Ecological Economics* 108:162–170

Coricelli G, Critchley HD, Joffily M, O'Doherty JP, Sirigu A, Dolan RJ. 2005. Regret and its avoidance: a neuroimaging study of choice behavior. *Nature neuroscience* 8(9):1255–1262

Coricelli G, Dolan RJ, Sirigu A. 2007. Brain, emotion and decision making: the paradigmatic example of regret. *Trends in cognitive sciences* 11(6):258–265

Deryugina T. 2013. How do people update? the effects of local weather fluctuations on beliefs about global warming. *Climatic change* 118(2):397–416

Desa U, et al. 2016. Transforming our world: The 2030 agenda for sustainable development

Dolnicar S, Grün B. 2009. Environmentally friendly behavior: Can heterogeneity among individuals and contexts/environments be harvested for improved sustainable management? *Environment and behavior* 41(5):693–714

Dugré JR, Dumais A, Bitar N, Potvin S. 2018. Loss anticipation and outcome during the monetary incentive delay task: a neuroimaging systematic review and meta-analysis. *PeerJ* 6:e4749

Dunn BD, Dalgleish T, Lawrence AD. 2006. The somatic marker hypothesis: A critical evaluation. *Neuroscience & Biobehavioral Reviews* 30(2):239–271

Durante R, Putterman L, Van der Weele J. 2014. Preferences for redistribution and perception of fairness: An experimental study. *Journal of the European Economic Association* 12(4):1059–1086

Eklund A, Nichols TE, Knutsson H. 2016. Cluster failure: Why fmri inferences for spatial extent have inflated false-positive rates. *Proceedings of the national academy of sciences* 113(28):7900–7905

Elliott ML, Knodt AR, Ireland D, Morris ML, Poulton R, et al. 2020. What is the test-retest reliability of common task-functional mri measures? new empirical evidence and a meta-analysis. *Psychological Science* 31(7):792–806

Engelmann JB, Meyer F, Fehr E, Ruff CC. 2015. Anticipatory anxiety disrupts neural valuation during risky choice. *Journal of Neuroscience* 35(7):3085–3099

Eurobarometer S. 2008. Attitudes of european citizens towards the environment. *European Commission* 295

Fanariotu IN, Skuras D. 2004. The contribution of scenic beauty indicators in estimating environ-

mental welfare measures: A case study. *Social Indicators Research* 65:145–165
Fehr E, Schmidt KM. 1999. A theory of fairness, competition, and cooperation. *The quarterly journal of economics* 114(3):817–868
Filkowski MM, Cochran RN, Haas BW. 2016. Altruistic behavior: Mapping responses in the brain. *Neuroscience and neuroeconomics* 5:65
Fischhoff B. 2021. Making behavioral science integral to climate science and action. *Behavioural Public Policy* 5(4):439–453
Galizzi MM, Navarro-Martinez D. 2019. On the external validity of social preference games: a systematic lab-field study. *Management Science* 65(3):976–1002
Gao X, Yu H, Sáez I, Blue PR, Zhu L, et al. 2018. Distinguishing neural correlates of context-dependent advantageous-and disadvantageous-inequity aversion. *Proceedings of the National Academy of Sciences* 115(33):E7680–E7689
Gifford R, Nilsson A. 2014. Personal and social factors that influence pro-environmental concern and behaviour: A review. *International journal of psychology* 49(3):141–157
Gray SG, Raimi KT, Wilson R, Árvai J. 2019. Will millennials save the world? the effect of age and generational differences on environmental concern. *Journal of environmental management* 242:394–402
Guagnano GA. 2001. Altruism and market-like behavior: An analysis of willingness to pay for recycled paper products. *Population and Environment* 22(4):425–438
Haber SN, Knutson B. 2010. The reward circuit: linking primate anatomy and human imaging. *Neuropsychopharmacology* 35(1):4–26
Hagmann D, Ho EH, Loewenstein G. 2019. Nudging out support for a carbon tax. *Nature Climate Change* 9(6):484–489
Hanemann WM. 1994. Valuing the environment through contingent valuation. *Journal of economic perspectives* 8(4):19–43
Hansson H, Lagerkvist CJ. 2012. Measuring farmers' preferences for risk: a domain-specific risk preference scale. *Journal of Risk Research* 15(7):737–753
Harbaugh WT, Mayr U, Burghart DR. 2007. Neural responses to taxation and voluntary giving reveal motives for charitable donations. *Science* 316(5831):1622–1625
Hardisty DJ, Weber EU. 2009. Discounting future green: money versus the environment. *Journal of Experimental Psychology: General* 138(3):329
Hare TA, Camerer CF, Knoepfle DT, O'Doherty JP, Rangel A. 2010. Value computations in ventral medial prefrontal cortex during charitable decision making incorporate input from regions involved in social cognition. *Journal of Neuroscience* 30(2):583–590
Harrison GW. 2008. Neuroeconomics: A critical reconsideration. *Economics & Philosophy* 24(3):303–344
Harrison GW, List JA. 2004. Field experiments. *Journal of Economic literature* 42(4):1009–1055
Hartmann P, Eisend M, Apaolaza V, D'Souza C. 2017. Warm glow vs. altruistic values: How important is intrinsic emotional reward in proenvironmental behavior? *Journal of Environmental Psychology* 52:43–55
He Q, Chen M, Chen C, Xue G, Feng T, Bechara A. 2016. Anodal stimulation of the left dlpfc increases igt scores and decreases delay discounting rate in healthy males. *Frontiers in Psychology* 7:1421
Heal G, Millner A. 2018. Uncertainty and ambiguity in environmental economics: conceptual issues. In *Handbook of environmental economics*, vol. 4. Elsevier, 439–468
Hepburn C, Duncan S, Papachristodoulou A. 2010. Behavioural economics, hyperbolic discounting and environmental policy. *Environmental and Resource Economics* 46(2):189–206
Herreras O. 2016. Local field potentials: myths and misunderstandings. *Frontiers in neural circuits* 10:101
Hsu M, Bhatt M, Adolphs R, Tranel D, Camerer CF. 2005. Neural Systems Responding to Degrees of Uncertainty in Human Decision-Making. *Science* 310(5754):1680–1683

Huang JY, Gupta A, Youn M. 2021. Survey of eu ethical guidelines for commercial ai: case studies in financial services. *AI and Ethics* 1(4):569–577

Iweala S, Spiller A, Nayga Jr RM, Lemken D. 2022. Warm glow and consumers' valuation of ethically certified products. *Q Open* 2(2):qoac020

Izuma K, Saito DN, Sadato N. 2008. Processing of social and monetary rewards in the human striatum. *Neuron* 58(2):284–294

Jang H, Lin Z, Lustig C. 2020. Losing money and motivation: Effects of loss incentives on motivation and metacognition in younger and older adults. *Frontiers in psychology* 11:1489

Kable JW, Glimcher PW. 2007. The neural correlates of subjective value during intertemporal choice. *Nature neuroscience* 10(12):1625–1633

Kahneman D, Tversky A. 2013. Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making: Part I*. World Scientific, 99–127

Khaw MW, Grab DA, Livermore MA, Vossler CA, Glimcher PW. 2015. The measurement of subjective value and its relation to contingent valuation and environmental public goods. *PloS one* 10(7):e0132842

Knez I. 2016. Is climate change a moral issue? effects of egoism and altruism on pro-environmental behavior. *Current Urban Studies* 4(2):157–174

Knight FH. 1921. Risk, uncertainty and profit, vol. 31. Houghton Mifflin

Knutson B, Fong GW, Adams CM, Varner JL, Hommer D. 2001. Dissociation of reward anticipation and outcome with event-related fmri. *Neuroreport* 12(17):3683–3687

Kraft-Todd G, Yoeli E, Bhanot S, Rand D. 2015. Promoting cooperation in the field. *Current Opinion in Behavioral Sciences* 3:96–101

Kurth F, Zilles K, Fox PT, Laird AR, Eickhoff SB. 2010. A link between the systems: functional differentiation and integration within the human insula revealed by meta-analysis. *Brain Structure and Function* 214(5):519–534

Langenbach BP, Savic B, Baumgartner T, Wyss AM, Knoch D. 2022. Mentalizing with the future: Electrical stimulation of the right tpj increases sustainable decision-making. *cortex* 146:227–237

Lee EJ, Kwon G, Shin HJ, Yang S, Lee S, Suh M. 2014. The spell of green: Can frontal eeg activations identify green consumers? *Journal of business ethics* 122(3):511–521

Levens SM, Larsen JT, Bruss J, Tranel D, Bechara A, Mellers BA. 2014. What might have been? the role of the ventromedial prefrontal cortex and lateral orbitofrontal cortex in counterfactual emotions and choice. *Neuropsychologia* 54:77–86

Liao C, Wu S, Luo Yj, Guan Q, Cui F. 2018. Transcranial direct current stimulation of the medial prefrontal cortex modulates the propensity to help in costly helping behavior. *Neuroscience Letters* 674:54–59

Linder NS, Uhl G, Fliessbach K, Trautner P, Elger CE, Weber B. 2010. Organic labeling influences food valuation and choice. *NeuroImage* 53(1):215–220

List JA, Price MK. 2013. Handbook on experimental economics and the environment. Edward Elgar Publishing

Litvine D, Wüstenhagen R. 2011. Helping" light green" consumers walk the talk: Results of a behavioural intervention survey in the swiss electricity market. *Ecological Economics* 70(3):462–474

Loewenstein G. 1999. Experimental economics from the vantage-point of behavioural economics. *The Economic Journal* 109(453):F25–F34

Logothetis NK, Pauls J, Augath M, Trinath T, Oeltermann A. 2001. Neurophysiological investigation of the basis of the fmri signal. *nature* 412(6843):150–157

Lonati S, Quiroga BF, Zehnder C, Antonakis J. 2018. On doing relevant and rigorous experiments: Review and recommendations. *Journal of Operations Management* 64:19–40

Loomes G, Sugden R. 1982. Regret theory: An alternative theory of rational choice under uncertainty. *The economic journal* 92(368):805–824

López-Mosquera N, Sánchez M. 2011. Emotional and satisfaction benefits to visitors as explanatory factors in the monetary valuation of environmental goods. an application to periurban green spaces. *Land Use Policy* 28(1):151–166

Luitse D, Denkena W. 2021. The great transformer: Examining the role of large language models in the political economy of ai. *Big Data & Society* 8(2):20539517211047734

Luo Y, Zhao J. 2021. Attentional and perceptual biases of climate change. *Current Opinion in Behavioral Sciences* 42:22–26

Mao B, Ao C, Wang J, Sun B, Xu L. 2020. Does regret matter in public choices for air quality improvement policies? a comparison of regret-based and utility-based discrete choice modelling. *Journal of Cleaner Production* 254:120052

Masson T, Fritsche I. 2021. We need climate change mitigation and climate change mitigation needs the 'we': A state-of-the-art review of social identity effects motivating climate change action. *Current opinion in behavioral sciences* 42:89–96

McClure SM, Ericson KM, Laibson DI, Loewenstein G, Cohen JD. 2007. Time Discounting for Primary Rewards. *Journal of Neuroscience* 27(21):5796–5804

Mehrabi N, Morstatter F, Saxena N, Lerman K, Galstyan A. 2021. A survey on bias and fairness in machine learning. *ACM Comput. Surv.* 54(6)

Menges R, Schroeder C, Traub S. 2005. Altruism, warm glow and the willingness-to-donate for green electricity: an artefactual field experiment. *Environmental and Resource Economics* 31(4):431–458

Michel CM, Murray MM. 2012. Towards the utilization of eeg as a brain imaging tool. *Neuroimage* 61(2):371–385

Milfont TL, Duckitt J, Cameron LD. 2006. A cross-cultural study of environmental motive concerns and their implications for proenvironmental behavior. *Environment and Behavior* 38(6):745–767

Mohr PN, Biele G, Heekeren HR. 2010. Neural processing of risk. *Journal of Neuroscience* 30(19):6613–6619

Morishima Y, Schunk D, Bruhin A, Ruff CC, Fehr E. 2012. Linking brain structure and activation in temporoparietal junction to explain the neurobiology of human altruism. *Neuron* 75(1):73–79

Moser AK. 2016. Buying organic–decision-making heuristics and empirical evidence from germany. *Journal of Consumer Marketing* 33(7):552–561

Mullainathan S, Thaler RH. 2000. Behavioral economics

Murray EA. 2007. The amygdala, reward and emotion. *Trends in cognitive sciences* 11(11):489–497

Nisbet EK, Zelenski JM. 2011. Underestimating nearby nature: Affective forecasting errors obscure the happy path to sustainability. *Psychological science* 22(9):1101–1106

Ölander F, Thøgersen J. 2014. Informing versus nudging in environmental policy. *Journal of Consumer Policy* 37(3):341–356

Ostrom E. 1990. Governing the commons: The evolution of institutions for collective action. Cambridge university press

Ostrom E. 2008. The challenge of common-pool resources. *Environment: Science and Policy for Sustainable Development* 50(4):8–21

Parkes DC, Wellman MP. 2015. Economic reasoning and artificial intelligence. *Science* 349(6245):267–272

Patt AG, Schrag DP. 2003. Using specific language to describe risk and probability. *Climatic change* 61(1):17–30

Persky J. 1995. The ethology of homo economicus. *Journal of Economic Perspectives* 9(2):221–231

Poldrack RA, Farah MJ. 2015. Progress and challenges in probing the human brain. *Nature* 526(7573):371–379

Priori A, Berardelli A, Rona S, Accornero N, Manfredi M. 1998. Polarization of the human motor cortex through the scalp. *Neuroreport* 9(10):2257–2260

Raihani N, Aitken D. 2011. Uncertainty, rationality and cooperation in the context of climate change. *Climatic Change* 108(1):47–55

Rakotonarivo OS, Schaafsma M, Hockley N. 2016. A systematic review of the reliability and validity of discrete choice experiments in valuing non-market environmental goods. *Journal of environmental management* 183:98–109

Ranney MA, Velautham L. 2021. Climate change cognition and education: given no silver bullet for denial, diverse information-hunks increase global warming acceptance. *Current Opinion in Behavioral Sciences* 42:139–146

Rasetti M. 2020. The new frontiers of ai in the arena of behavioral economics. *Mind & Society* 19(1):5–9

Reiss PC, White MW. 2008. What changes energy consumption? prices and public pressures. *The RAND Journal of Economics* 39(3):636–663

Richards TJ, Green GP. 2015. Environmental choices and hyperbolic discounting: an experimental analysis. *Environmental and Resource Economics* 62(1):83–103

Sawe N, Chawla K. 2021. Environmental neuroeconomics: how neuroscience can inform our understanding of human responses to climate change. *Current Opinion in Behavioral Sciences* 42:147–154

Sawe N, Knutson B. 2015. Neural valuation of environmental resources. *Neuroimage* 122:87–95

Schkade DA, Payne JW. 1994. How people respond to contingent valuation questions: a verbal protocol analysis of willingness to pay for an environmental regulation. *Journal of Environmental Economics and Management* 26(1):88–109

Serra D. 2021. Decision-making: from neuroscience to neuroeconomics—an overview. *Theory and Decision* 91(1):1–80

Shamosh NA, DeYoung CG, Green AE, Reis DL, Johnson MR, et al. 2008. Individual differences in delay discounting: relation to intelligence, working memory, and anterior prefrontal cortex. *Psychological science* 19(9):904–911

Sreen N, Yadav R, Kumar S, Gleim M. 2020. The impact of the institutional environment on green consumption in india. *Journal of Consumer Marketing*

Stoop J, Noussair CN, Van Soest D. 2012. From the lab to the field: Cooperation among fishermen. *Journal of Political Economy* 120(6):1027–1056

Subrahmanian V, Kumar S. 2017. Predicting human behavior: The next frontiers. *Science (New York, N.Y.)* 355(6324):489

Tricomi E, Rangel A, Camerer CF, O'Doherty JP. 2010. Neural evidence for inequality-averse social preferences. *Nature* 463(7284):1089–1091

Tunçel T, Hammitt JK. 2014. A new meta-analysis on the wtp/wta disparity. *Journal of Environmental Economics and Management* 68(1):175–187

Vaidya AR, Pujara MS, Petrides M, Murray EA, Fellows LK. 2019. Lesion studies in contemporary neuroscience. *Trends in cognitive sciences* 23(8):653–671

Van der Linden S. 2018. Warm glow is associated with low-but not high-cost sustainable behaviour. *Nature Sustainability* 1(1):28–30

van Dijk E, De Dreu CK. 2021. Experimental games and social decision making. *Annual Review of Psychology* :415–438

Van Doorn J, Verhoef PC. 2011. Willingness to pay for organic products: Differences between virtue and vice foods. *International Journal of Research in Marketing* 28(3):167–180

Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, et al. 2017. Attention is all you need, In *Advances in Neural Information Processing Systems*, eds. I Guyon, UV Luxburg, S Bengio, H Wallach, R Fergus, S Vishwanathan, R Garnett, vol. 30. Curran Associates, Inc.

Vedder A, Smigielski L, Gutyrchik E, Bao Y, Blautzik J, et al. 2015. Neurofunctional correlates of environmental cognition: an fmri study with images from episodic memory. *PloS one* 10(4):e0122470

Velez MA, Moros L. 2021. Have behavioral sciences delivered on their promise to influence environmental policy and conservation practice? *Current Opinion in Behavioral Sciences* 42:132–138

Venmans F, Groom B. 2021. Social discounting, inequality aversion, and the environment. *Journal of Environmental Economics and Management* 109:102479

Vezich IS, Gunter BC, Lieberman MD. 2017. The mere green effect: An fmri study of pro-environmental advertisements. *Social Neuroscience* 12(4):400–408

Wang Y, Hao F, Liu Y. 2021. Pro-environmental behavior in an aging world: Evidence from 31 countries. *International Journal of Environmental Research and Public Health* 18(4):1748

Weber EU. 2010. What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change* 1(3):332–342

Weber EU, Blais AR, Betz NE. 2002. A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of behavioral decision making* 15(4):263–290

Welsch H, Kühling J. 2009. Using happiness data for environmental valuation: issues and applications. *Journal of Economic Surveys* 23(2):385–406

Werfel SH. 2017. Household behaviour crowds out support for climate change policy when sufficient progress is perceived. *Nature Climate Change* 7(7):512–515

Werthschulte M, Löschel A. 2021. On the role of present bias and biased price beliefs in household energy consumption. *Journal of Environmental Economics and Management* 109:102500

Xu Y, Li W, Chi S. 2021. Altruism, environmental concerns, and pro-environmental behaviors of urban residents: a case study in a typical chinese city. *Frontiers in Psychology* :1917

Zeelenberg M, Beattie J, Van der Pligt J, De Vries NK. 1996. Consequences of regret aversion: Effects of expected feedback on risky decision making. *Organizational behavior and human decision processes* 65(2):148–158

Zeelenberg M, Pieters R. 2007. A theory of regret regulation 1.0. *Journal of Consumer psychology* 17(1):3–18

Zhang H, Dong Z, Cai S, Zhao J. 2022. Distinguishing the roles of the dorsomedial prefrontal cortex and right temporoparietal junction in altruism in situations of inequality: A tdcs study. *Frontiers in human neuroscience* :126

Zheng Y, Liu X. 2015. Blunted neural responses to monetary risk in high sensation seekers. *Neuropsychologia* 71:173–180

Zhengwu P, Cuihong Z, Shanshan X, Jie B, Shoufen Y, et al. 2018. Mechanism of repetitive transcranial magnetic stimulation for depression. *Shanghai archives of psychiatry* 30(2):84